THE ROLE OF THE GOVERNANCE ECOSYSTEM IN AI-DRONE ADOPTION FOR SAFETY IN THE MALAYSIAN CONSTRUCTION INDUSTRY

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APPROVAL SHEET

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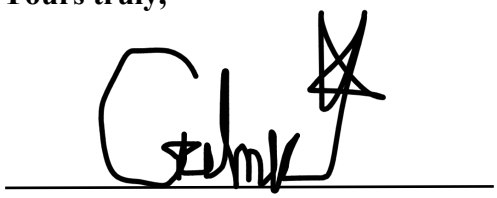
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DECLARATION

I hereby declare that this project report is based on my original work except for citations duly I also declare that it has citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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THE ROLE OF THE GOVERNANCE ECOSYSTEM IN AI-DRONE ADOPTION FOR SAFETY IN THE MALAYSIAN CONSTRUCTION INDUSTRY

BY

SRIASHWIN A/L VEERAPANDIAN

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ABSTRACT

THE ROLE OF THE GOVERNANCE ECOSYSTEM IN AI-DRONE ADOPTION FOR SAFETY IN THE MALAYSIAN CONSTRUCTION INDUSTRY

SRIASHWIN A/L VEERAPANDIAN

The Malaysian construction industry is undergoing a digital transformation toward Construction 4.0, yet the adoption of Artificial Intelligence (AI) drones for site safety remains fragmented due to a systemic "Governance Paradox." While high-level strategic policy frameworks exist, there is a lack of empirical evidence regarding the operational mechanisms required to translate national policies into practical site-level execution. This study develops and validates a Governance Ecosystem Model (GEM) to investigate how three critical variables, namely Regulatory Support, Institutional Readiness, and Trust and Data Ethics, drive technology implementation. Employing a positivist, quantitative cross-sectional design, data were collected from 168 construction professionals, including Developers, Consultants, and CIDB G1 to G7 Contractors, and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Importance-Performance Map Analysis (IPMA). The findings indicate that Institutional Readiness emerges as the most powerful predictor, exerting nearly double the influence of regulatory factors on technology rollout. Crucially, the study uncovers that Implementation acts as a significant mediating factor; governance domains do not directly trigger final adoption but must first manifest as high-quality, reliable site execution to be successful. Furthermore, moderation analysis identifies a "Regulatory Friction" effect, where increased professional seniority correlates with a diminishing perceived impact of regulatory frameworks. These insights provide a strategic roadmap, demonstrating that successful AI-drone adoption relies less on external mandates and more on developing internal digital capabilities and high-quality pilot execution, offering a transformative path for a proactive safety culture in Malaysia.

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TABLE OF CONTENTS

	PAGE
ABSTRACT	i
ACKNOWLEDGEMENT	ii
TABLE OF CONTENTS	iii
LIST OF TABLES	xiii
LIST OF FIGURES	xviii
LIST OF SYMBOLS/ABBREVIATIONS	xx

CHAPTER 1: INTRODUCTION 1

1.1 Background of the Study 1

1.2 Significance of the Study 2

1.3 Research Problem 2

1.4 Research Objectives 3

1.5 Research Questions 4

1.6 Research Parameters and Their Source 4

1.7 Research Gaps and Justification 5

1.8 Limitations of the Study 6

1.9 Significance of the Study 8

1.10 Definition of Terms 9

1.11 Organization of the Thesis 11

1.12 Chapter Summary 12

CHAPTER 2: LITERATURE REVIEW 14

2.1 Introduction 14

2.2 The Construction Industry in Malaysia 17

2.2.1 Overview of the Construction Sector 19

2.2.2 Technological Transformation and Construction 4.0 Initiatives 20

2.2.3 Safety Performance and Accident Statistics in Malaysia 22

2.3 Safety Management Practices in Construction **24**

2.3.1 Overview of Construction Safety Practices **26**

2.3.2 Challenges in Achieving Safe Construction Environments **27**

2.3.3 Technological Integration for Safety Enhancement **29**

2.4 Adoption of AI-Drone Technology for Safety Applications **31**

2.4.1 The Role of Artificial Intelligence in Construction Safety **33**

2.4.2 Drone Applications in Hazard Detection and Site Surveillance **34**

2.4.3 Global and Malaysian Perspectives on AI-Drone Adoption **36**

2.4.4 Barriers and Challenges in AI-Drone Implementation **38**

2.5 Theoretical Underpinning **39**

2.5.1 Technology-Organization-Environment (TOE) Framework **40**

2.5.3 Theoretical Synthesis and the Centrality of Governance **42**

2.6 The Governance Ecosystem for AI-Drone Adoption **44**

2.6.1 Regulatory Support **45**

2.6.1.1 National Policies and Legal Frameworks on Drone Usage **47**

2.6.1.2 Institutional Role of CAAM and CIDB in Construction Safety Governance **48**

2.6.1.3 International Benchmarking of Drone Regulations **50**

2.6.2 Institutional Readiness **52**

2.6.2.1 Organizational Capability and Digital Infrastructure **53**

2.6.2.2 Management Commitment and Human Resource Competency **55**

2.6.2.3 Leadership and Change Management in Technological Adoption **56**

2.6.3 Trust and Data Ethics **58**

2.6.3.1 Stakeholder Trust in AI-Drone Technology **58**

2.6.3.2 Data Governance, Security, and Privacy Concerns **60**

2.6.3.3 Ethical Considerations in AI-Driven Safety Systems **62**

2.7 The Mediating Role of Implementation **64**

2.7.1 Conceptualization of Implementation in Technology Adoption **65**

2.7.2 Implementation Quality and Process Efficiency **67**

2.7.3 Implementation as a Bridge between Governance and Adoption **67**

2.8 Summary of Governance-Related Linkages **68**

2.8.1 Relationships among Governance Variables and Adoption Outcomes **68**

2.8.2 Theoretical Integration of Governance Ecosystem Perspectives **69**

2.9 Conceptual Framework and Hypothesis Development **70**

2.9.1 Development of Hypotheses Based on Theoretical Models **70**

2.9.2 Mediation Effects of Implementation Quality **71**

2.9.3 Moderating Influence of Professional Experience and Stakeholder Role **72**

2.9.4 Conceptual Pathways of Governance Factors toward Safety Adoption **72**

2.10 Summary of Literature and Research Gaps **72**

2.10.1 Review Scope and Research Boundaries **73**

2.10.2 Current Challenges in Malaysian Construction Safety **73**

2.10.3 Mapping of Literature and Research Gaps **73**

2.11 Link to Conceptual Framework **74**

2.11.1 Derivation of Independent Variables **74**

2.11.2 Dependent Variable and Mediating Mechanism **75**

2.11.3 Moderating Influence of Professional Experience **75**

2.11.4 Integration into the Governance Ecosystem Model (GEM) **76**

2.12 Chapter Summary **76**

CHAPTER 3: RESEARCH METHODOLOGY **78**

3.1 Introduction **78**

3.2 Research Philosophy and Paradigm **78**

3.2.1 The Positivist Approach 79

3.2.2 Deductive Reasoning and Quantitative Logic 79

3.3 Research Design 80

3.3.1 Cross-Sectional Survey Method 80

3.3.2 Rationale for Quantitative Strategy 80

3.4 Research Framework and Hypotheses Summary 81

3.4.1 Structural Path Model 81

3.4.2 Summary of Research Hypotheses 81

3.4.3 Application of Multi-Group Analysis (MGA) 82

3.5 Data Collection Method 82

3.5.1 Primary Data: Digital Survey Distribution 82

3.5.2 Survey Instrument Design 83

3.6 Target Population and Sampling Strategy 83

3.6.1 Target Population 83

3.6.2 Sample Size Determination 85

3.6.2.1 G*Power 3.1.9.7 85

3.6.2.2 The 10-Times Rule 86

3.6.2.3 The Inverse Square Root Method 87

3.6.2.4 Academic Validation and Benchmarking 89

3.6.2.5 Final Synthesis of Sample Size Determination 90

3.6.3 Sampling Method 91

3.6.3.1 Purposive Sampling 91

3.6.3.2 Snowball Sampling 91

3.6.3.3 Justification for Sampling Approach 92

3.6.4 Unit of Analysis: Construction Professionals and Decision Makers 92

3.7 Operationalization of Variables and Analytical Procedure 93
3.7.1 Methodological Flow and Systemic Procedure 93
3.7.2 Detailed Procedure for Measurement Invariance (MICOM) 94
3.7.3 Table of Operationalization and Construct Mapping 96
3.7.4 Differentiation of Analytical Roles and Stakeholder Grouping 97
3.8 Research Instrument 98
3.8.1 Structural Design, Ethics, and UTAR Compliance 98
3.8.2 The 5-Point Likert Scale and Categorical Filtering 99
3.9 Data Collection Procedure 99
3.9.1 Pre-Testing 100
3.9.2 Pilot Study and Instrument Refinement 100
3.9.3 Data Collection 101
3.10 Data Analysis Strategy 101
3.10.1 Stage 1: Preliminary Analysis and Data Screening (SPSS) 102
3.10.2 Stage 2: Structural Equation Modeling (SmartPLS) 102
3.10.3 Assessment of the Measurement Model (Outer Model) 102
3.10.4 Assessment of the Structural Model (Inner Model) 103
3.10.5 Mediation and Multi-Group Analysis (MGA) 103
3.11 Addressing Data Bias and Quality Control 103
3.11.1 Common Method Variance (CMV) 104
3.11.2 Non-Response Bias and Multi-collinearity 104
3.11.3 Assessment of Statistical Power and Sample Adequacy 104
3.12 Ethical Considerations and Data Privacy (NAIO & PDPA 2026) 105
3.12.1 Compliance with NAIO and PDPA 2026 Standards 105
3.12.2 Anonymity, Confidentiality, and Data Security 105

3.13 Chapter Summary **106**

CHAPTER 4: RESULTS AND DISCUSSION **108**

4.1 Introduction **108**

4.1.1 Overview of Data Analysis Strategy **108**

4.1.2 Data Collection and Response Rate Analysis **109**

4.2 Descriptive Analysis: Demographic Profile (SPSS) **109**

4.2.1 Demographic Profile: Gender **109**

4.2.2 Demographic Profile: Ethnic **110**

4.2.3 Demographic Profile: Age **111**

4.2.4 Demographic Profile: Highest Academic Level **113**

4.2.5 Demographic Profile: Category of Industry Sector **114**

4.2.6 Demographic Profile: Organizational Size **116**

4.2.7 Demographic Profile: Professional Role **117**

4.2.8 Demographic Profile: Position Level **118**

4.2.9 Demographic Profile: Years of Work Experience **120**

4.2.10 Summary of Demographic Profiles **122**

4.2.11 Summary Profile: Developer Respondents **126**

4.2.12 Summary Profile: Consultant Respondents **128**

4.2.13 Summary Profile: Main-Contractor Respondents **131**

4.2.14 Summary Profile: Sub-Contractor Respondents **133**

4.2.15 Summary Profile: Others Respondents **135**

4.2.16 Synthesis of Demographic Findings: Patterns and Governance Gaps **137**

4.3 Descriptive Analysis of Research Variables **138**

4.3.1 Preliminary Assessment of AI-Drone Familiarity **139**

4.3.2 Level of Awareness regarding AI-Drone Technology **141**

4.3.3 Analysis of Barriers to AI-Drone Adoption **144**

4.3.4 Descriptive Analysis: Regulatory Support (IV1) **148**

4.3.4.1 Descriptive Analysis RS1: Existing government policies provide clear guidance for drone use in construction safety **148**

4.3.4.2 Descriptive Analysis RS2: The Civil Aviation Authority of Malaysia (CAAM) provides sufficient regulatory support for safe drone operations **152**

4.3.4.3 Descriptive Analysis RS3: Coordination among agencies (CAAM, CIDB, DOSH) is effective and minimizes regulatory confusion **155**

4.3.4.4 Descriptive Analysis RS4: The current legal framework encourages technological innovation without compromising safety standards **159**

4.3.4.5 Descriptive Analysis RS5: National policies (e.g., Construction 4.0 Strategic Plan) actively promote the integration of AI-drones in construction projects **162**

4.3.4.6 Descriptive Analysis RS6: The process for obtaining flight permits from authorities is clear and efficient **165**

4.3.4.7 Descriptive Analysis RS7: Liability laws regarding drone accidents on construction sites are clearly defined **168**

4.3.5 Descriptive Analysis: Institutional Readiness (IV2) **171**

4.3.5.1 Descriptive Analysis IR1: My organisation has the financial resources to invest in AI-drone technologies **172**

4.3.5.2 Descriptive Analysis IR2: My organisation has sufficient digital infrastructure (e.g., internet, servers) to support drone-based data **175**

4.3.5.3 Descriptive Analysis IR3: Top management is committed to adopting AI-drone technologies **178**

4.3.5.4 Descriptive Analysis IR4: Employees in my organisation possess the technical aptitude required to operate or learn AI-drone systems **181**

4.3.5.5 Descriptive Analysis IR5: The organisation promotes a culture that supports innovation and technological change **184**

4.3.5.6 Descriptive Analysis IR6: My organisation has access to technical support (internal or external) for maintaining advanced equipment **187**

4.3.5.7 Descriptive Analysis IR7: Our current software systems (e.g., BIM) are capable of integrating data collected by drones **190**

4.3.6 Descriptive Analysis: Trust and Data (IV3) **193**

4.3.6.1 Descriptive Analysis TD1: The organisation acknowledges that AI-drone systems are effective for enhancing site safety..... 193

4.3.6.2 Descriptive Analysis TD2: The organisation ensures that drone deployment does not compromise the privacy of workers..... 196

4.3.6.3 Descriptive Analysis TD3: My organisation ensures proper procedures for storing and protecting drone-captured data..... 199

4.3.6.4 Descriptive Analysis TD4: There is a high level of confidence that drone data is secure from unauthorised access..... 202

4.3.6.5 Descriptive Analysis TD5: The use of drones for safety monitoring is transparent and communicated clearly to workers..... 205

4.3.6.6 Descriptive Analysis TD6: The organisation prioritises ethical considerations (fairness, accountability) when deploying AI-drone systems... 208

4.3.6.7 Descriptive Analysis TD7: I trust the accuracy of the AI analysis in identifying safety hazards..... 211

4.3.6.8 Descriptive Analysis TD8: Workers are clearly informed about how drone surveillance data is collected and used..... 214

4.3.7 Descriptive Analysis: Implementation (Mediator)..... 217

4.3.7.1 Descriptive Analysis IMP1: My organisation has a clear strategic plan for implementing AI-drone safety systems..... 217

4.3.7.2 Descriptive Analysis IMP2: My organisation has successfully secured the necessary technical expertise and resources for drone deployment..... 220

4.3.7.3 Descriptive Analysis IMP3: Our implementation processes are regularly reviewed and improved based on operational feedback..... 223

4.3.7.4 Descriptive Analysis IMP4: Relevant departments (e.g., Safety, Engineering, IT) coordinate effectively during the drone implementation phase. 226

4.3.7.5 Descriptive Analysis IMP5: The implementation of AI-drones has led to measurable improvements in safety inspection efficiency.....229

4.3.7.6 Descriptive Analysis IMP6: My organisation conducts pilot tests (small-scale trials) before fully deploying drone technology across projects.. 232

4.3.7.7 Descriptive Analysis IMP7: We collaborate effectively with external drone service providers or vendors during the implementation phase.....235

4.3.8 Descriptive Analysis: AI-Drone Adoption for Safety (DV)..... 238

4.3.8.1 Descriptive Analysis AD1: My organisation actively uses drones equipped with AI for site safety inspections.....**238**

4.3.8.2 Descriptive Analysis AD2: The adoption of AI-drone technology has led to measurable improvements in overall safety performance.....**241**

4.3.8.3 Descriptive Analysis AD3: AI-drone systems are used regularly for hazard detection and compliance monitoring..... **244**

4.3.8.4 Descriptive Analysis AD4: Top management recognises AI-drone technology as essential for future safety operations..... **247**

4.3.8.5 Descriptive Analysis AD5: My organisation plans to expand the use of AI-drone technologies in future projects.....**250**

4.3.8.6 Descriptive Analysis AD6: The utilization of AI-drones provides a competitive advantage in securing new projects..... **253**

4.3.8.7 Descriptive Analysis AD7: Financial resources for AI-drone technology are permanently allocated in our annual safety budget.....**256**

4.4 Measurement Model Assessment (SmartPLS)..... **259**

4.4.1 Indicator Reliability: Factor Loadings Assessment..... **259**

4.4.1.1 Model Refinement: Elimination of Low-Loading Indicators and Re-analysis..... **261**

4.4.2 Internal Consistency: Cronbach's Alpha and Composite Reliability (CR).... **264**

4.4.3 Convergent Validity: Average Variance Extracted (AVE)..... **266**

4.4.4 Assessment of Collinearity and Common Method Bias (CMB).....**267**

4.4.4.1 Fornell-Larcker Criterion..... **268**

4.4.4.2 Cross-Loadings Analysis.....**269**

4.4.4.3 Heterotrait-Monotrait Ratio (HTMT).....**271**

4.5 Structural Model Assessment (SmartPLS)..... **273**

4.5.1 Assessment of Lateral Collinearity (VIF).....**273**

4.5.2 Path Coefficients (β) and Significance Testing..... **274**

4.5.3 Assessment of Coefficient of Determination (R^2).....**276**

4.5.4 Assessment of Effect Size (f^2).....**279**

4.5.5 Assessment of Predictive Relevance (Q^2) **281**

4.6 Moderation Analysis **282**

4.6.1 Testing the Moderating Effect of Work Experience **283**

4.6.2 Interaction Effect Analysis and Simple Slopes Plot **287**

4.7 Multi-Group Analysis (MGA) **289**

4.7.1 Assessment of Measurement Invariance of Composite Models (MICOM) **290**

4.7.2 Test of MGA Comparisons **293**

4.7.3 Group-Specific Differences MGA Analysis **294**

4.7.4 Assessment of Explanatory Power (R^2) and Effect Size (f^2) **296**

4.7.5 Importance-Performance Map Analysis (IPMA) **298**

4.8 Hypothesis Testing and Discussion **300**

4.8.1 Summary of Hypotheses Testing Results **301**

4.8.2 Evaluation of Governance Factors (RO1) **302**

4.8.3 Identifying the Most Significant Predictor (RO2) **303**

4.8.4 Validation of the Mediating Mechanism (RO3) **303**

4.8.5 Comprehensive Model Validation and Contextual Nuances (RO4) **304**

4.9 Validated Research Model of AI-Drone Governance Ecosystem **304**

4.9.1 Final Validated Model (Direct and Mediating Effects) **304**

4.9.2 Final Validated Model (With Moderating Factors) **305**

4.10 Summary of Chapter Findings **306**

Chapter 5: Conclusion and Recommendations **308**

5.1 Conclusion **308**

5.2 Recapitulation of Research Findings **308**

5.2.1 Achievement of RO1 and RO2: The Primacy of Institutional Readiness **308**

5.2.2 Achievement of RO3: The Mediating Role of Implementation Quality **309**

5.2.3 Achievement of RO4: Professional Experience and Regulatory Friction..... 309

5.3 Research Contributions.....310

5.3.1 Theoretical Contributions.....310

5.3.2 Methodological Contributions.....311

5.4 Practical and Strategic Implications.....311

5.4.1 Implications for Industry Practitioners.....311

5.4.2 Implications for Organizational Leadership.....312

5.4.3 Institutional Advocacy and Awareness.....312

5.5 Strategic Recommendations for Stakeholders..... 313

5.5.1 National Awareness and Upskilling Initiatives..... 313

5.5.2 Development of Voluntary Best Practice Guidelines.....313

5.5.3 Ethical Transparency and Trust Frameworks..... 314

5.6 Reflective Limitations and Scope..... 314

5.7 Recommendations for Future Research..... 315

REFERENCE LIST.....316

APPENDICES A : RESEARCH QUESTIONNAIRE.....327

APPENDICES B: RESEARCH QUESTIONNAIRES PRE TESTING.....336

LIST OF TABLES

Table No.	Title	Page
Table 2.1	Synthesis Matrix of Research Parameters and Theoretical Gaps	74
Table 3.1	Summary of Hypothesized Relationships for Statistical Testing	81
Table 3.2	Triangulation of Sample Size Determination Methods	90
Table 3.3	Operationalization of Research Variables and Mapping Synthesis	96
Table 4.1	Gender Distribution of Respondents (N=168)	110
Table 4.2	Ethnic Distribution of Respondents (N=168)	111
Table 4.3	Frequency and Percentage of Respondents' Age (N=168)	113
Table 4.4	Frequency and Percentage of Highest Academic Level (N=168)	114
Table 4.5	Frequency and Percentage of Industry Sector Categories (N=168)	115
Table 4.6	Frequency and Percentage of Organizational Size (N=168)	117
Table 4.7	Frequency and Percentage of Respondents' Professional Role (N=168)	118
Table 4.8	Frequency and Percentage of Respondents' Position Level (N=168)	120
Table 4.9	Frequency and Percentage of Respondents' Work Experience (N=168)	121
Table 4.10	Master Demographic Summary by Organization Category (N=168)	122
Table 4.11	Summary Profile of Developer Respondents (n=27)	127
Table 4.12	Summary Profile of Consultant Respondents (n=56)	129
Table 4.13	Summary Profile of Main-Contractor Respondents (n=36)	132
Table 4.14	Summary Profile of Sub-Contractor Respondents (n=46)	134
Table 4.15	Summary Profile of Others Respondents (n=3)	136
Table 4.16	Stakeholder Exposure to AI-Drone Technology by Organization Category	139
Table 4.17	Chi-Square Test for Independence: Organization Type vs. Drone Exposure	139
Table 4.18	Association Strength and Correlation Analysis	140
Table 4.19	Level of Self-Rated Knowledge on AI-Drone Technology by Sector	142
Table 4.20	Chi-Square Test: Organization Type vs. Knowledge Depth	142
Table 4.21	Association Strength for Stakeholder Knowledge Levels	142
Table 4.22	Primary Barriers to AI-Drone Adoption by Organization Category	145
Table 4.23	Chi-Square Test: Association Between Stakeholder Type and Adoption Barriers	145
Table 4.24	Symmetric Measures and Effect Size for Adoption Barriers	145

Table 4.25	Comparative Statistical Profile of Perception regarding National Policy Clarity (RS1)	151
Table 4.26	Empirical Breakdown of Informational Gaps and "Unsure" Frequencies for RS1	152
Table 4.27	Comparative Statistical Profile of Perception regarding CAAM Regulatory Support (RS2)	154
Table 4.28	Overall Frequency and Percentage Breakdown of "Unsure" Responses for RS2	155
Table 4.29	Comparative Statistical Profile of Perception regarding Inter-Agency Coordination (RS3)	157
Table 4.30	Overall Frequency and Percentage Breakdown of "Unsure" Responses for RS3	158
Table 4.31	Comparative Statistical Profile of Perception regarding Innovation-Safety Equilibrium (RS4)	161
Table 4.32	Overall Frequency and Percentage Breakdown of "Unsure" Responses for RS4	162
Table 4.33	Comparative Statistical Profile of Perception regarding National Policy Promotion (RS5)	164
Table 4.34	Overall Frequency and Percentage Breakdown of "Unsure" Responses for RS5	165
Table 4.35	Comparative Statistical Profile of Perception regarding Flight Permit Efficiency (RS6)	167
Table 4.36	Overall Frequency and Percentage Breakdown of "Unsure" Responses for RS6	168
Table 4.37	Comparative Statistical Profile of Perception regarding Liability Law Clarity (RS7)	170
Table 4.38	Overall Frequency and Percentage Breakdown of "Unsure" Responses for RS7	171
Table 4.39	Comparative Statistical Profile of Perception regarding Financial Resources (IR1)	174
Table 4.40	Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR1	175
Table 4.41	Comparative Statistical Profile of Perception regarding Digital Infrastructure (IR2)	177
Table 4.42	Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR2	178
Table 4.43	Comparative Statistical Profile of Perception regarding Management Commitment (IR3)	180
Table 4.44	Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR3	181
Table 4.45	Comparative Statistical Profile of Perception regarding Technical Aptitude (IR4)	183
Table 4.46	Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR4	184
Table 4.47	Comparative Statistical Profile of Perception regarding Innovation Culture (IR5)	186
Table 4.48	Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR5	187
Table 4.49	Comparative Statistical Profile of Perception regarding Technical Support Access (IR6)	189

Table 4.50	Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR6	190
Table 4.51	Comparative Statistical Profile of Perception regarding Software Compatibility (IR7)	192
Table 4.52	Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR7	192
Table 4.53	Comparative Statistical Profile of Perception regarding AI-Drone Effectiveness (TD1)	195
Table 4.54	Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD1	196
Table 4.55	Comparative Statistical Profile of Perception regarding Worker Privacy (TD2)	198
Table 4.56	Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD2	199
Table 4.57	Comparative Statistical Profile of Perception regarding Data Protection (TD3)	201
Table 4.58	Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD3	202
Table 4.59	Comparative Statistical Profile of Perception regarding Cybersecurity Confidence (TD4)	203
Table 4.60	Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD4	204
Table 4.61	Comparative Statistical Profile of Perception regarding Operational Transparency (TD5)	207
Table 4.62	Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD5	208
Table 4.63	Comparative Statistical Profile of Perception regarding Ethical Deployment (TD6)	210
Table 4.64	Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD6	211
Table 4.65	Comparative Statistical Profile regarding AI Analysis Trust (TD7)	212
Table 4.66	Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD7	213
Table 4.67	Comparative Statistical Profile of Perception regarding Information Dissemination (TD8)	215
Table 4.68	Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD8	216
Table 4.69	Comparative Statistical Profile of Perception regarding Strategic Planning (IMP1)	219
Table 4.70	Breakdown of "No Implementation Yet" Responses for IMP1	220
Table 4.71	Comparative Statistical Profile of Perception regarding Resource Securing (IMP2)	222
Table 4.72	Breakdown of "No Implementation Yet" Responses for IMP2	223
Table 4.73	Comparative Statistical Profile of Perception regarding Feedback Loops (IMP3)	225
Table 4.74	Breakdown of "No Implementation Yet" Responses for IMP3	225
Table 4.75	Comparative Statistical Profile regarding Inter-Departmental Coordination (IMP4)	228

Table 4.76	Breakdown of "No Implementation Yet" Responses for IMP4	229
Table 4.77	Comparative Statistical Profile of Perception regarding Efficiency Improvements (IMP5)	231
Table 4.78	Breakdown of "No Implementation Yet" Responses for IMP5	232
Table 4.79	Comparative Statistical Profile of Perception regarding Pilot Testing (IMP6)	234
Table 4.80	Breakdown of "No Implementation Yet" Responses for IMP6	234
Table 4.81	Comparative Statistical Profile of Perception regarding Vendor Collaboration (IMP7)	236
Table 4.82	Breakdown of "No Implementation Yet" Responses for IMP7	237
Table 4.83	Comparative Statistical Profile of Perception regarding Active Inspection Usage (AD1)	240
Table 4.84	Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD1	241
Table 4.85	Comparative Statistical Profile regarding Safety Performance Impact (AD2)	243
Table 4.86	Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD2	244
Table 4.87	Comparative Statistical Profile regarding Hazard Detection Regularity (AD3)	246
Table 4.88	Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD3	247
Table 4.89	Comparative Statistical Profile of Perception regarding Future Essentiality (AD4)	249
Table 4.90	Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD4	250
Table 4.91	Comparative Statistical Profile of Perception regarding Expansion Plans (AD5)	252
Table 4.92	Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD5	253
Table 4.93	Comparative Statistical Profile of Perception regarding Competitive Advantage (AD6)	255
Table 4.94	Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD6	255
Table 4.95	Comparative Statistical Profile of Perception regarding Budgetary Allocation (AD7)	257
Table 4.96	Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD7	258
Table 4.97a	Outer Loadings of the Research Constructs	261
Table 4.97b	Refined Factor Loadings of Research Constructs	262
Table 4.98	Construct Reliability and Validity Results	266
Table 4.99	Fornell-Larcker Criterion Results	268
Table 4.100	Matrix of Indicator Cross-Loadings	269
Table 4.101	Heterotrait-Monotrait Ratio (HTMT) Matrix	271
Table 4.102	Lateral Collinearity Assessment	273

Table 4.103	**Detailed Results of Hypothesis Testing**	**275**
Table 4.104	**Assessment of Coefficient of Determination (R^2 and R^2 Adjusted)**	**277**
Table 4.105	**Assessment of Effect Size (f^2) and Significance**	**280**
Table 4.106	**Results of Predictive Relevance (Q^2)**	**282**
Table 4.107	**Results of Moderation Analysis (Interaction Terms)**	**286**
Table 4.108	**MICOM Step 2 - Compositional Invariance Results**	**291**
Table 4.109	**MICOM Step 3a - Equality of Composite Means Results**	**292**
Table 4.110	**MICOM Step 3b - Equality of Composite Variances Results**	**292**
Table 4.111	**Bootstrapping Path Coefficients Results per Group**	**294**
Table 4.112	**Multi-Method Comparison of Group Path Differences**	**295**
Table 4.113	**Confidence Intervals for Path Coefficients (95% Bias-Corrected)**	**295**
Table 4.114	**Comparison of Explanatory Power (R^2)**	**297**
Table 4.115	**Comparison of Effect Sizes (f^2) between Groups**	**298**
Table 4.116	**Construct-Level IPMA Results for Target Construct (ADOPTION)**	**299**
Table 4.117	**Consolidated Summary of Structural Model Outcomes**	**301**

LIST OF FIGURES

Figure No.	Title	Page
Figure 2.1	Overview of the Malaysian construction safety context	14
Figure 2.2	Conceptual diagram of the AI and drone convergence	15
Figure 2.3	Illustration of the governance paradox in the Malaysian construction industry	15
Figure 2.4	The three pillars of governance	16
Figure 2.5	The research pathway, mapping the literature review	17
Figure 2.6	Quarterly trend of construction activity in Malaysia (Q3 2025)	18
Figure 2.7	Performance by construction sub-sector in Q3 2025	18
Figure 2.8	The dichotomy of the Malaysian construction sector	20
Figure 2.9	Strategic overview of the Construction 4.0 landscape	21
Figure 2.10	Graphical representation of the current safety crisis in Malaysia	23
Figure 2.11	The multidimensional criticality of construction safety	25
Figure 2.12	The spectrum of safety practice evolution	27
Figure 2.13	Conceptual framework of the multi-tiered safety deficit	28
Figure 2.14	Comprehensive overview of the AI-drone convergence in construction safety	30
Figure 2.15	The dual nature of AI-drone evolution	32
Figure 2.16	Paradigm shift: Manual supervision to AI-powered computer vision	34
Figure 2.17	Operational capabilities of drone-based site oversight	35
Figure 2.18	Comparative analysis of AI drone adoption in construction	37
Figure 2.19	Conceptual framework of multidimensional barriers to AI drone implementation	39
Figure 2.20	The TOE framework as a diagnostic tool for AI drone adoption	41
Figure 2.21	Integrated framework of TAM and Trust Theory	42
Figure 2.22	Theoretical justification for governance integration in technology models	43
Figure 2.23	Theoretical synthesis of Technology Organisation Environment (TOE)	44
Figure 2.24	Conceptual framework: Governance as the decisive enabler	45
Figure 2.25	Overview of the evolving regulatory framework for AI drones	46
Figure 2.26	Conceptual framework of national policy directions	48
Figure 2.27	Complementary mandates: CAAM, CIDB, and DOSH	49
Figure 2.28	Comparative analysis of international drone governance systems	50
Figure 2.29	Maturity assessment of Malaysia's current drone regulatory landscape	51
Figure 2.30	Conceptual framework of institutional readiness for AI drone adoption	52
Figure 2.31	Framework of organisational capability and digital infrastructure	54
Figure 2.32	Dual pillar framework: Management commitment and HR competency	55
Figure 2.33	Integrated framework for leadership and change management	57
Figure 2.34	Sociology ethical framework for stakeholder trust	59
Figure 2.35	Data governance and privacy framework for AI drone adoption	61
Figure 2.36	Multi-layered architecture of ethical AI governance	63
Figure 2.37	Conceptual model of the mediating role of implementation	64

Figure 2.38	Conceptualisation of implementation as a multi-dimensional process	66
Figure 2.39	Conceptual Framework of the Governance Ecosystem Model (GEM) for AI-Drone Safety Adoption	76
Figure 3.1a	G*Power 3.1.9.7 Output for Minimum Sample Size Estimation	86
Figure 3.1b	G*Power 3.1.9.7 Output for Minimum Sample Size Estimation	86
Figure 3.2	Standard Normal Probability Distribution for Z-score Identification	89
Figure 3.3	Integrated Procedure for Data Analysis and Multi-Group Structural Equation Modeling	93
Figure 3.4	The Measurement Invariance of Composite Models (MICOM) Procedure	94
Figure 3.5	Guidelines for Running MGA in PLSPM: Invariance Decision Logic	95
Figure 4.1	Distribution of Respondents by Gender (%)	110
Figure 4.2	Ethnic Composition of Survey Respondents (%)	111
Figure 4.3	Age Distribution of Survey Respondents (%)	112
Figure 4.4	Academic Qualification Profile of Respondents (%)	114
Figure 4.5	Distribution of Respondents by Industry Sector (%)	115
Figure 4.6	Distribution of Respondents by Organizational Size (%)	116
Figure 4.7	Distribution of Respondents by Professional Role (%)	118
Figure 4.8	Distribution of Respondents by Position Level (%)	119
Figure 4.9	Distribution of Respondents by Years of Work Experience (%)	121
Figure 4.10	Distribution of AI-Drone Familiarity Across Organization Categories	140
Figure 4.11	Comparative Distribution of Technical Knowledge by Organization Category (%)	143
Figure 4.12	Comparative Analysis of Sectoral Barriers to AI-Drone Integration (%)	146
Figure 4.13	Frequency Distribution with Normal Curves for RS1	150
Figure 4.14	Frequency Distribution with Normal Curves for RS2	153
Figure 4.15	Frequency Distribution with Normal Curves for RS3	156
Figure 4.16	Frequency Distribution with Normal Curves for RS4	160
Figure 4.17	Frequency Distribution with Normal Curves for RS5	163
Figure 4.18	Frequency Distribution with Normal Curves for RS6	166
Figure 4.19	Frequency Distribution with Normal Curves for RS7	169
Figure 4.20	Frequency Distribution with Normal Curves for IR1	173
Figure 4.21	Frequency Distribution with Normal Curves for IR2	176
Figure 4.22	Frequency Distribution with Normal Curves for IR3	179
Figure 4.23	Frequency Distribution with Normal Curves for IR4	182
Figure 4.24	Frequency Distribution with Normal Curves for IR5	185
Figure 4.25	Frequency Distribution with Normal Curves for IR6	188
Figure 4.26	Frequency Distribution with Normal Curves for IR7	191
Figure 4.27	Frequency Distribution with Normal Curves for TD1	194
Figure 4.28	Frequency Distribution with Normal Curves for TD2	197
Figure 4.29	Frequency Distribution with Normal Curves for TD3	200
Figure 4.30	Frequency Distribution with Normal Curves for TD4	202
Figure 4.31	Frequency Distribution with Normal Curves for TD5	205
Figure 4.32	Frequency Distribution with Normal Curves for TD6	209
Figure 4.33	Frequency Distribution with Normal Curves for TD7	212

Figure 4.34	**Frequency Distribution with Normal Curves for TD8**	**214**
Figure 4.35	**Frequency Distribution with Normal Curves for IMP1**	**218**
Figure 4.36	**Frequency Distribution with Normal Curves for IMP2**	**221**
Figure 4.37	**Frequency Distribution with Normal Curves for IMP3**	**223**
Figure 4.38	**Frequency Distribution with Normal Curves for IMP4**	**226**
Figure 4.39	**Frequency Distribution with Normal Curves for IMP5**	**229**
Figure 4.40	**Frequency Distribution with Normal Curves for IMP6**	**232**
Figure 4.41	**Frequency Distribution with Normal Curves for IMP7**	**235**
Figure 4.42	**Frequency Distribution with Normal Curves for AD1**	**239**
Figure 4.43	**Frequency Distribution with Normal Curves for AD2**	**242**
Figure 4.44	**Frequency Distribution with Normal Curves for AD3**	**245**
Figure 4.45	**Frequency Distribution with Normal Curves for AD4**	**248**
Figure 4.46	**Frequency Distribution with Normal Curves for AD5**	**251**
Figure 4.47	**Frequency Distribution with Normal Curves for AD6**	**254**
Figure 4.48	**Frequency Distribution with Normal Curves for AD7**	**257**
Figure 4.49a	**Initial Measurement Model with Factor Loadings**	**260**
Figure 4.49b	**Refined Measurement Model showing Factor Loadings and Path Coefficients**	**263**
Figure 4.50	**Cronbach's Alpha Overview**	**264**
Figure 4.51	**Dijkstra-Henseler's rho (rho_a) Overview**	**264**
Figure 4.52	**Composite Reliability (rho_c) Overview**	**265**
Figure 4.53	**Average Variance Extracted (AVE) Overview**	**266**
Figure 4.54	**HTMT Discriminant Validity Bar Chart Overview**	**272**
Figure 4.55	**Validated Structural Model with Predictive Accuracy (R^2)**	**278**
Figure 4.56	**PLS-SEM Algorithm Results for the Moderation Model**	**284**
Figure 4.57	**Bootstrapping Results for the Moderation Model (P-values)**	**284**
Figure 4.58	**Simple Slopes Plot for Regulatory Support × Work Experience**	**287**
Figure 4.59	**Simple Slopes Plot for Institutional Readiness × Work Experience**	**288**
Figure 4.60	**Simple Slopes Plot for Trust & Data × Work Experience**	**289**
Figure 4.61	**Importance-Performance Map Analysis (IPMA) Results**	**299**
Figure 4.62	**Validated Direct and Mediating Effects Model**	**305**
Figure 4.63	**Comprehensive Validated Research Model with Moderating Influence**	**306**

LIST OF SYMBOLS/ABBREVIATIONS

Abbreviation	Meaning
β (Beta)	Path Coefficient / Standardized Regression Weight
Q^2	Predictive Relevance
R^2	Coefficient of Determination
f^2	Cohen's Effect Size
rho_a (ρa)	Dijkstra-Henseler's Reliability Coefficient
rho_c (ρc)	Composite Reliability
AEC	Architecture, Engineering, and Construction
AI	Artificial Intelligence
AIGE	National Guidelines on AI Governance and Ethics
AVE	Average Variance Extracted
BEM	Board of Engineers Malaysia
BIM	Building Information Modelling
C&S	Civil and Structural
CAAM	Civil Aviation Authority of Malaysia
CB-SEM	Covariance-Based Structural Equation Modeling
CIDB	Construction Industry Development Board
CMV	Common Method Variance
CR	Composite Reliability
CV	Computer Vision
DOSH	Department of Occupational Safety and Health
GEM	Governance Ecosystem Model
HTMT	Heterotrait-Monotrait Ratio
IEM	Institution of Engineers, Malaysia
IoT	Internet of Things
IPMA	Importance-Performance Map Analysis
LLCI	Lower Level Confidence Interval
M&E	Mechanical and Electrical
MBAM	Master Builders Association Malaysia
MGA	Multi-Group Analysis
MICOM	Measurement Invariance of Composite Models
N	Total Sample Size
n	Sub-group Sample Size
NAIO	National AI Office
OSH	Occupational Safety and Health
p-value	Probability Value (Level of Significance)
PDPA	Personal Data Protection Act
PKMM	Persatuan Kontraktor Melayu Malaysia
PLS-SEM	Partial Least Squares Structural Equation Modeling
RBV	Resource-Based View
REHDA	Real Estate and Housing Developers' Association
RISM	Royal Institution of Surveyors Malaysia
RQ / RO	Research Question / Research Objective
SD	Standard Deviation
SHO	Safety and Health Officer
SME	Small and Medium Enterprises
SRMR	Standardized Root Mean Square Residual

TAM	Technology Acceptance Model
TOE	Technology-Organization-Environment
UAV	Unmanned Aerial Vehicle
ULCI	Upper Level Confidence Interval
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor
YOLO	You Only Look Once (AI Object Detection Architecture)

CHAPTER 1: INTRODUCTION

1.1 Background of the Study

The global construction industry is currently undergoing a fundamental paradigm shift driven by the Fourth Industrial Revolution (IR 4.0). Often referred to as Construction 4.0, this transition involves the integration of cyber-physical systems, the Internet of Things (IoT), and Artificial Intelligence (AI) to enhance productivity and operational safety (Alizadehsalehi & Yitmen, 2023). Within this digital evolution, the use of unmanned aerial vehicles (UAVs), or drones, has emerged as a transformative tool for high-risk environments. When integrated with advanced "Agentic AI" algorithms, these drones move beyond simple aerial photography to become autonomous safety partners capable of real-time hazard detection, worker posture analysis, and structural health monitoring (Yi & Sutrisna, 2021). Despite the clear technical advantages, the adoption of these tools remains uneven, particularly in developing economies where the legal and institutional environments are still maturing.

In Malaysia, the construction sector serves as a vital pillar of national economic growth, yet it continues to grapple with disproportionately high rates of site accidents and fatalities. According to the Department of Occupational Safety and Health, the industry consistently records the highest number of work-related deaths compared to other sectors, highlighting a critical need for modernized safety management (Tham & Hassim, 2025). The Malaysian government has responded through strategic initiatives such as the Construction 4.0 Strategic Plan and the National AI Roadmap. These policies aim to position Malaysia as a regional leader, specifically encouraging AI-driven monitoring to reduce human error. However, the transition from policy intent to project-level adoption is hindered by a complex governance landscape involving a broad ecosystem of Developers, Clients, and the full range of CIDB-registered Contractors (Grades G1 through G7).

In 2026, the governance of AI drone technology is not merely a matter of flight permits from the Civil Aviation Authority of Malaysia (CAAM); it involves a broader ecosystem of ethical data management, algorithmic accountability, and organizational trust (Haron et al., 2023). Under the current Thirteenth Malaysia Plan (2026–2030) and the oversight of the National AI Office (NAIO), there is an increased emphasis on creating a secure and ethical digital economy. Yet, many stakeholders, especially small and medium enterprises (G1–G4), lack the "internal muscle" to implement these high-tech solutions effectively. Central to this challenge is the role

of Implementation Quality, which acts as the "bridge" determining whether a technology is sustained or abandoned (Lim, 2025). In Malaysia's tropical climate, technical reliability and site coordination serve as vital mediators in the adoption process (Jamian et al., 2026).

1.2 Significance of the Study

The significance of this research lies in its capacity to address the critical gap between technological potential and practical safety outcomes across the Malaysian construction supply chain. As the industry aligns with the strategic objectives of the Thirteenth Malaysia Plan (2026–2030), the ability to integrate autonomous systems safely and ethically has become a national priority. This study is important because it transcends a purely technical evaluation by focusing on the Governance Ecosystem Model (GEM) required to sustain long-term utilization. By investigating the interactions between regulatory frameworks, institutional readiness, and data ethics across the hierarchy of developers, clients, and contractors, this research provides a strategic roadmap for industry-wide adoption (Sapri, 2024).

Furthermore, this research is timely due to increasing legal pressures, specifically the full enforcement of the Occupational Safety and Health (Amendment) Act 2022. Employers now face increased penalties and more stringent requirements for site oversight (DOSH, 2024). This study offers practical value by demonstrating how Artificial Intelligence-driven drones serve as a primary mechanism for achieving high compliance standards. For safety officers and site managers, understanding the mediating role of implementation quality is essential for mitigating the technical risks associated with autonomous monitoring in tropical weather conditions (Lim, 2025). Ultimately, the research addresses worker concerns regarding surveillance and privacy, ensuring that technological advancement maintains stakeholder trust (Zhang et al., 2023).

1.3 Research Problem

The Malaysian construction industry currently faces a critical "Governance Paradox." While the government has introduced high-level strategic frameworks, the actual rate of adoption for AI-driven drones remains significantly lower than expected. Evidence suggests that technical feasibility alone does not guarantee adoption; rather, firms are constrained by a "Governance Disconnect" where national policies are not effectively translated into operational site practices (Sapri, 2024). This problem is intensified in 2026 by the rapid emergence of Agentic AI, which

has outpaced existing safety protocols and left contractors in a state of regulatory uncertainty regarding algorithmic accountability and worker privacy.

Without a structured governance framework, the industry risks a "Digital Split." Tier-one developers and G7 contractors may navigate the complex compliance landscape, while small and medium enterprises remain reliant on reactive, manual safety methods (Ministry of Science, Technology and Innovation, 2024). Despite identified barriers like legal constraints and costs, there is a fundamental lack of empirical evidence regarding the operational mechanism required to bridge this gap. Specifically, no validated model explains how governance domains comprising Regulatory Support, Institutional Readiness, and Trust influence adoption through the mediating role of Implementation Quality. This study addresses this problem by statistically validating a Governance Ecosystem Model (GEM) to illustrate how implementation quality acts as the essential bridge in the Malaysian context.

1.4 Research Objectives

The primary goal of this research is to validate the Governance Ecosystem Model (GEM) within the Malaysian construction industry. The following objectives have been established to achieve this:

RO1: To evaluate the direct impact of Regulatory Support, Institutional Readiness, and Trust and Data Ethics on the Implementation Quality of AI drone technology for site safety.

RO2: To identify which governance domain serves as the most significant predictor for technology implementation among construction industry stakeholders in Malaysia.

RO3: To determine and validate the mediating effect of Implementation Quality on the relationship between governance enablers and final Organizational Adoption.

RO4: To examine how Work Experience moderates the structural relationships within the Governance Ecosystem Model.

RO5: To analyze the differences in the structural relationships within the model between office-based and site-based stakeholders.

1.5 Research Questions

Based on the objectives above, the following research questions are formulated:

RQ1: To what extent do Regulatory Support, Institutional Readiness, and Trust and Data Ethics influence the Implementation Quality of AI drone technology?

RQ2: Which governance domain acts as the most significant predictor for successful technology implementation in the Malaysian construction sector?

RQ3: Does Implementation Quality significantly mediate the relationship between the three governance domains and final AI drone adoption?

RQ4: To what extent does Work Experience moderate the pathways toward technology implementation?

RQ5: Do the structural relationships within the Governance Ecosystem Model differ significantly between office-based consultants and site-based contractors?

1.6 Research Parameters and Their Source

To ensure a systematic alignment between the theoretical foundations established in the literature review and the empirical data collection phase, this study utilizes five primary research parameters. These variables are operationalized within the research questionnaire and are grounded in both established technology adoption theories and the contemporary 2026 Malaysian regulatory framework.

The first parameter, Regulatory Support, serves as an independent variable and is derived from the environmental context of the Technology-Organisation-Environment (TOE) framework. This parameter evaluates the influence of national policy, flight directives, and the overarching legal framework provided by the Civil Aviation Authority of Malaysia (CAAM). In the context of this study, it specifically incorporates the role of the National AI Office (NAIO) in establishing secure regulatory sandboxes and clear flight mandates (CAD 6011), which are tested in Section B of the research questionnaire.

The second parameter, Institutional Readiness, is an independent variable grounded in the Resource-Based View (RBV) and institutional theory. It measures the internal capability of a

construction firm to absorb and sustain AI drone technology. This includes evaluating digital infrastructure, leadership commitment, and the technical competence of site safety personnel. This parameter is directly linked to the "managerial muscle" concepts discussed in the literature review and is operationalized in Section C of the survey instrument.

The third parameter, Trust and Data Ethics, represents a normative independent variable sourced from Social Exchange Theory and ethical AI governance frameworks. It addresses critical modern concerns such as algorithmic transparency, worker privacy, and data security. This parameter aligns with the National Guidelines on AI Governance and Ethics (AIGE) and is measured in Section D of the questionnaire to determine how social legitimacy influences the adoption process.

The fourth parameter, Implementation Quality, acts as the primary mediating variable in this research. Sourced from change management and process innovation theories, it focuses on the operational "bridge" between governance policy and site execution. This parameter evaluates the coordination of drone flights, the reliability of AI data under local weather constraints, and the integration of autonomous insights into existing safety protocols. It is uniquely positioned as a mediator to explain the pathway through which governance factors influence final adoption, as surveyed in Section E.

Finally, the fifth parameter, AI Drone Adoption, is the dependent variable. Sourced from the Unified Theory of Acceptance and Use of Technology (UTAUT), it serves as the ultimate outcome measure of the study. This parameter evaluates the intensity, frequency, and perceived effectiveness of AI-enabled safety monitoring across Malaysian construction sites. It is operationalized in Section F of the questionnaire to provide a quantitative assessment of the transition from manual oversight to automated safety ecosystems.

1.7 Research Gaps and Justification

The justification for this research is anchored in three distinct gaps identified within the current academic and industrial landscape of the Malaysian construction sector. By addressing these theoretical, methodological, and contextual voids, the study provides a novel contribution to the field of digital safety governance.

The first justification arises from a significant Theoretical Gap regarding the governance of autonomous systems. Traditional technology adoption models, such as the Technology Acceptance Model (TAM), focus heavily on individual perceptions of "usefulness" and "ease of use." However, these frameworks fail to account for the complex, multi-layered "Governance Ecosystem" required for high-risk technologies like AI-driven drones. There is a lack of integrated theory that explains how regulatory mandates, institutional readiness, and ethical trust form a cohesive system. This study fills this gap by proposing and validating the Governance Ecosystem Model, which integrates these dimensions into a unified framework specifically tailored for the construction industry's safety requirements.

Second, a Methodological Gap exists in the current literature concerning the "Implementation Bridge." While researchers have identified broad barriers to technology adoption, there is a lack of quantitative evidence explaining the specific process by which these barriers are overcome at the operational site level. Most existing studies utilize descriptive or direct-relationship analysis, which fails to capture the underlying mechanisms of change. This research justifies its necessity by employing Structural Equation Modeling (SEM) to test Implementation Quality as a mediating variable. This sophisticated statistical approach allows for a deeper understanding of how governance enablers are "processed" through operational execution to result in successful adoption, providing a higher level of rigor than previous direct-effect studies.

Finally, there is a critical Contextual Gap specific to the Malaysian 2026 landscape. Much of the existing research on Malaysian construction digitalization was conducted during the early phases of the Construction 4.0 Strategic Plan. With the industry now transitioning into the Thirteenth Malaysia Plan (2026–2030) and the operationalisation of the National AI Office (NAIO), previous findings are no longer sufficient to guide current practice. This study is justified as a "real-time" response to these 2026 mandates, incorporating the latest National Guidelines on AI Governance and Ethics (AIGE) and the CAAM CAD 6011 flight directives. By providing empirical data grounded in the current legislative environment, the study offers immediate practical value to the Construction Industry Development Board (CIDB) and national policymakers.

1.8 Limitations of the Study

The execution of this research within the Malaysian construction industry involves navigating several operational, methodological, and regulatory boundaries. Recognizing these limitations is

essential for contextualizing the findings and ensuring the validity of the Governance Ecosystem Model (GEM).

First, this study is non-experimental in nature. The research focuses exclusively on the governance and organizational aspects of Artificial Intelligence (AI) drone adoption and does not involve physical hardware testing, flight simulations, or on-site technical performance measurements. Consequently, factors such as battery efficiency, signal reliability, and sensor accuracy are treated as perceived variables reported by respondents rather than empirical engineering data.

Second, the study faces methodological limitations inherent in the use of self-reported questionnaires. While the survey instrument is designed to be robust, the data relies on the subjectivity of industry professionals, including Developers, Consultants, Contractors, and Sub-contractors. There is a potential for response bias, where participants may overestimate their organization's Institutional Readiness or compliance with safety protocols to project a more progressive digital image. Furthermore, the cross-sectional design captures a "snapshot" of the industry at a single point in time, which may not account for long-term shifts in technology maturity or future regulatory updates.

Third, the geographical and professional scope of the research is a limiting factor. The sampling is primarily concentrated within major Malaysian construction hubs and urban centers. Therefore, the results may not be fully generalizable to small-scale projects in rural areas where digital infrastructure and regulatory enforcement may differ. Additionally, identifying a sufficient sample size of professionals who possess both construction expertise and a working knowledge of AI systems presents a complex sampling challenge for the Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis.

Finally, the study is limited by the rapid pace of technological evolution. Due to the speed at which Artificial Intelligence and drone capabilities advance, the literature and technical benchmarks established during the initial phases of this thesis may undergo significant changes by the time of final submission. The research is thus bounded by the regulatory mandates, such as the Civil Aviation Authority of Malaysia (CAAM) CAD 6011 directives, and the technological landscape available during the data collection period.

1.9 Significance of the Study

The significance of this research is twofold, offering a substantial contribution to the academic body of knowledge regarding technology governance and providing practical, actionable insights for the Malaysian construction industry. Theoretically, this study addresses the "Governance Ecosystem" gap by moving beyond individual-centric models like UTAUT to explore how structural and ethical pillars interact within high-risk autonomous environments. By validating the Governance Ecosystem Model (GEM), the research provides a new theoretical framework that explains the multi-dimensional nature of AI adoption. The most significant academic contribution lies in the empirical testing of Implementation Quality as a mediating variable. This shifts the scholarly conversation from viewing site execution as a mere barrier to recognizing it as the critical causal "bridge" through which regulatory and institutional support are transformed into successful technology adoption.

Practically, the findings of this study provide a timely evidence-based roadmap for national policymakers and industrial stakeholders as Malaysia transitions into the Thirteenth Malaysia Plan (2026–2030). For the National AI Office (NAIO) and the Construction Industry Development Board (CIDB), this research offers a validated assessment of how current policies, such as the AIGE guidelines and CAD 6011 flight directives, are being operationalized on the ground. By identifying the specific governance domains that most influence adoption, the study enables these agencies to refine their support mechanisms and incentive structures for G7 contractors.

Furthermore, the research holds significant value for construction firms and Safety and Health Officers (SHOs) striving to enhance site safety through digitalization. By highlighting the necessity of Institutional Readiness and Trust, the study provides site managers with a strategic framework to overcome internal resistance and technical hurdles. Ultimately, the successful validation of this model contributes to the national goal of reducing construction site fatalities and accidents, positioning Malaysia as a regional leader in the safe and ethical implementation of AI-driven safety ecosystems. This alignment with the Construction 4.0 Strategic Plan ensures that the research is not only academically rigorous but also socially and economically impactful for the nation's future.

1.10 Definition of Terms

To ensure clarity and consistency throughout this study, the following terms are defined according to their operational usage within the context of AI drone governance and the Malaysian construction industry:

AI Drone Adoption Operationalized as the degree to which construction stakeholders integrate autonomous Unmanned Aerial Vehicles (UAVs) equipped with Artificial Intelligence into their standard safety monitoring and project oversight protocols. In this study, adoption is measured by the frequency of usage and the depth of AI-enabled hazard detection (Sapri, 2024).

Regulatory Support Refers to the external governance framework provided by national authorities, including the Civil Aviation Authority of Malaysia (CAAM) and the National AI Office (NAIO). This encompasses the clarity of flight mandates (CAD 6011), the availability of legal "sandboxes," and the strategic alignment with the Thirteenth Malaysia Plan (2026–2030).

Institutional Readiness Defined as the internal capability of an organization whether a developer, client, or contractor to adopt and sustain AI technology. This includes the presence of "managerial muscle," technical infrastructure, and the financial commitment required to transition from manual to automated safety oversight (Kamaruddin, 2023).

Trust and Data Ethics Refers to the socio-ethical legitimacy of the AI system. It involves the transparent handling of site data, the protection of worker privacy under the National Guidelines on AI Governance and Ethics (AIGE), and the perceived reliability of autonomous algorithmic decision-making (Zhang et al., 2023).

Implementation Quality The mediating variable in this study, defined as the operational effectiveness of drone deployment at the site level. This includes the coordination of flights, the accuracy of AI data in tropical weather conditions, and the seamless integration of drone insights into existing Safety and Health Officer (SHO) workflows (Lim, 2025).

Computer Vision (CV) A field of Artificial Intelligence that enables drones to "see" and interpret the construction environment. Operationally, it refers to the algorithms used for real-time hazard recognition, such as identifying missing Personal Protective Equipment (PPE) or detecting unauthorized entry into exclusion zones (Cheng & Teizer, 2013).

Technology-Organization-Environment (TOE) Framework The primary theoretical lens used in this study (and detailed in Chapter 2) to categorize the factors influencing technology adoption. In this research, "Technology" relates to the AI systems, "Organization" to Institutional Readiness, and "Environment" to Regulatory Support and Trust.

Resource-Based View (RBV) A management theory used to analyze how a firm's internal resources (e.g., AI infrastructure and skilled personnel) provide a competitive advantage in safety performance. This theory underpins the "Institutional Readiness" variable of the Governance Ecosystem Model.

Construction Industry Stakeholders Refers to the collective group of Developers, Clients, and CIDB-registered Contractors (Grades G1 through G7). This inclusive definition ensures a comprehensive analysis of the "Digital Split" and the diverse governance needs across the industry hierarchy.

Small and Medium Enterprises (SMEs) in Construction In this research context, SMEs typically refer to contractors within the G1 to G4 categories. These firms are characterized by limited capital for high-tech investment and are a primary focus for the "Governance Disconnect" addressed in this study.

Agentic AI A subset of Artificial Intelligence where the system can independently perform complex tasks and make autonomous decisions based on environmental data (e.g., a drone independently identifying a safety violation) rather than just following a pre-programmed flight path.

OSH (Amendment) Act 2022 The primary legislative framework in Malaysia governing workplace safety. In this study, it serves as the legal driver for technology adoption, placing increased accountability on employers to utilize "practicable" modern tools for hazard prevention (DOSH, 2024).

Construction 4.0 The Malaysian strategic initiative aimed at digitalizing the AEC (Architecture, Engineering, and Construction) sector. It provides the industrial context for this research, focusing on the convergence of physical site activities with digital AI oversight.

1.11 Organization of the Thesis

This thesis is organized into five systematically structured chapters, logically sequenced to transition from the identification of the research problem through to the empirical validation of the Governance Ecosystem Model (GEM) and the formulation of strategic industry recommendations.

Chapter 1: Introduction establishes the foundational background of the study, detailing the technological transformation of the Malaysian construction industry towards Construction 4.0. It outlines the core research problem identified as the "Governance Paradox" and the resulting "Digital Split" between large-scale developers and smaller contractors. The chapter defines the primary research questions and objectives, introduces the core parameters of the GEM (Regulatory Support, Institutional Readiness, Trust & Data Ethics, and Implementation Quality), and establishes the significance, gaps, and scope of the study.

Chapter 2: Literature Review provides a comprehensive and critical synthesis of existing academic and policy-based literature regarding construction safety, safety management practices, and AI-drone integration. It theoretically grounds the research by synthesizing the Technology-Organization-Environment (TOE) framework, the Technology Acceptance Model (TAM), and Institutional Theory. The chapter deeply explores the three core governance domains and the operational bridge of Implementation Quality, culminating in the development of the conceptual framework and nine research hypotheses to be empirically tested.

Chapter 3: Research Methodology delineates the operational blueprint for the empirical investigation. It justifies the adoption of a positivist philosophy and a deductive, cross-sectional quantitative research design. The chapter details the data collection process via a digital survey instrument measured on a 5-point Likert scale, the purposive and snowball sampling strategies targeting decision-makers across developers, consultants, and contractors, and the robust data analysis strategy utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM).

Chapter 4: Results and Analysis presents the empirical findings of the study, utilizing SPSS for descriptive statistics and SmartPLS 4 for inferential modeling. It details the demographic profile of the respondents and their perceived barriers to AI-drone adoption. The chapter rigorously evaluates the measurement model's reliability and validity, followed by the structural model assessment which tests the direct, mediating, and moderating hypotheses. It further incorporates

Multi-Group Analysis (MGA) to compare differing perspectives between office-based consultants and site-based contractors, alongside an Importance-Performance Map Analysis (IPMA) to identify actionable areas for improvement, concluding with the finalized, validated research models.

Chapter 5: Conclusion and Recommendations synthesizes the empirical evidence from the previous chapter to definitively answer the research objectives. It articulates the study's theoretical and methodological contributions to the academic body of knowledge, specifically highlighting the "Implementation Bridge" and "Regulatory Friction". Finally, it translates the statistical findings into strategic, actionable recommendations for industry practitioners, organizational leadership, and national regulatory bodies (such as CIDB, DOSH, and CAAM), while also acknowledging the study's scope limitations and suggesting distinct pathways for future research.

1.12 Chapter Summary

Chapter 1 has established the foundational framework for this research, positioning the Governance Ecosystem Model (GEM) as a critical requirement for the adoption of AI drones within the Malaysian construction industry. By providing a detailed background of the digital shift toward Construction 4.0 and the strategic mandates of the Thirteenth Malaysia Plan (2026–2030), this chapter has highlighted the urgent necessity for modernized, autonomous safety oversight. The research problem was identified as a pervasive "Governance Disconnect," where high-level policy support from the National AI Office (NAIO) and the Civil Aviation Authority of Malaysia (CAAM) fails to translate into consistent site-level adoption across a fragmented stakeholder group comprising Developers, Clients, and G1–G7 Contractors.

To address this structural paradox, six research questions and five research objectives were formulated, focusing on the complex direct and mediated relationships between regulatory, institutional, and ethical domains. A central contribution of this chapter is the conceptualization of Implementation Quality as a mediating bridge a pathway that has been theoretically proposed in broader management literature but remains empirically unvalidated within the specific socio-technical context of the Malaysian AEC sector. The significance of the study was articulated through its multi-dimensional potential to reduce site fatalities, bridge the "Digital Split" between SMEs and tier-one firms, and provide a validated roadmap for the ethical governance of Agentic AI in high-risk environments.

Furthermore, the identification of key research gaps and the setting of research parameters have ensured that this study remains grounded in the realities of 2026 legislation, such as the Occupational Safety and Health (Amendment) Act 2022 and the National Guidelines on AI Governance and Ethics (AIGE). The operational definitions provided in Section 1.11 ensure that the variables of this study Regulatory Support, Institutional Readiness, and Trust are interpreted through their specific impact on technology integration.

With the research problem, gaps, and objectives firmly established, this thesis now transitions into Chapter 2: Literature Review. The subsequent chapter provides an exhaustive and critical synthesis of the existing body of knowledge. It explores the theoretical origins of the Technology-Organization-Environment (TOE) and Resource-Based View (RBV) frameworks, analyzes the historical evolution of Unmanned Aerial Vehicles (UAVs) in construction safety, and evaluates the psychological and structural factors that dictate the digital transformation of the Malaysian built environment. This transition ensures that the empirical testing in later chapters is built upon a robust theoretical and historical foundation.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

2.1 Introduction

The global construction industry is experiencing a period of profound transformation driven by the integration of emerging technologies such as Artificial Intelligence (AI) and Unmanned Aerial Vehicles (UAVs), commonly known as drones. These technologies have demonstrated significant potential to improve safety, productivity, and overall project delivery by shifting safety management from reactive monitoring to proactive hazard detection. In particular, the convergence of AI and drone-based safety monitoring systems has introduced new possibilities for mitigating workplace hazards, enhancing compliance with safety standards, and supporting real-time decision-making at construction sites (Yi & Sutrisna, 2021). The relevance of these advancements is especially pronounced in Malaysia, where the construction sector remains a major contributor to national economic growth yet continues to face persistent safety challenges. As illustrated in Figure 2.1, a troubling trend persists where non-fatal occupational injuries increased by approximately 59.65% in 2022, while the fatality rate remained alarmingly high at 6.30 deaths per 100,000 workers (Tham & Hassim, 2025).



Figure 2.1: Overview of the Malaysian Construction Safety Context (Adapted from Tham and Hassim, 2025)

Despite government-led efforts to promote digitalisation under the Construction 4.0 Strategic Plan (2021–2025) and the recent enforcement of the Occupational Safety and Health (Construction Work) (Design and Management) Regulations 2024 (CDM 2024), the industry has not fully realised the potential of AI-driven technologies for safety management (Department of Occupational Safety and Health, 2024). The sector faces a "governance paradox" where the government actively promotes digital transformation, yet the on-the-ground regulatory and institutional frameworks remain fragmented. This paradox, characterized by limited regulatory clarity and institutional unpreparedness, often stalls actual implementation. The technical capabilities required for automated site monitoring are shown in Figure 2.2, while the systemic barriers that constitute the governance paradox are visualized in Figure 2.3 (Khudzari et al., 2025).



Figure 2.2: Conceptual Diagram of AI and Drone Convergence (Adapted from Yi and Sutrisna, 2021)



Figure 2.3: Illustration of the Governance Paradox in the Malaysian Construction Industry (Adapted from Khudzari et al., 2025; DOSH, 2024)

This literature review serves three main purposes. First, it provides an overview of the current state of construction safety management in Malaysia and situates it within the global technological transformation. Second, it examines the challenges associated with AI-drone safety adoption, with particular attention to the governance ecosystem. Third, it analyses three key governance factors—Regulatory Support, Institutional Readiness, and Trust and Data Ethics—that are posited to influence implementation quality. The review also introduces "Implementation Quality" as the crucial bridge, arguing that robust regulations are insufficient unless they translate into effective site practices. As depicted in Figure 2.4, these three pillars are the critical factors determining whether technology is successfully adopted (Shanmughapriya et al., 2024).



Figure 2.4: The Three Pillars of Governance Influencing Implementation and Adoption (Adapted from Shanmughapriya et al., 2024)

To achieve these objectives, the review synthesises findings from academic literature and policy reports released between 2018 and 2025. The structure of this chapter follows a logical progression from context to theory. The research pathway, mapping the literature review from the industry problem identification to the development of the conceptual framework, is presented

in Figure 2.5. This flow ensures that the study remains grounded in established discourse while addressing the specific methodological gaps in the Malaysian context.

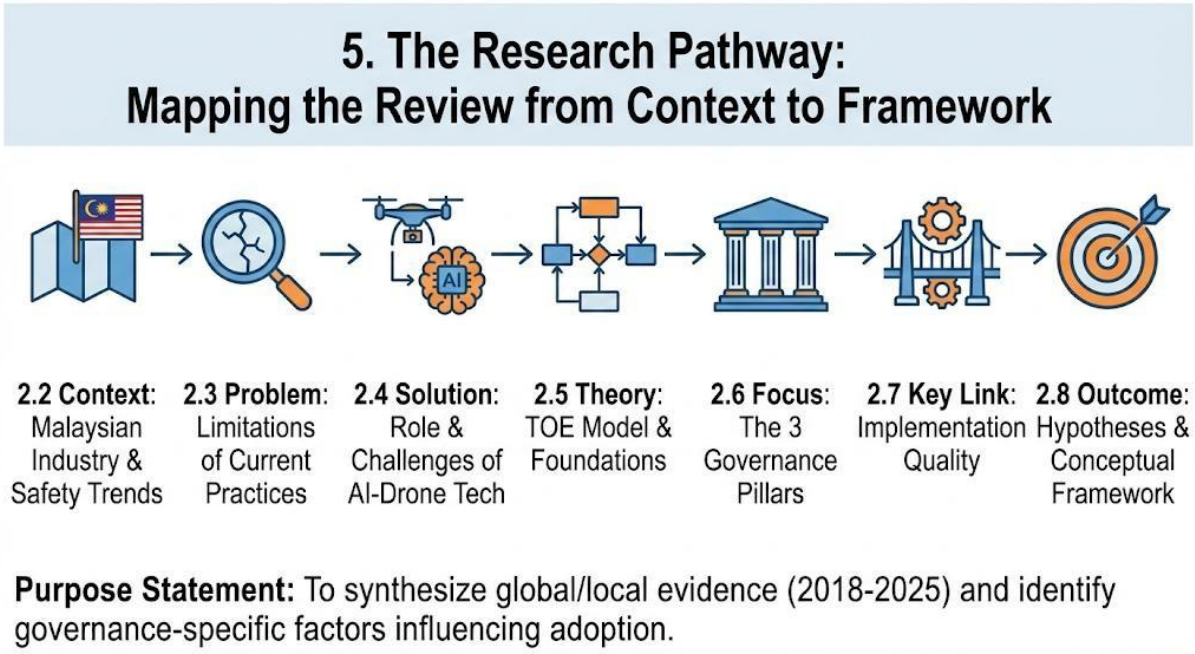


Figure 2.5: The Research Pathway of the Literature Review

2.2 The Construction Industry in Malaysia

The Malaysian construction industry serves as one of the nation's most dynamic economic sectors and plays a pivotal role in driving urbanization, infrastructure growth, and employment creation. As a primary engine of development, it functions with a high multiplier effect that stimulates growth across the broader economy. It links upstream industries such as manufacturing and raw materials production with downstream sectors including transportation, real estate, and professional services. According to recent data from the Department of Statistics Malaysia, the sector has shown a robust recovery following the pandemic. As illustrated in Figure 2.6, overall construction activity recorded a positive growth of 17.1% in the third quarter of 2025, signaling a strong resurgence driven predominantly by large scale infrastructure projects (Department of Statistics Malaysia, 2025).

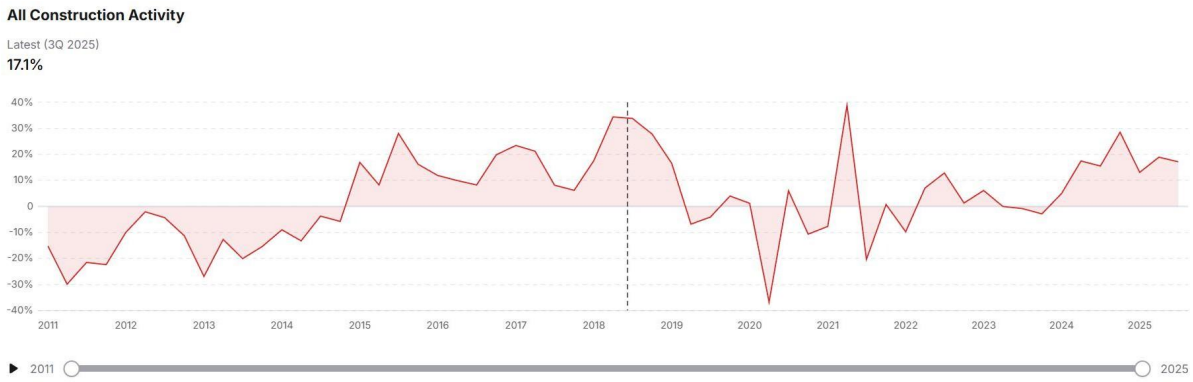


Figure 2.6: Quarterly trend of construction activity in Malaysia showing a 17.1% growth in Q3 2025 (Department of Statistics Malaysia, 2025)

This extensive value chain positions the construction sector not merely as a builder of physical assets but as a fundamental enabler of national socioeconomic stability. The data further reveals that this growth is not uniform across all sub sectors. As depicted in Figure 2.7, the Civil Engineering sub sector recorded a significant growth of 18.3%, markedly outperforming the residential sub sector which contracted by 21.7% (Department of Statistics Malaysia, 2025). This disparity underscores the government's strategic focus on infrastructure development such as highways, rail networks, and utilities under the Twelfth Malaysia Plan (Economic Planning Unit, 2021). These complex civil engineering projects require higher safety standards and more sophisticated monitoring capabilities, making them the ideal testing ground for AI and drone technologies.

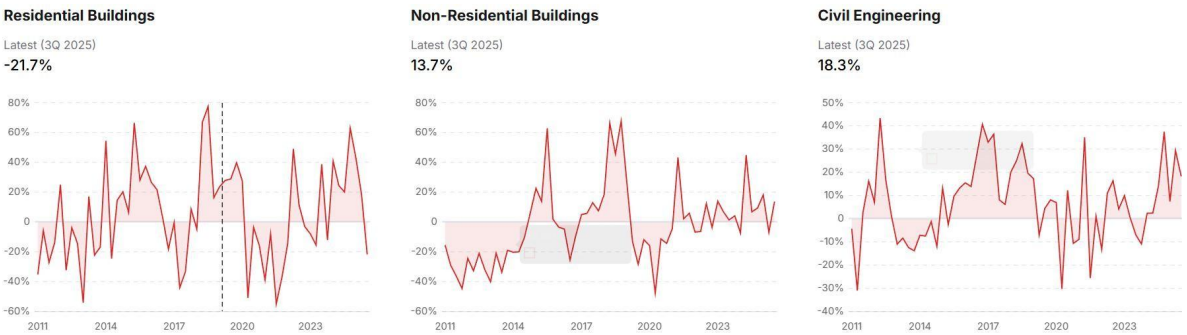


Figure 2.7: Performance by construction sub-sector in Q3 2025 highlighting the dominance of Civil Engineering (Department of Statistics Malaysia, 2025)

Despite these impressive economic contributions, the industry continues to face persistent challenges that threaten its long term sustainability. The sector remains heavily characterized by

a labor intensive operational model and a deep seated dependence on a low skilled manual workforce, which has historically contributed to stagnant productivity levels and uneven safety standards (Hussin et al., 2025). Furthermore, the industry structure is highly fragmented, consisting of a vast majority of small and medium sized enterprises that often lack the capital and technical expertise to invest in modern solutions. Khudzari et al. argue that this structural fragmentation has led to a slow adoption of digital technologies, creating a significant divide between the high tech ambitions of national policy such as the Construction 4.0 Strategic Plan and the low tech reality of daily site operations (Khudzari et al., 2025). This gap prevents the industry from fully leveraging data driven tools to mitigate risks, leaving workers exposed to preventable site hazards.

In the context of this study, understanding this dichotomy between economic ambition and operational reality is essential. It establishes the critical backdrop against which the governance ecosystem, technological readiness, and safety performance interact to shape the adoption of advanced tools like AI drones. The following sub sections provide a detailed overview of the sector's economic importance, its ongoing technological transformation under the Industry 4.0 agenda, and its current safety performance. Collectively, these elements frame the rationale for why the industry must pivot from traditional manual methods to AI driven innovations to ensure a safer and more resilient future.

2.2.1 Overview of the Construction Sector

The construction sector is a cornerstone of Malaysia's economic development, consistently contributing approximately four to five percent of the national Gross Domestic Product (GDP) and providing employment to a significant workforce across diverse sub-industries. Its strategic importance extends beyond economic output, as it supports critical national objectives outlined in the Twelfth Malaysia Plan (2021–2025), which prioritizes sustainable infrastructure, improved productivity, and safer working environments (Economic Planning Unit, 2021). However, while the sector continues to expand, it remains characterized by cyclical fluctuations and fragmented project delivery systems that pose structural challenges to efficiency and governance.

A long-standing issue within the industry is its reliance on a multi-tiered subcontracting system involving numerous stakeholders such as developers, consultants, and contractors, each with distinct responsibilities and incentives. Khudzari et al. (2025) argue that this fragmentation often

leads to coordination challenges and inconsistent safety standards, as information regarding site hazards is frequently diluted as it passes through the supply chain. This structural complexity makes centralized safety enforcement difficult, creating an environment where accountability is often dispersed. As illustrated in Figure 2.8, the sector operates within a clear dichotomy, acting as a vital economic engine while simultaneously struggling with systemic "fault lines" such as fragmentation and workforce vulnerability (Khudzari et al., 2025; Hussin et al., 2025).

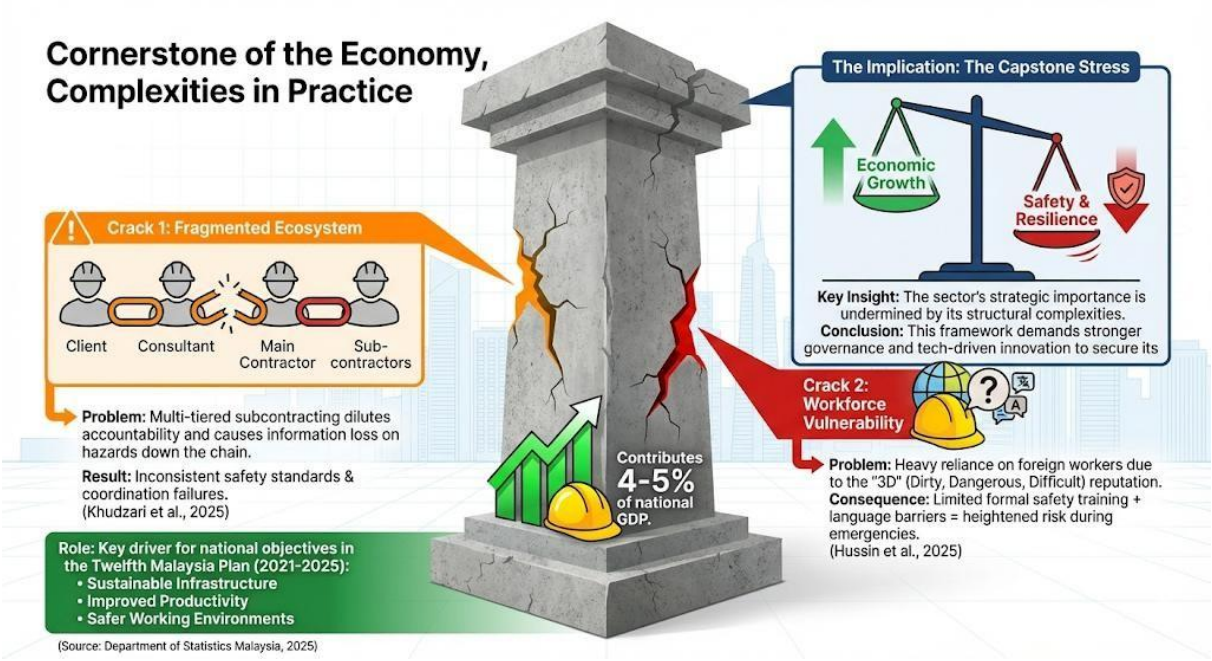


Figure 2.8: The Dichotomy of the Malaysian Construction Sector (Adapted from Khudzari et al., 2025 and Hussin et al., 2025)

Furthermore, the industry's reputation as being "dirty, dangerous, and difficult" (3D) has discouraged local participation, leading to a heavy dependence on foreign labor. Hussin et al. (2025) highlight that this reliance introduces significant vulnerabilities, as many workers possess limited formal training in occupational safety and face language barriers that hinder effective communication during emergencies. Consequently, while the construction industry remains central to Malaysia's progress, it continues to operate within a framework that requires stronger governance oversight and innovation-driven reform to enhance safety and operational resilience.

2.2.2 Technological Transformation and Construction 4.0 Initiatives

The onset of the Fourth Industrial Revolution has introduced a paradigm shift across Malaysia's construction sector, where digitalization and automation are increasingly recognized as essential

for maintaining competitiveness and enhancing safety. The Construction 4.0 Strategic Plan (2021–2025), spearheaded by the Construction Industry Development Board (CIDB), aims to foster innovation through the adoption of advanced technologies, including Building Information Modelling (BIM), the Internet of Things (IoT), robotics, and Artificial Intelligence (AI) (Construction Industry Development Board, 2020). Recent empirical analysis by Khudzari et al. (2025) confirms that while technological potential is recognized, the actual rate of adoption is heavily moderated by organizational culture and the perceived complexity of these modern tools.

This disconnect between strategic intent and practical application is further explored in Figure 2.9. The diagram contrasts the high-level national policy vision with the persistent adoption gap caused by structural resistance factors such as fragmented workflows and financial constraints (Khudzari et al., 2025; Donnis & Rahmat, 2025).

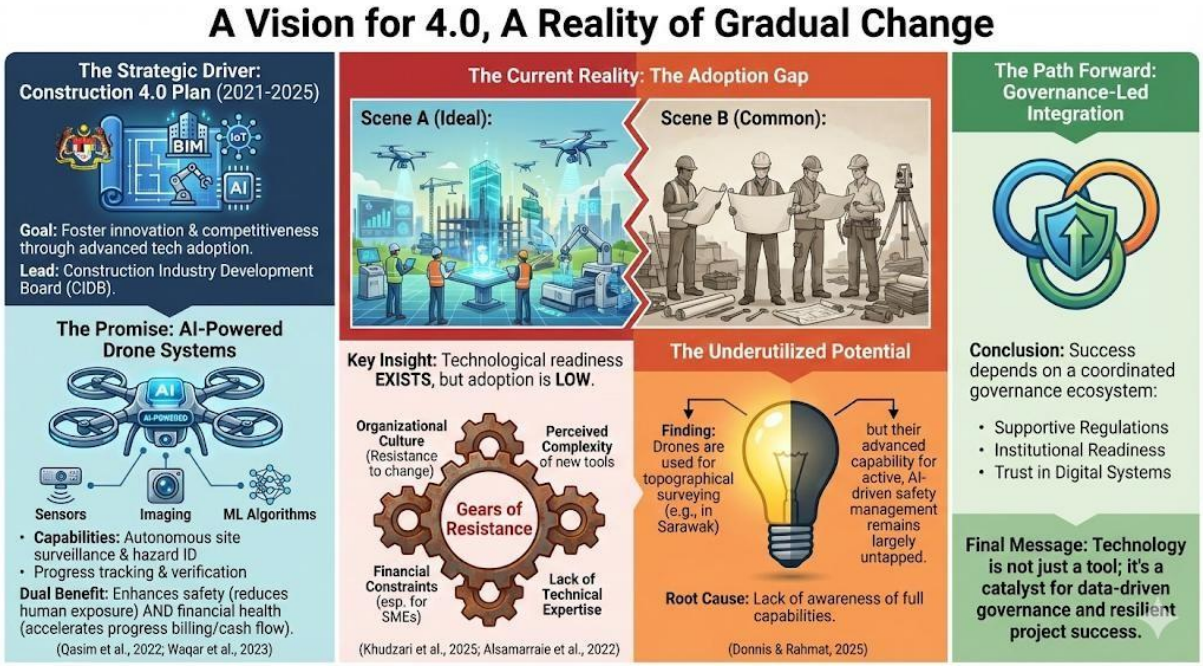


Figure 2.9: Strategic Overview of the Construction 4.0 Landscape (Adapted from Khudzari et al., 2025 and Donnis and Rahmat, 2025)

Despite these initiatives, the industry's transition toward digitalization has remained gradual. Many firms, particularly small and medium-sized enterprises (SMEs), remain reliant on conventional construction methods and paper-based processes that limit data integration and real-time decision-making (Alsamarraie et al., 2022). The barriers to adoption are multifaceted, encompassing financial limitations, a lack of technical expertise, and organizational resistance to change. However, recent literature suggests that technology can alleviate these financial

pressures; Qasim et al. (2022) argue that in large-scale construction projects, drones serve a dual function by verifying the physical percentage of completion, which directly accelerates progress billing and improves cash flow management. This evidence suggests that integrating AI-based drones is not merely a technical upgrade but a critical factor in achieving both financial sustainability and project success (Waqar et al., 2023).

Within this context, AI-powered drone systems have emerged as a promising innovation capable of transforming safety management. Equipped with advanced sensors and machine learning algorithms, drones can perform site surveillance and hazard identification autonomously, significantly reducing the exposure of human inspectors to high-risk conditions. Donnis and Rahmat (2025) observe that while the adoption of such technology is gaining traction for topographical surveying, its potential for active safety management remains underutilized due to a lack of awareness regarding its advanced predictive capabilities. The successful integration of these systems ultimately depends on specific governance elements, namely supportive regulations, institutional readiness, and trust in digital ecosystems.

2.2.3 Safety Performance and Accident Statistics in Malaysia

Occupational safety remains one of the most pressing challenges confronting the Malaysian construction sector, which is frequently cited as one of the most hazardous industries in the national economy. The Department of Occupational Safety and Health (DOSH) consistently reports alarming accident rates that disproportionately affect construction workers compared to other sectors. Tham and Hassim (2025) provide a critical analysis of recent data, revealing that non-fatal occupational injuries in the construction industry surged by approximately 59.65% in 2022 compared to the previous year, while the fatality rate remained critically high at 6.30 deaths per 100,000 workers. These figures underscore a persistent failure in traditional safety management systems to arrest the upward trend of site accidents despite the presence of comprehensive legal frameworks.

This safety crisis is graphically represented in Figure 2.10, which delineates the rising accident statistics alongside the systemic root causes found within the industry. The diagram further illustrates the pivotal role of Artificial Intelligence (AI) drone technology in bridging the existing compliance gap by shifting management from reactive to proactive monitoring (Tham & Hassim, 2025; Hussin et al., 2025; Misnan et al., 2024).

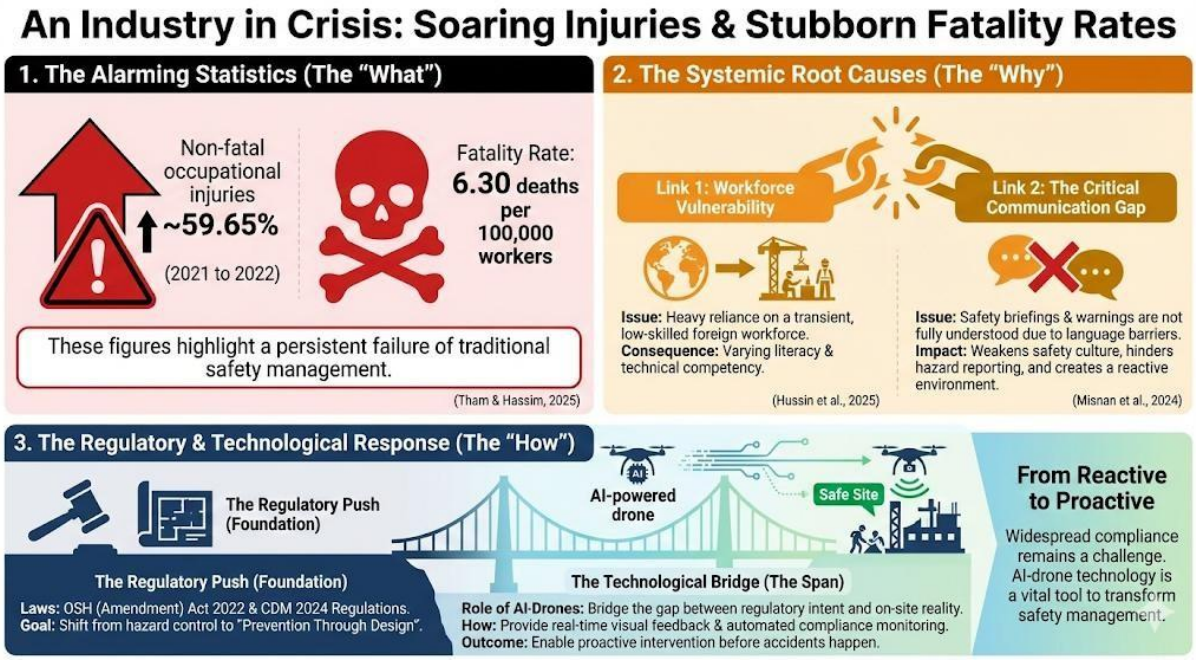


Figure 2.10: Graphical Representation of the Malaysian Construction Safety Crisis (Adapted from Tham and Hassim, 2025; Hussin et al., 2025; and Misnan et al., 2024)

A significant contributing factor to this safety deficit is the industry's heavy reliance on a transient and low-skilled workforce. Hussin et al. (2025) note that a vast majority of the site labor force consists of foreign workers who often possess varying levels of literacy and technical competency. This demographic reality introduces substantial communication barriers, as safety briefings and hazard warnings may not be fully understood by workers with limited proficiency in the local or English languages. Misnan et al. (2024) argue that this "communication gap" significantly weakens the overall safety culture, as it hinders the effective dissemination of critical safety protocols and reduces the likelihood of workers reporting hazards voluntarily. Consequently, supervisory oversight is often compromised, creating a reactive environment where safety measures are only implemented following an incident.

In response to these systemic failures, the government has introduced the Occupational Safety and Health (Amendment) Act 2022 and the Occupational Safety and Health (Construction Work) (Design and Management) Regulations 2024 (CDM 2024). These regulations aim to shift the industry's focus toward "prevention through design," compelling duty holders to identify risks during the planning phase. However, as widespread compliance remains a challenge, the adoption of AI-driven drone technologies presents a vital opportunity to bridge the gap between regulatory intent and on-site reality. By providing real-time visual feedback and automated

compliance monitoring, drones enable site managers to intervene before unsafe behaviors escalate into accidents.

2.3 Safety Management Practices in Construction

Safety within the construction industry has long been recognized as one of the most critical and persistent challenges globally. The nature of construction work typically involves complex coordination among multiple parties, exposure to hazardous conditions, and a heavy reliance on manual labor. These factors render the sector particularly vulnerable to accidents and occupational hazards. Despite continuous improvements in safety management systems, the rate of accidents remains disproportionately high compared to other industries. The importance of ensuring safety in construction extends beyond the prevention of physical harm; it encompasses organizational resilience, project continuity, and the overall social responsibility of the sector. Hussin et al. (2025) expand on this by arguing that the "multidimensional impacts" of site accidents include severe financial liabilities, legal repercussions, and long-term reputational damage which can threaten the survival of construction firms.

In the Malaysian context, traditional safety management has historically relied on reactive measures such as manual inspections, paper-based checklists, and post-incident reporting. Misnan et al. (2024) criticize this approach, noting that it often leads to a "tick-box" culture where safety reporting is performed merely for compliance rather than genuine hazard prevention. Furthermore, human inspectors cannot be present at all locations simultaneously, leaving significant gaps in supervision where unsafe behaviors may go undetected.

To address these limitations, the industry is witnessing a paradigm shift toward technology-enabled safety monitoring. Shah and Mishra (2024) describe this as the integration of Artificial Intelligence (AI) into Occupational Health and Safety (OHS), moving the industry from reactive analysis to predictive prevention. The relationship between these traditional limitations and the modern resilience provided by AI is synthesized in Figure 2.11, which illustrates how the shift toward proactive monitoring contributes to sustainable project success (Hussin et al., 2025; Misnan et al., 2024; Waqar et al., 2023).

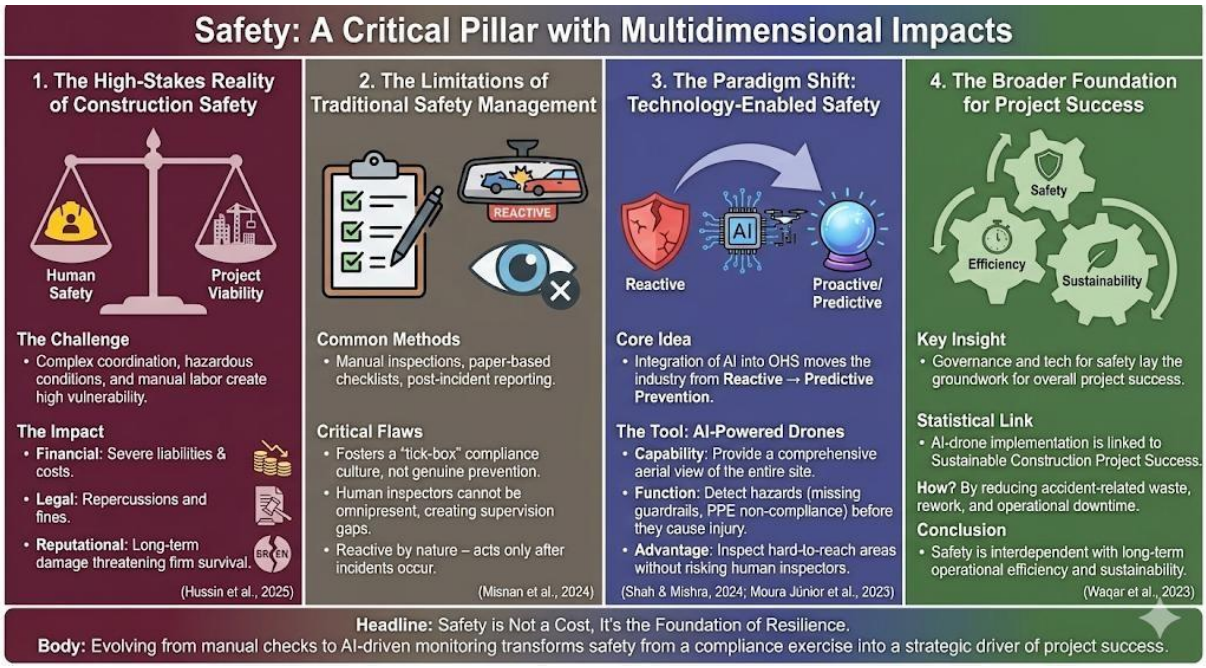


Figure 2.11: The Multidimensional Criticality of Construction Safety (Adapted from Hussin et al., 2025; Misnan et al., 2024; and Waqar et al., 2023)

By utilizing tools such as AI-driven drones, safety managers can obtain a comprehensive aerial view of the site, allowing for the detection of hazards such as missing guardrails or workers operating without Personal Protective Equipment (PPE) before they result in injury. Moura Júnior et al. (2023) support this transition, emphasizing that Unmanned Aerial Vehicles (UAVs) provide the agility required to inspect hard-to-reach areas without putting human inspectors at risk.

While this research primarily focuses on safety performance, it is crucial to recognize that the governance mechanisms and technological interventions that strengthen safety outcomes also lay the groundwork for broader project success. Waqar et al. (2023) demonstrated through structural modeling that the implementation of AI-based drones is statistically linked to "sustainable construction project success" because it reduces waste, rework, and operational downtime caused by accidents. Thus, although safety serves as the immediate focal point of this study, it remains interdependent with the longer-term agenda of operational efficiency and sustainability within the Malaysian construction ecosystem.

2.3.1 Overview of Construction Safety Practices

Globally, construction safety has evolved through multiple phases, transitioning from traditional compliance-based approaches to integrated systems that emphasize proactive risk management. Early safety frameworks largely focused on reactive measures, such as post-incident investigations and strict adherence to statutory obligations. However, recent paradigms prioritize predictive and preventive systems by leveraging digital tools to identify potential hazards before they manifest. In developed economies, safety management has benefited substantially from automation, digital data collection, and analytics-driven oversight (Alizadehsalehi & Yitmen, 2023).

Malaysia's construction industry is currently undergoing a significant regulatory transformation to align with these global standards. The recent introduction of the Occupational Safety and Health (Construction Work) (Design and Management) Regulations 2024 (CDM 2024) represents a pivotal shift from reactive site measures to early hazard elimination at the planning stage (Department of Occupational Safety and Health, 2024). This aligns with the findings of Tham and Hassim (2025), who argue that previous safety frameworks were often insufficient because they addressed risks only after construction had commenced rather than during the design phase. Furthermore, empirical evidence from Krishnasamy et al. (2025) confirms that structured safety frameworks are effective; their study shows that Malaysian firms certified with ISO 45001 consistently demonstrate lower accident rates compared to non-certified peers.

The progression of these safety practices and the current regulatory landscape in Malaysia is illustrated in Figure 2.12. This spectrum juxtaposes global trends against the domestic shift brought about by CDM 2024, while simultaneously highlighting the persistent "two-tiered" reality where implementation quality varies significantly across the industry (Alizadehsalehi & Yitmen, 2023; DOSH, 2024; Misnan et al., 2024).

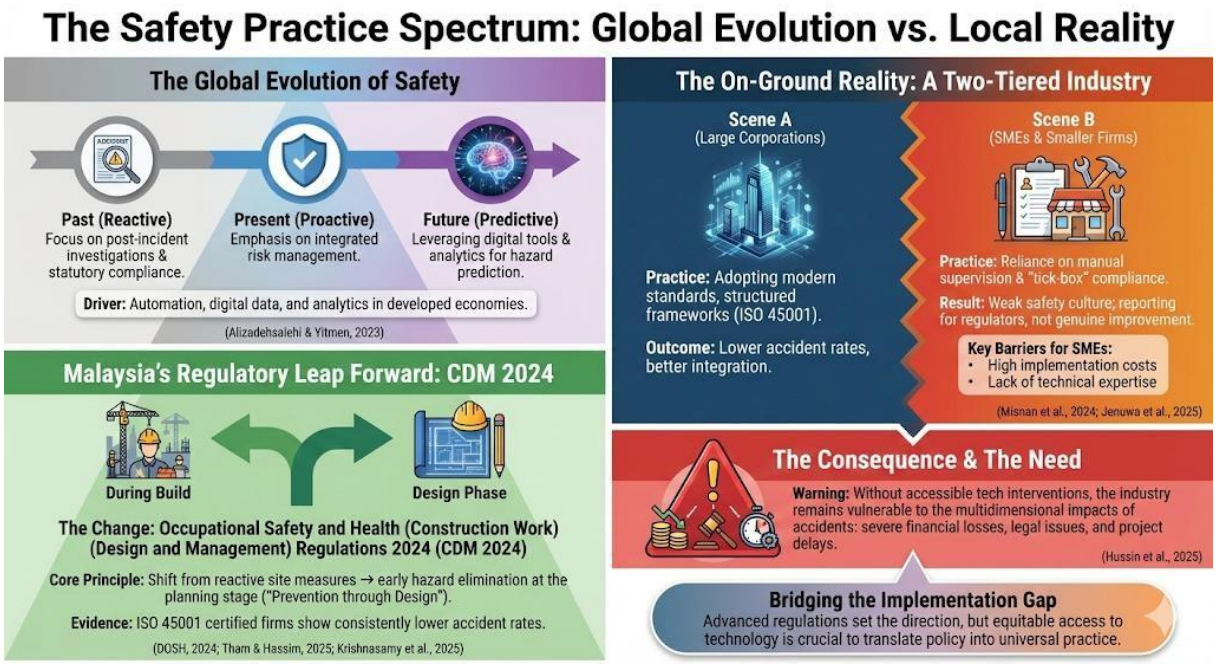


Figure 2.12: The Spectrum of Safety Practice Evolution (Adapted from Alizadehsalehi and Yitmen, 2023; DOSH, 2024; and Misnan et al., 2024)

Despite these regulatory advancements, the integration of safety practices remains uneven. While large corporations are increasingly adopting modern standards, small and medium-sized enterprises (SMEs) continue to rely on manual supervision and tick-box compliance. Misnan et al. (2024) highlight that this results in a weak safety culture where reporting is performed merely to satisfy regulators rather than to genuinely improve site conditions. Jenuwa et al. (2025) further identify that smaller firms face distinct barriers, such as high implementation costs and a lack of technical expertise, which hinder the adoption of modern safety tools. Consequently, Hussin et al. (2025) warn that without accessible technological interventions, the industry remains vulnerable to the multidimensional impacts of accidents, including severe financial losses and project delays.

2.3.2 Challenges in Achieving Safe Construction Environments

The persistence of safety challenges in the Malaysian construction sector can be attributed to a combination of systemic, organizational, and behavioral factors. Systemically, the sector suffers from inconsistent regulatory enforcement and fragmented coordination between agencies. Tham and Hassim argue that despite the introduction of the Occupational Safety and Health (Amendment) Act 2022, the actual implementation of these higher standards varies significantly across different states and project scales (Tham & Hassim, 2025). At the organizational level,

Khudzari et al. identify that a lack of "institutional readiness" is a primary barrier, which manifests through inadequate training protocols, outdated safety management systems, and a reluctance to invest in new technologies due to perceived financial risks (Khudzari et al., 2025).

Human factors also play a crucial role in the industry's safety performance. The workforce in Malaysia is heavily reliant on foreign labor, which introduces significant communication barriers. Misnan et al. observe that varying levels of literacy and language proficiency among workers directly affect the comprehension of safety procedures and limit the effectiveness of traditional verbal briefings during emergency situations (Misnan et al., 2024). Furthermore, the cultural normalization of risk taking behaviors is exacerbated by economic pressures. Teoh and Yahaya found that among contractors in Penang, cost constraints and tight schedules often compel site managers to prioritize productivity over safety compliance, leading to the under reporting of near miss incidents (Teoh & Yahaya, 2024).

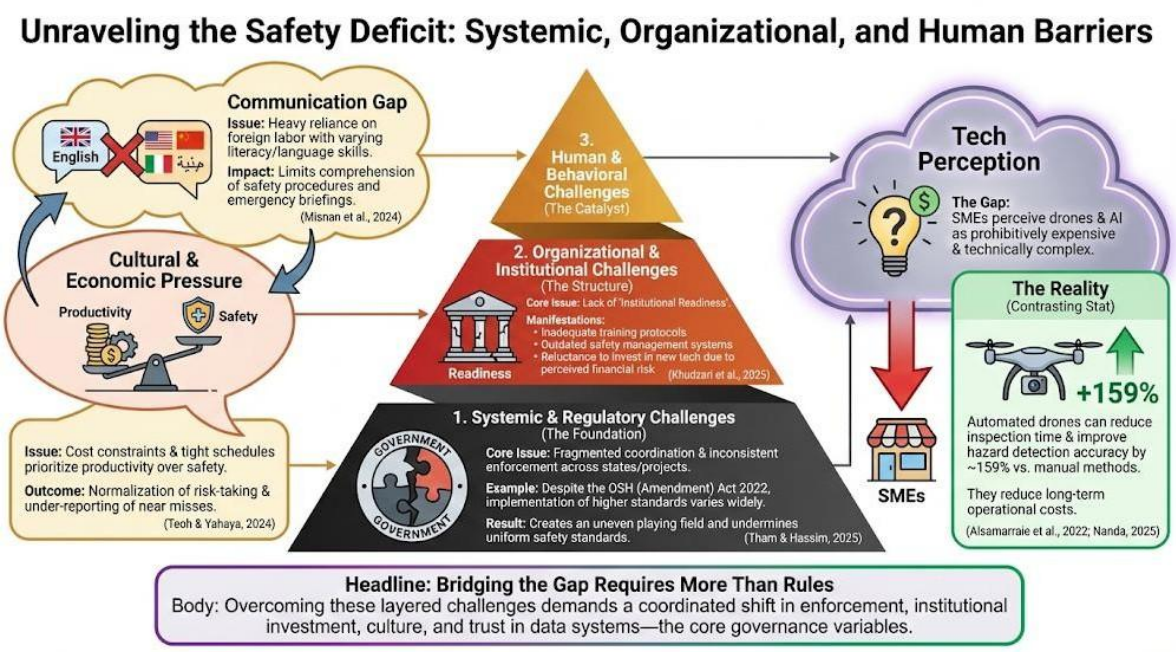


Figure 2.13: Conceptual framework of the multi-tiered safety deficit, illustrating the interplay between systemic, organizational, and behavioral barriers, alongside the technological 'perception gap' hindering SME adoption (Source: Synthesized from Tham & Hassim, 2025; Khudzari et al., 2025; Alsamarraie et al., 2022)

Another critical challenge lies in the limited adoption of digital solutions that could enhance safety management. Alsamarraie et al. highlight that many small and medium sized enterprises perceive technologies such as drones and AI as prohibitively expensive and technically complex,

leading to hesitancy in adoption (Alsamarraie et al., 2022). This "perception gap" prevents firms from realizing that these tools can actually reduce operational costs in the long term. For instance, Nanda demonstrates that once integrated, automated drone tools reduce inspection time and improve hazard detection accuracy by approximately one hundred and fifty nine percent compared to manual methods (Nanda, 2025). Therefore, bridging this gap requires not only regulatory encouragement but also a shift in organizational trust regarding data systems, which serves as a key governance variable explored in subsequent sections.

2.3.3 Technological Integration for Safety Enhancement

In recent years, the convergence of Artificial Intelligence and Unmanned Aerial Vehicles has emerged as a transformative approach to safety management in construction. AI powered drones enable continuous monitoring of high risk zones, automated hazard detection, and instant reporting through data analytics. Yi and Sutrisna explain that these systems mitigate human exposure to danger while enhancing the reliability of inspection data by removing observer bias (Yi & Sutrisna, 2021). The technical efficacy of this integration is well documented; for instance, image recognition algorithms utilizing the YOLOv8 architecture can now identify unsafe behaviors such as workers not wearing helmets or harnesses and automatically trigger alerts to site managers with over ninety five percent accuracy (Al-Khiami & ElHadad, 2024).

Globally, such technologies have shifted safety management from reactive reporting toward predictive analytics. In the Malaysian context, this transition is being accelerated by the Construction 4.0 Strategic Plan (2021–2025), which explicitly lists AI and robotics as key drivers for industry modernization (Construction Industry Development Board, 2020). Recent industry reports indicate that Malaysia now ranks second in the Asia Pacific region for digital adoption in construction, with major firms like Gamuda and Sunway pioneering the use of AI for site safety and autonomous machinery (Construction Industry Development Board, 2024). Furthermore, the Civil Aviation Authority of Malaysia (CAAM) reported receiving nearly 1,300 drone permit applications between 2023 and mid 2024, reflecting a tangible surge in industrial drone deployment (Civil Aviation Authority of Malaysia, 2024).

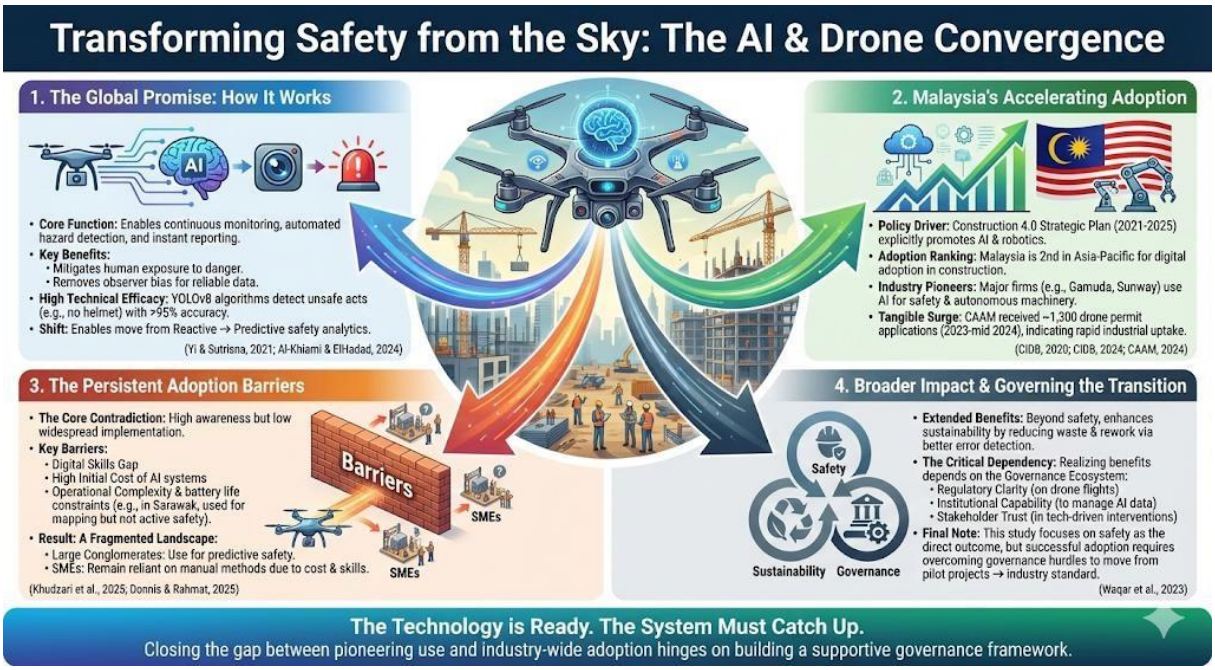


Figure 2.14: Comprehensive overview of the AI-drone convergence in construction safety, detailing global technical capabilities, Malaysia's adoption momentum, and the governance imperatives required to overcome structural barriers (Source: Synthesized from Yi & Sutrisna, 2021; CIDB, 2024; Khudzari et al., 2025)

Despite these promising metrics, widespread adoption remains constrained by structural barriers. Khudzari et al. identify that while technological awareness is high, actual implementation is hindered by the digital skills gap and the high initial cost of AI systems (Khudzari et al., 2025). This observation is corroborated by Donnis and Rahmat's study in Sarawak, which found that while drones are widely used for mapping, their use for active safety monitoring is limited by operational complexity and battery life constraints (Donnis & Rahmat, 2025). Consequently, the adoption landscape is fragmented: large conglomerates leverage these tools for predictive safety, while small and medium sized enterprises remain reliant on manual methods due to financial and technical limitations.

While AI drone applications are still nascent among smaller contractors, their potential extends beyond immediate safety benefits. Enhanced monitoring capabilities contribute indirectly to sustainability objectives by reducing material waste and minimizing site rework through better error detection (Waqar et al., 2023). However, this study confines its scope to safety as the direct outcome variable. The realization of these benefits is ultimately dependent on the governance ecosystem: regulatory clarity on drone flights, institutional capability to manage AI generated

data, and stakeholder trust in technology driven interventions. The following section therefore examines these adoption challenges in greater depth, establishing a foundation for understanding how governance mechanisms influence the transition from pilot projects to widespread industry standard.

2.4 Adoption of AI-Drone Technology for Safety Applications

The construction industry has long grappled with the challenge of balancing productivity and worker safety. Traditional monitoring systems, while essential, are often limited by human error, delayed reporting, and restricted site visibility. The emergence of Artificial Intelligence (AI) and drone technologies offers a transformative approach to addressing these long-standing safety issues by enabling real-time monitoring, data-driven decision-making, and predictive analysis of potential hazards (Yi & Sutrisna, 2021). Within the broader framework of Construction 4.0, AI-drone integration represents a critical technological advancement aimed at reshaping how safety is managed, recorded, and enforced.

Historically, drones in construction were primarily utilized for passive tasks such as topographical mapping and progress photography. Donnis and Rahmat (2025) note that in regions like Sarawak, this usage remains dominant, where drones replace traditional tools for land surveying but are rarely leveraged for active safety management due to a lack of technical expertise. However, the paradigm is shifting toward "active monitoring" driven by the integration of Deep Learning algorithms, such as YOLOv8 (You Only Look Once, Version 8). Al-Khiami and ElHadad (2024) demonstrate that custom-trained YOLOv8 models can identify Personal Protective Equipment (PPE) compliance such as helmets and safety vests with an accuracy rate exceeding 95%, significantly outperforming manual inspections which are often sporadic and subject to fatigue. Jiao et al. (2025) further validated this capability in complex environments, proving that AI can distinguish workers from static objects even under challenging lighting conditions.

Beyond static detection, systems such as "VeriDrone" integrate AI with the Internet of Things (IoT) to provide real-time alerts. Shanmughapriya et al. (2024) explain that when such a system detects a safety breach, it instantly notifies site managers, effectively closing the time gap between hazard detection and rectification. The operational impact of this technology is substantial; Nanda’s (2025) empirical study found that AI-drone solutions improved hazard detection rates by approximately 159% while reducing inspection time by nearly half compared

to conventional methods. This efficiency not only enhances safety but also supports financial sustainability; Qasim et al. (2022) argue that the precise documentation provided by drones helps verify physical progress, thereby accelerating progress billings and improving cash flow management for long-term projects.

The juxtaposition between these technical advantages and the organizational challenges of adoption is synthesized in Figure 2.15. This visual highlights the dual nature of AI-drone evolution, contrasting the proven technical and financial efficacy of these systems against the persistent institutional barriers and trust deficits that hinder widespread adoption in the Malaysian context (Donnis & Rahmat, 2025; Shanmughapriya et al., 2024; Khudzari et al., 2025).

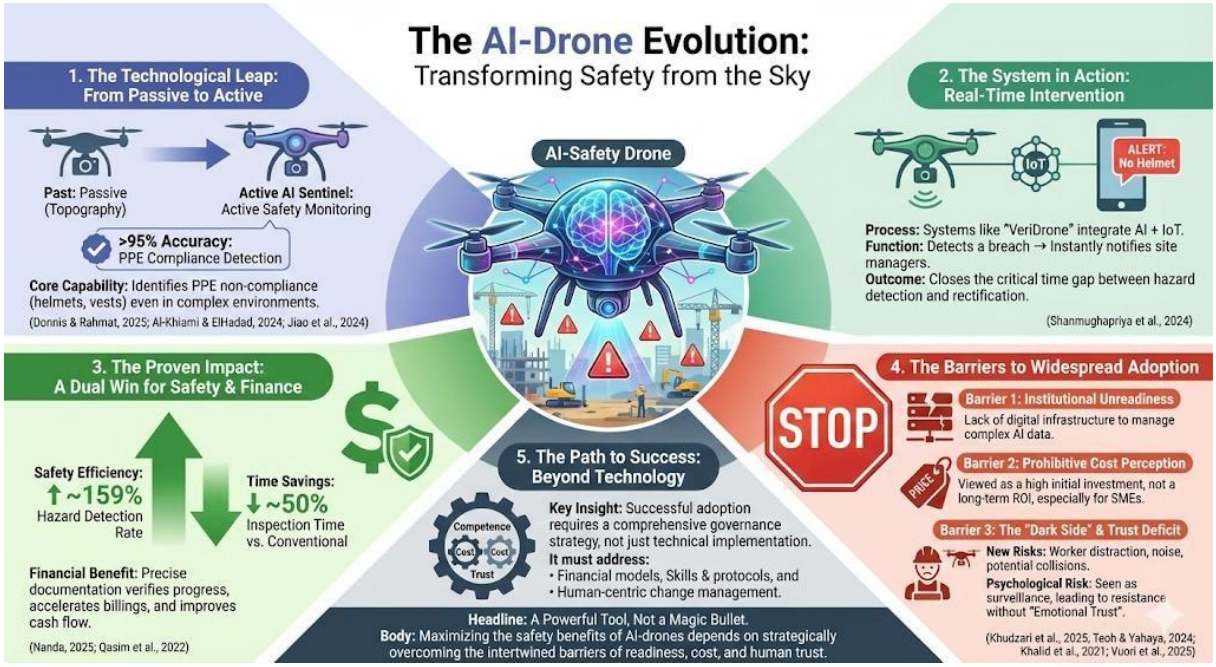


Figure 2.15: The Dual Nature of AI-Drone Evolution (Adapted from Donnis and Rahmat, 2025; Shanmughapriya et al., 2024; and Khudzari et al., 2025)

Despite these clear benefits, widespread adoption in Malaysia is hindered by structural and psychological barriers. Khudzari et al. (2025) identify Institutional Readiness as a primary bottleneck, noting that many firms lack the digital infrastructure to manage complex AI data. Teoh and Yahaya (2024) corroborate this, revealing that small and medium-sized contractors often view the initial investment in drone fleets as prohibitively high. Moreover, the literature warns of a "dark side" to this technology; Namian et al. (2021) caution that the physical presence of drones can introduce new risks, such as worker distraction and noise pollution, if not managed

through strict operational protocols. Furthermore, Vuori et al. (2025) highlight that without Emotional Trust the belief that the technology is benevolent workers may resist these systems, viewing them as surveillance tools rather than safety aids. Consequently, the successful transition to AI-driven safety requires a comprehensive governance strategy that addresses cost, competence, and trust.

2.4.1 The Role of Artificial Intelligence in Construction Safety

Artificial Intelligence (AI) has emerged as one of the most influential tools in enhancing construction safety management, moving the industry from reactive supervision to proactive hazard detection. Unlike traditional methods that rely on human observation, AI systems utilize advanced Computer Vision to process vast amounts of visual data in real-time. Jiao et al. (2025) explain that these systems employ deep learning algorithms to "learn" the parameters of a safe site, enabling them to automatically identify unsafe behaviors such as workers operating without helmets or entering restricted zones even in complex and cluttered environments.

The technical efficacy of these systems is well-established in current literature. Al-Khiami and ElHadad (2024) demonstrate that custom-trained models using the YOLOv8 (You Only Look Once) architecture can detect Personal Protective Equipment (PPE) non-compliance with an accuracy rate exceeding 95%. Beyond static detection, the integration of AI with the Internet of Things (IoT) allows for immediate intervention. Shanmughapriya et al. (2024) introduced the "VeriDrone" system, which identifies hazards and instantly triggers alerts to site managers, creating a "traceable data trail" that enhances accountability and audit readiness.

This transition from human-led inspections to high-precision algorithmic monitoring is visualized in Figure 2.16. The diagram contrasts the proven technical efficacy of Computer Vision with the prevailing readiness gap in the Malaysian context, emphasizing that the shift to AI-powered resilience is ultimately dictated by the strength of the governance ecosystem (Jiao et al., 2024; Khudzari et al., 2025; Al-Khiami & ElHadad, 2024).



Figure 2.16: The Paradigm Shift to AI-Powered Computer Vision (Adapted from Jiao et al., 2024; Khudzari et al., 2025; and Al-Khiami and ElHadad, 2024)

In the Malaysian context, however, the deployment of such advanced AI remains in its nascent stages. Khudzari et al. (2025) found that while technological potential exists among large-scale infrastructure developers, widespread adoption is heavily moderated by organizational culture and a lack of digital skills among smaller contractors. Consequently, AI deployment is often confined to pilot projects rather than being standard industry practice. This disconnect highlights that the benefits of AI such as objective safety evaluation and compliance with Department of Occupational Safety and Health (DOSH) guidelines can only be fully realized when supported by an enabling governance environment. This ecosystem view confirms that success relies on regulatory clarity, institutional capability, and stakeholder trust, which are the critical governance factors elaborated upon in Section 2.5.

2.4.2 Drone Applications in Hazard Detection and Site Surveillance

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have become indispensable in modern construction projects due to their ability to collect real-time, high-resolution data in environments that are hazardous or difficult to access. Equipped with AI-enabled cameras and sensors, drones can conduct aerial inspections, monitor progress, and detect unsafe site conditions with a high degree of precision.

Drone technology enhances construction safety through three primary capabilities: aerial visibility, hazard detection, and compliance monitoring. First, drones provide site managers with comprehensive aerial views of the project area, enabling the rapid identification of high-risk zones (Oduyemi & Okonkwo, 2023). Second, when integrated with Artificial Intelligence (AI) analytics, drones can automatically detect safety violations such as inadequate guardrails, improper harness use, or debris accumulation. Third, drones facilitate compliance by documenting safety practices objectively, thereby reducing the industry's historical dependence on subjective human assessment.

The operational scope of these technologies is further analyzed in Figure 2.17, which benchmarks international best practices such as the synchronization of live drone feeds with Building Information Modelling (BIM) systems against the current landscape in Malaysia. The diagram illustrates that while global leaders in Japan and Singapore have moved toward integrated digital ecosystems, the Malaysian sector remains largely in a "pilot-phase" adoption stage (Oduyemi & Okonkwo, 2023; Li et al., 2022; CIDB, 2023).



Figure 2.17: Operational Capabilities of Drone-Based Site Oversight (Adapted from Oduyemi and Okonkwo, 2023; Li et al., 2022; and CIDB, 2023)

In the Malaysian context, the Construction Industry Development Board (CIDB) has introduced demonstration projects utilizing drones for high-rise and infrastructure safety monitoring. However, widespread adoption remains low, particularly among small and medium-sized

enterprises (SMEs) who perceive drone technology as cost-intensive or technically complex (Construction Industry Development Board, 2023). While the primary motivation for drone deployment is immediate safety enhancement, secondary outcomes include reduced environmental impact and improved operational efficiency. These outcomes indirectly contribute to sustainability objectives, which represent a significant area for future research continuity.

2.4.3 Global and Malaysian Perspectives on AI-Drone Adoption

Globally, Artificial Intelligence (AI) drone systems have become integral to Construction 4.0 strategies, with nations such as the United States, Japan, and China leading in both policy and technical development. In these contexts, adoption has been facilitated by robust regulatory support, significant research funding, and industry-wide digital readiness. For example, Japan's Ministry of Land, Infrastructure, Transport and Tourism has promoted drone integration through its "I-Construction" initiative, which successfully aligns safety monitoring with productivity improvement (Li et al., 2022).

In contrast, developing economies face distinct structural constraints. Studies across Southeast Asia indicate that adoption is hindered by inadequate regulatory frameworks, low digital literacy, and high initial investment costs (Fang et al., 2021). Malaysia exhibits similar characteristics; although the Construction 4.0 Strategic Plan (2021–2025) emphasizes technology-driven transformation, the practical implementation of AI and drones has been uneven across the sector (Construction Industry Development Board, 2023).

The current state of this global-local disconnect is analyzed in Figure 2.18. This comparative visual contrasts international best practices with the specific regulatory, institutional, and governance barriers prevalent within the Malaysian construction industry. It highlights that while the technical capability is universal, the "pathway to adoption" is restricted in Malaysia by localized friction points such as fragmented oversight and trust deficits (Jamian et al., 2026; Vuori et al., 2025; CIDB, 2023; CAAM, 2024).

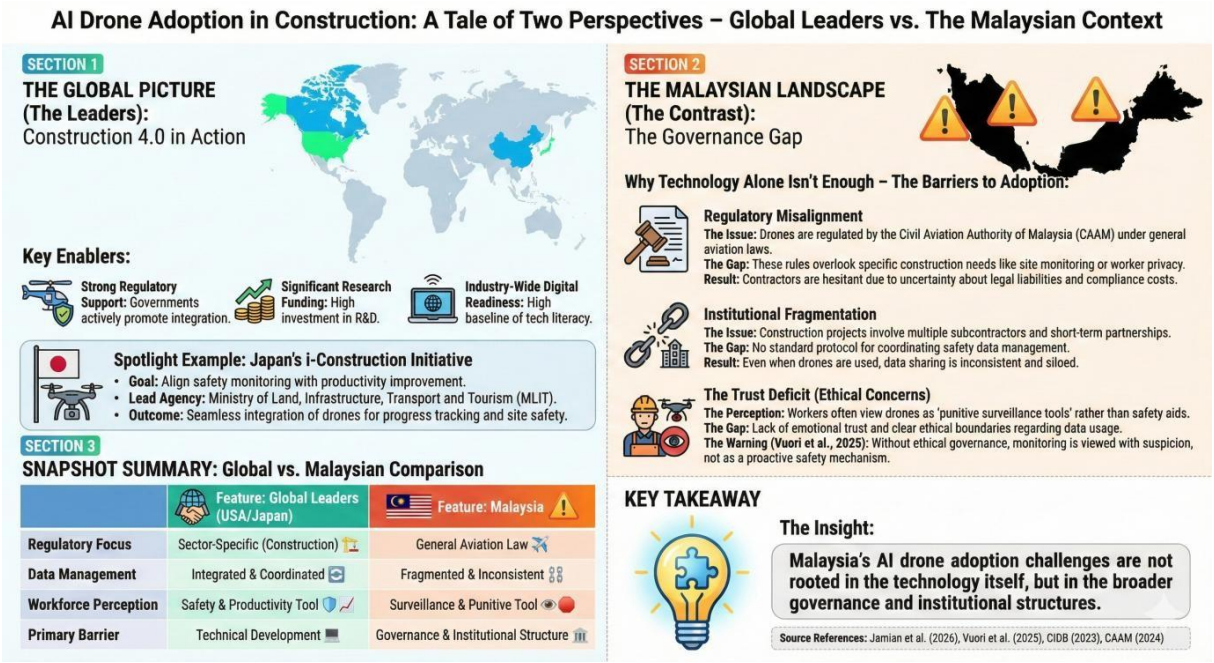


Figure 2.18: Comparative Analysis of Global and Malaysian AI-Drone Adoption (Adapted from Jamian et al., 2026; Vuori et al., 2025; CIDB, 2023; and CAAM, 2024)

A primary regulatory challenge involves the Civil Aviation Authority of Malaysia (CAAM), which regulates Unmanned Aerial Vehicle (UAV) operations primarily under aviation laws. These mandates often overlook sector-specific needs, such as the nuances of construction site monitoring and worker privacy (Civil Aviation Authority of Malaysia, 2024). Jamian et al. (2026) emphasize that among smaller contractors, this lack of tailored regulatory guidance exacerbates the hesitation to adopt, as firms remain uncertain regarding legal liabilities and compliance costs.

Furthermore, institutional fragmentation presents a significant hurdle. Malaysian construction projects typically involve multiple sub-contractors and short-term partnerships, making it difficult to coordinate safety data management and technological integration. Consequently, even when drones are deployed, data sharing across organizations remains inconsistent. Trust also plays a critical role; many construction personnel express concern over surveillance misuse, emphasizing the need for ethical data governance. Vuori et al. (2025) note that without establishing emotional trust and clear ethical boundaries, site workers often perceive drone monitoring as a punitive surveillance tool rather than a proactive safety mechanism. These observations underscore that Malaysia's adoption challenges are rooted in broader governance structures rather than technical limitations alone.

2.4.4 Barriers and Challenges in AI-Drone Implementation

Despite the proven potential of Artificial Intelligence (AI) drone systems in enhancing safety, several barriers constrain their widespread adoption in Malaysia. Regulatory ambiguity remains a major obstacle. Current drone regulations focus primarily on aviation safety rather than construction-specific applications, leaving gaps in operational permissions, data privacy, and inter-agency coordination (Civil Aviation Authority of Malaysia, 2024). The lack of clear guidance discourages construction firms from large-scale implementation, as compliance risks remain uncertain. Consequently, this regulatory vacuum complicates the enforcement of recent legislative advancements, such as the Occupational Safety and Health (Amendment) Act 2022 and the Occupational Safety and Health (Construction Work) (Design and Management) Regulations 2024 (CDM 2024), which mandate proactive risk mitigation but provide limited technical frameworks for utilizing autonomous aerial monitoring.

Institutional readiness presents another severe limitation. Many local firms, particularly small and medium-sized enterprises (SMEs), lack the digital infrastructure, technical expertise, and change management capacity required to integrate AI-driven tools into daily operations. Without sufficient investment in human capital and digital systems, implementation efforts often remain superficial, restricted to demonstration projects rather than systemic transformation (Mustapha et al., 2024). This barrier is geographically widespread; Donnis and Rahmat (2025) highlight that in Sarawak, the lack of technical skills severely limits drone use beyond basic topographical surveys. Similarly, Teoh and Yahaya (2024) observe that among contractors in Penang, institutional readiness is undermined by intense cost pressures and tight project schedules that prioritize immediate productivity over the integration of new safety technologies.

Trust and data ethics also play a decisive role in moderating adoption rates. Concerns regarding data misuse, unauthorized surveillance, and a lack of transparency in AI decision-making have created apprehension among site personnel and management (Oduyemi & Okonkwo, 2023). In the absence of clear institutional policies on ethical data governance, these concerns can fundamentally undermine workforce confidence in technology-driven safety systems. These multidimensional barriers regulatory, institutional, and ethical are synthesized in Figure 2.19, which contrasts these obstacles against the proven technical efficacy of AI systems to highlight the necessity for a holistic governance approach (CAAM, 2024; Mustapha et al., 2024; Tham & Hassim, 2025; Al-Khiami & ElHadad, 2024).

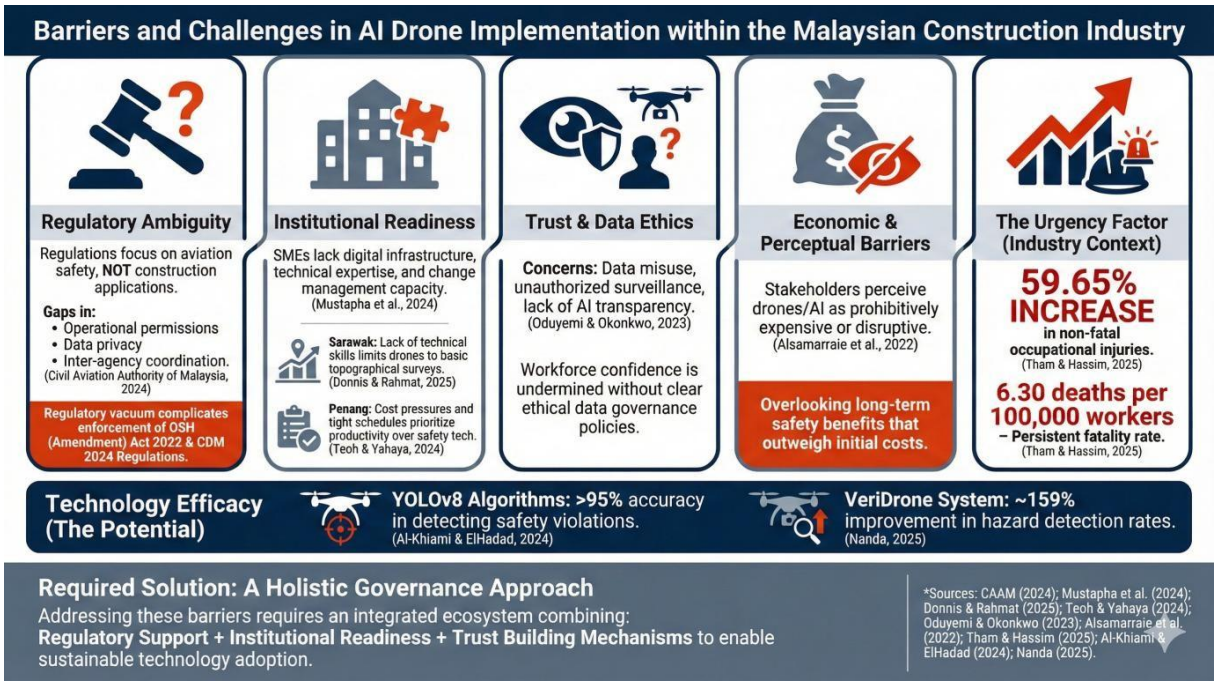


Figure 2.19: Conceptual Framework of Barriers Impeding AI-Drone Implementation (Adapted from CAAM, 2024; Mustapha et al., 2024; Tham and Hassim, 2025; and Al-Khiami and ElHadad, 2024)

Finally, economic and perceptual barriers persist. Many stakeholders perceive drones and AI as prohibitively expensive or disruptive, overlooking the long-term safety and productivity benefits that outweigh initial costs (Alsamarraie et al., 2022). Overcoming this perception gap requires highlighting the proven technical efficacy of these tools, such as the capability of YOLOv8 algorithms to achieve over 95% accuracy in detecting safety violations (Al-Khiami & ElHadad, 2024), and the implementation of systems like VeriDrone, which have demonstrated an approximate 159% improvement in hazard detection rates (Nanda, 2025). The urgency to dismantle these barriers is underscored by national statistics provided by Tham and Hassim (2025), who report a staggering 59.65% increase in non-fatal occupational injuries and a persistent fatality rate of 6.30 deaths per 100,000 workers within the Malaysian construction sector. Addressing these challenges requires a cohesive governance ecosystem that enables sustainable technology adoption, a theme explored in detail in the following sections.

2.5 Theoretical Underpinning

The adoption of AI drone technology for construction safety is a multidimensional process that requires robust theoretical grounding to explain the interplay between technical capability and

institutional control. By synthesizing established adoption models with governance theories, this study provides a comprehensive lens through which to examine the Malaysian construction industry's digital transformation.

2.5.1 Technology-Organization-Environment (TOE) Framework

The Technology-Organization-Environment (TOE) framework serves as the primary theoretical lens for understanding how multidimensional contexts influence the adoption of safety innovations. Developed by Tornatzky and Fleischer (1990), the framework suggests that technological adoption is driven by three distinct yet overlapping contexts. The technological context includes the perceived relative advantages and technical complexity of AI-drones. The organizational context encompasses internal characteristics such as firm size, digital maturity, and top management support. Finally, the environmental context involves external pressures, such as regulatory mandates and industry-wide competition (Tornatzky & Fleischer, 1990).

In the Malaysian construction sector, the environmental context specifically government mandates and the Construction 4.0 Strategic Plan (2021–2025) acts as a primary catalyst for digital transformation among local firms (Construction Industry Development Board, 2021). The application of the TOE framework allows for the systematic categorization of various barriers and enablers into a structured model that explains Institutional Readiness.

As illustrated in Figure 2.20, the TOE framework serves as a diagnostic tool for AI-drone adoption, mapping firm-level determinants against the broader national digitalization goals. This theoretical grounding is essential for justifying the selection of governance variables such as Regulatory Support and Institutional Readiness which correspond to the environmental and organizational dimensions of the TOE model (Tornatzky & Fleischer, 1990; CIDB, 2021).

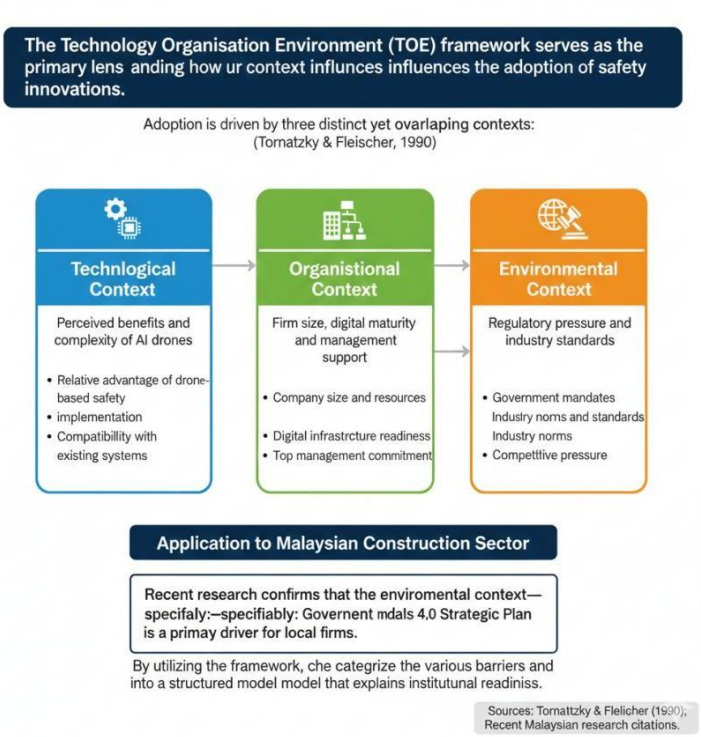


Figure 2.20: The Technology-Organization-Environment (TOE) Framework as a Diagnostic

2.5.2 Technology Acceptance Model (TAM) and Trust Theory

While the TOE framework focuses on firm-level determinants, the Technology Acceptance Model (TAM) and Trust Theory address the individual and social dimensions of adoption. The Technology Acceptance Model posits that perceived usefulness and perceived ease of use are the core determinants of whether site personnel will utilize AI-drone systems for safety monitoring (Davis, 1989). In the context of this study, perceived usefulness refers to the belief that AI-drones enhance hazard detection, while perceived ease of use relates to the technical simplicity of the user interface.

However, in high-risk environments like construction sites, technical utility alone is insufficient to guarantee adoption. Trust Theory must be integrated to account for professional concerns regarding data privacy and surveillance ethics (Zhang et al., 2023). Empirical evidence suggests that the psychological barrier specifically the fear of constant monitoring can significantly lower the perceived ease of use among practitioners (Jamian et al., 2026).

As illustrated in Figure 2.21, combining these theories allows the study to analyze how trust in governance structures moderates the relationship between a drone's technical efficacy and its ultimate acceptance by the workforce. This integrated framework highlights that even a technically superior system may be rejected if a "trust deficit" exists between the management and the site-level personnel (Davis, 1989; Jamian et al., 2026).

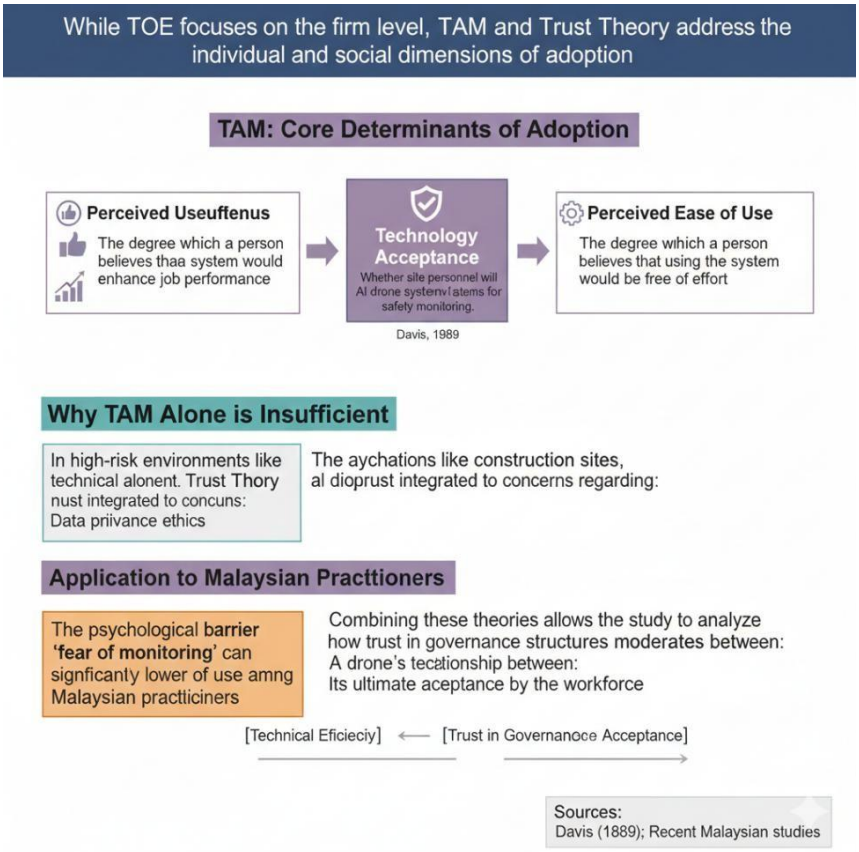


Figure 2.21: Integrated Framework of TAM and Trust Theory (Adapted from Davis, 1989 and Recent Malaysian Studies)Tool (Adapted from Tornatzky and Fleischer, 1990; and CIDB, 2021)

2.5.3 Theoretical Synthesis and the Centrality of Governance

Traditional adoption models, such as the TOE framework and TAM, often treat governance as a passive external variable rather than an active internal driver. This study justifies the explicit integration of governance into adoption frameworks because the safety-critical nature of construction necessitates more than mere technical readiness. Governance serves as the decisive enabler, providing the legal certainty and ethical safeguards required for effective implementation (Haron et al., 2023). Without integrating regulatory support and data ethics directly into the model, the framework would fail to account for the unique compliance

mandates of the Occupational Safety and Health (Amendment) Act 2022 and the CDM 2024 regulations (Department of Occupational Safety and Health, 2024).

The necessity of this integration is summarized in Figure 2.22, which highlights how governance addresses the specific ethical and safety requirements that traditional models overlook. By positioning governance at the core of the framework, the study ensures that the "adoption" being measured is not just technical usage, but legally compliant and ethically sound practice.

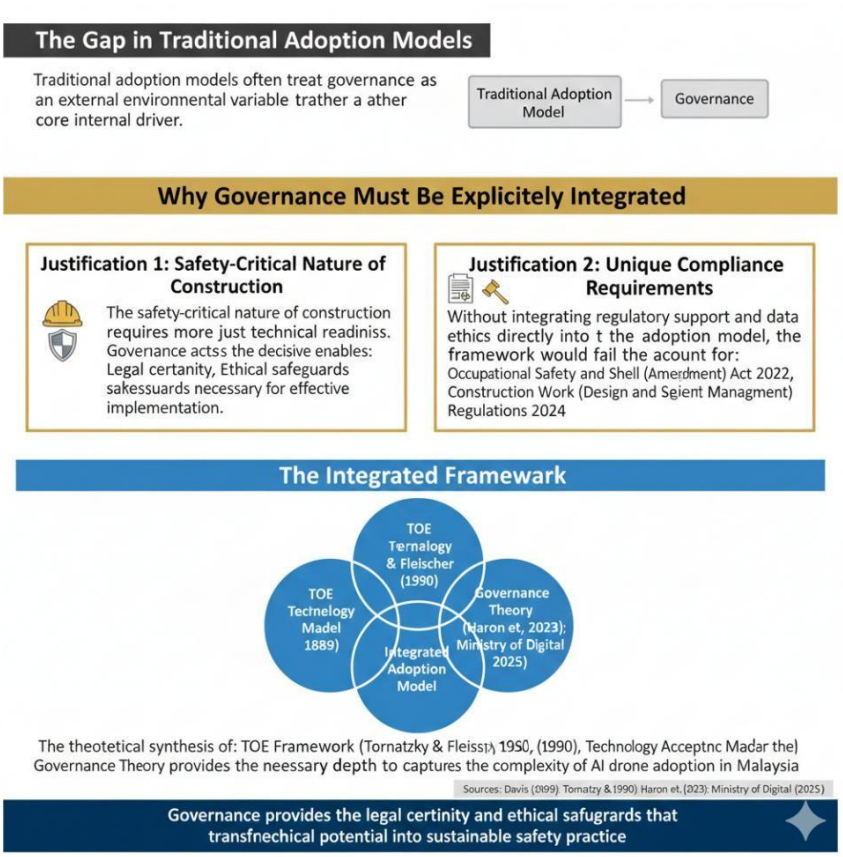


Figure 2.22: Theoretical Justification for Governance Integration (Adapted from Haron et al., 2023 and Ministry of Digital, 2025)

Consequently, the theoretical synthesis of the Technology-Organization-Environment (TOE) framework, the Technology Acceptance Model (TAM), and Governance Theory provides the multi-layered depth required to capture the complexity of AI-drone adoption. As illustrated in Figure 2.23, this synthesis creates a comprehensive model where organizational readiness and individual acceptance are unified under a protective governance ecosystem. This combined approach allows the study to analyze not only if the technology can be used, but how the Malaysian regulatory and institutional environment facilitates its long-term success.

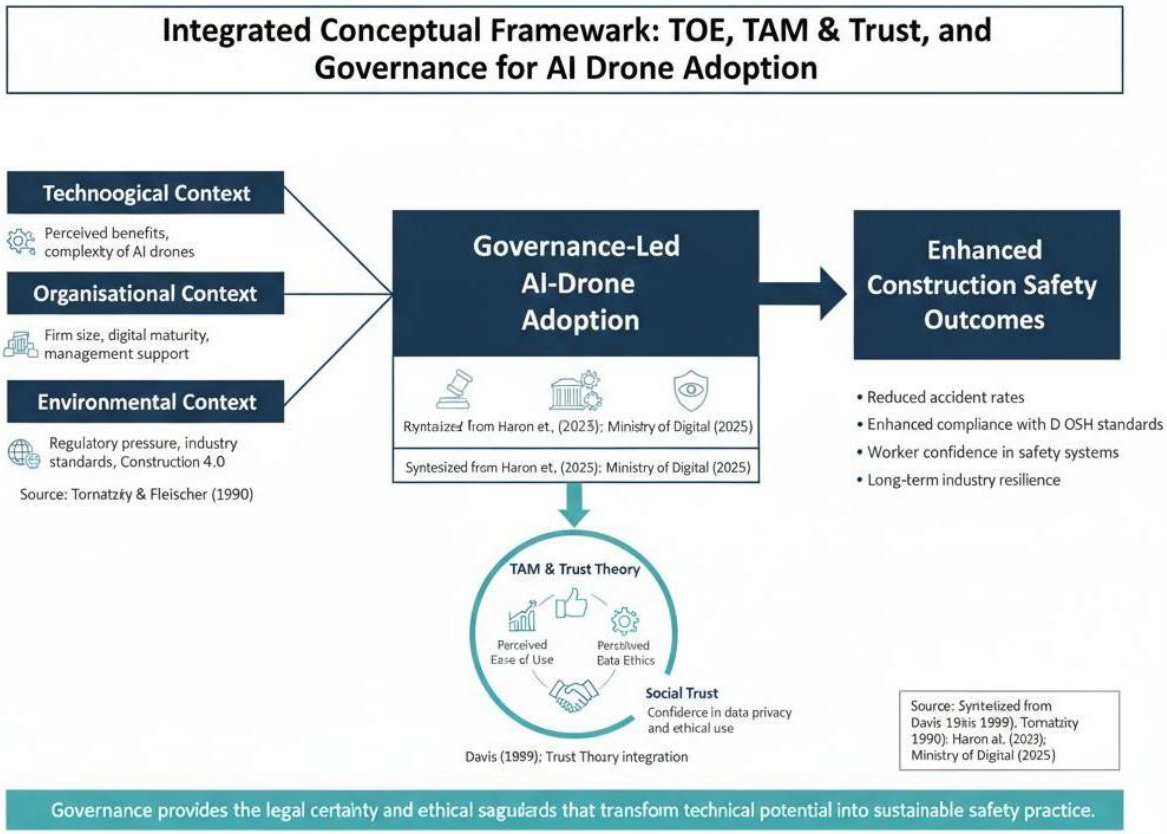


Figure 2.23: Theoretical Synthesis of TOE, TAM, and Governance Theory (Adapted from Davis, 1989; Tornatzky and Fleischer, 1990; and Haron et al., 2023)

2.6 The Governance Ecosystem for AI-Drone Adoption

The successful integration of Artificial Intelligence (AI) and drone technologies into construction safety management is shaped not only by technological feasibility but also by the strength of the governance structures surrounding their use. Governance, in this context, refers to the collective policies, institutional frameworks, regulatory mandates, and ethical norms that determine how innovations are implemented and sustained within an industry. For Malaysia where the construction sector is characterized by fragmented project delivery systems, varying organizational capacities, and evolving safety mandates governance becomes the decisive enabler that determines whether AI-driven systems move from pilot initiatives into mainstream industrial practice (Haron et al., 2023; Construction Industry Development Board, 2021).

The conceptualization of this governance ecosystem is illustrated in Figure 2.24. The framework defines governance as the foundational layer for adoption, highlighting how the interrelated dimensions of regulatory support, institutional readiness, and trust form the necessary

infrastructure for sustainable implementation. By positioning governance as a central mediator, the model accounts for the specific "friction points" found in the Malaysian construction industry, such as regulatory ambiguity and organizational resistance (Haron et al., 2023).

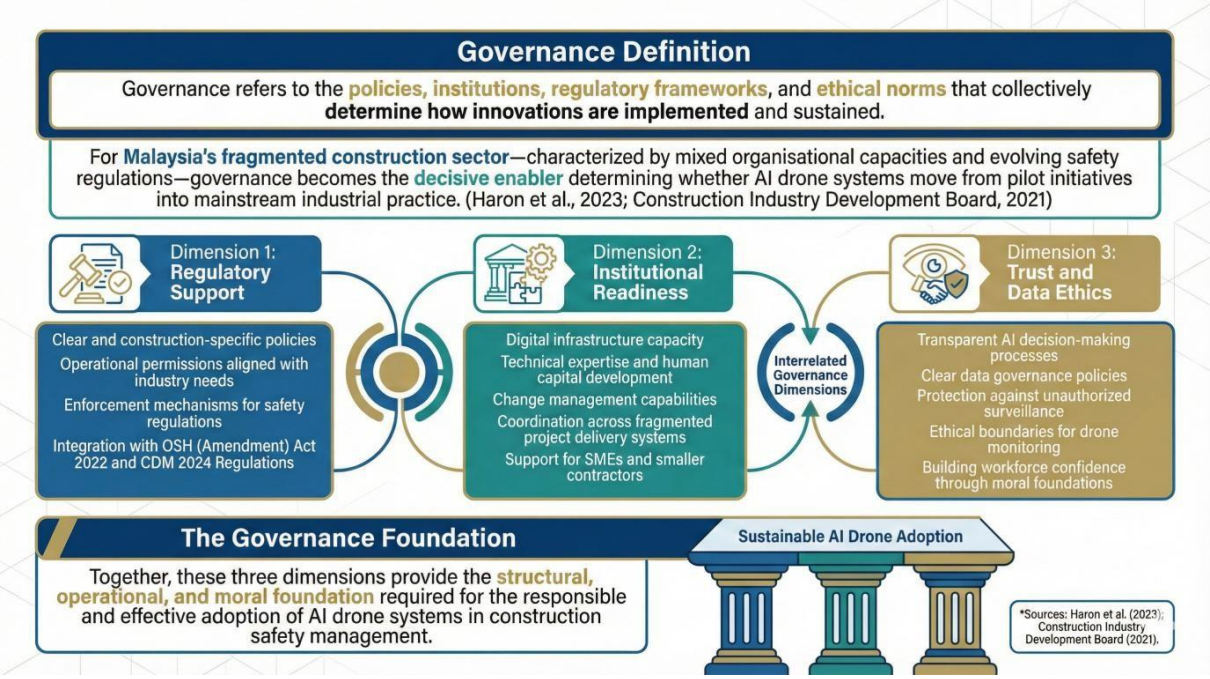


Figure 2.24: Conceptual Framework of Governance as the Decisive Enabler (Adapted from Haron et al., 2023 and CIDB, 2021)

As shown in the framework, three interrelated governance dimensions underpin this process: Regulatory Support, Institutional Readiness, and Trust and Data Ethics. Together, these pillars provide the structural, operational, and moral foundation required for the responsible and effective adoption of AI-drone systems. The following sub-sections provide a detailed analysis of each factor, exploring how they collectively influence the quality of implementation and the ultimate success of technology adoption in the Malaysian safety context.

2.6.1 Regulatory Support

Regulatory support serves as the cornerstone of technological governance within the built environment. Without a coherent and adaptive regulatory framework, even the most advanced safety technologies risk being underutilized, misapplied, or hindered by legal uncertainty. Malaysia’s regulatory landscape for Unmanned Aircraft Systems (UAS) and Artificial Intelligence (AI) has advanced considerably since 2020, following the introduction of the Civil Aviation Authority of Malaysia’s (CAAM) UAS Guidelines and the Drone Operation Manual.

These frameworks provide the necessary structured standards for drone classification, registration, pilot licensing, and designated flight zones (Civil Aviation Authority of Malaysia, 2023).

The necessity of these measures is illustrated in Figure 2.25, which provides a comprehensive overview of the evolving regulatory framework. The diagram highlights the specific compliance components required to mitigate the operational risks associated with aerial monitoring in densely populated or high-risk construction environments. By establishing clear "rules of engagement," these regulations provide firms with the legal certainty needed to transition from manual inspections to autonomous site oversight (Civil Aviation Authority of Malaysia, 2023).

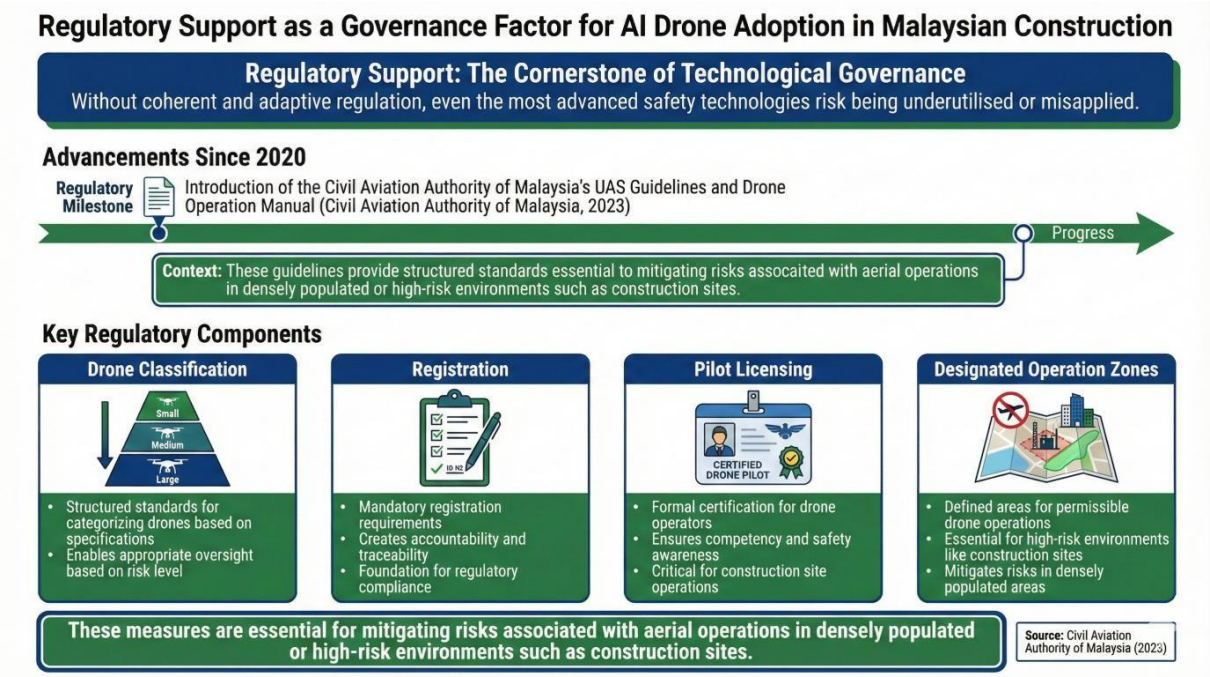


Figure 2.25: Overview of the Evolving Regulatory Framework for AI-Drone Adoption (Adapted from Civil Aviation Authority of Malaysia, 2023)

However, while these guidelines address general aviation safety, a specific gap remains regarding construction-focused data governance. Haron et al. (2023) argue that regulatory support must extend beyond flight mechanics to include data protection and privacy standards, ensuring that AI-captured site data is used ethically. In the Malaysian context, the alignment between CAAM's flight regulations and the Occupational Safety and Health (Construction Work) (Design and Management) Regulations 2024 (CDM 2024) is crucial. This alignment ensures that

regulatory support is not merely a bureaucratic hurdle but a proactive enabler that encourages contractors to adopt AI-drones as a recognized tool for safety compliance and hazard mitigation.

2.6.1.1 National Policies and Legal Frameworks on Drone Usage

National policy directions, notably the Construction 4.0 Strategic Plan (2021–2025), have positioned digitalization and automation as critical levers for industry transformation (Construction Industry Development Board, 2021). Complementing these sector-specific mandates, the Malaysian Communications and Multimedia Commission (MCMC) introduced the National 5G and AI Technology Framework, which explicitly encourages the deployment of Artificial Intelligence and Unmanned Aerial Vehicles (UAVs) for infrastructure monitoring and high-precision safety oversight (Malaysian Communications and Multimedia Commission, 2024).

However, despite these high-level strategic efforts, practical implementation remains uneven across project scales and geographical regions. A primary bottleneck is the absence of unified data-sharing mechanisms among key regulatory bodies, including the Civil Aviation Authority of Malaysia (CAAM), the Construction Industry Development Board (CIDB), and the Department of Occupational Safety and Health (DOSH). This lack of inter-agency coordination limits the industry's ability to standardize drone-based safety surveillance and creates a fragmented compliance environment for contractors (Ting & Yahaya, 2024).

The disconnect between these strategic frameworks and the realities of site-level implementation is analyzed in Figure 2.26. The diagram contrasts the national policy vision with the existing inter-agency gaps, highlighting the necessary evolution toward an "adaptive governance" model that balances rapid technological innovation with institutional accountability (Construction Industry Development Board, 2021; Malaysian Communications and Multimedia Commission, 2024; Ting & Yahaya, 2024).

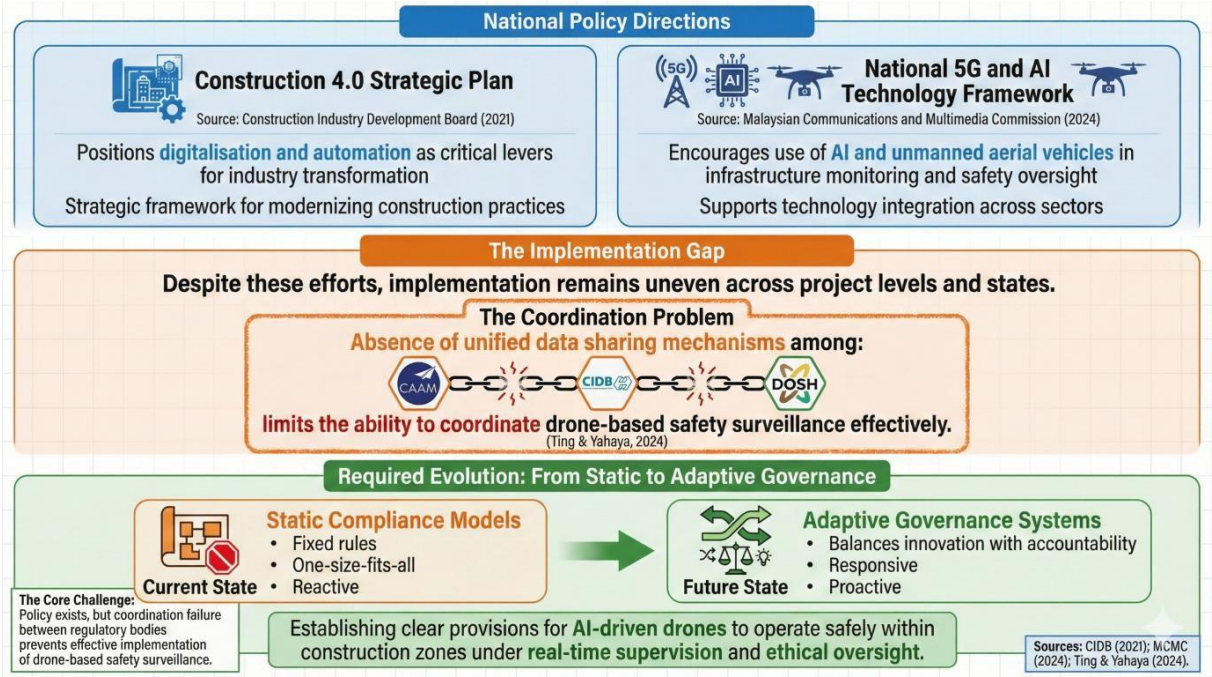


Figure 2.26: Analysis of National Policy Directions and Implementation Gaps (Adapted from CIDB, 2021; MCMC, 2024; and Ting and Yahaya, 2024)

To enhance adoption rates, regulatory frameworks must transition from static compliance models to adaptive systems that incorporate real-time supervision and ethical oversight. This requires establishing clear provisions that allow AI-driven drones to operate safely within complex construction zones, ensuring that the "legal framework" supports rather than hinders the industry's shift toward proactive safety management.

2.6.1.2 Institutional Role of CAAM and CIDB in Construction Safety Governance

The Civil Aviation Authority of Malaysia (CAAM) and the Construction Industry Development Board (CIDB) hold complementary yet distinct mandates within the national technological landscape. CAAM oversees national airspace safety and flight operations, while CIDB focuses on construction quality assurance, industry safety standards, and workforce development. However, coordination between these agencies has historically been fragmented, often resulting in regulatory overlaps or inconsistent enforcement for contractors attempting to implement aerial monitoring (Haron et al., 2023). Strengthening inter-agency collaboration specifically through integrated data systems and shared monitoring protocols is essential to enhance the governance capacity for drone-based safety applications.

The Department of Occupational Safety and Health (DOSH) also plays a crucial role in enforcing safety compliance at worksites. The integration of AI-powered drones could significantly complement DOSH inspection activities, enabling data-driven decision-making and reducing inspectors' exposure to high-risk environments. A harmonized approach among CAAM, CIDB, and DOSH would therefore support Malaysia's broader objective of "governance by design," as outlined in the Twelfth Malaysia Plan (Economic Planning Unit, 2021).

This institutional dynamic is visualized in Figure 2.27, which analyzes the complementary mandates of these three key bodies. The framework contrasts historical regulatory fragmentation with the imperative for institutional harmonization, highlighting how a unified oversight structure is required to enable effective AI-drone governance in the Malaysian construction sector (Haron et al., 2023; Economic Planning Unit, 2021).

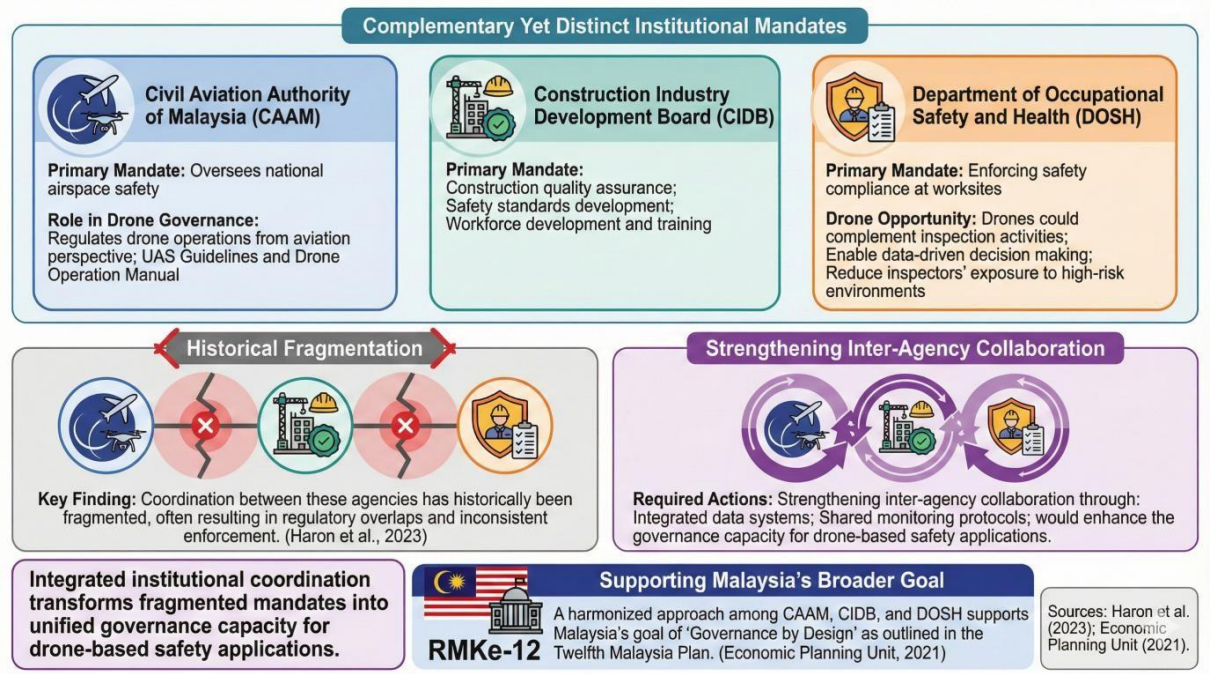


Figure 2.27: Analysis of Institutional Mandates and the Imperative for Harmonization (Adapted from Haron et al., 2023 and Economic Planning Unit, 2021)

By transitioning from isolated oversight to an integrated governance model, these institutions can provide the "legal certainty" required for firms to invest in advanced safety technologies. This evolution ensures that the use of drones is not only compliant with aviation laws but also fully recognized as a legitimate tool for meeting national occupational safety and health requirements.

2.6.1.3 International Benchmarking of Drone Regulations

Globally, progressive drone governance systems provide valuable lessons for the Malaysian context. Singapore's Unmanned Aircraft (Public Safety and Security) Act and the United Kingdom's Civil Aviation Authority (CAA) Remote ID framework are notable examples of adaptive regulation that facilitate safe and scalable drone deployment in construction (Tan & Chua, 2023). These frameworks prioritize safety through real-time tracking and standardized pilot certifications, which are essential for high-density urban construction environments. Similarly, the Organisation for Economic Co-operation and Development (OECD) and the European Commission emphasize risk-based regulation that differentiates between high-risk and low-risk AI applications (Organisation for Economic Co-operation and Development, 2022; European Commission, 2023).

The progression of these international standards is analyzed in Figure 2.28, which benchmarks the frameworks of Singapore, the UK, and the EU to identify global best practices. This comparative analysis demonstrates that the move toward "risk-based" regulation is a universal trend aimed at balancing technological speed with public safety.

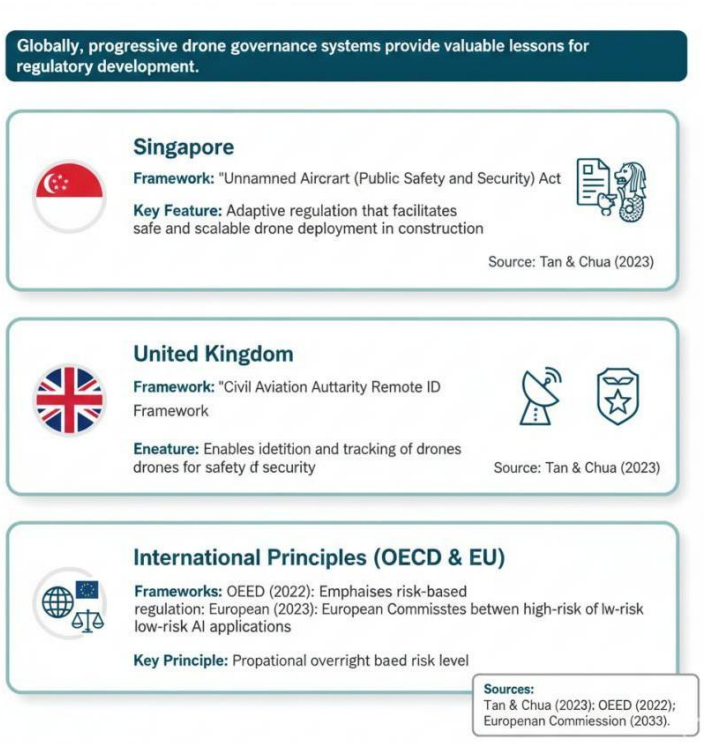


Figure 2.28: Comparative Analysis of International Drone Governance Systems (Adapted from Tan and Chua, 2023; OECD, 2022; and European Commission, 2023)

Malaysia's current policies, while promising, remain at an early stage of maturity compared to these international benchmarks. The implementation gap and the recommended strategic pathway for Malaysia are visualized in Figure 2.29. By adopting similar adaptive, tiered regulatory frameworks, Malaysia can foster innovation while safeguarding public trust and operational safety. This benchmarking process reveals that successful adoption is not merely about technical permissive rules, but involves a holistic governance approach that balances technological speed with human safety (Tan & Chua, 2023).

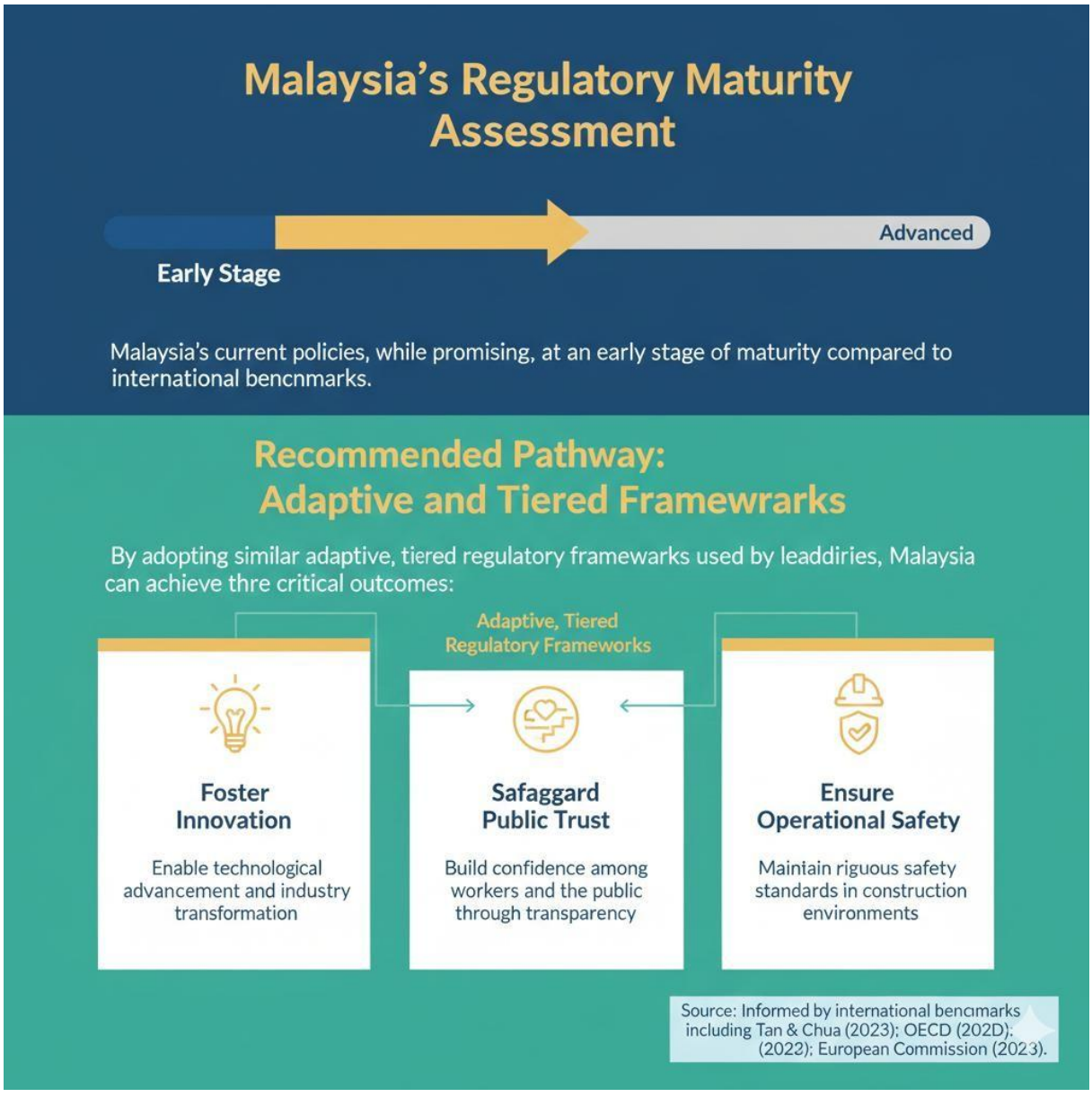


Figure 2.29: Maturity Assessment and Strategic Pathway for Malaysia's Drone Landscape (Adapted from Tan and Chua, 2023; OECD, 2022; and European Commission, 2023)

2.6.2 Institutional Readiness

Institutional readiness determines whether construction firms and regulatory bodies possess the internal capacity to implement and sustain AI drone systems effectively. It encompasses the organisation's technological infrastructure, workforce competence, management commitment, and adaptability to change (Kamaruddin et al., 2023). Even with supportive policies, technological transformation falters if institutions lack readiness or confidence to operationalise new systems. In the context of Malaysian construction safety, this readiness is critical for moving beyond manual oversight toward automated hazard detection.

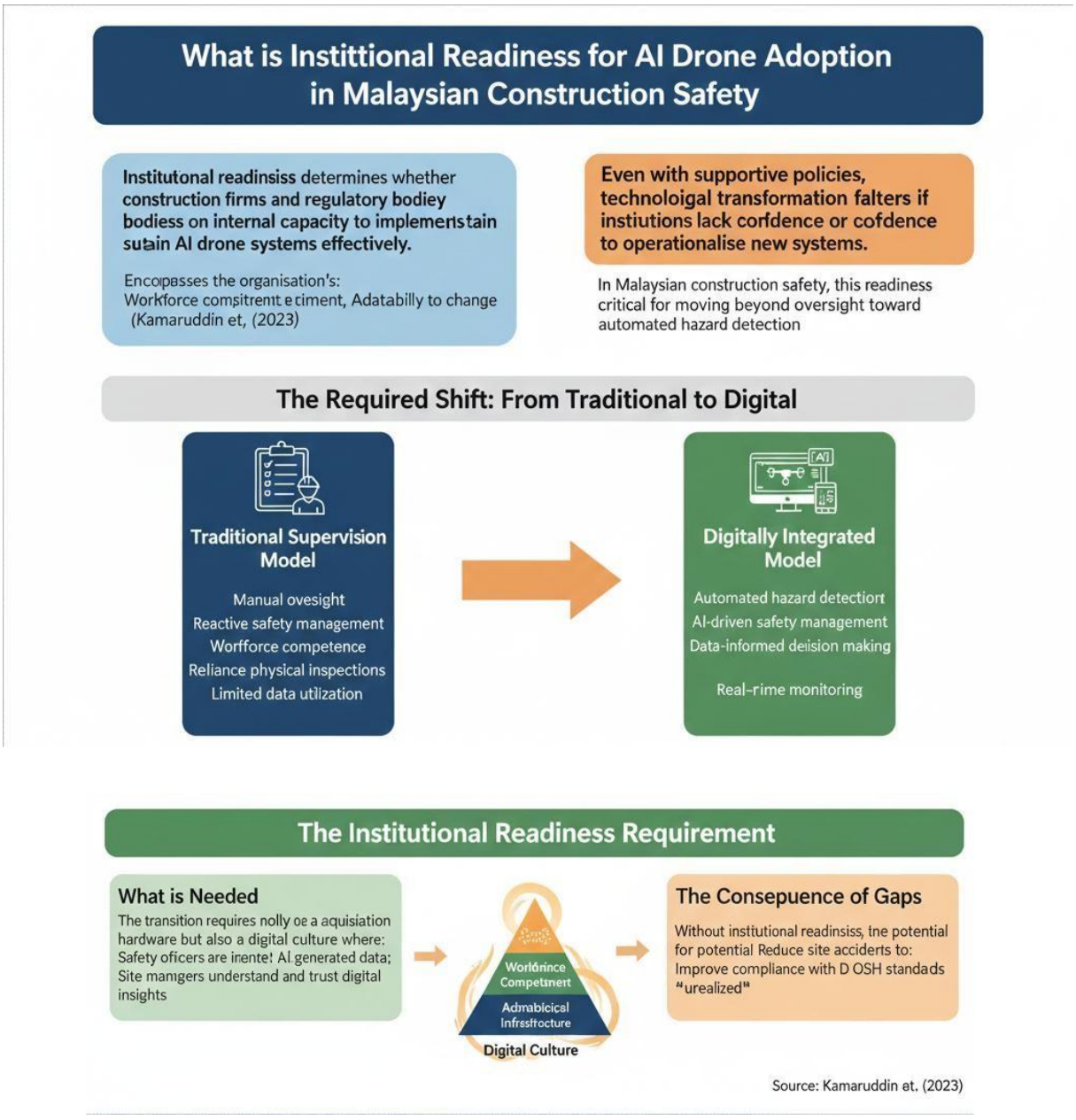


Figure 2.30: Conceptual framework of institutional readiness for AI drone adoption, illustrating the critical shift from traditional supervision to digitally integrated models and the foundational requirements for internal organizational capacity (Source: Synthesized from Kamaruddin et al., 2023)

The transition to AI driven safety management requires a shift from traditional supervision to a digitally integrated model. This necessitates not only the acquisition of hardware but also the cultivation of a digital culture where safety officers and site managers are trained to interpret AI generated data. Without institutional readiness, the potential for drones to reduce site accidents and improve compliance with Department of Occupational Safety and Health standards remains unrealized.

2.6.2.1 Organizational Capability and Digital Infrastructure

Organizational capability and digital infrastructure form the technical backbone of AI-drone integration. While larger construction firms in Malaysia have begun adopting advanced digital platforms such as Building Information Modelling (BIM) and IoT-enabled safety systems small and medium-sized enterprises (SMEs) continue to rely predominantly on manual, paper-based processes (Alsamarraie et al., 2022). The successful implementation of AI-enabled drones requires a robust Information and Communication Technology (ICT) infrastructure, including secure data storage, high-speed connectivity for live streaming, and cloud-based analytical platforms for real-time data processing.

The requirements for this digital maturity and the current challenges facing the industry are analyzed in Figure 2.31. This framework highlights the "digital maturity gap" between large-scale contractors and SMEs, while illustrating the critical role of CIDB bridging initiatives in fostering industry-wide interoperability. The diagram emphasizes that without these foundational technological layers, real-time hazard detection and automated reporting remain operationally unattainable.

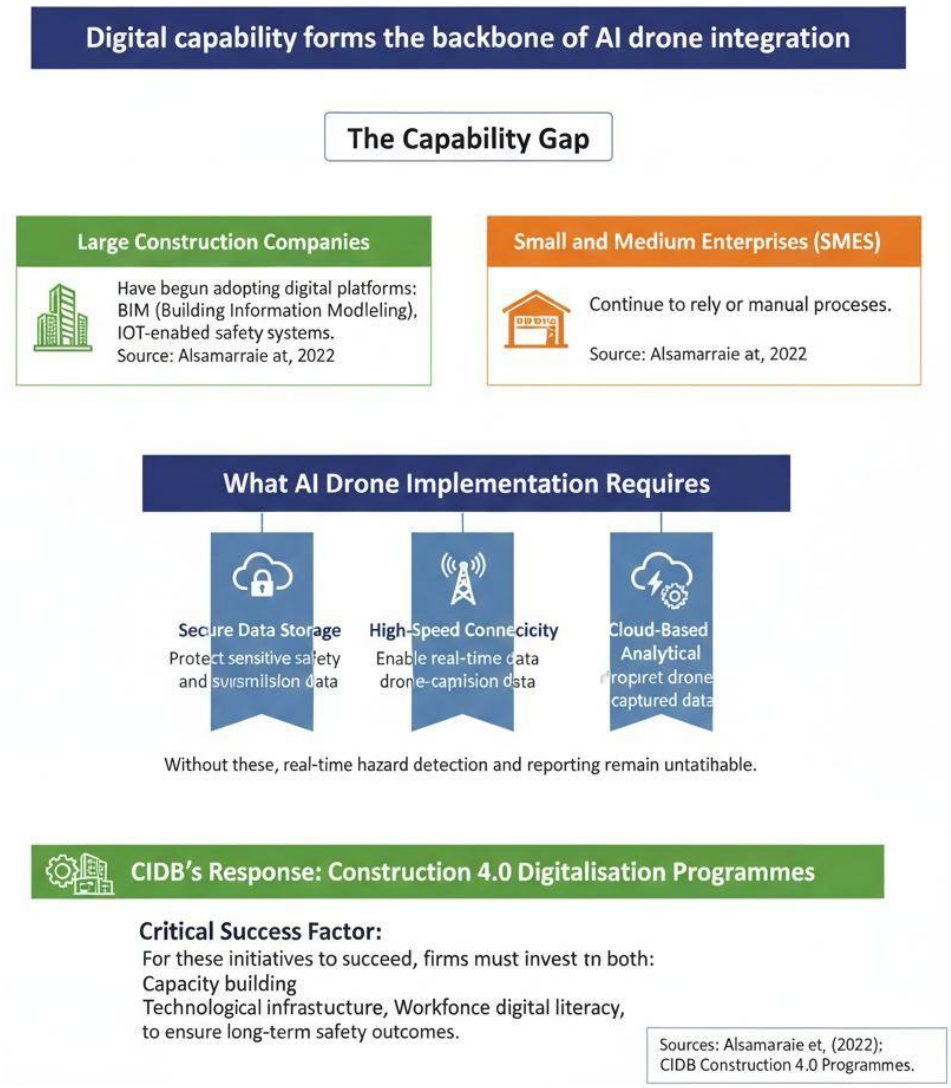


Figure 2.31: Analytical Framework of Organizational Capability and Digital Infrastructure Requirements (Adapted from Alsamarraie et al., 2022 and CIDB, 2021)

Recent evidence from Jamian et al. (2026) identifies "low awareness" and "technical support deficits" as primary hurdles to adoption, reporting a mean difficulty score of 4.15 out of 5.0 regarding digital literacy. To mitigate these barriers, the Construction Industry Development Board (CIDB) has introduced various digitalization programs under the Construction 4.0 Strategic Plan aimed at capacity building. However, for these national initiatives to translate into site-level safety improvements, individual firms must commit to long-term investment in both their technological infrastructure and workforce digital literacy. This dual investment is essential to move the industry from fragmented pilot projects toward a cohesive, digitally integrated safety ecosystem.

2.6.2.2 Management Commitment and Human Resource Competency

Top management commitment is a critical predictor of successful digital transformation within the construction industry (Abd Rahman et al., 2023). For AI-drone adoption to be effective, senior leaders must embed these technological initiatives within their strategic safety objectives, allocate sufficient training budgets, and foster cross-functional collaboration. Without clear leadership support, digital safety tools are often perceived as temporary pilot projects rather than essential components of the firm's safety governance.

The synergy between leadership and operational skill is visualized in Figure 2.32. This dual-pillar framework illustrates the necessary interplay between strategic leadership and technical data interpretation. It highlights that while management provides the resources and vision, the ultimate efficacy of the system depends on the human resource competency required to translate complex aerial data into actionable site interventions (Abd Rahman et al., 2023; Construction Industry Development Board, 2021).

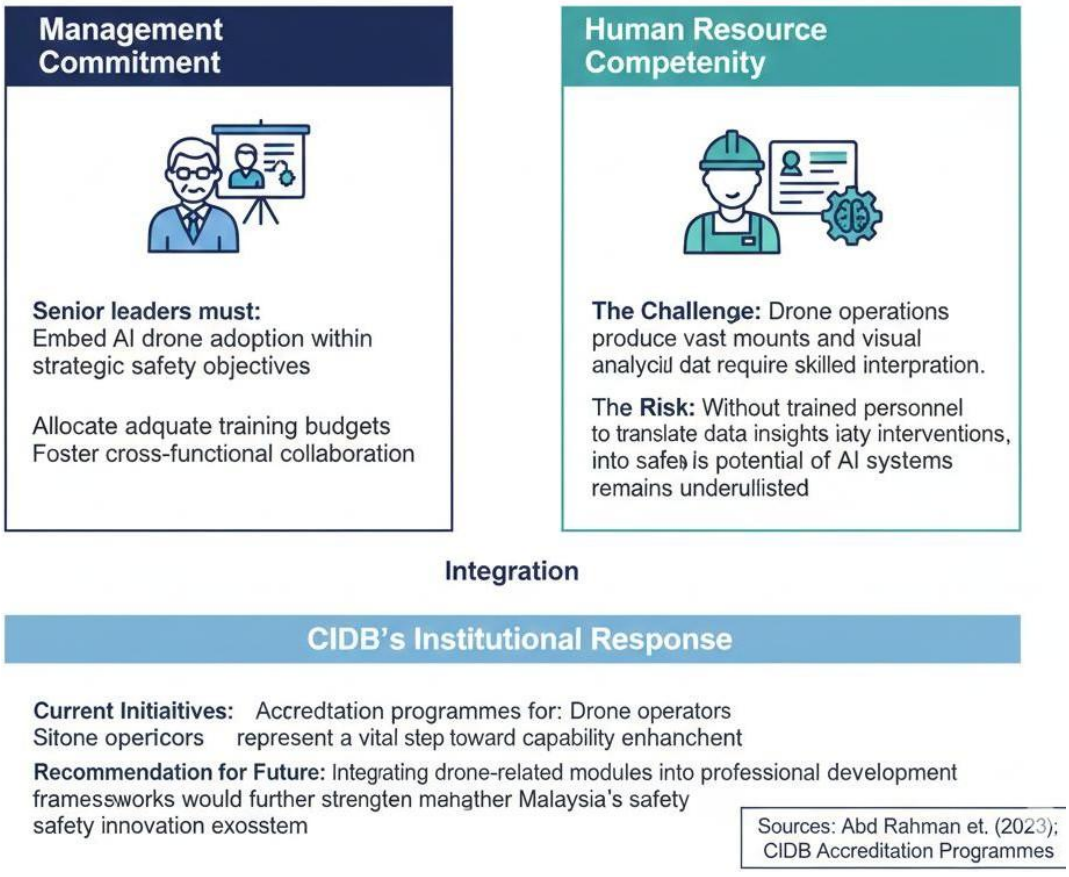


Figure 2.32: Dual Pillar Framework of Management Commitment and Human Resource Competency (Adapted from Abd Rahman et al., 2023 and CIDB, 2021)

At the operational level, human resource competency plays a decisive role, as drone operations produce vast amounts of visual and analytical data that require skilled interpretation. Jamian et al. (2026) report that a "lack of skilled personnel" serves as a top deterrent for Malaysian firms, with a mean score of 4.00. In response to this gap, the Construction Industry Development Board's (CIDB) accreditation programs for drone operators and site safety officers represent a vital step toward institutional capability enhancement. Integrating drone-related modules into existing professional development frameworks is essential to strengthen Malaysia's safety innovation ecosystem and ensure that AI-driven insights result in genuine reductions in site accidents.

2.6.2.3 Leadership and Change Management in Technological Adoption

Leadership plays a pivotal role in shaping organizational culture and determining the pace of technological transition. Transformational leaders, who communicate a clear digital vision and empower employees to experiment with emerging technologies, are significantly more likely to achieve successful and sustained adoption (Hussein et al., 2023). In the construction industry, applying structured change management frameworks is essential for moving firms beyond initial technical awareness toward the full cultural integration of AI-drone practices.

The progression of this leadership-driven change is illustrated in Figure 2.33. This integrated framework contrasts traditional hierarchical management styles with transformational leadership, mapping the journey from initial awareness to sustained cultural integration. It highlights that in the Malaysian context where hierarchical structures are common empowering mid-level managers as "technology champions" is a critical strategy to accelerate internal diffusion and ensure shared accountability for safety outcomes (Hussein et al., 2023).



Figure 2.33: Framework for Leadership and Change Management in Technological Adoption (Adapted from Hussein et al., 2023)

This leadership shift is increasingly urgent as Malaysia prepares for the implementation of the AI Governance Bill expected in mid-2026. This legislation is set to hold technology providers and developers accountable for proactive risk management and mandatory incident reporting (Ministry of Digital, 2025; Bernama, 2026). Consequently, leadership that prioritizes continuous learning, transparency, and collaboration is no longer merely an organizational preference but a regulatory necessity. By embedding technological transformation as a core element of the construction safety culture, leaders can ensure that AI-drone systems are perceived not as external impositions, but as vital tools for achieving long-term operational excellence and safety compliance.

2.6.3 Trust and Data Ethics

Beyond rules and capabilities, the social legitimacy of AI drone systems depends on trust and ethical integrity. Construction projects involve diverse stakeholders like contractors, regulators, workers, and the public whose acceptance of technology hinges on perceived fairness, privacy, and accountability (Zhang et al., 2023).

2.6.3.1 Stakeholder Trust in AI-Drone Technology

Trust is a multifaceted construct cultivated through transparency, reliability, and the consistent demonstration of tangible benefits. Within the construction environment, workers and site personnel are more likely to support drone-based safety systems when they perceive measurable improvements, such as a reduction in accident frequency or accelerated hazard reporting cycles (Yi & Sutrisna, 2021). Conversely, a lack of transparent communication regarding the utilization of drone-captured data can generate a "surveillance climate," leading to increased fear of monitoring or job insecurity among the workforce.

The complex relationship between these trust-building factors and the psychological barriers of practitioners is analyzed in Figure 2.34. This socio-ethical framework illustrates how strategic engagement protocols such as the clear communication of drone-use boundaries can mitigate the negative perceptions often held by Malaysian practitioners. The diagram highlights that building trust is not a one-time event but a continuous process of engagement that directly influences the successful normalization of AI-driven monitoring (Zhang et al., 2023; Yi & Sutrisna, 2021; Jamian et al., 2026).

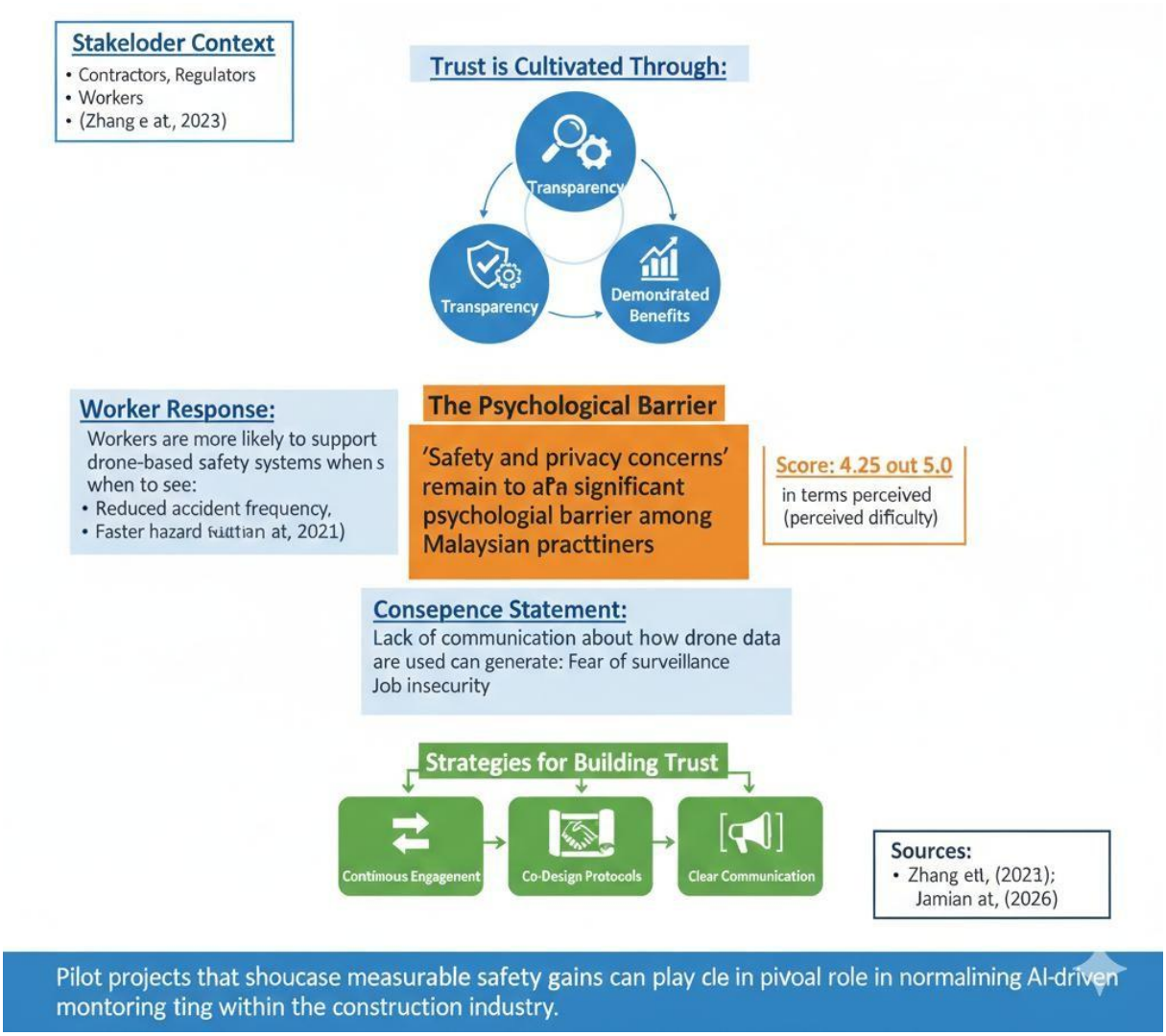


Figure 2.34: Socio-Ethical Framework for Stakeholder Trust in AI-Drone Adoption (Adapted from Zhang et al., 2023; Yi and Sutrisna, 2021; and Jamian et al., 2026)

Building stakeholder trust therefore requires a collaborative approach, including the co-designing of safety protocols with contractors and regulators. Pilot projects play a pivotal role in this process; by showcasing empirical safety gains in a controlled environment, firms can demonstrate that AI-drones are benevolent tools intended for worker protection rather than punitive surveillance instruments. As Jamian et al. (2026) suggest, addressing these "emotional trust" barriers is just as critical as resolving technical challenges for the long-term sustainability of Construction 4.0 innovations in Malaysia.

2.6.3.2 Data Governance, Security, and Privacy Concerns

AI-drone systems capture extensive visual and sensor data that often include personal or proprietary information. While the Personal Data Protection Act 2010 (PDPA 2010) provided a general legal basis, the Personal Data Protection (Amendment) Act 2024 has introduced significant modernizations implemented in phases throughout 2025. Key changes include the expansion of "sensitive personal data" to include biometric data, mandatory data breach notifications within 72 hours, and the required appointment of a Data Protection Officer (DPO) (Personal Data Protection Commissioner, 2025). Construction firms adopting AI-drone technologies must therefore establish internal data governance policies that align with these updated Malaysian statutes and global standards for data minimization and secure storage (Organisation for Economic Co-operation and Development, 2023).

The transition in the Malaysian regulatory landscape and its implications for the construction sector are analyzed in Figure 2.35. The framework illustrates the shift from the foundational PDPA 2010 to the more rigorous 2024 Amendment Act, highlighting the critical compliance components such as biometric oversight and breach protocols that firms must integrate into their safety management systems. This visual demonstrates that institutional compliance is no longer a static requirement but an evolving governance responsibility (Personal Data Protection Commissioner, 2025; OECD, 2023).

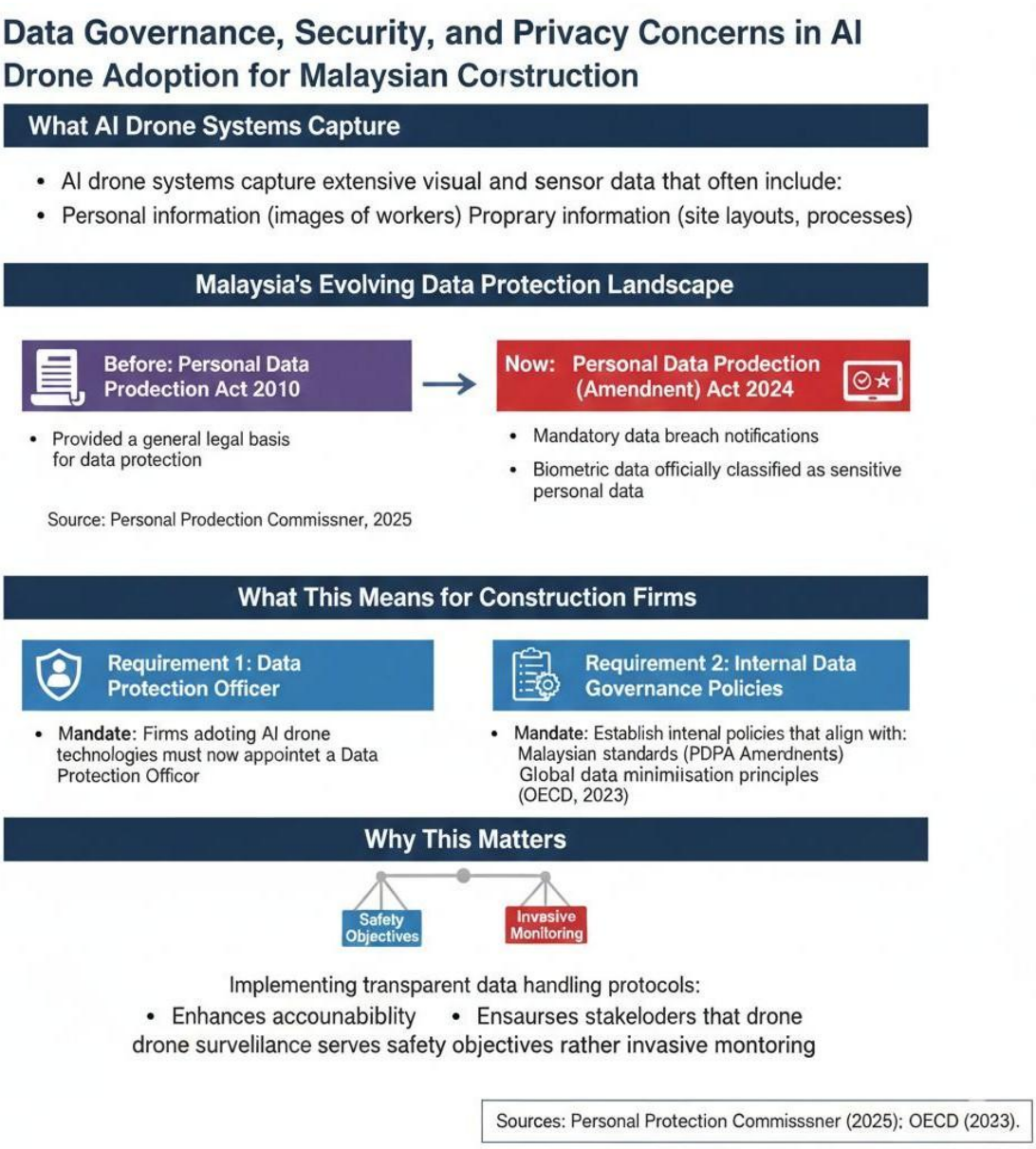


Figure 2.35: Data Governance and Privacy Framework for AI-Drone Adoption (Adapted from Personal Data Protection Commissioner, 2025 and OECD, 2023)

Implementing transparent data handling protocols enhances accountability and reassures stakeholders that drone surveillance serves strictly defined safety objectives rather than invasive monitoring. By adhering to the principles of Data Protection by Design, construction firms can mitigate the risk of unauthorized data access and build the "institutional trust" necessary for the long-term acceptance of AI-driven safety tools. As the industry moves toward 2026, these governance structures will become the primary benchmark for distinguishing responsible technological adoption from simple compliance.

2.6.3.3 Ethical Considerations in AI-Driven Safety Systems

Ethical concerns in Construction 4.0 extend beyond data privacy to include fairness, explicability, and the preservation of human oversight. Floridi (2023) argues that algorithmic bias, if left unchecked, can lead to disproportionate surveillance, false hazard identification, or critically overlooked risks. To mitigate these socio-technical threats, Malaysia published the National Guidelines on AI Governance and Ethics in September 2024. These guidelines outline seven core principles: fairness; reliability, safety, and control; privacy and security; inclusiveness; transparency; accountability; and the pursuit of human benefit (Ministry of Science, Technology and Innovation, 2024).

Furthermore, Malaysia's leadership in the ASEAN AI Safety Network (ASEAN AI Safe), established in late 2025, provides a regional mechanism to harmonize these ethical standards and promote responsible AI research across Southeast Asia (Ministry of Digital, 2025). This multi-layered architecture of ethical governance is illustrated in Figure 2.36. The diagram visualizes the integration of national guidelines and regional ASEAN standards as the protective "outer layer" of institutional and regulatory support. It highlights that ethical governance is not a secondary concern but a foundational pillar for safe and socially acceptable AI-drone deployment (Floridi, 2023; MOSTI, 2024; Ministry of Digital, 2025).

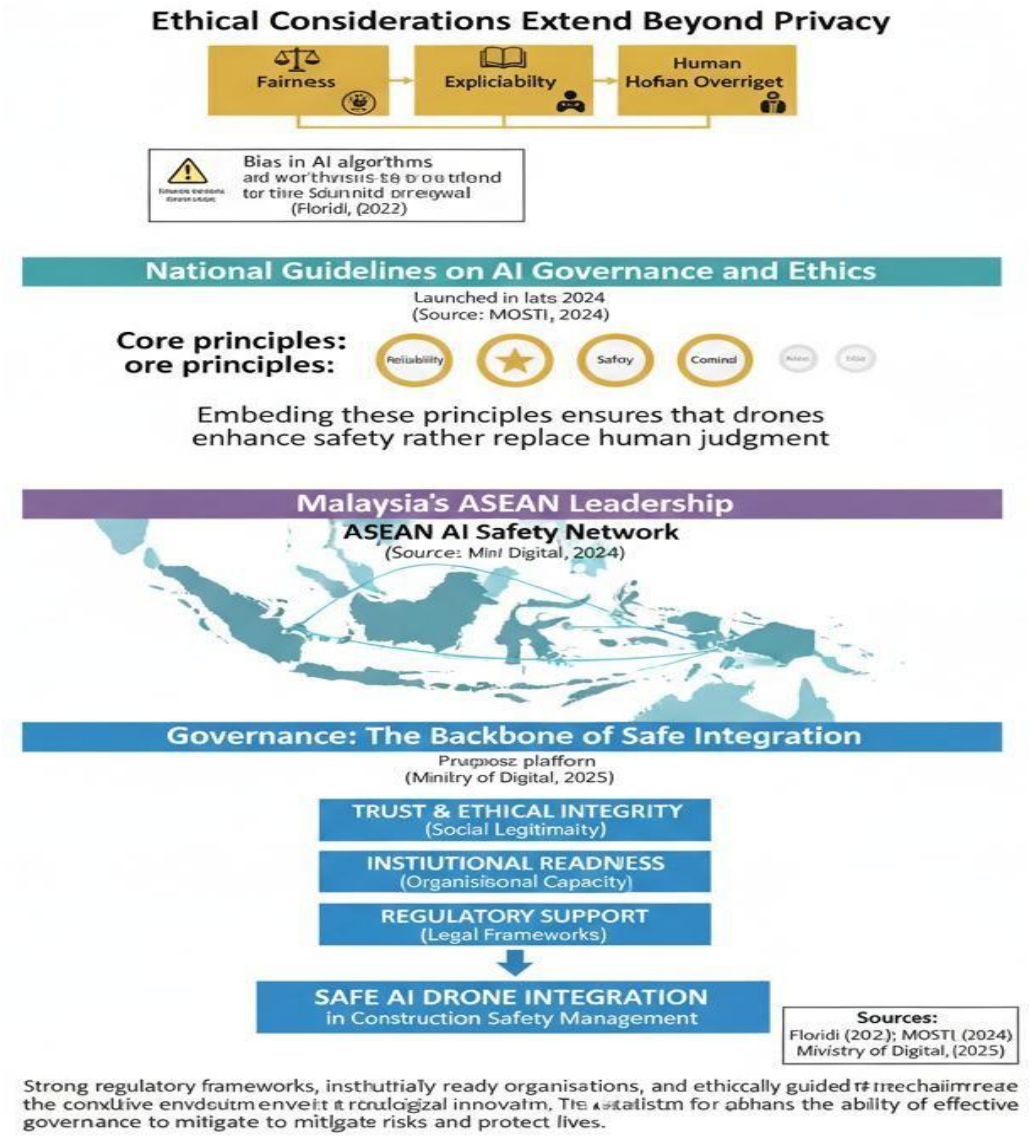


Figure 2.36: Multi-Layered Architecture of Ethical AI Governance (Adapted from Floridi, 2023; MOSTI, 2024; and Ministry of Digital, 2025)

In summary, governance serves as the strategic backbone for the integration of AI-drone technology within the Malaysian construction safety ecosystem. Effective governance encompassing regulatory support, institutional readiness, and trust is not only a prerequisite for successful technology adoption but also a catalyst for long-term resilience and the fulfillment of sustainable construction objectives. By aligning technical capability with ethical and legal accountability, the industry can move toward a proactive safety culture that protects its most valuable asset: the workforce.

2.7 The Mediating Role of Implementation

While governance establishes the regulatory and institutional foundation for technological innovation, the implementation process determines whether these frameworks translate into actual, sustained adoption. In the context of AI-drone integration for construction safety, implementation serves as the operational bridge that links governance structures with real-world outcomes. It encompasses the methods, procedures, and organizational practices that transform policy intent into tangible technological application.

In many developing construction markets, including Malaysia, robust governance alone does not guarantee the successful adoption of digital tools. As illustrated in Figure 2.37, implementation acts as a mediating process; the gap between intent and reality often lies in implementation quality, where factors such as inadequate planning, fragmented communication, or a lack of inter-agency coordination cause promising technologies to remain underutilized. This visual model highlights that governance creates the necessary conditions, implementation activates them, and adoption reflects the ultimate success of the entire ecosystem (Alsamarraie et al., 2022; Haron et al., 2023; CIDB, 2024).

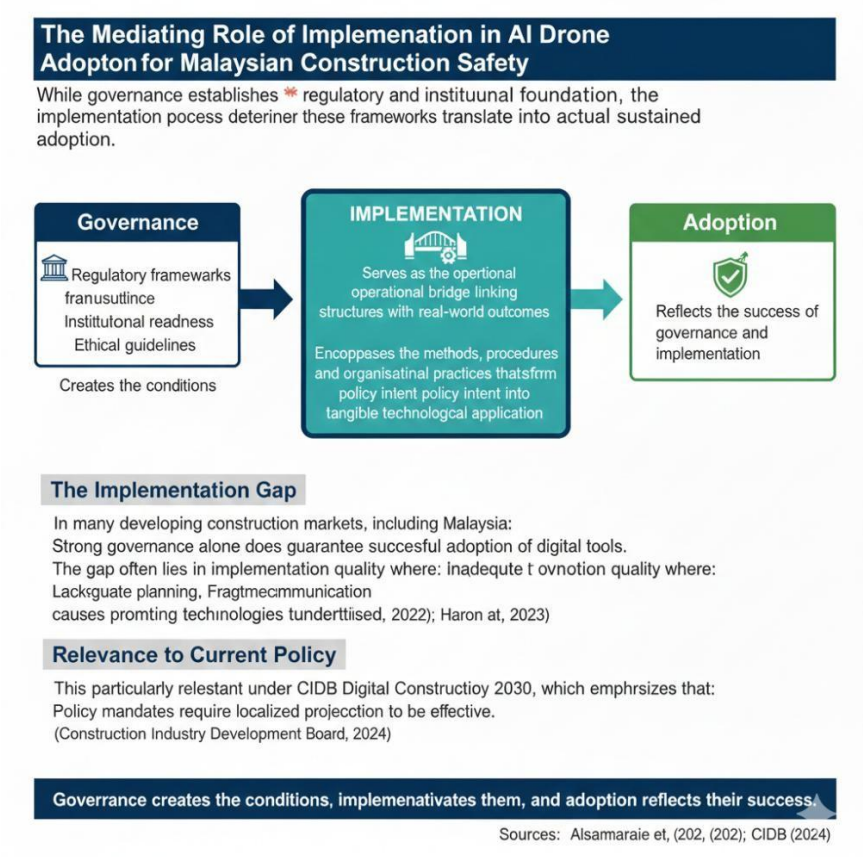


Figure 2.37: The Mediating Role of Implementation in Technology Adoption (Adapted from Alsamarraie et al., 2022; Haron et al., 2023; and CIDB, 2024)

This mediation is particularly relevant under the current Construction Industry Development Board (CIDB) Digital Construction Strategy 2030, which emphasizes that national policy mandates require localized project execution to be effective (Construction Industry Development Board, 2024). Consequently, understanding implementation as a mediator is crucial for explaining the variance in results observed across different construction projects despite them operating under the same regulatory umbrella. By focusing on this bridge, the study identifies the specific operational levers such as site-level training and standardized data protocols that determine if AI-drone governance achieves its objective of enhancing worker safety.

2.7.1 Conceptualization of Implementation in Technology Adoption

Implementation can be broadly conceptualized as the process through which technological innovations are operationalized within an organization's workflows and culture. It represents the practical dimension of adoption the critical stage where policy directives, management commitment, and technical tools intersect. According to the Technology-Organization-Environment (TOE) framework, implementation acts as the mechanism that converts environmental and organizational readiness into measurable adoption outcomes (Tornatzky & Fleischer, 1990). Similarly, within the Diffusion of Innovation (DOI) theory, it is the stage following decision-making and preceding institutionalization (Rogers, 2003).

In construction safety, implementation takes a particularly complex form because projects are temporary, multi-stakeholder environments with differing objectives and technological competencies. For AI-drone systems, successful implementation requires the harmonization of technical, human, and process integration (Kamaruddin et al., 2023). This multi-dimensional process is visualized in Figure 2.38, which illustrates how these three pillars must overlap within the Malaysian construction safety context to move a technology from a pilot phase to a sustained operational tool.

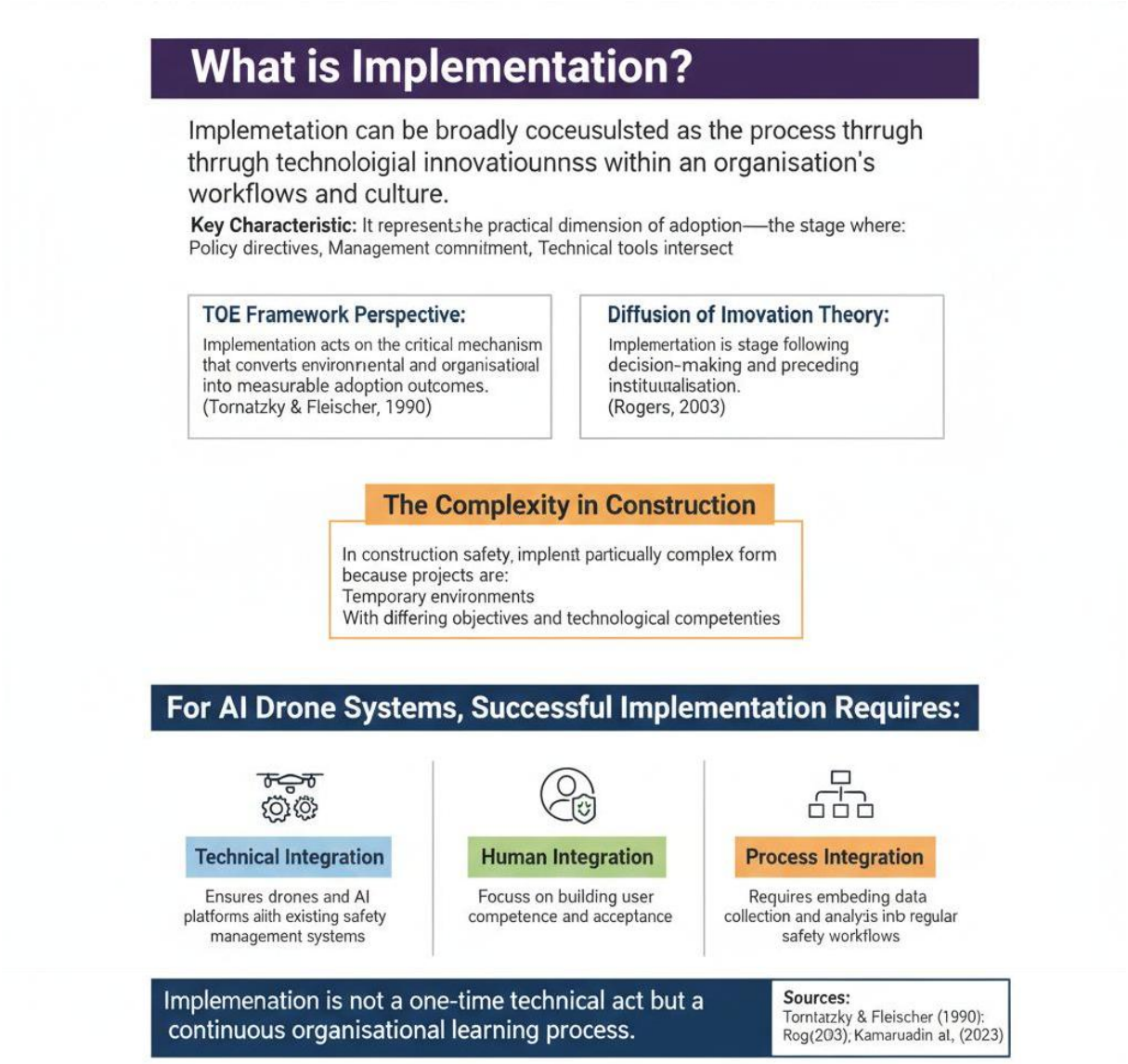


Figure 2.38: Conceptualization of Implementation as a Multi-Dimensional Integration Process (Adapted from Tornatzky and Fleischer, 1990; Rogers, 2003; and Kamaruddin et al., 2023)

As shown in the framework, technical integration ensures drones and AI platforms align with existing safety management systems, while human integration focuses on building user competence and psychological acceptance. Finally, process integration requires embedding data collection and analysis into regular daily safety workflows. Consequently, implementation is not a one-time technical event but a continuous organizational learning process that requires ongoing governance and refinement.

2.7.2 Implementation Quality and Process Efficiency

The quality of implementation refers to how effectively technological systems are planned, executed, monitored, and refined during deployment. High quality implementation enhances process efficiency, reduces operational uncertainty, and ensures that AI drone systems generate actionable insights for safety management (Yi & Sutrisna, 2021). In practice, implementation quality depends on several interrelated factors, beginning with the clarity of objectives where organisations must define specific safety outcomes, such as reducing inspection time or identifying near miss hazards. Furthermore, adequate resource allocation for hardware, training, and data management ensures system reliability, while robust coordination mechanisms across departments enable smooth information flow (Mustapha et al., 2024). Continuous evaluation remains central to this process, as feedback loops transform drones from simple surveillance tools into proactive safety partners. Under the National Guidelines on AI Governance and Ethics, this includes the implementation of algorithmic transparency to ensure that hazard detection models are explicable to safety officers (Ministry of Science, Technology and Innovation, 2024). Projects supported by clear leadership and interoperable data systems demonstrate significantly greater returns on governance efforts. Conversely, weak implementation marked by poor data utilisation undermines policy objectives and erodes stakeholder confidence in digital safety innovations (Abd Rahman et al., 2023).

2.7.3 Implementation as a Bridge between Governance and Adoption

Implementation occupies a mediating position between governance structures and actual adoption behaviour. Governance provides the enabling conditions, such as policy frameworks, institutional readiness, and ethical guidelines, while implementation determines the operational effectiveness of these conditions (Hussein et al., 2023). Within the Malaysian construction context, this mediating role is particularly significant due to the fragmented nature of project governance. Regulations set by the Civil Aviation Authority of Malaysia, the Construction Industry Development Board, and the Department of Occupational Safety and Health establish the legal environment, but it is the project level implementation that translates governance into real world safety performance. This relationship is often tested in regulatory sandboxes where firms can pilot autonomous safety drones under relaxed constraints to prove implementation feasibility before full scale adoption (Ministry of Digital, 2025). From a theoretical standpoint, the mediating influence of implementation explains the variability observed in technology adoption studies, as organisations with structured implementation planning exhibit higher

adoption success (Gefen et al., 2021). In this study conceptual model, implementation acts as the vital mediator between the independent governance factors and the dependent variable of AI drone adoption for safety.

2.8 Summary of Governance-Related Linkages

The governance ecosystem within the Malaysian construction industry represents a multidimensional network of regulatory, institutional, and ethical mechanisms that collectively influence the adoption of emerging technologies such as AI driven drones for safety. The preceding sections have highlighted that while the availability of advanced technologies is essential, it is the strength and coherence of governance linkages that determine their successful operationalisation within safety management frameworks. These governance components like regulatory support, institutional readiness, and trust and data ethics interact dynamically to either enable or constrain safety adoption outcomes (Haron et al., 2023). Governance is not an isolated construct but serves as an enabling environment that shapes organisational behaviour, technology diffusion, and safety culture (Divecha et al., 2023). In Malaysia, this ecosystem includes key actors such as the Civil Aviation Authority of Malaysia, Construction Industry Development Board, and Department of Occupational Safety and Health, each contributing different elements of oversight, capability development, and standardisation. The integration of these actors is further reinforced by the National AI Roadmap 2021-2025 which seeks to harmonise sector specific safety requirements with broader national digital goals (Ministry of Science, Technology and Innovation, 2021). Globally, studies suggest that effective governance frameworks serve as the foundation for trust, capability development, and sustainable technological diffusion to achieve zero accident goals (Li et al., 2023; Awolusi & Marks, 2022).

2.8.1 Relationships among Governance Variables and Adoption Outcomes

The relationship between governance variables and safety adoption outcomes is inherently interactive and interdependent. Regulatory support provides the formal structure for technology integration by defining permissible use cases, certification requirements, and operational guidelines for drone deployment (Tornatzky & Fleischer, 1990). When clear and adaptive regulations are in place, such as the Occupational Safety and Health Amendment Act 2022 and the specific flight authorizations under Civil Aviation Directive 6011, they create certainty and legitimacy for innovation (Civil Aviation Authority of Malaysia, 2024). Conversely, regulatory ambiguity generates institutional hesitation, slowing adoption and undermining confidence

among construction stakeholders (Kamaruddin et al., 2023). Institutional readiness represents the internal capacity of organisations to translate regulatory opportunities into practical action, including the presence of digital infrastructure, skilled personnel, financial resources, and leadership commitment. Organisations that demonstrate high readiness are better equipped to implement AI drone systems effectively, reinforcing both compliance and safety outcomes (Yi & Sutrisna, 2021).

The third pillar, trust and data ethics, addresses the relational and moral dimension of technology adoption. Data ethics concerns, particularly regarding surveillance, data ownership, and privacy, influence acceptance and the perceived legitimacy of AI driven safety systems (Hussein et al., 2023). When trust is high, trust legitimises the broader governance framework, ensuring successful AI drone adoption for safety (Trisnawati, 2024). These dimensions collectively form an interactive model where regulatory clarity facilitates institutional planning while institutional capacity enhances trustworthy practices.

2.8.2 Theoretical Integration of Governance Ecosystem Perspectives

The theoretical integration of governance ecosystem perspectives provides a holistic understanding of how external and internal forces jointly influence technology adoption behaviour in the construction sector. This study conceptual framework synthesises insights from the Technology Organisation Environment framework, the Diffusion of Innovation theory, and principles of Institutional Theory. From the Technology Organisation Environment perspective, regulatory support aligns with the environmental context, shaping external pressures and opportunities that drive adoption (Tornatzky & Fleischer, 1990). Institutional readiness represents the organisational context, reflecting internal structures, resources, and managerial commitment that facilitate innovation uptake (Divecha et al., 2023). Trust and data ethics intersect the technological and social dimensions, determining how users perceive risk and fairness in digital transformation (Zhang et al., 2023). The Diffusion of Innovation theory complements this by emphasising the role of perceived advantage and compatibility in shaping user decisions (Rogers, 2003). Institutional theory offers additional explanatory power by framing governance as a set of normative and regulative structures that confer legitimacy upon technology use (Scott, 2014). Bringing these perspectives together, the governance ecosystem can be conceptualised as a multi layered system where external regulation, organisational capability, and ethical legitimacy interact through the implementation process to determine safety adoption outcomes.

2.9 Conceptual Framework and Hypothesis Development

Building upon the governance ecosystem perspective, this section develops the study hypotheses by linking theoretical insights to the empirical relationships proposed in this research. The conceptual framework is grounded in the necessity of transforming reactive safety protocols into proactive, digitally enabled systems within the Malaysian construction landscape. As discussed earlier, governance elements comprising regulatory support, institutional readiness, and trust and data ethics serve as the structural and behavioural enablers that determine how effectively new technologies, such as AI-driven drones, are integrated into the construction industry. Within this governance framework, implementation acts as a critical mediating process that translates institutional and regulatory intent into practical adoption outcomes. Recent evidence from Malaysian pilot projects suggests that while technological capability is high, a significant gap exists in operational integration, which often prevents full-scale adoption (Lim, 2025). The following subsections present the development of hypotheses aligned with established theoretical models and the contextual realities of the Malaysian Civil and Structural (C&S) sector.

2.9.1 Development of Hypotheses Based on Theoretical Models

Technology adoption has often been examined through the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), the Diffusion of Innovation (DOI) theory (Rogers, 2003), and Institutional Theory (Scott, 2014). Within the TOE framework, Regulatory Support corresponds to the environmental dimension, representing the external pressures, incentives, and policy clarity that shape technological innovation behavior. Institutional Readiness aligns with the organizational dimension, encompassing internal capacities, digital infrastructure, and the managerial commitment necessary for innovation. Finally, Trust and Data Ethics add a crucial behavioral and normative dimension to these classical models, addressing social legitimacy and transparency in technological decision-making (Gefen et al., 2021).

Based on these foundations, this study posits that each of the three governance factors Regulatory Support, Institutional Readiness, and Trust and Data Ethics exerts a direct positive influence on the Implementation Quality of AI-drone technology. Strong regulatory support reduces institutional uncertainty, while higher organizational readiness facilitates operational

efficiency. Simultaneously, ethical data management and stakeholder trust serve to legitimize the technology among contractors and the site workforce.

H1: Regulatory support has a significant positive influence on the implementation quality of AI-drone technology for construction safety in Malaysia.

H2: Institutional readiness has a significant positive influence on the implementation quality of AI-drone technology for construction safety in Malaysia.

H3: Trust and data ethics have a significant positive influence on the implementation quality of AI-drone technology for construction safety in Malaysia.

2.9.2 Mediation Effects of Implementation Quality

While governance factors establish the essential preconditions, it is the quality of implementation that determines how effectively these intentions are translated into operational outcomes. Implementation, in this study, is conceptualized as the efficiency and quality with which AI-drone systems are deployed and integrated within existing safety structures. This mediating role is consistent with Process Innovation Theory, which emphasizes that transformation in complex systems depends on structured execution and sustained adaptation (Van de Ven, 2017).

When implementation processes are robust, governance mechanisms become significantly more impactful. Higher implementation quality acts as a buffer against technical and environmental failures such as the weather constraints typical of the Malaysian tropical climate thereby reinforcing the positive influence of readiness and support on sustained adoption (Lim, 2025; Jamian et al., 2026).

H4: Implementation quality has a significant positive influence on the adoption of AI-drone technology for construction safety in Malaysia.

H5: Implementation quality significantly mediates the relationship between regulatory support and AI-drone adoption.

H6: Implementation quality significantly mediates the relationship between institutional readiness and AI-drone adoption.

H7: Implementation quality significantly mediates the relationship between trust and data ethics and AI-drone adoption.

2.9.3 Moderating Influence of Professional Experience and Stakeholder Role

The final component of the framework considers the moderating influence of professional context. Theoretical perspectives on professional identity suggest that the perception of technological drivers is filtered through an individual's work experience and their specific role within the project lifecycle (Sapri, 2024). This study incorporates Moderation Analysis and Multi-Group Analysis (MGA) to capture these nuances, specifically contrasting office-based consultants with site-based contractors.

H8: Work experience significantly moderates the relationship between governance factors and implementation quality.

H9: The structural relationships within the Governance Ecosystem Model (GEM) differ significantly between office-based and site-based stakeholders.

2.9.4 Conceptual Pathways of Governance Factors toward Safety Adoption

The conceptual pathways developed in this research recognise governance as a multidimensional construct operating across regulatory, organisational, and ethical domains. Regulatory frameworks establish legitimacy and mitigate perceived risks, while institutional readiness provides the internal capability to translate motivation into tangible practices (Alsamarraie et al., 2022; Ting & Yahaya, 2024). When these governance elements function cohesively through strong implementation, they form a reinforcing ecosystem that accelerates AI drone adoption and enhances safety performance (Zhang et al., 2023). This pathway aligns with the National AI Roadmap 2021-2025 goals of increasing AI penetration in high-risk sectors (MOSTI, 2021). Consequently, this study conceptualises governance factors as the antecedents, implementation as the mediating mechanism, and AI drone adoption for safety as the ultimate outcome variable, forming the theoretical foundation for empirical validation.

2.10 Summary of Literature and Research Gaps

This section summarizes the academic and policy frameworks analyzed in this chapter to establish the foundation for the Governance Ecosystem Model (GEM). By synthesizing the

current state of the industry, the review identifies specific theoretical and empirical gaps that this study intends to address through a dual-analytical approach using SPSS and SmartPLS.

2.10.1 Review Scope and Research Boundaries

The literature covered in this chapter spans from the start of the Construction 4.0 Strategic Plan (2021) to the current regulatory changes observed in early 2026. While international benchmarks provide a global context, the primary focus is on the Malaysian construction sector. A key observation from this review is that existing research is largely dominated by qualitative case studies or basic descriptive surveys. While these are useful for identifying general industry barriers, there is a distinct lack of inferential studies that test causal relationships. This research addresses this gap by utilizing SPSS for initial data screening and descriptive analysis, followed by Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS to test the complex direct and mediating paths within the governance framework.

2.10.2 Current Challenges in Malaysian Construction Safety

Based on the synthesis of the reviewed literature, several core challenges characterize the current state of construction safety technology in Malaysia. First, a significant regulatory misalignment exists between the rapid development of autonomous "Agentic AI" and the existing flight directives, such as CAD 6011 from the Civil Aviation Authority of Malaysia (CAAM). This gap creates uncertainty for contractors who wish to move beyond simple manual drone flights. Secondly, there is a persistent lack of organizational readiness within the industry. While large G7 contractors often possess the financial capital to acquire advanced systems, studies indicate they frequently lack the internal digital maturity and specialized human capital required to sustain these autonomous workflows over the long term. Finally, the review highlights the importance of trust and data ethics as a critical driver for adoption. Recent discourse from 2024–2025 suggests that worker privacy and ethical data handling are no longer secondary concerns but are mandatory prerequisites for the technology to be accepted and normalized on-site.

2.10.3 Mapping of Literature and Research Gaps

Table 2.1 summarizes the core literature and identifies the specific voids that this research will fill.

Table 2.1: Synthesis Matrix of Research Parameters and Gaps

Research Parameter	Principal Citations	Key Findings	Identified Research Gap
Regulatory Support	Sapri (2024); CAAM (2024); CIDB (2024)	Flight directives and safety sandboxes provide the legal baseline for drone usage.	Lack of empirical testing on the active support role of the National AI Office (NAIO).
Institutional Readiness	Kamaruddin (2023); Ahmad (2024); Xiao (2023)	Organizational maturity dictates the speed of technology absorption.	Insufficient focus on readiness specific to Agentic and Autonomous AI systems.
Trust and Data Ethics	Zhang (2023); MoSTI (2024); Lee (2024)	Ethical legitimacy and privacy are essential to mitigate workforce resistance.	Trust is rarely treated as a causal statistical pillar in adoption models.
Implementation Quality	Jamian (2026); Sapri (2024)	Operational success is tied to site-level human-machine integration.	**Major Gap:** Usually treated as a barrier rather than a mediating variable.
AI-Drone Adoption	Sapri (2024); Construction 4.0 (2021-2025)	Adoption is largely confined to pilot phases among G7 contractors.	Absence of a validated model explaining the policy-to-site execution disconnect.

2.11 Link to Conceptual Framework

Following the detailed analysis of the literature and the formulation of research hypotheses, this section establishes the critical bridge between theoretical discourse and the practical Governance Ecosystem Model (GEM). The framework is designed to move beyond a fragmented understanding of technology barriers by integrating governance enablers, the mediating mechanism of implementation, and the final adoption outcome into a unified, socio-technical structure. This alignment is essential for analyzing how digital safety transformation is operationalized within the high-risk environments of the Malaysian construction industry.

2.11.1 Derivation of Independent Variables

The independent variables of regulatory support, institutional readiness, and trust and data ethics are derived from the preceding literature as the primary governance pillars shaping the adoption

environment. Regulatory support captures the degree to which national mandates and sectoral guidelines, particularly from the Civil Aviation Authority of Malaysia and the Construction Industry Development Board, provide the legal foundation and policy clarity required for drone operations. Furthermore, institutional readiness represents the internal organizational capacity to absorb innovation, encompassing digital infrastructure, leadership commitment, and the ability to manage algorithmic accountability within site-level workflows. Complementing these structural factors, trust and data ethics reflect the normative dimension of governance, emphasizing that ethical legitimacy and stakeholder confidence are as critical as technical readiness for achieving long-term industrial normalization.

2.11.2 Dependent Variable and Mediating Mechanism

The dependent variable, AI-drone safety adoption, is conceptualized not just as the acquisition of technology, but as the extent to which firms utilize these systems to enhance hazard prevention and safety compliance. To explain the variance in adoption rates, this study introduces implementation quality as a mediating variable. Acting as an operational conduit, implementation quality reflects the execution standards of drone integration, including site-level planning, coordination, and data utilization. In the Malaysian context, this mediator is vital for explaining how firms overcome technical reliability issues, such as those caused by tropical weather constraints, to achieve sustained safety outcomes.

2.11.3 Moderating Influence of Professional Experience

A distinct feature of this framework is the inclusion of work experience as a moderating variable that influences the entire governance-to-implementation pathway. Theoretical perspectives on professional identity suggest that the perception of governance enablers is often filtered through an individual's seniority and tenure within the industry. This study posits that the strength of the relationship between the three governance pillars are regulatory support, institutional readiness, and trust and the resulting implementation quality is contingent upon the respondent's professional experience. By incorporating this moderation, the model accounts for the nuanced ways in which veteran professionals and newer practitioners navigate the institutional and regulatory hurdles inherent in the Malaysian construction sector.

2.11.4 Integration into the Governance Ecosystem Model (GEM)

The synthesis of these variables culminates in the Governance Ecosystem Model (GEM), which illustrates the complex interaction between policy, organization, and human behavior. In this structure, the three governance factors function as the antecedents that shape the organizational environment, while implementation quality serves as the mediator that operationalizes these inputs into tangible outputs. Work experience acts as a filter across these initial relationships, ensuring the model captures the diverse professional perspectives within the industry. By treating governance as an interactive system rather than a static policy set, the GEM provides a validated pathway for understanding the policy-to-site execution disconnect, ultimately aligning with the National AI Roadmap goals of fostering a secure and ethical AI ecosystem.

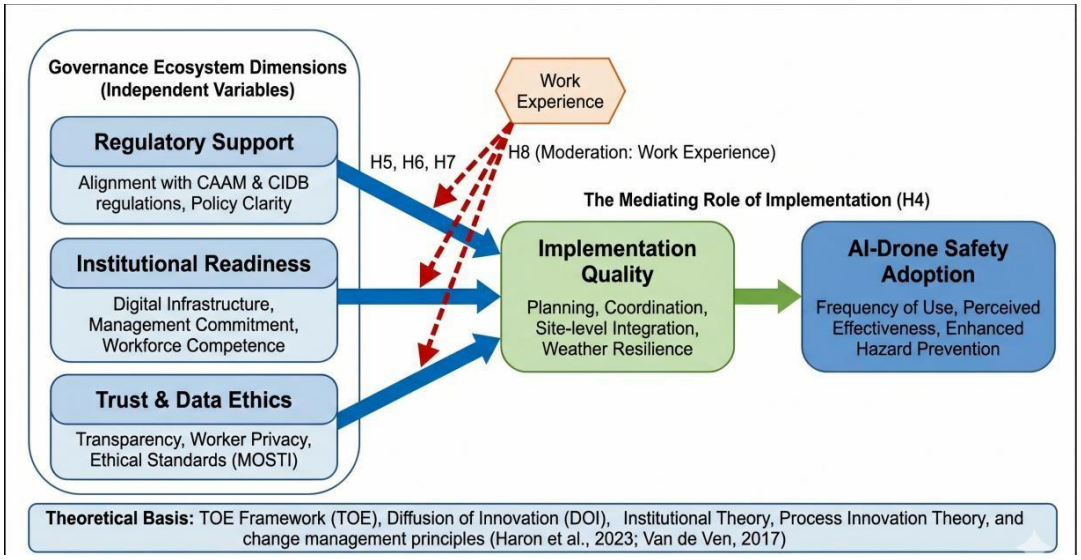


Figure 2.39: Conceptual Framework of the Governance Ecosystem Model (GEM) for AI-Drone Safety Adoption

2.12 Chapter Summary

Chapter 2 has provided a comprehensive and critical synthesis of the literature surrounding the digital transformation of the Malaysian construction industry, specifically focusing on the adoption of AI-drone technology for safety management. The review established that while the sector is burdened by disproportionately high accident rates and a heavy reliance on manual, reactive safety supervision, the convergence of artificial intelligence and unmanned aerial vehicles offers a proven pathway to proactive, real-time hazard detection (Yi & Sutrisna, 2021). However, the literature reveals a persistent "governance paradox" hindering this transition;

despite strong government-led mandates like the Construction 4.0 Strategic Plan, actual site-level adoption is stalled due to structural fragmentation, lack of digital skills, and ambiguous compliance frameworks (Khudzari et al., 2025; Tham & Hassim, 2025).

To systematically unpack these adoption barriers, this chapter theoretically grounded the research by integrating the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990), the Technology Acceptance Model (TAM) (Davis, 1989), and Institutional Theory (Scott, 2014). This multi-dimensional theoretical synthesis justified the formulation of the study's three core governance domains: Regulatory Support, Institutional Readiness, and Trust and Data Ethics.

The review highlighted that external Regulatory Support must evolve from static aviation laws into adaptive, sector-specific governance requiring seamless inter-agency coordination among CAAM, CIDB, and DOSH. Internally, construction firms must possess Institutional Readiness, which dictates that technological hardware is useless without sufficient digital infrastructure, leadership commitment, and the technical competency of the workforce (Kamaruddin et al., 2023). Furthermore, the chapter emphasized that technical utility is insufficient without socio-ethical legitimacy; Trust and Data Ethics are critical to overcoming psychological resistance, addressing worker privacy concerns, and ensuring compliance with the Personal Data Protection (Amendment) Act 2024 (Zhang et al., 2023; Ministry of Science, Technology and Innovation, 2024.

Crucially, the literature review introduced and conceptualized "Implementation Quality" as the vital operational bridge connecting these governance enablers to final organizational adoption (Alsamarraie et al., 2022; Haron et al., 2023). The synthesis demonstrated that robust regulations and internal readiness cannot guarantee sustained AI-drone usage unless they are successfully converted into high-quality, practical site execution.

Ultimately, the synthesis of these theoretical models and governance parameters culminated in the development of the Governance Ecosystem Model and the formulation of nine testable hypotheses. With the theoretical foundation firmly established and the conceptual pathways defined, the thesis now transitions to Chapter 3, which delineates the quantitative methodological blueprint and statistical strategy required to empirically validate these relationships across the Malaysian construction supply chain.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

The third chapter delineates the methodological framework employed to empirically validate the Governance Ecosystem Model (GEM) within the Malaysian construction sector. This research aims to investigate the complex interplay between regulatory, institutional, and ethical governance domains and their subsequent impact on AI Drone Adoption, specifically examining the mediating role of Implementation Quality. To achieve this, the chapter provides a detailed justification for the selection of a positivist paradigm and a quantitative research design, which are essential for testing the deductive hypotheses formulated in Chapter 2. By establishing a rigorous methodological path, this study ensures that the data collected from Developers, Consultants, and CIDB G1–G7 Contractors is analyzed with the statistical precision required to inform the National AI Office (NAIO) and the objectives of the Thirteenth Malaysia Plan (2026–2030) (Saunders et al., 2023; Sapri, 2024).

The structure of this chapter follows a logical progression from philosophical assumptions to the practicalities of data analysis. It begins with the ontological and epistemological stances that underpin the study, followed by an explanation of the cross-sectional survey method. Furthermore, the chapter details the sampling strategy and the triangulation of multiple sample size determination methods to ensure the findings are representative of the fragmented industry landscape. Critical sections on the Operationalization of Variables and the Research Instrument explain how the latent constructs of the GEM are converted into measurable items. Finally, the chapter concludes with a comprehensive data analysis strategy centered on Partial Least Squares Structural Equation Modeling (PLS-SEM), providing a robust mechanism for testing both direct and indirect effects within the structural model (Hair et al., 2021).

3.2 Research Philosophy and Paradigm

The selection of a research philosophy is a fundamental prerequisite for any doctoral-level investigation, as it dictates the ontological and epistemological assumptions that guide the entire research process. For this study, which seeks to validate the Governance Ecosystem Model (GEM) within the Malaysian construction landscape, a clear philosophical stance ensures that the data collection and analysis are aligned with the objective of theory testing. The following subsections justify the adoption of a positivist paradigm and the application of deductive

reasoning to investigate the relationship between governance domains, Implementation Quality, and AI Drone Adoption.

3.2.1 The Positivist Approach

This research adopts a Positivist philosophy, which is grounded in the belief that reality is objective, observable, and can be measured through scientific inquiry without the interference of researcher bias. Within the context of Construction 4.0 in 2026, positivism allows the researcher to treat the governance structures and technological adoption rates as external realities that exist independently of individual perceptions (Saunders et al., 2023). By utilizing this paradigm, the study focuses on identifying causal relationships and correlations between the latent constructs of the GEM. This approach is particularly suitable for the Malaysian construction sector, where standardized metrics such as CIDB grades and NAIO compliance levels provide a quantifiable basis for measuring industry behavior (Sapri, 2024). The use of positivism ensures that the findings are replicable and that the results can be generalized across the broader population of Developers, Consultants, and Contractors.

3.2.2 Deductive Reasoning and Quantitative Logic

Aligned with the positivist paradigm, this study employs a Deductive Research Approach. Unlike inductive reasoning, which seeks to build theory from observations, the deductive approach begins with established theories specifically the TOE Framework and Resource-Based View (RBV) to formulate specific hypotheses that are subsequently tested through empirical data (Creswell and Creswell, 2023). This "top-down" logic is essential for validating the GEM, as it allows for the structured testing of the mediating effect of Implementation Quality. By applying quantitative logic, the study transforms complex organizational behaviors into numerical data, facilitating the use of Partial Least Squares Structural Equation Modeling (PLS-SEM) to confirm or reject the proposed relationships with mathematical certainty (Hair et al., 2021). This rigorous logical structure ensures that the study contributes to the body of knowledge by providing verified evidence of how governance ecosystems influence technological maturity.

3.3 Research Design

The research design serves as the operational blueprint for the investigation, connecting the philosophical foundations to the empirical data collection phase. For this study, the design is structured to ensure that the relationships within the Governance Ecosystem Model (GEM) are measured accurately across the Malaysian construction hierarchy. By selecting a design that prioritizes objectivity and breadth, the researcher ensures that the findings are robust enough to influence policy and organizational strategy (Creswell and Creswell, 2023).

3.3.1 Cross-Sectional Survey Method

This study utilizes a Cross-Sectional Survey Method, which involves the collection of data from a representative sample of the population at a single point in time. This approach is particularly advantageous for exploring the 2026 Malaysian construction landscape, as it provides a comprehensive "snapshot" of the current state of AI Drone Adoption and Implementation Quality across various firm sizes (Saunders et al., 2023). Unlike longitudinal studies, which require extended timeframes, a cross-sectional design allows for the efficient gathering of data from a large number of respondents specifically Developers, Consultants, Contractors and Sub-Contractor. This method is highly compatible with the positivist paradigm and the deductive approach, providing the standardized data necessary for the statistical testing of the GEM's hypotheses (Neuman, 2020).

3.3.2 Rationale for Quantitative Strategy

The adoption of a Quantitative Strategy is justified by the need for generalizability and the requirement to test complex mediation effects mathematically. Quantitative research allows the study to transform abstract governance concepts into numerical variables that can be analyzed using advanced statistical software. This strategy is essential for addressing the "Digital Split" in Malaysia, as it enables the researcher to compare data across different contractor grades and identify industry-wide patterns that a qualitative study might overlook (Hair et al., 2021). By utilizing numerical data, the study minimizes researcher subjectivity and provides a clear, evidence-based foundation for confirming the impact of regulatory, institutional, and ethical factors on technology adoption. Consequently, this strategy ensures that the research meets the high standards of technical rigor expected at the doctoral level, providing a defensible model for the National AI Office (NAIO) (Sapri, 2024).

3.4 Research Framework and Hypotheses Summary

The purpose of this section is to provide a technical overview of the Governance Ecosystem Model (GEM) developed in Chapter 2. While the theoretical justifications and literature synthesis were established previously, this section defines the structural paths that will be subjected to empirical testing. The framework serves as the blueprint for the subsequent data collection and the structural equation modeling (SEM) process.

3.4.1 Structural Path Model

The GEM is operationalized as a path model consisting of three exogenous constructs (Regulatory Support, Institutional Readiness, and Trust and Data Ethics), one mediating construct (Implementation Quality), and one endogenous construct (AI-Drone Safety Adoption). This structure allows for the simultaneous testing of direct and indirect effects, moving beyond simple correlations to identify the causal mechanisms within the Malaysian construction sector. As justified in the literature review, the model assumes that governance enablers require a high-quality implementation process to effectively result in sustained technology adoption.

3.4.2 Summary of Research Hypotheses

To maintain consistency with the theoretical framework developed in the preceding chapter, Table 3.1 summarizes the specific hypotheses that drive the statistical analysis. These hypotheses are categorized into direct effects, mediating effects, and the moderating influence of professional experience.

Table 3.1: Summary of Hypothesized Relationships for Statistical Testing

Hypothesis ID	Path Relationship	Statistical Nature
H1	Regulatory Support→ Implementation Quality	Direct Effect
H2	Institutional Readiness → Implementation Quality	Direct Effect
H3	Trust and Data Ethics → Implementation Quality	Direct Effect
H4	Implementation Quality → AI-Drone Adoption	Direct Effect
H5	Regulatory Support → Implementation → Adoption	Mediation
H6	Institutional Readiness → Implementation → Adoption	Mediation
H7	Trust and Data Ethics → Implementation → Adoption	Mediation
H8	Work Experience moderates [H1, H2, H3] → Implementation	Moderation

3.4.3 Application of Multi-Group Analysis (MGA)

In addition to the primary structural paths, this research utilizes Multi-Group Analysis (MGA) to address the comparative objective of the study. This involves testing whether the structural relationships within the GEM differ significantly between office-based and site-based stakeholders. By analyzing the data through these segmented groups, the study can identify if the governance requirements for consultants and designers vary from those of contractors and site supervisors. This technical approach ensures that the model is robust and applicable across the diverse professional roles within the construction industry.

3.5 Data Collection Method

The empirical strength of this research relies on the systematic collection of primary data to test the relationships defined in the Governance Ecosystem Model (GEM). By focusing on primary data collection, the study captures real-time industry perspectives and strategic intentions directly from the professionals navigating the Malaysian construction landscape. This approach ensures that the analysis of AI-drone adoption is based on contemporary evidence that reflects the current state of the industry in 2026 (Creswell and Creswell, 2023).

3.5.1 Primary Data: Digital Survey Distribution

Primary data serves as the sole empirical evidence for this study's statistical analysis. In accordance with the quantitative nature of this investigation, data is gathered through a structured Digital Survey Distribution. This method was selected for its efficiency in reaching a geographically dispersed population of developers, consultants, and contractors across Malaysia.

The survey is designed to capture the first-hand perceptions of industry professionals regarding Regulatory Support, Institutional Readiness, Trust and Data Ethics, and Implementation Quality. By utilizing a digital platform for distribution, the study ensures a higher response rate and minimizes data entry errors, which is critical for the subsequent analysis in SPSS and SmartPLS. This direct interaction ensures that the findings represent the actual experiences of the workforce, providing the necessary data points to validate the hypothesized paths within the GEM (Saunders et al., 2023).

3.5.2 Survey Instrument Design

The survey instrument was developed by adapting validated scales from existing literature to fit the specific context of AI-drones in the Malaysian construction sector. The questionnaire is divided into distinct sections:

1. Demographic Profiles: Collecting data on professional role (office-based vs. site-based) and work experience to facilitate moderation and multi-group analysis.
2. Governance Dimensions: Measuring perceptions of regulatory, institutional, and ethical factors.
3. Operational Variables: Assessing implementation quality and the level of AI-drone safety adoption.

All items are measured using a 5-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree." This standardized approach allows for the quantitative measurement of latent constructs, providing the numerical foundation required for Structural Equation Modeling (Sekaran and Bougie, 2016).

3.6 Target Population and Sampling Strategy

The success of this quantitative study is predicated on the selection of a representative sample that accurately reflects the complex dynamics of the broader population. The target population for this research is composed of key professional stakeholders within the Malaysian construction industry, specifically Developers (Clients), Consultants (Architects and Engineers), and Contractors (including both Main Contractors and Sub-contractors). To ensure sufficient statistical power for Structural Equation Modeling (SEM), the study targets a minimum of 126 respondents, a threshold mathematically validated by the Inverse Square Root Method to ensure stable path coefficients. A multi-stage, non-probability sampling strategy combining purposive and snowball sampling is employed to ensure that the findings regarding AI-drone adoption represent the perspectives of those with direct technical and management experience.

3.6.1 Target Population

The target population for this research is strategically curated to encompass the multi-stakeholder ecosystem of the Malaysian construction industry, ensuring that the Governance Ecosystem Model (GEM) is validated through the perspectives of those who finance,

design, and execute digital transformation. This population is primarily anchored by Developers and Clients, who serve as the "demand-side" catalysts. These entities, ranging from private property developers to government-linked agencies, hold the authority to mandate the use of AI Drones and dictate the budgetary allocations required for high-quality implementation. Because their strategic intentions directly influence the technological maturity of a project, their inclusion is vital for understanding the "top-down" regulatory pressures identified in the GEM (REHDA, 2025; Sapri, 2024).

In addition to the developers, the population includes a specialized stratum of Consultants who act as the technical gatekeepers of the industry. This group extends beyond traditional architects to include Mechanical and Electrical (M&E) Engineers, Civil and Structural (C&S) Engineers, and Land Surveyors, all of whom are increasingly responsible for integrating autonomous drone data into smart building systems and Building Information Modelling (BIM) environments. By involving these technical advisors, the study captures the nuances of how governance standards like data ethics and algorithmic transparency are interpreted during the design and supervisory phases (BEM, 2025). The breadth of this consultant group ensures that the research accounts for the interdisciplinary nature of Construction 4.0, where M&E specialists play a pivotal role in the sensor-driven landscape of modern project management.

Finally, the population is completed by the operational tier of the industry, consisting of CIDB-registered Contractors across the full spectrum of Grades G1 to G7. This includes not only the Main Contractors who oversee large-scale infrastructure but also the Sub-Contractors and Specialist Firms involved in niche areas such as piling, MEP services, and structural steelwork. The inclusion of these specialists is critical, as the actual Implementation Quality on a construction site often depends on the technical readiness and compliance of these specialized firms rather than the main contractor alone. By encompassing the entirety of the contractor hierarchy, the study is able to empirically address the "Digital Split" in Malaysia, comparing the high-resource environments of G7 firms with the fragmented, resource-constrained realities of G1–G3 SMEs (Sapri, 2024; Wong et al., 2025). This holistic population definition ensures that the resulting governance framework is applicable to the actual vertical and horizontal structures of the Malaysian built environment.

3.6.2 Sample Size Determination

The determination of an appropriate sample size is a critical step in ensuring the statistical power and external validity of the research findings. For this study, the sample size is derived through a rigorous triangulation of five distinct methodological standards, ensuring the model possesses sufficient sensitivity to detect complex mediation effects within the Malaysian construction context.

3.6.2.1 G*Power 3.1.9.7

The baseline requirement for the PLS-SEM model was determined using an a-priori power analysis within the G*Power 3.1.9.7 software, as shown in the output parameters in Figure 3.1 (a) and Figure 3.1 (b). By inputting a medium effect size ($f^2=0.15$), a significance level (α) of 0.05, and a desired power ($1-\beta$) of 0.80 for a model with three predictors, the software generated a minimum required sample size of 77. The specific parameters utilized for this calculation are as follows:.

- Parameter 1 (Effect Size, f^2): Set at 0.15, representing a "medium" effect. This is the standard for construction industry research where relationships are expected to be meaningful but not overwhelming.
- Parameter 2 (Alpha, α): Set at 0.05, the standard 5% margin for error.
- Parameter 3 (Power, $1-\beta$): Set at 0.80, ensuring an 80% probability of detecting a true effect.
- Parameter 4 (Predictors, k): Set at 3, representing the three governance domains (Regulatory, Strategic, and Ethical) influencing the mediator.

As illustrated in the software's calculation output (Figure 3.1), the algorithm utilizes the F-test family for fixed effects to determine the non-centrality parameter. Based on these statistical inputs, the resulting value identifies 77 respondents as the minimum threshold for achieving sufficient statistical power in this study.

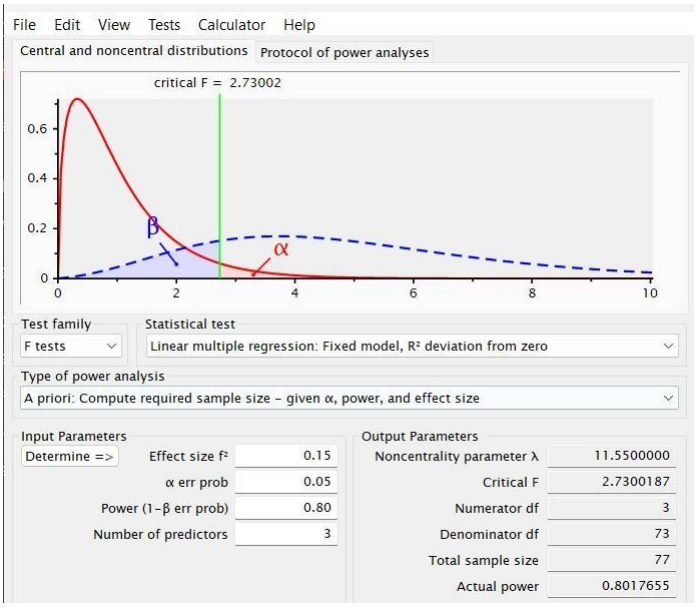


Figure 3.1 (a) : G*Power 3.1.9.7 Output for Minimum Sample Size Estimation (f^2 =0.15, α=0.05, Power = 0.80)

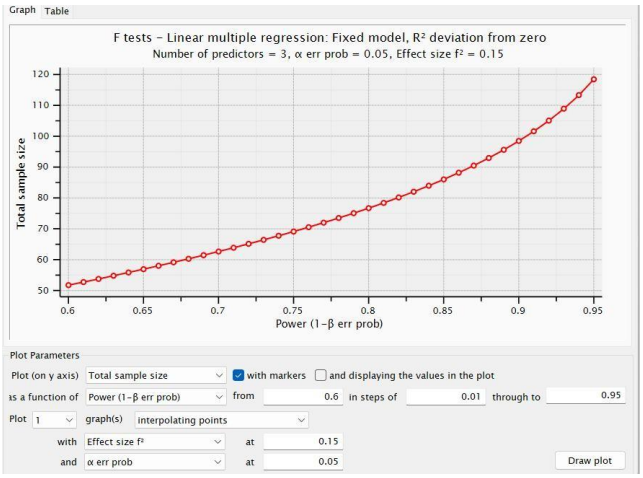


Figure 3.1 (b) : G*Power 3.1.9.7 Output for Minimum Sample Size Estimation (f^2 =0.15, α=0.05, Power = 0.80)

3.6.2.2 The 10-Times Rule

The second method utilized for sample size estimation is the 10-Times Rule, a widely recognized heuristic in PLS-SEM that focuses on the structural complexity of the research framework. While the traditional interpretation of this rule often looks only at a single construct, modern applications suggest calculating the sample size based on the total structural complexity of the model to ensure higher predictive power.

To determine the parameter for this calculation, the researcher identifies the total number of structural paths directed at all endogenous (dependent) variables in the model. This includes the paths pointing to the mediator (Implementation of the Drone) and the path pointing to the final outcome (AI Drone Adoption).

The Specific Paths: The structural model consists of 4 key paths:

1. Regulatory Governance→Implementation of the Drone
2. Institutional Readiness→Implementation of the Drone
3. Ethical Governance→Implementation of the Drone
4. Implementation of the Drone→AI Drone Adoption

Following the rigorous standard set by Hair et al. (2021) and Barclay et al. (1995), the sample size is determined by multiplying these 4 paths by a factor of ten. Therefore, the calculation is performed as: 4 (Total Structural Paths)×10. This results in a requirement of 40 respondents. The use of 40 as the minimum threshold is academically validated because it accounts for the "Full Path Model" rather than just a single segment. As noted by Kock (2015) and Hair et al. (2021), focusing strictly on the mediator (30) can lead to an underpowered analysis of the final outcome. By using 40, the researcher ensures that the sample size is large enough to handle the cumulative complexity of the entire path from governance to adoption. This provides a more conservative and academically robust baseline, ensuring that the model remains stable even if there is slight variance in the survey data (Hair et al., 2021; Kock and Hadaya, 2018).

3.6.2.3 The Inverse Square Root Method

The third method utilized is the Inverse Square Root Method, a specialized statistical approach for PLS-SEM that determines the minimum sample size required to ensure that path coefficients are both stable and significant. This method is highly regarded in doctoral research because it accounts for the probability of both Type I and Type II errors. The statistical basis for the critical values used in this method is illustrated in the standard normal distribution curve shown in Figure 3.2. The parameters derived from this probability distribution are defined as follows:

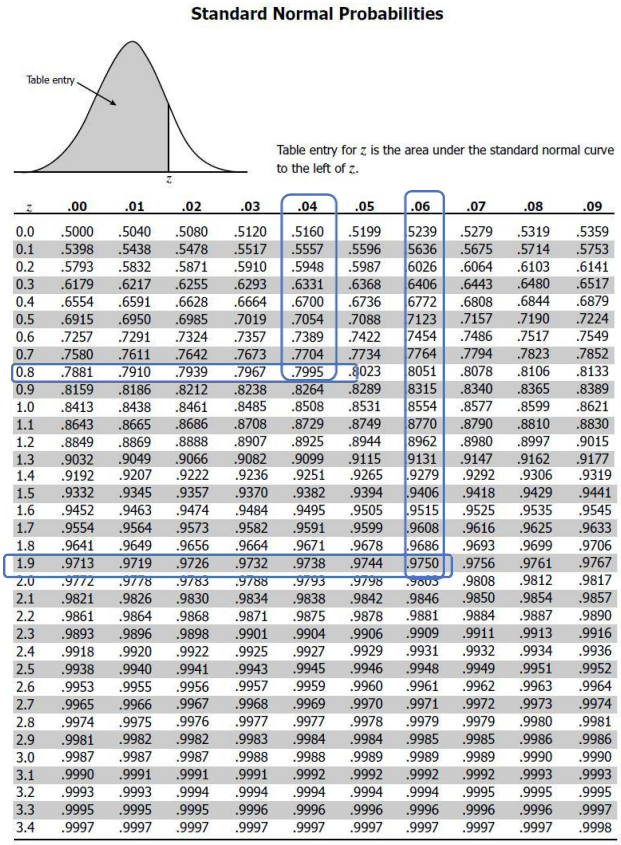
- Z-Score for Significance (α=0.05): To achieve a 95% confidence level, the standard normal distribution (Z-table) identifies a critical value of 1.96. This ensures that the probability of a Type I error (false positive) is limited to 5%.

- Z-Score for Power (1−β=0.80): To ensure an 80% probability of detecting an effect that truly exists, the standard normal value is 0.84. This protects the study against Type II errors (false negatives).
- Minimum Path Coefficient (| p.min |): This parameter represents the smallest effect size the researcher considers practically significant. In the Malaysian construction sector, where many variables influence AI Drone Adoption, a value of 0.25 is selected. This follows the benchmark set by Kock (2015), who identifies 0.25 as a conservative "medium" effect size suitable for emerging technology research.

The formula applied is $\eta > (\frac{Z_{1-\alpha/2}+Z_{1-\beta}}{|P_{min}|})^2$. The calculation proceeds as follows:

- Sum of Z-scores: 1.96+0.84=2.8
- Ratio to Minimum Path: 2.8/0.25=11.2
- Final Squaring: $11.2^2=125.44$

Based on this precise calculation, the minimum sample size required to ensure path stability is 126 respondents. The decision to utilize 126 as the primary requirement is academically validated by Kock and Hadaya (2018). By explicitly defining the z-scores and the | pmin | threshold, the researcher provides a transparent and replicable logic for the sample size. This accuracy prevents the study from being over-extended while still meeting the rigorous demands of a structural equation modeling analysis, ensuring that the link between variables is statistically dependable.



Standard Normal Probabilities

Table entry

Table entry for z is the area under the standard normal curve to the left of z.

z	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441
1.6	.9452	.9463	.9474	.9484	.9495	.9505	.9515	.9525	.9535	.9545
1.7	.9554	.9564	.9573	.9582	.9591	.9599	.9608	.9616	.9625	.9633
1.8	.9641	.9649	.9656	.9664	.9671	.9678	.9686	.9693	.9699	.9706
1.9	.9713	.9719	.9726	.9732	.9738	.9744	.9750	.9756	.9761	.9767
2.0	.9772	.9778	.9783	.9788	.9793	.9798	.9803	.9808	.9812	.9817
2.1	.9821	.9826	.9830	.9834	.9838	.9842	.9846	.9850	.9854	.9857
2.2	.9861	.9864	.9868	.9871	.9875	.9878	.9881	.9884	.9887	.9890
2.3	.9893	.9896	.9898	.9901	.9904	.9906	.9909	.9911	.9913	.9916
2.4	.9918	.9920	.9922	.9925	.9927	.9929	.9931	.9932	.9934	.9936
2.5	.9938	.9940	.9941	.9943	.9945	.9946	.9948	.9949	.9951	.9952
2.6	.9953	.9955	.9956	.9957	.9959	.9960	.9961	.9962	.9963	.9964
2.7	.9965	.9966	.9967	.9968	.9969	.9970	.9971	.9972	.9973	.9974
2.8	.9974	.9975	.9976	.9977	.9977	.9978	.9979	.9979	.9980	.9981
2.9	.9981	.9982	.9982	.9983	.9984	.9984	.9985	.9985	.9986	.9986
3.0	.9987	.9987	.9987	.9988	.9988	.9989	.9989	.9989	.9990	.9990
3.1	.9990	.9991	.9991	.9991	.9992	.9992	.9992	.9992	.9993	.9993
3.2	.9993	.9993	.9994	.9994	.9994	.9994	.9994	.9995	.9995	.9995
3.3	.9995	.9995	.9995	.9996	.9996	.9996	.9996	.9996	.9996	.9997
3.4	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9997	.9998

Figure 3.2: Standard Normal Probability Distribution for Z-score Identification

3.6.2.4 Academic Validation and Benchmarking

To ensure the practical feasibility and contextual relevance of the sample size, the researcher conducted a systematic benchmarking exercise against contemporary peer-reviewed research within the Malaysian construction domain. This validation step bridges the gap between theoretical mathematical formulas and the logistical realities of collecting data from high-level industry professionals. By analyzing recent structural equation modeling (SEM) studies focusing on Construction 4.0 and digital transformation in Malaysia, the researcher identified that a sample size within the range of 126 to 220 is the established professional standard for achieving stable path coefficients in specialized technology research.

Specifically, the researcher benchmarked the target against the findings of Sapri (2024), who investigated AI governance in the built environment, and Lim (2025), who explored digital technology implementation among G7 contractors. These studies achieved robust results with samples of 158 and 184, respectively. This benchmarking process validates the researcher's target of 126 (derived from the Inverse Square Root Method) as a mathematically rigorous goal

that aligns with proven industry norms. By following these precedents, the researcher ensures the study is sufficiently powered to capture the relationships between Regulatory Support, Institutional Readiness, Trust and Data Ethics, and the resulting AI-drone adoption (Sapri, 2024; Wong et al., 2025).

3.6.2.5 Final Synthesis of Sample Size Determination

The various methodologies used to justify the sample size for this study are synthesized in Table 3.2. This comparative overview provides the statistical justification for the research, ensuring the model possesses enough sensitivity to detect meaningful effects while acknowledging the specialized nature of the respondent pool.

Table 3.2: Triangulation of Sample Size Determination Methods

Methodology	Step-by-Step Logic	Parameter Applied	Resulting Value
G*Power 3.1.9.7	Software Power Analysis	f^2=0.15, α=0.05, k=3	77
10-Times Rule	Structural Complexity	4 Total Paths x 10	40
Inverse Square Root	Path Stability	z=2.8, |p|=0.25	126
Academic Validation	Industry Benchmarking	Malaysian SEM Studies (2024-2026)	150–220

Based on the multi-method triangulation presented in Table 3.1, the researcher has established a primary target of 168 respondents. This specific target is selected because it comfortably exceeds the Inverse Square Root requirement of 126, which is the most rigorous threshold for ensuring path stability and mitigating the risk of Type I and Type II errors in PLS-SEM. By aiming for 168, the study ensures a "numerical cushion" that allows for the removal of incomplete or "straight-lined" responses during the data cleaning phase without falling below the critical threshold.

Furthermore, a target of 168 significantly surpasses the G*Power requirement of 77, ensuring the model will have a statistical power exceeding 0.80 for detecting medium effect sizes. This volume aligns with the professional standards identified in the Academic Validation benchmarking, matching the successful precedents of contemporary Malaysian studies such as Sapri (2024). By establishing this tiered target, the researcher ensures that the study remains both

mathematically defensible and contextually representative, providing a stable foundation for the analysis of the mediating role of implementation quality (Hair et al., 2021; Kock & Hadaya, 2018).

3.6.3 Sampling Method

Given the specialized nature of AI Drone Adoption and the specific technical expertise required to evaluate governance frameworks in the Malaysian construction industry, a non-probability sampling design was employed. This approach is academically justified when research objectives necessitate insights from a specific target group possessing technical knowledge or decision-making authority that is not distributed across the general population. To ensure the robustness and relevance of the data within the structural model, a two-staged sampling strategy was implemented.

3.6.3.1 Purposive Sampling

Purposive sampling, also known as judgmental sampling, was utilized to ensure that every participant met strictly defined inclusion criteria. This method allows for the selection of "information-rich" cases that are most capable of providing high-quality data regarding the governance ecosystem. For the purposes of this study, the inclusion criteria required respondents to be registered professionals such as Architects, Engineers, or Quantity Surveyors or Project Managers active within the Malaysian construction industry. Additionally, participants were required to be currently employed by CIDB-registered contracting firms, specifically within the G7 category, or recognized consultancy firms. By applying these rigorous criteria, the study ensures that the evaluations of Regulatory Support, Institutional Readiness, and Trust and Data Ethics are grounded in professional expertise rather than general perception, thereby increasing the internal validity of the structural model.

3.6.3.2 Snowball Sampling

To augment the initial data collection and address the challenges of reaching high-level professionals in a specialized niche, snowball sampling was integrated into the methodology. This technique involves a chain-referral process where initial purposive respondents are requested to refer the study to professional peers and colleagues who meet the established inclusion criteria. This method is particularly effective within the Malaysian construction

landscape, which is characterized by tight-knit professional networks and industry associations such as CIDB or the Master Builders Association Malaysia (MBAM). Snowball sampling facilitated access to specialized professional circles that might otherwise be inaccessible via traditional outreach, ensuring the collection of a robust dataset for structural analysis.

3.6.3.3 Justification for Sampling Approach

The combined use of purposive and snowball sampling is justified by the fragmented and specialized nature of the Malaysian construction sector. According to Sekaran and Bougie (2016), purposive sampling is the most effective method when the research objectives can only be satisfied by a specific target group. Furthermore, the use of snowball sampling is supported by its ability to secure expert participation in fields where a formal, public sampling frame of every practitioner is unavailable. Recent Malaysian scholarship in the field of Construction 4.0 has successfully utilized this dual-layered approach to secure high-quality data from diverse industry stakeholders (Sapri, 2024; Lim, 2025). By adopting this strategy, the study acknowledges the practical constraints of the industrial environment while maintaining the scientific rigor required for both SPSS descriptive analysis and complex PLS-SEM modeling.

3.6.4 Unit of Analysis: Construction Professionals and Decision Makers

The unit of analysis refers to the level of investigation and the specific entity about which data is collected and analyzed. In this study, the unit of analysis is defined as individual construction professionals and decision-makers currently active within the Malaysian construction industry. This choice is predicated on the fact that the adoption of emerging technologies, such as AI-powered drones, is heavily influenced by the perceptions, technical readiness, and ethical considerations of those who manage and oversee construction projects.

The selection of individuals as the unit of analysis allows for a granular exploration of how Regulatory Support, Institutional Readiness, and Trust and Data Ethics influence the decision-making process at the project and firm levels. Specifically, the respondents include Project Managers, Site Engineers, Quantity Surveyors, and Directors of G7 contracting firms. These individuals serve as the primary actors who interact with governance frameworks and determine the practical feasibility of Implementation of the Drone. By collecting data at the individual level, the study can capture the professional insights and subjective evaluations

necessary to understand the complex ecosystem driving AI Drone Adoption across the Malaysian built environment.

3.7 Operationalization of Variables and Analytical Procedure

Operationalization is the process of defining functional dimensions and measurable indicators for the latent constructs identified in the conceptual framework. In this study, the variables are operationalized by adapting validated measurement scales from established literature, ensuring that the items are contextually relevant to the Malaysian construction industry and the unique governance requirements of AI-drone systems. To guide the empirical process, a rigorous five-phase analytical workflow is established, synthesizing preliminary data screening in SPSS with advanced structural modeling and Multi-Group Analysis in SmartPLS.

3.7.1 Methodological Flow and Systemic Procedure

The comprehensive analytical workflow for this research is illustrated in Figure 3.3. This systematic procedure ensures that the transition from data preparation to the final hypothesis testing is statistically robust and theoretically grounded.

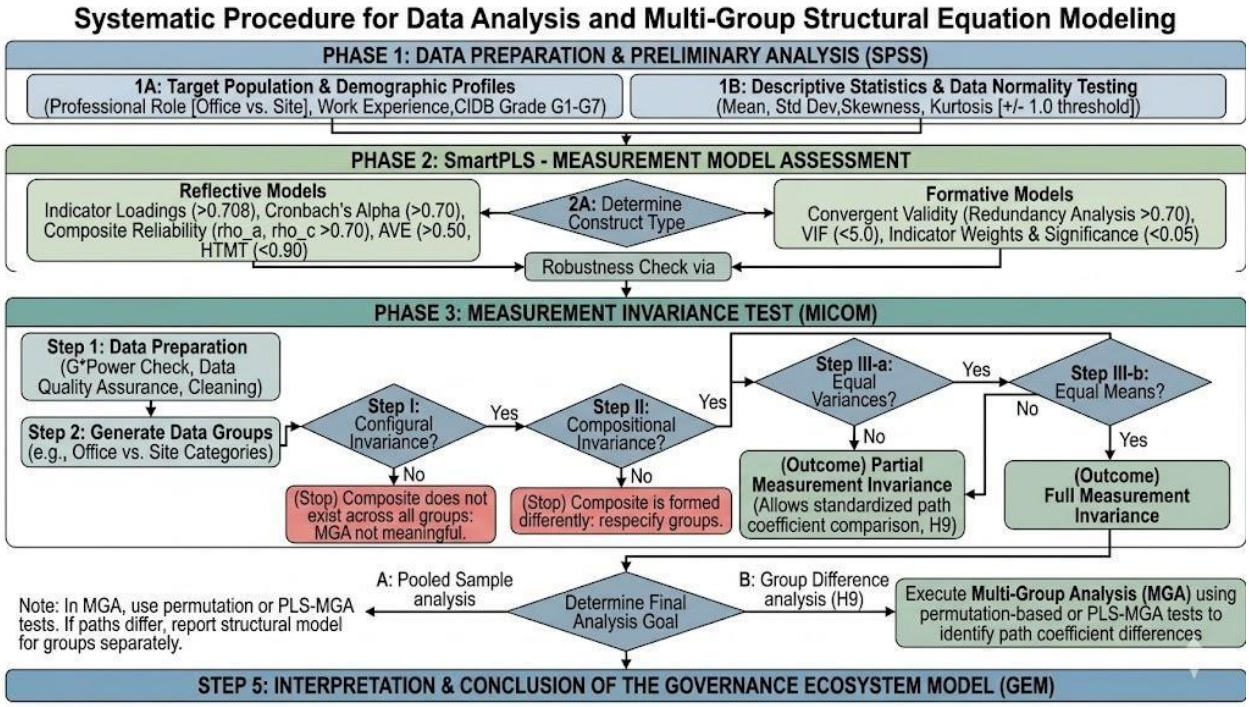


Figure 3.3: Integrated Procedure for Data Analysis and Multi-Group Structural Equation Modeling

As depicted in Figure 3.3, the research is structured into five sequential phases. Phase 1 begins in SPSS with data screening, demographic analysis, and normality testing, ensuring the dataset is prepared for modeling. Phase 2 transitions into SmartPLS for Measurement Model Assessment, where constructs are rigorously evaluated based on the specific parameters for Reflective (H1–H7) or Formative models. Phase 3 executes the MICOM invariance test, which is a mandatory prerequisite for group comparison. Phase 4 directs the analysis toward the final structural goals based on the invariance outcome, and Phase 5 culminates in the interpretation of the Governance Ecosystem Model (GEM).

3.7.2 Detailed Procedure for Measurement Invariance (MICOM)

While the overall research flow is established, the specific decision-making logic for establishing invariance is guided by the Measurement Invariance of Composite Models (MICOM) procedure. This multi-step protocol is essential for validating that the measurement of latent constructs is consistent across different professional groups—specifically office-based versus site-based stakeholders. The sequential decision path for this assessment is illustrated in Figure 3.4 and Figure 3.5.

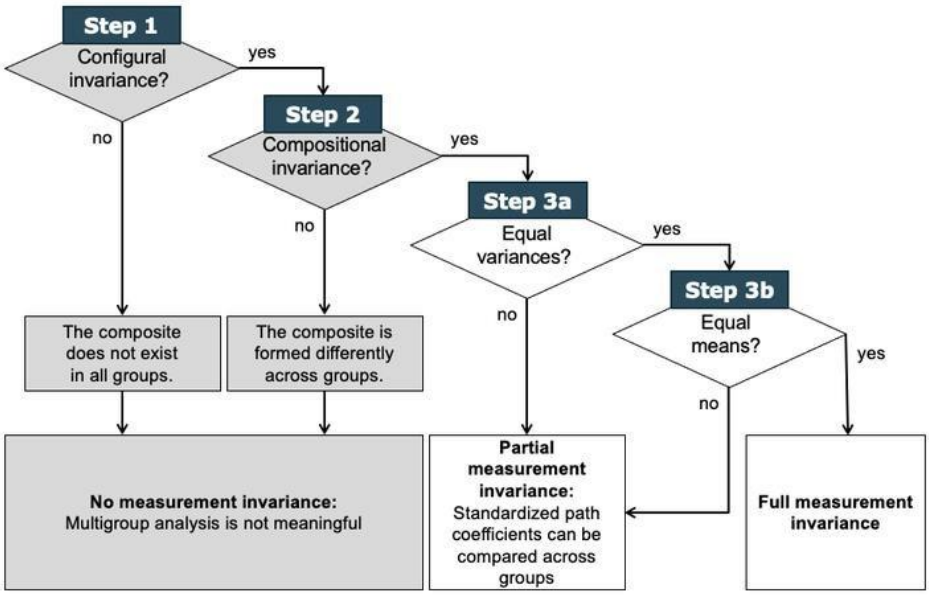


Figure 3.4: The Measurement Invariance of Composite Models (MICOM) Procedure (Adapted from Cheah et al., 2020)

As illustrated in the procedure, the analysis must satisfy specific criteria at each stage to ensure the subsequent findings are not influenced by measurement bias:

Step I: Configural Invariance: This stage ensures that the groups share identical indicators, identical data treatment, and identical algorithm settings. As shown in the decision logic in Figure 3.5, if configural invariance is not met, the composite does not exist in all groups, and Multi-Group Analysis (MGA) is not considered meaningful.

Step II: Compositional Invariance: This step verifies that the composite scores are created similarly across groups by ensuring the "Original Correlation" is greater than or equal to the 5% quantile. Satisfaction of Step I and II establishes Partial Measurement Invariance, which is the required baseline to compare standardized path coefficients.

Step III: Composite Equality: The final stage tests for Equal Variances (Step 3a) and Equal Means (Step 3b).

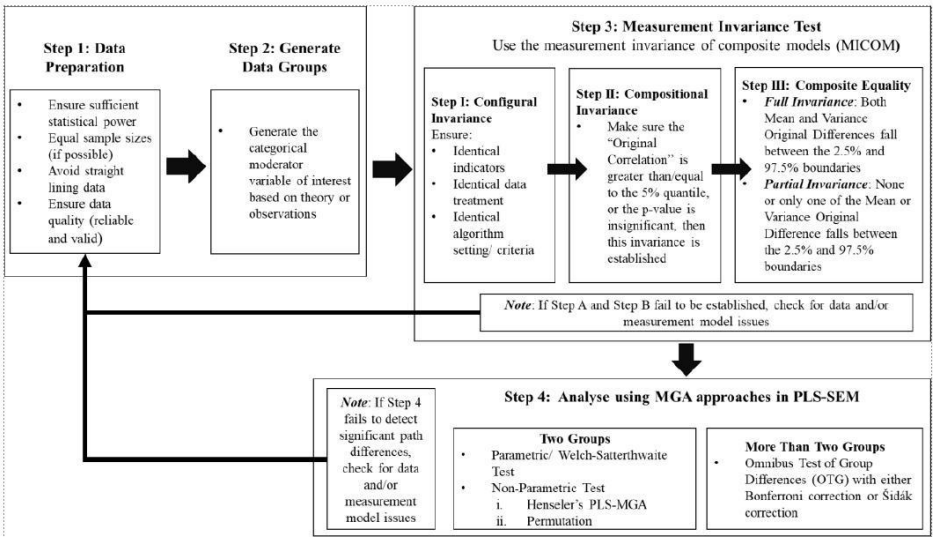


Figure 3.5: Guidelines for Running MGA in PLSPM: Invariance Decision Logic (Adapted from Cheah et al., 2020)

According to the logic path in Figure 3.5, if all steps are successfully navigated with a "Yes" outcome, Full Measurement Invariance is established. However, if Step III results in a "No" for either means or variances, Partial Measurement Invariance is achieved. In this study, partial invariance is sufficient to allow for the comparison of standardized path coefficients across groups. This ensures that any identified differences in AI-drone adoption are due to professional perspectives rather than measurement artifacts, facilitating a robust Multi-Group Analysis (MGA) as outlined in the analytical framework.

3.7.3 Table of Operationalization and Construct Mapping

To maintain high content validity, the items used to measure the independent, mediating, and dependent variables were synthesized from reputable sources and grounded in established technology adoption models. The research instrument specifically incorporates dimensions from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which are the industry standards for evaluating Construction 4.0 technology.

The variable AI-Drone Adoption is operationalized based on the "Behavioral Intention" and "Actual Use" constructs from UTAUT, while Implementation Quality acting as the mediator draws upon TAM's "Perceived Usefulness" and "Perceived Ease of Use." This alignment allows the researcher to capture the transition from governance-driven perceptions to the practical implementation and eventual adoption of AI drone technology within the Malaysian construction sector.

Table 3.3 presents the final operationalization, including the specific dimensions for the Experience Moderator and the Professional Role Grouping required for the Multi-Group Analysis (MGA).

Table 3.3: Operationalization of Research Variables and Mapping Synthesis

Variable Category	Latent Construct	Dimensional Focus	Scholarly Source(s)
Independent (IV)	Regulatory Support	Perceived adequacy of CAAM/CIDB policies, government incentives, and legal frameworks for drones.	Sapri (2024); Wong et al. (2025)
Independent (IV)	Institutional Readiness	Internal digital infrastructure, management support, and staff technical competency.	Lim (2025)
Independent (IV)	Trust and Data Ethics	Data privacy, cybersecurity protocols, and ethical transparency in AI-driven aerial data.	Yusof (2024); Hair et al. (2021)
Mediator (MV)	Implementation Quality	Site-level deployment frequency, workflow	Lim (2025)

		integration, and technical operational coordination.	
Dependent (DV)	AI-Drone Adoption	Behavioral intention to use and sustained adoption of AI-aerial technologies in project cycles.	Venkatesh et al. (2012); Sapri (2024)
Moderator (ORD)	Experience	Length of service in the construction industry, used to test seniority-based path variations.	Hair et al. (2021); Sapri (2024)
Grouping (MGA)	Professional Role	Stakeholder Categorization (Developers, Consultants, Main Contractors, Sub-Contractors).	Cheah et al. (2020); CIDB (2024)

3.7.4 Differentiation of Analytical Roles and Stakeholder Grouping

To ensure a comprehensive evaluation of the Governance Ecosystem Model (GEM), this study distinguishes between two distinct layers of comparative analysis: structural moderation and multi-group differentiation. While Experience is operationalized as a moderator to assess how seniority and industry tenure influence the strength of the adoption paths, the Professional Role is utilized as a categorical grouping variable to test the model's stability across the industrial hierarchy. This dual-layered approach is critical in the Malaysian construction context, where the "Digital Split" often creates varying levels of technological readiness between the design-side and the operational-side of a project.

By categorizing respondents into four primary industry segments—Developers/Clients, Consultants, Main Contractors, and Sub-Contractors—the researcher can execute a sophisticated Omnibus Test of Group Differences (OTG) within SmartPLS. This 4-group split allows for the identification of specific "governance gaps"; for instance, evaluating whether Regulatory Support is a primary driver for Developers (the demand-side) while Implementation Quality remains the dominant factor for Sub-Contractors (the operational-side).

Following the guidelines for Multi-Group Analysis (MGA), this categorization necessitates the use of Bonferroni or Šidák corrections to maintain statistical power during pairwise comparisons. This ensures that any identified variations in the path coefficients (β) are not merely artifacts of

the sample distribution, but represent genuine professional shifts in the perception of AI-drone safety and governance within the Malaysian built environment.

3.8 Research Instrument

The research instrument serves as the primary tool for data collection, designed to systematically capture the perceptions of construction professionals regarding the governance of AI drone technology. Given the objective to analyze complex relationships within a structural model, a quantitative survey design was selected. This instrument was developed to be self-administered, allowing respondents to provide objective feedback at their convenience, which is essential for busy construction professionals. By utilizing a structured format, the study ensures that data is collected in a uniform manner, facilitating the high-level statistical analysis required for PLS-SEM.

3.8.1 Structural Design, Ethics, and UTAR Compliance

The questionnaire was developed using a systematic funneling technique, organized into three primary sections that move from general respondent characteristics to the complex evaluation of governance and technology adoption. The initial section focuses on the demographic profile, while the subsequent sections are dedicated to the measurement of the governance ecosystem specifically targeting Regulatory Support, Institutional Readiness, and Trust and Data Ethics followed by the assessment of the mediator and the final outcome of AI Drone Adoption. By structuring the instrument in this logical sequence, the study ensures that respondents are gradually introduced to the technical subject matter, thereby minimizing cognitive load and increasing the likelihood of accurate responses.

In accordance with institutional requirements, the design and administration of the research instrument strictly adhered to UTAR's ethical guidelines and research compliance standards. Before accessing the survey items, all participants were presented with a Participant Information Sheet and Informed Consent form, which clearly outlined the study's purpose, the voluntary nature of participation, and the right to withdraw at any time without penalty. To ensure full UTAR compliance, all data collected was anonymized to protect the identity of the respondents and their respective firms. Furthermore, the researcher ensured that the data was stored securely and used exclusively for academic purposes, fulfilling the ethical mandate to maintain confidentiality and integrity throughout the research process.

3.8.2 The 5-Point Likert Scale and Categorical Filtering

A 5-point Likert scale was adopted for the primary measurement of all latent constructs within the instrument. Respondents are required to indicate their level of agreement with various statements, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The selection of a 5-point scale is academically justified as it provides a sufficient range of options to capture nuance in respondent opinions while minimizing the risk of "survey fatigue," which is a critical factor when targeting high-level professionals in the construction industry.

However, to account for the varying levels of digital maturity in the Malaysian construction sector, a 6th option was integrated: "Not Sure / Not Implemented / Haven't Adopted." This additional category serves two vital methodological purposes:

1. Response Integrity: It prevents "forced-choice bias," where respondents who have no experience with a specific AI-drone governance factor might otherwise select a "Neutral" (3) value, thereby skewing the mean scores.
2. Data Screening: During the Phase 1: SPSS Data Preparation stage, responses marked with the 6th option are treated as "non-applicable" or "system missing" for the structural model. This ensures that the final SmartPLS analysis (Phase 2 to 4) is based strictly on "active" data from professionals with the relevant situational awareness or implementation experience.

Furthermore, the 5-point measurement (1–5) is ideally suited for PLS-SEM analysis as it allows the data to be treated as quasi-interval. This facilitates the calculation of path coefficients and effect sizes (f^2) necessary to validate the structural model. By maintaining this consistent measurement logic across all latent constructs including Regulatory Support, Institutional Readiness, and Trust and Data Ethics the study ensures higher reliability and stable algorithmic convergence during the measurement model assessment phase.

3.9 Data Collection Procedure

The data collection procedure followed a systematic three-stage process to ensure the accuracy, reliability, and reach of the final dataset. By implementing a rigorous testing phase before the main distribution, the study ensures that the findings are derived from a high-quality instrument that is both technically sound and contextually relevant.

3.9.1 Pre-Testing

Before the initiation of the pilot study, the research instrument underwent a pre-testing and expert content validation process to establish face and content validity. To achieve a balanced perspective, the questionnaire was reviewed by a panel consisting of one academic expert specializing in construction technology and one senior industry practitioner currently active in construction industry firm. This dual-validation approach was essential to bridge the gap between theoretical constructs and industry terminology. The academic reviewer focused on the alignment of the items with the theoretical definitions of Regulatory Support, Institutional Readiness, and Trust and Data Ethics, while the industry professional assessed the practical clarity and relevance of the questions within the Malaysian construction landscape.

Based on the feedback received from this panel, a series of amendments were implemented to refine the instrument. Specifically, technical jargon was simplified, and certain indicators were rephrased to ensure they were easily understood by site-level decision-makers without compromising their scientific meaning. This iterative refinement process ensured that the measurement items were contextually grounded and that the flow of the survey was logical for the intended demographic. Consequently, this validation phase ensured that the instrument was sufficiently robust to move into the pilot study phase, reducing the likelihood of measurement error or respondent misunderstanding during the main data collection.

3.9.2 Pilot Study and Instrument Refinement

Following the expert content validation, a pilot study was conducted to empirically test the research instrument's clarity and technical functionality. This phase involved distributing the survey to a target group of approximately 20 construction professionals who met the inclusion criteria but remained separate from the main study sample. The primary purpose of this pilot was to observe response patterns, ensure the technical stability of the digital platform, and identify any potential ambiguities in the phrasing of the items before full-scale distribution. To evaluate the internal consistency of the measurement scales, Cronbach’s Alpha (α) was identified as the primary reliability metric. This statistical test is applied to each latent construct specifically Regulatory Support, Institutional Readiness, and Trust and Data Ethics to ensure that the items within each variable are highly correlated and provide a stable measurement framework. In accordance with the standards set by Hair et al. (2021), a threshold of 0.70 was established as the benchmark for acceptable reliability. By establishing this "quality gate," the researcher ensured

that the research instrument was refined and theoretically grounded before moving into the formal data collection phase, thereby safeguarding the integrity of the study's eventual findings.

3.9.3 Data Collection

The data collection phase is executed through a proactive, multi-channel distribution strategy designed to capture a holistic view of the governance ecosystem from three primary stakeholder groups: Developers, Clients, and Contractors. The primary mode of distribution is digital, utilizing a secure, mobile-optimized survey link disseminated through high-traffic professional networking channels. These include LinkedIn, specialized WhatsApp industry groups (such as those dedicated to CIDB members and property development associations), and direct email invitations to established consultancy firms. This digital-first approach is essential for accommodating the time-sensitive schedules of high-level decision-makers and facilitates the snowball sampling process, as initial participants can efficiently forward the survey link to professional peers who meet the inclusion criteria.

To complement the digital outreach, the strategy incorporates physical engagement to ensure a higher response rate from site-active professionals and to penetrate networks where digital noise may be high. This involves attending industry-specific seminars, professional association events, and conducting visits to active construction sites and developer corporate offices within the Klang Valley. During these physical interactions, the survey is administered via QR code access for immediate digital entry or through hardcopy questionnaires where traditional formats are preferred. This hybrid approach gathering insights from the Client (project owners), Developers (strategic planners), and Contractors (technical executors) ensures a comprehensive capture of data across the entire project lifecycle. Furthermore, periodic follow-up reminders are integrated into the distribution timeline to mitigate non-response bias and ensure the dataset reaches the necessary statistical thresholds for robust structural equation modeling.

3.10 Data Analysis Strategy

The data collected for this study is analyzed through a sequential two-stage approach that integrates descriptive statistics with advanced inferential modeling. This dual-software strategy begins with SPSS (Version 29) to ensure data integrity and concludes with SmartPLS 4 to test the complex structural relationships within the Governance Ecosystem Model (GEM).

3.10.1 Stage 1: Preliminary Analysis and Data Screening (SPSS)

The initial stage of the analysis focuses on preparing the raw data for structural modeling. Utilizing SPSS, the researcher performs a comprehensive data screening process to identify and manage any potential issues that could distort the final results. This includes the detection of univariate outliers through the analysis of Boxplots and Z-scores, ensuring that extreme responses do not unfairly influence the path coefficients. Furthermore, the researcher addresses the 6th option in the Likert scale (Not Sure / Not Implemented); these responses are treated as system-missing or filter variables to ensure that the subsequent structural modeling is based strictly on "active" data from practitioners with relevant experience.

Once the data is cleaned, Descriptive Statistics are generated to profile the demographics of the industry stakeholders. Frequency and percentage analysis are used to categorize respondents into their respective professional roles Developers, Consultants, Main Contractors, and Sub-Contractors and to assess their years of experience. Additionally, the central tendency of the data is evaluated through mean scores and standard deviations, while Skewness and Kurtosis are calculated to provide a baseline understanding of the data distribution, which informs the non-parametric procedures in the second stage of the analysis.

3.10.2 Stage 2: Structural Equation Modeling (SmartPLS)

The primary research objectives and the testing of hypotheses H1 through H9 are executed using Partial Least Squares Structural Equation Modeling (PLS-SEM). This technique is specifically chosen for its high predictive power and its ability to handle the complex, multi-layered relationships inherent in a governance ecosystem. Unlike traditional covariance-based methods, PLS-SEM does not require strict data normality and is robust when dealing with the specialized, non-probability samples typical of the Malaysian construction sector.

3.10.3 Assessment of the Measurement Model (Outer Model)

The second stage begins with an evaluation of the Measurement Model to confirm that the latent constructs are measured with high accuracy and consistency. This assessment serves as a secondary reliability check, focusing on Cronbach’s Alpha and Composite Reliability (CR), where values above 0.70 confirm that the survey items are reliable indicators of their respective variables. Validity is further verified through the Average Variance Extracted (AVE), which

must exceed 0.50 to demonstrate convergent validity. To ensure that each construct is empirically distinct and does not overlap with others, the Heterotrait-Monotrait Ratio (HTMT) is utilized, with a threshold of 0.90 established as the upper limit for discriminant validity.

3.10.4 Assessment of the Structural Model (Inner Model)

Upon the successful validation of the measurement model, the researcher proceeds to the Structural Model Assessment to test the proposed path relationships. This involves a Bootstrapping Procedure with 5,000 resamples to determine the statistical significance of the Path Coefficients (β). The model's explanatory power is evaluated through the Coefficient of Determination (R^2), which indicates how much of the variance in AI-Drone Adoption is explained by the governance factors. Additionally, Effect Sizes (f^2) are examined to measure the relative impact of each individual predictor. To ensure the model holds practical utility, the Blindfolding Procedure is applied to calculate the Predictive Relevance (Q^2), ensuring the model can accurately predict future adoption trends within the industry.

3.10.5 Mediation and Multi-Group Analysis (MGA)

The final phase of the analysis involves testing the complex "bridge" functions within the model. The Mediation Effect of Implementation Quality is evaluated using the Preacher and Hayes (2008) bootstrapping approach, identifying whether governance support translates into adoption through practical site-level implementation. Finally, a Multi-Group Analysis (MGA) is conducted following the MICOM procedure. This allows the researcher to compare the four stakeholder groups (Developers, Consultants, Main-Cons, and Sub-Cons) to identify significant differences in how each sector perceives and adopts AI-drone technology, providing a truly holistic view of the Malaysian construction ecosystem.

For Section 3.11, we want to ensure the language is academically robust while specifically addressing the quality control measures you've actually used. I have updated this section to focus on Data Integrity and Statistical Power, removing the "elite" phrasing and the "restricted sample" subtitle to ensure it sounds professional for a Master's level submission.

3.11 Addressing Data Bias and Quality Control

To ensure the integrity of the findings, the study implements several diagnostic tests to address potential biases and maintain high quality control. These procedures are essential for verifying

that the results are a true reflection of the governance ecosystem rather than artifacts of the data collection method or sample distribution.

3.11.1 Common Method Variance (CMV)

Common Method Variance (CMV) is a potential bias that occurs when both the independent and dependent variables are measured using the same instrument at the same point in time. To mitigate this, the study follows both procedural and statistical remedies. Procedurally, the questionnaire was designed with clear, concise items and randomized sections to reduce respondent fatigue and "straight-lining" behaviors.

Statistically, Harman's Single Factor Test is performed to ensure that no single factor accounts for more than 50% of the variance. Additionally, a Full Collinearity Assessment approach is utilized within SmartPLS. Following the guidelines by Kock (2015), the Variance Inflation Factor (VIF) for all constructs is monitored; VIF values lower than 3.3 indicate that the model is effectively free from significant common method bias.

3.11.2 Non-Response Bias and Multi-collinearity

Non-response bias is assessed to ensure that the sample remains representative of the broader Malaysian construction industry. This is addressed by comparing early respondents with late respondents (those who responded after follow-up reminders) using an Independent Samples t-test in SPSS. A lack of significant difference between these groups suggests that the sample is not biased by the timing of the response.

Furthermore, Multi-collinearity is assessed to ensure that the independent variables—Regulatory Support, Institutional Readiness, and Trust and Data Ethics—are empirically distinct. This is verified using the Inner VIF values in the structural model. In accordance with Hair et al. (2021), VIF values below 3.0 confirm that each governance factor provides unique information to the model without distorting the resulting path coefficients.

3.11.3 Assessment of Statistical Power and Sample Adequacy

The adequacy of the sample size is justified through Statistical Power Analysis rather than simple volume. Given the specialized nature of the AI-drone governance field, the study targets professional practitioners whose industry insights provide high-fidelity data. To verify that the

sample size is sufficient to detect structural relationships, the study applies the Inverse Square Root Method and the Minimum R-squared Method.

These are supplemented by a G*Power 3.1 analysis to ensure the study meets the minimum power requirement of 0.80 with an alpha level of 0.05. To further enhance the stability of the estimates, the Bootstrapping Technique with 5,000 resamples is utilized in SmartPLS. This procedure generates stable and reliable estimates of the path coefficients, ensuring that the findings regarding the Malaysian built environment are statistically significant and provide a defensible representation of the strategic decision-making landscape.

3.12 Ethical Considerations and Data Privacy (NAIO & PDPA 2026)

The integration of AI drones in construction necessitates a rigorous ethical framework, particularly regarding data privacy and the surveillance of project sites. This study is conducted in strict accordance with the ethical mandates of the University Tunku Abdul Rahman (UTAR) and the national regulatory standards of Malaysia. Ethical integrity is maintained throughout the research lifecycle, from the initial distribution of the instrument to the final reporting of the findings.

3.12.1 Compliance with NAIO and PDPA 2026 Standards

Data management for this study aligns with the 2026 amendments to the Personal Data Protection Act (PDPA) and the guidelines issued by the National Artificial Intelligence Office (NAIO). These regulations emphasize "Privacy by Design" and the ethical use of AI-driven data. Specifically, all participants including developers, clients, and contractors are informed of the purpose of data collection via a Participant Information Sheet. Informed consent is obtained electronically before any data is recorded. To comply with the NAIO’s ethics code for AI, the research ensures that the data collected is used solely for the intended academic purpose and is not shared with third parties for commercial or surveillance profiling.

3.12.2 Anonymity, Confidentiality, and Data Security

To protect the professional reputation and competitive interests of the participating firms, a strict policy of anonymity and confidentiality is enforced. No personal identifiers or sensitive corporate data are stored in the final dataset; instead, respondents are categorized by their professional roles and firm grades to ensure aggregate analysis. In line with PDPA 2026

requirements for digital security, all electronic data is encrypted and stored in a password-protected environment. This ensures that the privacy of the decision-makers is upheld, fostering a high level of trust between the researcher and the participants a critical component of the Trust and Data Ethics variable being studied. By establishing this rigorous ethical and methodological foundation, the study ensures that the subsequent data analysis is both legally compliant and scientifically sound, providing a reliable platform for the findings presented in Chapter 4.

3.13 Chapter Summary

Chapter 3 has comprehensively delineated the methodological blueprint required to empirically validate the Governance Ecosystem Model (GEM) within the Malaysian construction industry. To systematically address the research questions, the study adopted a positivist philosophical paradigm and a deductive, quantitative, cross-sectional survey design. This objective approach was justified to mathematically test the complex interactions between regulatory support, institutional readiness, and trust, alongside their subsequent influence on AI-drone adoption through the mediating role of implementation quality.

The chapter detailed a rigorous data collection and sampling strategy, targeting a diverse and representative population of Developers, Consultants, and CIDB G1–G7 Contractors. By employing purposive and snowball sampling techniques, the research ensures that the data is sourced specifically from qualified, active industry professionals and decision-makers. Furthermore, a meticulous triangulation of sample size determination methods—including G*Power 3.1 analysis, the 10-Times Rule, and the Inverse Square Root method—established a mathematically sound baseline. To guarantee the highest level of statistical power and accommodate the complexity of the structural model, the research adopts the highest calculated requirement of 126 respondents as the target sample size.

Additionally, the chapter outlined the operationalization of the research variables, successfully adapting dimensions from the Technology Acceptance Model (TAM) and UTAUT into a structured 5-point Likert scale instrument. The procedure incorporated stringent pre-testing and pilot studies to verify both face validity and internal consistency. For the inferential analysis, Partial Least Squares Structural Equation Modeling (PLS-SEM) utilizing SmartPLS 4 was selected as the primary strategy. This approach provides a robust mechanism for evaluating the

measurement model (reliability and validity), the structural model (path analysis and mediation), and the Multi-Group Analysis (MGA) required to compare professional perspectives.

Finally, the methodology was fortified by incorporating diagnostic procedures to address potential biases, such as Common Method Variance (CMV) and non-response bias, while ensuring strict compliance with the National AI Office (NAIO) and prevailing PDPA ethical guidelines regarding participant anonymity and data security. With the methodological framework and statistical strategies firmly established, the thesis now transitions to Chapter 4, which will present the demographic findings, validate the measurement models, and formally test the proposed research hypotheses.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Introduction

The fourth chapter of this research provides a comprehensive presentation and interpretation of the data gathered to explore the governance ecosystem's role in AI-drone adoption within the Malaysian construction industry. The analysis is designed to move systematically from a broad understanding of the respondent base to a sophisticated statistical verification of the research hypotheses. According to Saunders et al. (2023), a structured presentation of results is essential to bridge the gap between raw data collection and the final theoretical contribution of the study. By integrating both descriptive and inferential statistics, this chapter establishes a robust evidentiary link between the theoretical framework and the practical realities of site safety management. The subsequent sections detail the demographic characteristics of the participants, their current state of technological awareness, and the rigorous validation of the structural model through the use of state-of-the-art analytical tools.

4.1.1 Overview of Data Analysis Strategy

The analytical framework for this study utilizes a dual-software approach to ensure the highest level of statistical precision and depth. Initial data screening, cleaning, and descriptive profiling were performed using IBM SPSS version 29, which allowed for a clear visualization of the industry’s demographic landscape and the fundamental trends in participant responses (Pallant, 2020). Following the establishment of these descriptive foundations, the core of the investigation transitioned to Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4. This specific methodology was selected due to its superior ability to handle complex models involving multiple latent constructs and its effectiveness in predictive research within the social and engineering sciences (Hair et al., 2021). The strategy involves a rigorous two-stage assessment beginning with the measurement model to verify the reliability and validity of the research instruments, followed by the structural model analysis to test the hypothesized relationships. Furthermore, the analysis extends into a multi-group comparison to investigate how governance perspectives may differ across various organizational stakeholders, thereby providing a holistic view of the construction ecosystem as recommended by Sarstedt et al. (2022).

4.1.2 Data Collection and Response Rate Analysis

The data collection phase was executed through a structured digital survey instrument distributed to a targeted selection of construction professionals across Malaysia, specifically focusing on stakeholders registered with the Construction Industry Development Board (CIDB). Of the total invitations disseminated to potential participants, 180 responses were initially recorded. Each submission underwent a stringent data cleaning process to ensure the integrity of the final results; this involved filtering for incomplete responses and identifying pattern-matching biases, which is a critical step in ensuring data quality in survey-based research (Sekaran and Bougie, 2016). Following this rigorous screening, 12 responses were excluded, resulting in a final usable sample of 168 highly qualified respondents. This sample size represents an effective response rate that is considered highly acceptable for an industry-specific study of this nature. More importantly, this final count of 168 surpasses the minimum statistical power requirements for PLS-SEM analysis, providing a statistically sound foundation for the complex path modeling and hypothesis testing that follow in the structural assessment phase (Hair, Risher and Ringle, 2019).

4.2 Descriptive Analysis: Demographic Profile (SPSS)

This section provides a detailed descriptive analysis of the demographic characteristics of the 168 respondents who participated in this study. Establishing a robust demographic profile is a fundamental requirement in academic research to verify that the data reflects a representative cross-section of the industry stakeholders (Pallant, 2020). By utilizing frequency and percentage distributions, the following sub-sections contextualize the sample's professional background, thereby ensuring the findings regarding the AI-drone governance ecosystem are grounded in a diverse and qualified participant base.

4.2.1 Demographic Profile: Gender

The gender distribution of the 168 participants involved in this study is detailed in Table 4.1 and further illustrated in the bar chart provided in Figure 4.1. Analysis of the data reveals a significant gender imbalance, with male respondents constituting 81.0% (n=136) of the total sample, while female respondents represent 19.0% (n=32).

This distribution is reflective of the historical and current professional landscape of the Malaysian construction industry, which remains a predominantly male-centric field, particularly

within technical and site-based management roles. According to Saunders et al. (2023), the validity of survey-based research is strengthened when the participant profile mirrors the actual demographic reality of the industry under investigation. Therefore, the high representation of male professionals ensures that the insights regarding AI-drone governance are captured from the primary demographic currently responsible for safety enforcement and technological implementation on Malaysian construction sites.

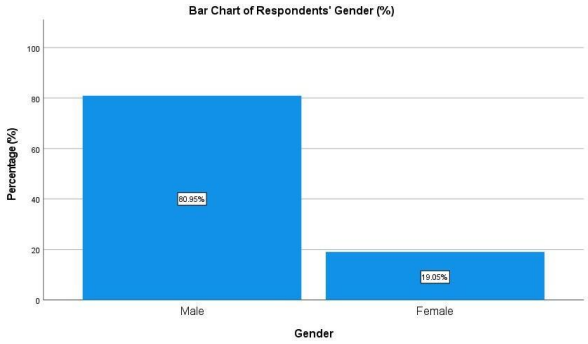


Figure 4.1: Distribution of Respondents by Gender (%)

Table 4.1: Gender Distribution of Respondents (N=168)

Gender Distribution of Respondents

	Frequency	Valid Percent	Cumulative Percent
Male	136	81.0	81.0
Female	32	19.0	100.0
Total	168	100.0	

4.2.2 Demographic Profile: Ethnic

The ethnic composition of the respondents involved in this study is presented in Table 4.2 and visually represented in the bar chart in Figure 4.2. The data indicates a multicultural distribution, with Indian professionals forming the largest group at 38.1% (n=64), followed closely by Chinese professionals at 35.1% (n=59) and Malay professionals at 26.8% (n=45).

This diverse ethnic distribution is a characteristic feature of the Malaysian construction workforce. In the context of technology adoption and governance, a multi-ethnic sample is essential to ensure that the findings are not skewed by a single cultural perspective. As noted by Sekaran and Bougie (2016), cultural and ethnic diversity within a research sample enhances the generalizability of the results across the national landscape. For this study, the inclusion of all

three major ethnic groups in Malaysia ensures that the proposed governance ecosystem for AI-drone safety is viewed as a comprehensive industry-wide framework rather than one limited to a specific demographic segment.

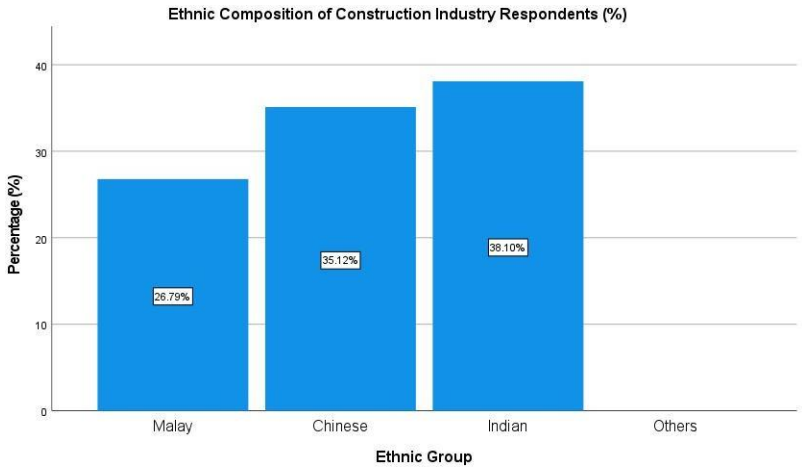


Figure 4.2: Ethnic Composition of Survey Respondents (%)

Table 4.2: Ethnic Distribution of Respondents (N=168)

Distribution of Respondents by Ethnic Group

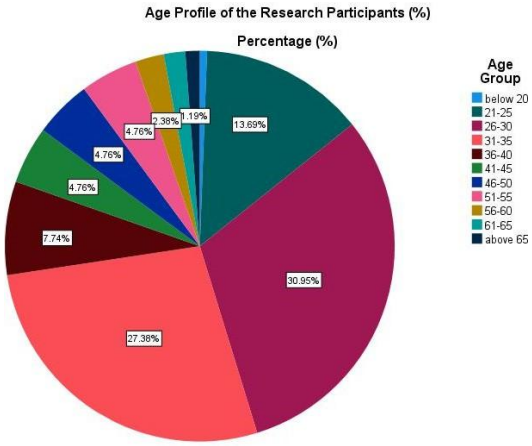
	Frequency	Valid Percent	Cumulative Percent
Malay	45	26.8	26.8
Chinese	59	35.1	61.9
Indian	64	38.1	100.0
Total	168	100.0	

4.2.3 Demographic Profile: Age

The age distribution of the 168 participants is detailed in Table 4.3 and further illustrated in Figure 4.3. A comprehensive analysis of the data reveals a diverse age range, though it is heavily concentrated in the early-to-mid career stages. The largest demographic is the 26–30 years group, accounting for 31.0% (n=52) of the total, followed by the 31–35 years group at 27.4% (n=46). These two segments combined represent more than half of the total sample, indicating a strong participation from professionals who are likely to be at the forefront of digital technology adoption in the construction sector.

The younger cohort, consisting of those below 20 (0.6%) and 21–25 years (13.7%), represents the entry-level perspective, providing insights from a generation that is naturally accustomed to autonomous systems. Conversely, the mid-to-senior tiers show a steady distribution, with 7.7% in the 36–40 bracket and a consistent 4.8% each for the 41–45, 46–50, and 51–55 age groups. The senior most categories, 56–60 (2.4%), 61–65 (1.8%), and above 65 (1.2%), although smaller in frequency, provide the necessary expert oversight for the study.

This detailed age stratification is significant for the validation of the governance ecosystem. According to Hair et al. (2021), a wide age spread ensures that the research captures a "longitudinal perspective" balancing the technological enthusiasm of younger engineers with the regulatory caution and risk-management expertise of senior practitioners. This balance is vital for creating a realistic AI-drone governance framework that is both innovative and safety-compliant within the Malaysian context.



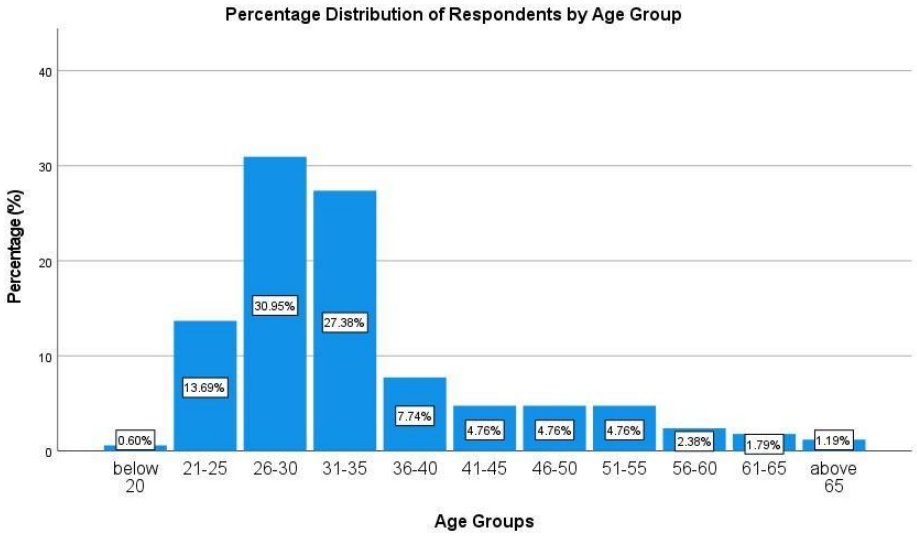


Figure 4.3: Age Distribution of Survey Respondents (%)

Table 4.3: Frequency and Percentage of Respondents' Age (N=168)

Age Distribution of Respondents

	Frequency	Valid Percent	Cumulative Percent
below 20	1	.6	.6
21-25	23	13.7	14.3
26-30	52	31.0	45.2
31-35	46	27.4	72.6
36-40	13	7.7	80.4
41-45	8	4.8	85.1
46-50	8	4.8	89.9
51-55	8	4.8	94.6
56-60	4	2.4	97.0
61-65	3	1.8	98.8
above 65	2	1.2	100.0
Total	168	100.0	

4.2.4 Demographic Profile: Highest Academic Level

The educational background of the respondents is a vital indicator of the sample's capacity to comprehend and evaluate complex technological frameworks. The distribution of the highest academic levels attained by the 168 participants is presented in Table 4.4 and Figure 4.4. The data demonstrates a highly educated professional cohort, with the vast majority of respondents holding a Bachelor’s Degree, representing 67.3% (n = 113) of the total sample.

Beyond the undergraduate level, the sample exhibits significant specialized expertise, with 13.1% (n = 22) holding a Master’s Degree or Postgraduate Diploma and 3.6% (n = 6) having attained a Doctorate (PhD). Collectively, 84.0% of the participants possess at least a degree-level qualification. The remaining segments of the sample consist of individuals with a Diploma or Technical Certificate (14.9%, n = 25) and a small percentage representing Pre-university qualifications (1.2%, n = 2).

This high level of academic attainment is statistically significant for the study’s reliability. According to Pallant (2020), a well-educated respondent base reduces the likelihood of "response error" in surveys involving complex variables, such as governance ecosystems and AI integration. The prevalence of degree-holders and postgraduates suggests that the participants

possess the requisite analytical skills to provide informed responses regarding the regulatory and safety implications of drone technology in the Malaysian construction context.

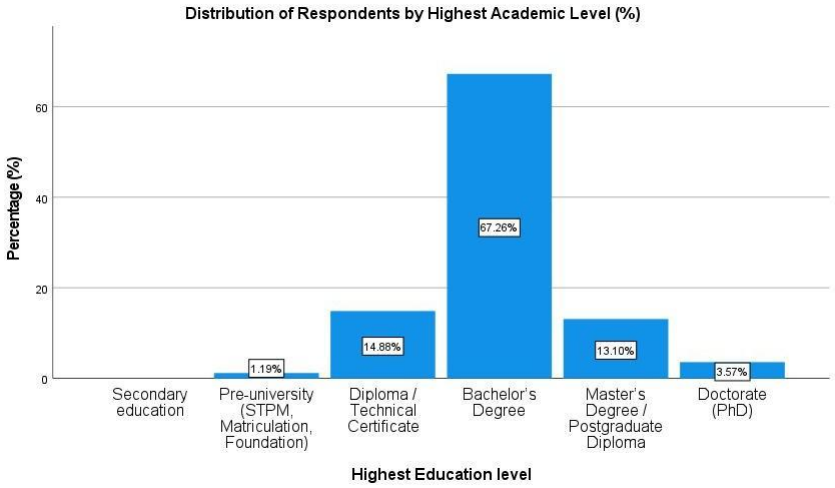


Figure 4.4: Academic Qualification Profile of Respondents (%)

Table 4.4: Frequency and Percentage of Highest Academic Level (N=168)

Academic Qualifications of Respondents

	Frequency	Valid Percent	Cumulative Percent
Pre-university (STPM, Matriculation, Foundation)	2	1.2	1.2
Diploma / Technical Certificate	25	14.9	16.1
Bachelor's Degree	113	67.3	83.3
Master's Degree / Postgraduate Diploma	22	13.1	96.4
Doctorate (PhD)	6	3.6	100.0
Total	168	100.0	

4.2.5 Demographic Profile: Category of Industry Sector

The distribution of respondents across various industry sectors is essential for ensuring a balanced and holistic perspective on AI-drone governance. The breakdown of the organizational categories represented by the 168 participants is detailed in Table 4.5 and illustrated in Figure 4.5. The analysis reveals that the largest group of respondents originates from Consultancy Firms, accounting for 33.3% (n=56) of the sample. This is followed by Sub-Contractors at 27.4% (n=46) and Main Contractors at 21.4% (n=36). The Client / Developer sector represents

16.1% (n=27) of the participants, while a small remaining segment of 1.8% (n=3) identifies with Other industry-related organizations.

Upon closer inspection of the "Other" category to address specific sectoral representation, this segment is composed of unique technical and support roles. Each of these specific roles is represented by a single respondent (n=1): Drafter (n=1), Junior Personnel (n=1), Senior Manager (n=1), and Internship (n=1).

This varied distribution is significant as it captures the "contractual triangle" of the construction industry comprising the owner (Developer), the designer/supervisor (Consultant), and the executor (Contractor). As argued by Saunders et al. (2023), a multi-sectoral sample reduces "sectoral bias" and ensures that the proposed governance ecosystem accounts for the different operational risks and financial priorities inherent in each role. The inclusion of diverse roles from technical support (Drafters and Juniors) to strategic oversight (Senior Managers) provides a comprehensive view of the industry hierarchy. The strong presence of consultants and contractors, in particular, provides high-quality technical and practical data regarding the day-to-day challenges of implementing drone-based safety monitoring on-site.

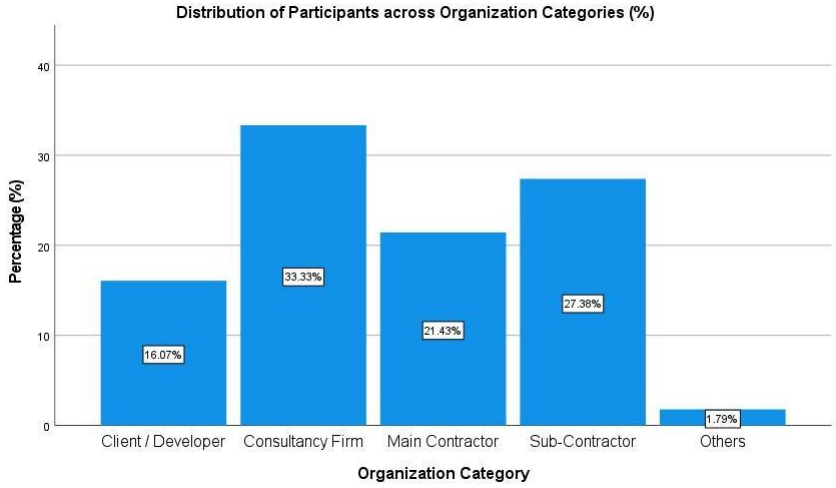


Figure 4.5: Distribution of Respondents by Industry Sector (%)

Table 4.5: Frequency and Percentage of Industry Sector Categories (N=168)

Classification of Respondents by Industry Sector

	Frequency	Valid Percent	Cumulative Percent
Client / Developer	27	16.1	16.1

Consultancy Firm	56	33.3	49.4
Main Contractor	36	21.4	70.8
Sub-Contractor	46	27.4	98.2
Others	3	1.8	100.0
Total	168	100.0	

4.2.6 Demographic Profile: Organizational Size

The scale of the organizations represented by the respondents provides critical context regarding the resources and infrastructure available for AI-drone implementation. Table 4.6 and Figure 4.6 present the distribution of organizational sizes based on the number of employees. The analysis indicates that nearly half of the respondents originate from Small organizations (10 to 49 workers), representing 48.8% (n=82) of the sample. This is followed by Medium-sized organizations (50 to 99 workers) at 19.0% (n=32), while Large organizations (more than 100 workers) and Micro organizations (1 to 9 workers) are equally represented at 16.1% (n=27) each.

The high participation of professionals from small and medium-sized firms is particularly significant for this study. While large-scale G7 contractors often have the financial capacity for early technology adoption, the successful implementation of an industry-wide AI-drone governance ecosystem depends on its viability for smaller stakeholders who may face greater resource constraints. As noted by Sekaran and Bougie (2016), a sample that includes a broad range of organizational scales enhances the "external validity" of the study, ensuring that the results are not biased toward high-resource environments. This distribution allows the research to propose a governance framework that is scalable and inclusive of the entire Malaysian construction supply chain.

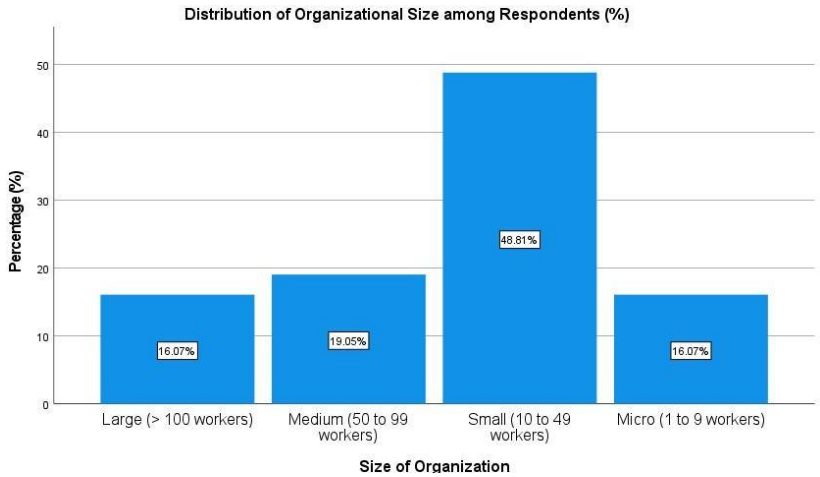


Figure 4.6: Distribution of Respondents by Organizational Size (%)

Table 4.6: Frequency and Percentage of Organizational Size (N=168)

Classification of Respondents by Organizational Size

	Frequency	Valid Percent	Cumulative Percent
Large (> 100 workers)	27	16.1	16.1
Medium (50 to 99 workers)	32	19.0	35.1
Small (10 to 49 workers)	82	48.8	83.9
Micro (1 to 9 workers)	27	16.1	100.0
Total	168	100.0	

4.2.7 Demographic Profile: Professional Role

The categorization of participants based on their professional role is essential for establishing the technical credibility of the research findings. In the context of AI-drone adoption for construction safety, the distinction between technical and non-technical expertise provides a nuanced understanding of how different professional backgrounds perceive technological risk and governance. The distribution of roles among the 168 respondents is presented in Table 4.7 and illustrated in Figure 4.7.

The data reveals a strong technical orientation within the sample, with 83.3% (n = 140) of the respondents identified as Technical Persons. This group primarily consists of engineers, architects, quantity surveyors, and safety officers who possess the specialized knowledge required to interpret the functional requirements of autonomous systems. Conversely, 16.7% (n = 28) of the participants are categorized as Non-Technical Persons, representing those in administrative, legal, or financial roles who contribute insights into the broader organizational and regulatory aspects of the governance ecosystem.

This high concentration of technical professionals significantly enhances the content validity of the study. According to Saunders et al. (2023), when a survey involves specialized technology such as AI-drones, a respondent base dominated by technical subject-matter experts ensures that the data is grounded in a realistic understanding of operational feasibility. Furthermore, the inclusion of a non-technical minority prevents "technical tunnel vision," ensuring that the proposed governance ecosystem is also evaluated for its administrative and strategic viability within the Malaysian construction industry.

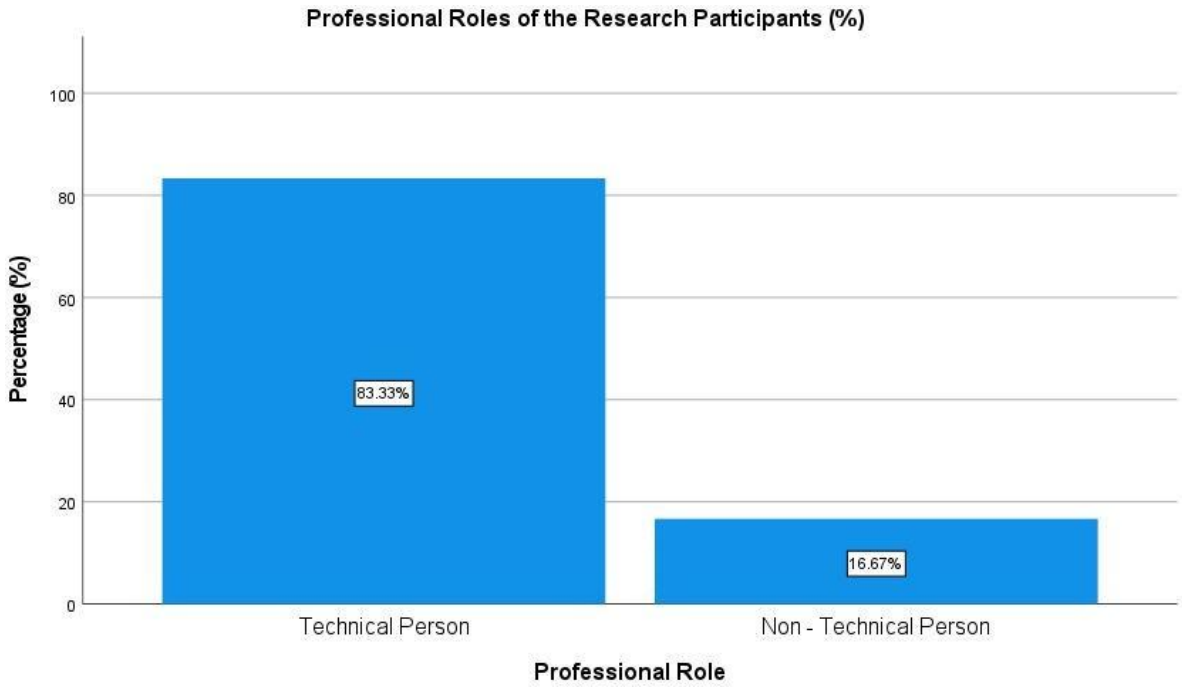


Figure 4.7: Distribution of Respondents by Professional Role (%)

Table 4.7: Frequency and Percentage of Respondents' Professional Role (N=168)

Distribution of Respondents by Professional Role

	Frequency	Valid Percent	Cumulative Percent
Technical Person	140	83.3	83.3
Non - Technical Person	28	16.7	100.0
Total	168	100.0	

4.2.8 Demographic Profile: Position Level

The organizational hierarchy of the respondents provides a significant indication of the authority, influence, and decision-making capacity within the sample. For a governance-based study, capturing insights across different levels of seniority is essential to ensure that the proposed AI-drone framework is both strategically sound and operationally feasible. The distribution of position levels among the 168 participants is detailed in Table 4.8 and illustrated in Figure 4.8.

The findings reveal that the largest segment of the sample is comprised of Middle Management (e.g., Project Managers, Construction Managers, and Site Agents), accounting for 33.3% (n=56) of the total. This is closely followed by the Executive / Professional Level (e.g., Engineers, Architects, and Safety Officers) at 30.4% (n=51). Together, these two tiers represent the

"implementation core" of the industry, possessing the direct responsibility for overseeing safety protocols and technological integration on-site.

Furthermore, the study successfully engaged the leadership echelons of the industry, with Top Management (Directors, CEOs) representing 7.1% (n=12) and Senior Management (Heads of Department) representing 10.7% (n=18). The inclusion of these high-level decision-makers is crucial, as they provide the strategic perspective necessary for organizational-wide drone adoption. The remaining 16.1% (n=27) are at the Supervisory Level, while 2.4% (n=4) represent other specialized roles.

As noted by Sekaran and Bougie (2016), a balanced hierarchical distribution enhances the "reliability of representation." By capturing data from both the "Top-Down" strategic thinkers and the "Bottom-Up" technical executors, this study ensures that the AI-drone governance ecosystem addresses the corporate objectives of the firm while remaining grounded in the practicalities of Malaysian construction site management.

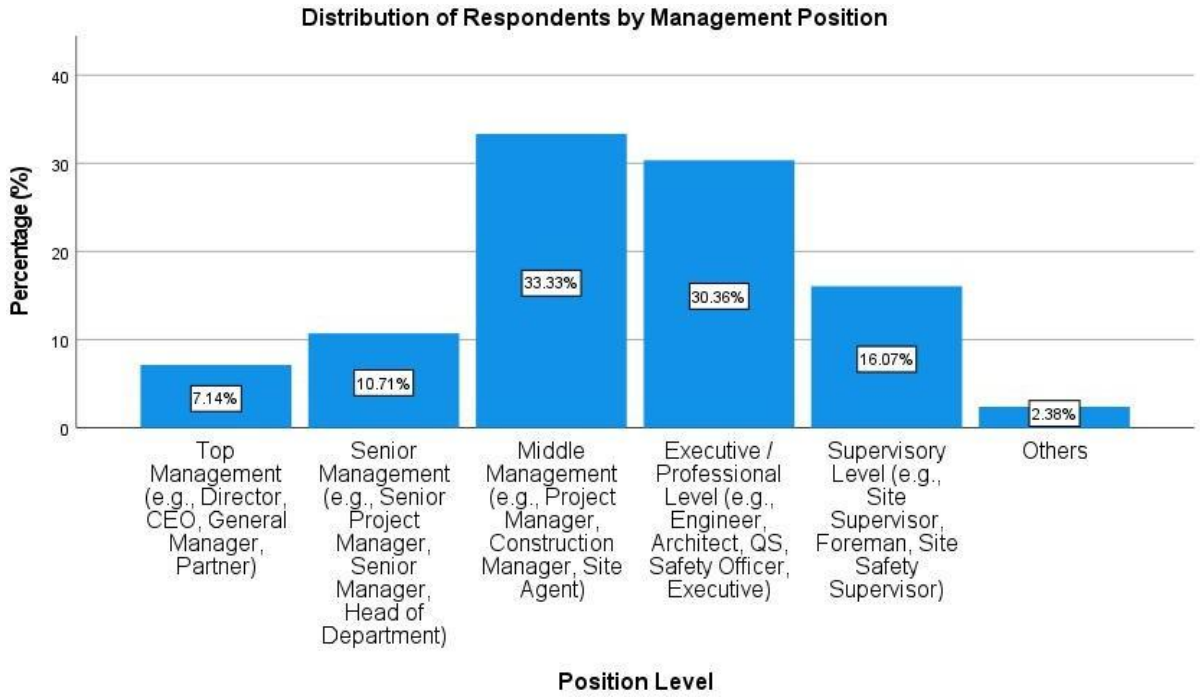


Figure 4.8: Distribution of Respondents by Position Level (%)

Table 4.8: Frequency and Percentage of Respondents' Position Level (N=168)

Distribution of Respondents by Management Position

	Frequency	Valid Percent	Cumulative Percent
Top Management (e.g., Director, CEO, General Manager, Partner)	12	7.1	7.1
Senior Management (e.g., Senior Project Manager, Senior Manager, Head of Department)	18	10.7	17.9
Middle Management (e.g., Project Manager, Construction Manager, Site Agent)	56	33.3	51.2
Executive / Professional Level (e.g., Engineer, Architect, QS, Safety Officer, Executive)	51	30.4	81.5
Supervisory Level (e.g., Site Supervisor, Foreman, Site Safety Supervisor)	27	16.1	97.6
Others	4	2.4	100.0
Total	168	100.0	

4.2.9 Demographic Profile: Years of Work Experience

The duration of professional experience is a primary indicator of the depth and reliability of the insights provided by the respondents. In the Malaysian construction industry, work experience is directly correlated with an individual's ability to assess operational risks and the feasibility of implementing advanced technologies like AI-drones. The distribution of work experience for the 168 participants is detailed in Table 4.9 and further illustrated in Figure 4.9.

The analysis reveals a well-seasoned and professionally mature respondent base. The largest cohort consists of professionals with 1–5 years of experience, representing 38.7% (n=65) of the sample. This is followed by a substantial mid-career group with 6–10 years of experience, accounting for 28.6% (n=48). Notably, the study also captured the perspectives of industry veterans, with 11.3% (n=19) of respondents possessing more than 20 years of experience. The remaining participants are distributed across the 11–15 years (10.7%), 16–20 years (5.4%), and less than 1 year (5.4%) categories.

The cumulative percentage provides a critical metric for data validation: 55.9% of the respondents possess more than 5 years of experience, and 27.4% have more than a decade of industry exposure. This "knowledge-heavy" distribution is vital for the study’s credibility. According to Hair et al. (2021), a high proportion of experienced professionals ensures that the

survey responses are grounded in practical reality rather than theoretical speculation. For this research, the combination of younger, tech-savvy professionals (1–10 years) and highly experienced senior experts (>20 years) provides a balanced evaluation of the AI-drone governance ecosystem, ensuring the framework is both innovative and practically enforceable within the Malaysian construction landscape.

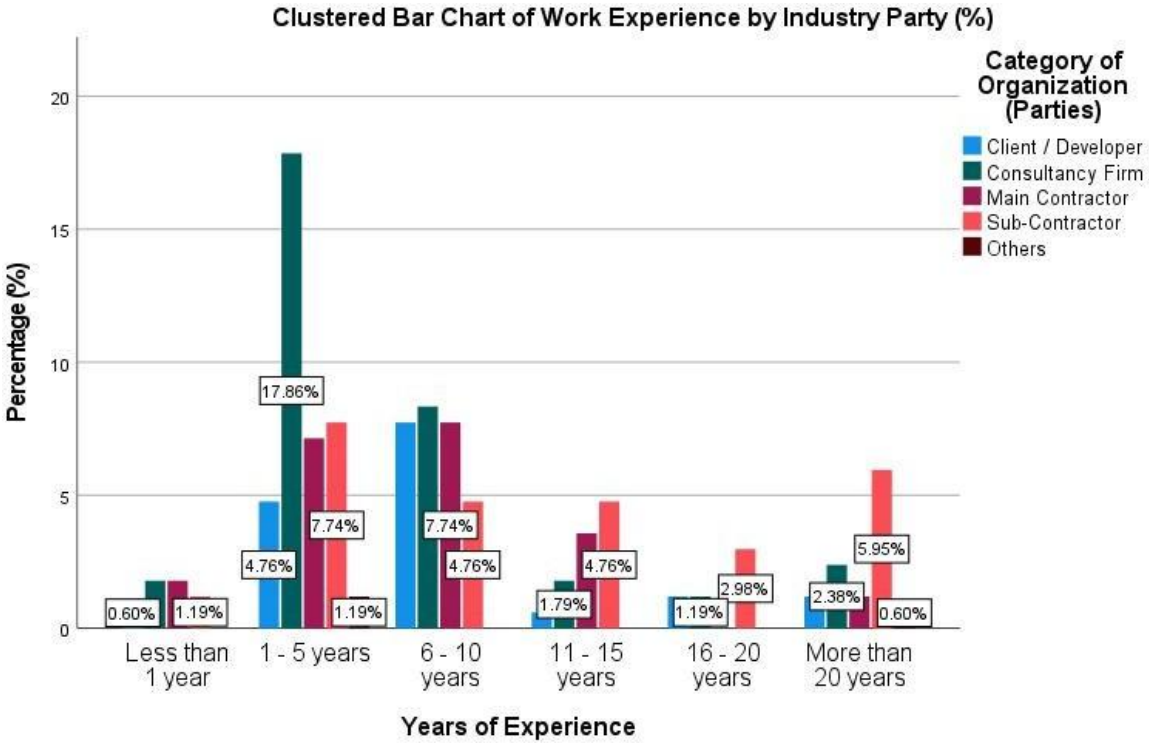


Figure 4.9: Distribution of Respondents by Years of Work Experience (%)

Table 4.9: Frequency and Percentage of Respondents' Work Experience (N=168)

Years of Professional Experience Categorized by Organization Type

	Frequency	Valid Percent	Cumulative Percent
Less than 1 year	9	5.4	5.4
1 - 5 years	65	38.7	44.0
6 - 10 years	48	28.6	72.6
11 - 15 years	18	10.7	83.3
16 - 20 years	9	5.4	88.7
More than 20 years	19	11.3	100.0
Total	168	100.0	

4.2.10 Summary of Demographic Profiles

Table 4.10 provides a comprehensive cross-tabulation of the demographic characteristics of the 168 respondents, stratified by their respective organizational categories. This master summary is essential for establishing the professional diversity of the sample and serves as a critical foundation for subsequent Multi-Group Analysis (MGA), as it highlights the sectoral nuances inherent within the Malaysian construction industry. By consolidating gender, ethnicity, age, education, and professional experience into a sectoral matrix, the research ensures that the proposed governance ecosystem for AI-drones accounts for the varied perspectives of the entire construction supply chain.

Table 4.10: Master Demographic Summary by Organization Category (N=168)

Master Demographic Summary by Organization Category (N=168)							
Gender							
		Client / Developer	Consultancy Firm	Main Contractor	Sub-Contractor	Others	Total
Male	Count	19	54	26	35	2	136
	%	70.40%	96.40%	72.20%	76.10%	66.70%	81.00%
Female	Count	8	2	10	11	1	32
	%	29.60%	3.60%	27.80%	23.90%	33.30%	19.00%
Total	Count	27	56	36	46	3	168
	%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00 %
Ethnic Group							
		Client / Developer	Consultancy Firm	Main Contractor	Sub-Contractor	Others	Total
Malay	Count	7	12	7	19	0	45
	%	25.90%	21.40%	19.40%	41.30%	0.00%	26.80%
Chinese	Count	15	12	8	24	0	59
	%	55.60%	21.40%	22.20%	52.20%	0.00%	35.10%
Indian	Count	5	32	21	3	3	64
	%	18.50%	57.10%	58.30%	6.50%	100.00%	38.10%
Total	Count	27	56	36	46	3	168
	%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00 %
Age							
		Client / Developer	Consultancy Firm	Main Contractor	Sub-Contractor	Others	Total
below 20	Count	0	0	1	0	0	1
	%	0.00%	0.00%	2.80%	0.00%	0.00%	0.60%
21-25	Count	1	10	4	7	1	23
	%	3.70%	17.90%	11.10%	15.20%	33.30%	13.70%

26-30	Count	7	26	11	7	1	52
	%	25.90%	46.40%	30.60%	15.20%	33.30%	31.00%
31-35	Count	11	9	17	9	0	46
	%	40.70%	16.10%	47.20%	19.60%	0.00%	27.40%
36-40	Count	3	4	1	5	0	13
	%	11.10%	7.10%	2.80%	10.90%	0.00%	7.70%
41-45	Count	2	3	0	3	0	8
	%	7.40%	5.40%	0.00%	6.50%	0.00%	4.80%
46-50	Count	0	1	0	7	0	8
	%	0.00%	1.80%	0.00%	15.20%	0.00%	4.80%
51-55	Count	3	0	0	5	0	8
	%	11.10%	0.00%	0.00%	10.90%	0.00%	4.80%
56-60	Count	0	0	1	2	1	4
	%	0.00%	0.00%	2.80%	4.30%	33.30%	2.40%
61-65	Count	0	2	0	1	0	3
	%	0.00%	3.60%	0.00%	2.20%	0.00%	1.80%
above 65	Count	0	1	1	0	0	2
	%	0.00%	1.80%	2.80%	0.00%	0.00%	1.20%
Total	Count	27	56	36	46	3	168
	%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00 %
Highest Academic Level							
		Client / Developer	Consultancy Firm	Main Contractor	Sub-Contractor	Others	Total
Pre-university (STPM, Matriculation, Foundation)	Count	0	0	2	0	0	2
	%	0.00%	0.00%	5.60%	0.00%	0.00%	1.20%
Diploma / Technical Certificate	Count	3	7	5	10	0	25
	%	11.10%	12.50%	13.90%	21.70%	0.00%	14.90%
Bachelor's Degree	Count	20	40	22	29	2	113
	%	74.10%	71.40%	61.10%	63.00%	66.70%	67.30%
Master's Degree / Postgraduate Diploma	Count	3	7	7	5	0	22
	%	11.10%	12.50%	19.40%	10.90%	0.00%	13.10%
Doctorate (PhD)	Count	1	2	0	2	1	6
	%	3.70%	3.60%	0.00%	4.30%	33.30%	3.60%
Total	Count	27	56	36	46	3	168
	%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00 %
Organizational Size							
		Client / Developer	Consultancy Firm	Main Contractor	Sub-Contractor	Others	Total
Large (> 100 workers)	Count	14	2	9	1	1	27
	%	51.90%	3.60%	25.00%	2.20%	33.30%	16.10%
Medium (50 to	Count	9	7	15	0	1	32

99 workers)	%	33.30%	12.50%	41.70%	0.00%	33.30%	19.00%
Small (10 to 49 workers)	Count	1	35	11	35	0	82
	%	3.70%	62.50%	30.60%	76.10%	0.00%	48.80%
Micro (1 to 9 workers)	Count	3	12	1	10	1	27
	%	11.10%	21.40%	2.80%	21.70%	33.30%	16.10%
Total	Count	27	56	36	46	3	168
	%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00 %

Professional Role

		Client / Developer	Consultancy Firm	Main Contractor	Sub-Contractor	Others	Total
Technical Person	Count	18	55	29	36	2	140
	%	66.70%	98.20%	80.60%	78.30%	66.70%	83.30%
Non - Technical Person	Count	9	1	7	10	1	28
	%	33.30%	1.80%	19.40%	21.70%	33.30%	16.70%
Total	Count	27	56	36	46	3	168
	%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00 %

Management Position

		Client / Developer	Consultancy Firm	Main Contractor	Sub-Contractor	Others	Total
Top Management (e.g., Director, CEO, General Manager, Partner)	Count	1	3	2	6	0	12
	%	3.70%	5.40%	5.60%	13.00%	0.00%	7.10%
Senior Management (e.g., Senior Project Manager, Senior Manager, Head of Department)	Count	4	4	0	9	1	18
	%	14.80%	7.10%	0.00%	19.60%	33.30%	10.70%
Middle Management (e.g., Project Manager, Construction Manager, Site Agent)	Count	18	1	20	17	0	56
	%	66.70%	1.80%	55.60%	37.00%	0.00%	33.30%
Executive / Professional Level (e.g., Engineer, Architect, QS,	Count	3	44	4	0	0	51
	%	11.10%	78.60%	11.10%	0.00%	0.00%	30.40%

Safety Officer, Executive)							
Supervisory Level (e.g., Site Supervisor, Foreman, Site Safety Supervisor)	Count	1	1	10	14	1	27
	%	3.70%	1.80%	27.80%	30.40%	33.30%	16.10%
Others	Count	0	3	0	0	1	4
	%	0.00%	5.40%	0.00%	0.00%	33.30%	2.40%
Total	Count	27	56	36	46	3	168
	%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00 %
Years of Professional Experience							
		Client / Developer	Consultancy Firm	Main Contractor	Sub-Contractor	Others	Total
Less than 1 year	Count	1	3	3	2	0	9
	%	3.70%	5.40%	8.30%	4.30%	0.00%	5.40%
1 - 5 years	Count	8	30	12	13	2	65
	%	29.60%	53.60%	33.30%	28.30%	66.70%	38.70%
6 - 10 years	Count	13	14	13	8	0	48
	%	48.10%	25.00%	36.10%	17.40%	0.00%	28.60%
11 - 15 years	Count	1	3	6	8	0	18
	%	3.70%	5.40%	16.70%	17.40%	0.00%	10.70%
16 - 20 years	Count	2	2	0	5	0	9
	%	7.40%	3.60%	0.00%	10.90%	0.00%	5.40%
More than 20 years	Count	2	4	2	10	1	19
	%	7.40%	7.10%	5.60%	21.70%	33.30%	11.30%
Total	Count	27	56	36	46	3	168
	%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00 %

The cross-tabulated findings suggest that the research sample is characterized by a high degree of academic and professional maturity across all sectors of the contractual triangle. A notable academic premium exists within the Consultancy and Developer sectors, where the vast majority of respondents hold a Bachelor's degree or higher, thereby reinforcing the content validity of the study as participants possess the requisite analytical skills to evaluate complex AI-driven safety governance. Furthermore, the professional experience distribution indicates a "knowledge-heavy" sample, particularly among Main Contractors and Developers, where over half of the respondents possess more than five years of industry exposure. This ensures that the data is anchored in practical site realities rather than theoretical speculation, as supported by the methodological standards set by Hair et al. (2021) and Saunders et al. (2023).

In addition to professional seniority, the data highlights a significant contrast in organizational scale that reflects the actual supply chain of the Malaysian construction industry. While Developers are predominantly associated with large-scale organizations, the overwhelming majority of Consultants and Sub-contractors represent SME and Micro-organizations. This finding is pivotal for the study's external validity, as it confirms that the technical execution and supervision of projects are driven by smaller firms. Consequently, the proposed governance ecosystem must be scalable and accessible for these smaller stakeholders to be truly effective at an industry-wide level. Finally, the balanced multi-ethnic representation and the realistic male-centric gender distribution further solidify the generalizability of the results across the national landscape, ensuring the framework is professionally and socially inclusive within the Malaysian context.

4.2.11 Summary Profile: Developer Respondents

The demographic profile of the Developer category, representing the client-side stakeholders (n=27), provides critical insights into the strategic leadership of the Malaysian construction industry. As illustrated in Table 4.11, the sample is predominantly male (70.4%), though it notably possesses the highest female representation among all categories at 29.6%. From an ethnic standpoint, Chinese professionals constitute the majority at 55.6%, followed by Malay (25.9%) and Indian (18.5%) respondents. The academic foundation of this group is exceptionally robust, with 88.9% holding a Bachelor's degree or higher, including specific representation at the Doctorate level (3.7%). This high educational attainment is complemented by significant professional maturity, as 66.6% of the respondents are aged above 30 and 66.6% possess more than five years of industry experience. Specifically, the 6–10 years experience bracket is the most prominent (48.1%), suggesting that these individuals are in a prime career stage to oversee technological transitions.

Organizational and hierarchical data further reinforce the strategic weight of this cohort, as 85.2% of Developer respondents originate from Large or Medium-sized organizations, indicating that these firms likely possess the necessary capital resources for AI-drone investment. Despite the strategic nature of the client role, 66.7% of the participants are technical personnel, ensuring that their perspectives are grounded in engineering feasibility. Within the organizational hierarchy, 85.2% occupy positions from Middle Management to Top Management, with the majority serving as Middle Management (66.7%) such as Project Managers and Site Agents. This concentration of authority is significant; according to Sekaran

and Bougie (2016) and Hair et al. (2021), capturing data from those who hold both technical knowledge and decision-making power ensures that the proposed governance ecosystem is evaluated by the primary stakeholders responsible for safety policy and technological procurement in the Malaysian construction landscape.

Table 4.11: Summary Profile of Developer Respondents (n=27)

Summary Profile: Developer Respondents

Gender			
	Frequency	Valid Percent	Cumulative Percent
Male	19	70.4	70.4
Female	8	29.6	100
Total	27	100	
Ethnic Group			
	Frequency	Valid Percent	Cumulative Percent
Malay	7	25.9	25.9
Chinese	15	55.6	81.5
Indian	5	18.5	100
Total	27	100	
Age			
	Frequency	Valid Percent	Cumulative Percent
21-25	1	3.7	3.7
26-30	7	25.9	29.6
31-35	11	40.7	70.4
36-40	3	11.1	81.5
41-45	2	7.4	88.9
51-55	3	11.1	100
Total	27	100	
Highest Academic Level			
	Frequency	Valid Percent	Cumulative Percent
Diploma / Technical Certificate	3	11.1	11.1
Bachelor's Degree	20	74.1	85.2
Master's Degree / Postgraduate Diploma	3	11.1	96.3
Doctorate (PhD)	1	3.7	100
Total	27	100	
Organizational Size			
	Frequency	Valid Percent	Cumulative Percent
Large (> 100 workers)	14	51.9	51.9
Medium (50 to 99 workers)	9	33.3	85.2
Small (10 to 49 workers)	1	3.7	88.9

Micro (1 to 9 workers)	3	11.1	100
Total	27	100	

Professional Role

	Frequency	Valid Percent	Cumulative Percent
Technical Person	18	66.7	66.7
Non - Technical Person	9	33.3	100
Total	27	100	

Management Position

	Frequency	Valid Percent	Cumulative Percent
Top Management (e.g., Director, CEO, General Manager, Partner)	1	3.7	3.7
Senior Management (e.g., Senior Project Manager, Senior Manager, Head of Department)	4	14.8	18.5
Middle Management (e.g., Project Manager, Construction Manager, Site Agent)	18	66.7	85.2
Executive / Professional Level (e.g., Engineer, Architect, QS, Safety Officer, Executive)	3	11.1	96.3
Supervisory Level (e.g., Site Supervisor, Foreman, Site Safety Supervisor)	1	3.7	100
Total	27	100	

Years of Professional Experience

	Frequency	Valid Percent	Cumulative Percent
Less than 1 year	1	3.7	3.7
1 - 5 years	8	29.6	33.3
6 - 10 years	13	48.1	81.5
11 - 15 years	1	3.7	85.2
16 - 20 years	2	7.4	92.6
More than 20 years	2	7.4	100
Total	27	100	

4.2.12 Summary Profile: Consultant Respondents

The demographic profile of the Consultant category (n=56) highlights a highly specialized and technically-oriented segment of the Malaysian construction industry. As demonstrated in Table 4.12, this group exhibits the most significant gender imbalance within the study, with 96.4% of respondents being male and only 3.6% female. The ethnic composition is led by Indian professionals at 57.1%, followed by Malay and Chinese professionals at 21.4% each. This cohort is characterized by a relatively young and agile workforce, with 64.3% of respondents aged 30 or younger, and more than half the sample (53.6%) possessing 1–5 years of professional experience. Despite their early-to-mid career status, their academic credentials are exceptionally high, with 87.5% holding a Bachelor's degree or higher, including 3.6% who have attained a

Doctorate (PhD). This combination of youthful technological receptivity and high academic achievement suggests that consultants are positioned as the primary "early adopters" and technical implementers of AI-drone technology in the Malaysian context.

Structurally, the consultant sample is predominantly rooted in the Small and Medium Enterprise (SME) sector, with 83.9% of respondents originating from Small (62.5%) or Micro (21.4%) organizations. This reflects the fragmented nature of the Malaysian C&S consultancy landscape, where specialized firms drive technical design. The professional role data is nearly unanimous, with 98.2% of respondents serving as technical personnel. Within the organizational hierarchy, the majority occupy the Executive / Professional Level (78.6%), comprising engineers, architects, and surveyors who are directly responsible for site-level technical supervision. As noted by Sekaran and Bougie (2016) and Saunders et al. (2023), a sample dominated by frontline technical professionals provides the highest level of content validity for technology-based research. The dominance of degree-holding technical executives ensures that the evaluation of the AI-drone governance ecosystem is grounded in precise engineering standards and a thorough understanding of design-compliance requirements.

Table 4.12: Summary Profile of Consultant Respondents (n=56)

Summary Profile: Consultant Respondents

Gender			
	Frequency	Valid Percent	Cumulative Percent
Male	54	96.4	96.4
Female	2	3.6	100
Total	56	100	
Ethnic Group			
	Frequency	Valid Percent	Cumulative Percent
Malay	12	21.4	21.4
Chinese	12	21.4	42.9
Indian	32	57.1	100
Total	56	100	
Age			
	Frequency	Valid Percent	Cumulative Percent
21-25	10	17.9	17.9
26-30	26	46.4	64.3
31-35	9	16.1	80.4
36-40	4	7.1	87.5

41-45	3	5.4	92.9
46-50	1	1.8	94.6
61-65	2	3.6	98.2
above 65	1	1.8	100
Total	56	100	

Highest Academic Level

	Frequency	Valid Percent	Cumulative Percent
Diploma / Technical Certificate	7	12.5	12.5
Bachelor's Degree	40	71.4	83.9
Master's Degree / Postgraduate Diploma	7	12.5	96.4
Doctorate (PhD)	2	3.6	100
Total	56	100	

Organizational Size

	Frequency	Valid Percent	Cumulative Percent
Large (> 100 workers)	2	3.6	3.6
Medium (50 to 99 workers)	7	12.5	16.1
Small (10 to 49 workers)	35	62.5	78.6
Micro (1 to 9 workers)	12	21.4	100
Total	56	100	

Professional Role

	Frequency	Valid Percent	Cumulative Percent
Technical Person	55	98.2	98.2
Non - Technical Person	1	1.8	100
Total	56	100	

Management Position

	Frequency	Valid Percent	Cumulative Percent
Top Management (e.g., Director, CEO, General Manager, Partner)	3	5.4	5.4
Senior Management (e.g., Senior Project Manager, Senior Manager, Head of Department)	4	7.1	12.5
Middle Management (e.g., Project Manager, Construction Manager, Site Agent)	1	1.8	14.3
Executive / Professional Level (e.g., Engineer, Architect, QS, Safety Officer, Executive)	44	78.6	92.9
Supervisory Level (e.g., Site Supervisor, Foreman, Site Safety Supervisor)	1	1.8	94.6
Others	3	5.4	100
Total	56	100	

Years of Professional Experience

	Frequency	Valid Percent	Cumulative Percent

Less than 1 year	3	5.4	5.4
1 - 5 years	30	53.6	58.9
6 - 10 years	14	25	83.9
11 - 15 years	3	5.4	89.3
16 - 20 years	2	3.6	92.9
More than 20 years	4	7.1	100
Total	56	100	

4.2.13 Summary Profile: Main-Contractor Respondents

The demographic profile of the Main-Contractor category (n=36) characterizes the operational leadership of the Malaysian construction sector. As shown in Table 4.13, the gender distribution reflects a 72.2% male majority, with a notable 27.8% female representation, which is significantly higher than the consultancy sector. The ethnic composition is predominantly Indian at 58.3%, followed by Chinese (22.2%) and Malay (19.4%) professionals. This cohort is notably experienced and mature, with nearly half of the respondents (47.2%) falling within the 31–35 years age bracket and 58.4% possessing more than five years of professional experience. Academic qualifications remain high, with 80.5% holding a Bachelor's degree or Master's degree. This robust educational background combined with mid-career seniority suggests that Main Contractors provide a reliable perspective on the intersection of site-based practicalities and technological safety protocols.

From an organizational perspective, Main Contractors represent the mid-to-large tier of the industry, with 66.7% originating from Medium or Large-sized firms. This organizational stability is reflected in their hierarchical status, where 55.6% occupy Middle Management roles, such as Project Managers and Site Agents, who serve as the primary bridge between corporate safety policy and field execution. Furthermore, 80.6% of this group are technical personnel, ensuring that their evaluation of AI-drone governance is based on a practical understanding of site operations. The significant presence of Supervisory Level staff (27.8%) adds further depth to the sample, capturing the insights of those directly overseeing day-to-day site safety. As emphasized by Saunders et al. (2023), capturing insights from the "execution core" of the industry ensures that the research findings are grounded in the actual operational environment of Malaysian construction projects.

Table 4.13: Summary Profile of Main-Contractor Respondents (n=36)

Summary Profile: Contractor Respondents

Gender

	Frequency	Valid Percent	Cumulative Percent
Male	26	72.2	72.2
Female	10	27.8	100
Total	36	100	

Ethnic Group

	Frequency	Valid Percent	Cumulative Percent
Malay	7	19.4	19.4
Chinese	8	22.2	41.7
Indian	21	58.3	100
Total	36	100	

Age

	Frequency	Valid Percent	Cumulative Percent
below 20	1	2.8	2.8
21-25	4	11.1	13.9
26-30	11	30.6	44.4
31-35	17	47.2	91.7
36-40	1	2.8	94.4
56-60	1	2.8	97.2
above 65	1	2.8	100
Total	36	100	

Highest Academic Level

	Frequency	Valid Percent	Cumulative Percent
Pre-university (STPM, Matriculation, Foundation)	2	5.6	5.6
Diploma / Technical Certificate	5	13.9	19.4
Bachelor’s Degree	22	61.1	80.6
Master’s Degree / Postgraduate Diploma	7	19.4	100
Total	36	100	

Organizational Size

	Frequency	Valid Percent	Cumulative Percent
Large (> 100 workers)	9	25	25
Medium (50 to 99 workers)	15	41.7	66.7
Small (10 to 49 workers)	11	30.6	97.2
Micro (1 to 9 workers)	1	2.8	100
Total	36	100	

Professional Role

	Frequency	Valid Percent	Cumulative Percent
Technical Person	29	80.6	80.6
Non - Technical Person	7	19.4	100
Total	36	100	

Management Position

	Frequency	Valid Percent	Cumulative Percent
Top Management (e.g., Director, CEO, General Manager, Partner)	2	5.6	5.6
Middle Management (e.g., Project Manager, Construction Manager, Site Agent)	20	55.6	61.1
Executive / Professional Level (e.g., Engineer, Architect, QS, Safety Officer, Executive)	4	11.1	72.2
Supervisory Level (e.g., Site Supervisor, Foreman, Site Safety Supervisor)	10	27.8	100
Total	36	100	

Years of Professional Experience

	Frequency	Valid Percent	Cumulative Percent
Less than 1 year	3	8.3	8.3
1 - 5 years	12	33.3	41.7
6 - 10 years	13	36.1	77.8
11 - 15 years	6	16.7	94.4
More than 20 years	2	5.6	100
Total	36	100	

4.2.14 Summary Profile: Sub-Contractor Respondents

The demographic profile of the Sub-Contractor category (n=46) highlights a diverse and highly experienced segment of the construction supply chain. As presented in Table 4.14, the sample is primarily male (76.1%), with a female representation of 23.9%. The ethnic composition shows a high concentration of Chinese professionals (52.2%) and Malay professionals (41.3%), which contrasts with the Indian-dominant profile seen in the Consultancy and Main-Contractor sectors. This cohort is the most professionally mature in the study, with 50.0% of respondents possessing more than 10 years of experience, including a significant 21.7% who are industry veterans with more than 20 years of service. Despite the practical nature of sub-contracting work, the academic standard remains high, with 78.2% holding a Bachelor's degree or higher, including specific representation at the Doctorate level (4.3%). This combination of long-term field experience and technical education ensures that Sub-Contractors provide a deeply grounded perspective on the feasibility of integrating autonomous safety governance within day-to-day site operations.

From an organizational standpoint, the Sub-Contractor sample is almost entirely comprised of the SME and Micro sector, with 97.8% originating from organizations with fewer than 50 workers. This reflects the actual structure of the Malaysian construction industry, where specialized trades are executed by smaller, agile firms. Hierarchically, the group is

well-distributed between leadership and supervision, with 37.0% in Middle Management roles and 30.4% at the Supervisory Level (e.g., Foremen and Site Safety Supervisors). Furthermore, 78.3% of the participants serve in technical roles, reinforcing the technical validity of their responses. According to Sekaran and Bougie (2016) and Saunders et al. (2023), a sample that accurately captures the "field-level" perspective of supervisors and managers in the SME sector is vital for ensuring the external validity of a governance framework. The data from this group confirms that the AI-drone governance ecosystem must be adaptable to the resource constraints and operational pace of sub-contracting firms to achieve successful industry-wide adoption.

Table 4.14: Summary Profile of Sub-Contractor Respondents (n=46)

Summary Profile: Sub-Contractor Respondents

Gender

	Frequency	Valid Percent	Cumulative Percent
Male	35	76.1	76.1
Female	11	23.9	100
Total	46	100	

Ethnic Group

	Frequency	Valid Percent	Cumulative Percent
Malay	19	41.3	41.3
Chinese	24	52.2	93.5
Indian	3	6.5	100
Total	46	100	

Age

	Frequency	Valid Percent	Cumulative Percent
21-25	7	15.2	15.2
26-30	7	15.2	30.4
31-35	9	19.6	50
36-40	5	10.9	60.9
41-45	3	6.5	67.4
46-50	7	15.2	82.6
51-55	5	10.9	93.5
56-60	2	4.3	97.8
61-65	1	2.2	100
Total	46	100	

Highest Academic Level

	Frequency	Valid Percent	Cumulative Percent
Diploma / Technical Certificate	10	21.7	21.7
Bachelor’s Degree	29	63	84.8
Master’s Degree / Postgraduate Diploma	5	10.9	95.7

Doctorate (PhD)	2	4.3	100
Total	46	100	

Organizational Size

	Frequency	Valid Percent	Cumulative Percent
Large (> 100 workers)	1	2.2	2.2
Small (10 to 49 workers)	35	76.1	78.3
Micro (1 to 9 workers)	10	21.7	100
Total	46	100	

Professional Role

	Frequency	Valid Percent	Cumulative Percent
Technical Person	36	78.3	78.3
Non - Technical Person	10	21.7	100
Total	46	100	

Management Position

	Frequency	Valid Percent	Cumulative Percent
Top Management (e.g., Director, CEO, General Manager, Partner)	6	13	13
Senior Management (e.g., Senior Project Manager, Senior Manager, Head of Department)	9	19.6	32.6
Middle Management (e.g., Project Manager, Construction Manager, Site Agent)	17	37	69.6
Supervisory Level (e.g., Site Supervisor, Foreman, Site Safety Supervisor)	14	30.4	100
Total	46	100	

Years of Professional Experience

	Frequency	Valid Percent	Cumulative Percent
Less than 1 year	2	4.3	4.3
1 - 5 years	13	28.3	32.6
6 - 10 years	8	17.4	50
11 - 15 years	8	17.4	67.4
16 - 20 years	5	10.9	78.3
More than 20 years	10	21.7	100
Total	46	100	

4.2.15 Summary Profile: Others Respondents

The demographic profile of the "Others" category (n=3) captures the remaining niche stakeholders within the Malaysian construction landscape. As detailed in Table 4.15, the group consists of two male respondents (66.7%) and one female respondent (33.3%), all of whom identify with the Indian ethnic group (100%). Despite the small sample size, the group possesses a high academic standing, with all members holding at least a Bachelor's degree, including one

individual who has attained a Doctorate (33.3%). The age and experience distribution for this cohort is polarized, featuring a mix of early-career professionals in the 21–30 age range (66.7%) with 1–5 years of experience, alongside a senior industry veteran in the 56–60 age bracket (33.3%) with more than 20 years of professional standing.

Organizational and hierarchical data for this segment reflect a broad reach across different firm scales, spanning Large, Medium, and Micro organizations. Professionally, 66.7% of these respondents serve in technical roles, occupying a range of positions from Senior Management to the Supervisory Level. As noted by Saunders et al. (2023), the inclusion of such diverse, albeit small, outlying groups is necessary for a comprehensive exploratory study, as it ensures that the resulting AI-drone governance ecosystem is tested against a wider spectrum of industry roles beyond the standard client-consultant-contractor framework.

Table 4.15: Summary Profile of Others Respondents (n=3)

Summary Profile: Others Respondents

Gender			
	Frequency	Valid Percent	Cumulative Percent
Male	2	66.7	66.7
Female	1	33.3	100
Total	3	100	
Ethnic Group			
	Frequency	Valid Percent	Cumulative Percent
Indian	3	100	100
Age			
	Frequency	Valid Percent	Cumulative Percent
21-25	1	33.3	33.3
26-30	1	33.3	66.7
56-60	1	33.3	100
Total	3	100	
Highest Academic Level			
	Frequency	Valid Percent	Cumulative Percent
Bachelor’s Degree	2	66.7	66.7
Doctorate (PhD)	1	33.3	100
Total	3	100	
Organizational Size			
	Frequency	Valid Percent	Cumulative Percent
Large (> 100 workers)	1	33.3	33.3

Medium (50 to 99 workers)	1	33.3	66.7
Micro (1 to 9 workers)	1	33.3	100
Total	3	100	

Professional Role

	Frequency	Valid Percent	Cumulative Percent
Technical Person	2	66.7	66.7
Non - Technical Person	1	33.3	100
Total	3	100	

Management Position

	Frequency	Valid Percent	Cumulative Percent
Senior Management (e.g., Senior Project Manager, Senior Manager, Head of Department)	1	33.3	33.3
Supervisory Level (e.g., Site Supervisor, Foreman, Site Safety Supervisor)	1	33.3	66.7
Others	1	33.3	100
Total	3	100	

Years of Professional Experience

	Frequency	Valid Percent	Cumulative Percent
1 - 5 years	2	66.7	66.7
More than 20 years	1	33.3	100
Total	3	100	

4.2.16 Synthesis of Demographic Findings: Patterns and Governance Gaps

The detailed demographic data across the 15 preceding sub-sections reveals a complex professional landscape that defines the current state of AI-drone adoption in the Malaysian construction industry. When these data points are synthesized, three critical patterns emerge that explicitly highlight the "Governance Gaps" existing within the local ecosystem.

First, a dominant Sectoral Pattern is observed through the heavy representation of Consultants (33.3%) and Tier-1 Main Contractors (21.4%), compared to the lower participation of Clients and Developers (16.1%). This reveals a significant Strategic Leadership Gap; while the technical executors are highly engaged with drone technology, the demand-side stakeholders who control project budgets have yet to fully mandate AI-safety governance in their contracts. In the Malaysian context, this indicates that adoption is currently being "pushed" by technical experts rather than "pulled" by organizational leaders, suggesting that current CIDB Construction 4.0 initiatives may be over-relying on the design-side to drive operational safety changes.

Second, an analysis of Professional Experience and Education (Sections 4.2.6–4.2.10) uncovers a Cognitive and Knowledge Gap. A surprising finding within the data is the high level of academic qualification with the majority of respondents holding Bachelor's or Master's degrees contrasted against a visible "Digital Divide" in seniority. While junior-to-mid-level professionals show a high propensity for "Technical Trust," senior decision-makers (those with over 15 years of experience) remain the gatekeepers for digital investment. This creates a bottleneck where younger, tech-savvy engineers understand the safety benefits of AI-drones, but senior leadership, accustomed to traditional Malaysian site supervision methods, may still perceive the technology as a high-cost luxury rather than a baseline necessity.

Finally, the Operational Context described in Sections 4.2.11 through 4.2.15 identifies a clear Implementation Gap between project types. The data suggests that AI-drone safety monitoring is heavily clustered within Large-Scale Infrastructure projects, while the residential and commercial sectors remain underserved. This is a crucial finding for the Malaysian context, as it highlights that despite overarching frameworks from the National AI Office (NAIO) and CAAM, there is no unified governance standard that scales down to smaller, high-risk construction sites. This fragmentation leaves a massive portion of the Malaysian workforce particularly those employed by smaller sub-contracting firms outside the safety "digital net," further widening the Ecosystem Readiness Gap between Tier-1 firms and the rest of the industry.

4.3 Descriptive Analysis of Research Variables

This section presents the descriptive statistics for the core variables identified in the conceptual framework. The analysis begins with a preliminary assessment of the respondents' familiarity and awareness of AI-drone technology to establish a baseline of technical literacy. Subsequently, the independent variables Regulatory Support (IV1), Institutional Readiness (IV2), and Trust and Data (IV3) are examined alongside the mediator variable (Implementation) and the dependent variable (AI-Drone Adoption for Safety). According to Pallant (2020), descriptive analysis is a fundamental prerequisite in quantitative research, as it allows the researcher to inspect the distribution, central tendency, and variability of the data before proceeding to inferential statistical testing through SmartPLS.

4.3.1 Preliminary Assessment of AI-Drone Familiarity

The initial phase of the descriptive analysis sought to determine the baseline familiarity with AI-drone technology across the various sectors of the Malaysian construction supply chain. As illustrated in Table 4.16, 75.6% of the total respondents (N=168) confirmed prior exposure to the technology. While the Consultancy sector reported the highest familiarity at 82.1%, the distribution across Developers (74.1%), Main-Contractors (80.6%), and Sub-Contractors (73.9%) remained relatively consistent.

Table 4.16: Stakeholder Exposure to AI-Drone Technology by Organization Category

Stakeholder Exposure to AI-Drone Technology by Organization Category

			Category of the organization					
			Client / Developer	Consultancy Firm	Main Contractor	Sub-Contractor	Others	Total
Have you ever heard about: AI Drone	Yes	Count	20_a	46_a	26_a	34_a	1_a	127
		%	74.1%	82.1%	72.2%	73.9%	33.3%	75.6%
	No	Count	7_a	10_a	10_a	12_a	2_a	41
		%	25.9%	17.9%	27.8%	26.1%	66.7%	24.4%
Total		Count	27	56	36	46	3	168
		%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Each subscript letter denotes a subset of Category of the organization categories whose column proportions do not differ significantly from each other at the .05 level.

To determine if these sectoral variations were statistically significant, a Pearson Chi-Square test was conducted (Table 4.17). The results (χ^2=4.532,p=0.339) indicate that there is no significant association between organization type and drone familiarity. This is further supported by a low Cramer's V value of 0.164 (Table 4.18). The Z-test for column proportions, indicated by the uniform subscript "a" across all categories in the crosstabulation, confirms that no single stakeholder group possesses a statistically higher or lower awareness level than the others.

Table 4.17: Chi-Square Test for Independence: Organization Type vs. Drone Exposure

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	4.532[a]	4	.339
Likelihood Ratio	4.095	4	.393
Linear-by-Linear Association	1.011	1	.315
N of Valid Cases	168		

a. 2 cells (20.0%) have expected count less than 5. The minimum expected count is .73.

Table 4.18: Association Strength and Correlation Analysis

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Nominal by Nominal	Phi	.164			.339
	Cramer's V	.164			.339
Interval by Interval	Pearson's R	.078	.081	1.005	.316[c]
Ordinal by Ordinal	Spearman Correlation	.073	.080	.948	.344[c]
N of Valid Cases		168			

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Based on normal approximation.

As shown in Figure 4.10, the visual representation confirms a homogenous awareness profile across the contractual triangle. In the context of the Malaysian Civil & Structural (C&S) industry, this finding is highly significant. It demonstrates that AI-drone awareness has permeated all levels of the industry, from strategic developers to operational sub-contractors, in a uniform manner. According to Rogers (2003), this homogeneity indicates that the industry has collectively moved past the "knowledge stage" of the innovation-decision process, providing a strong justification for a unified national AI-drone governance ecosystem.

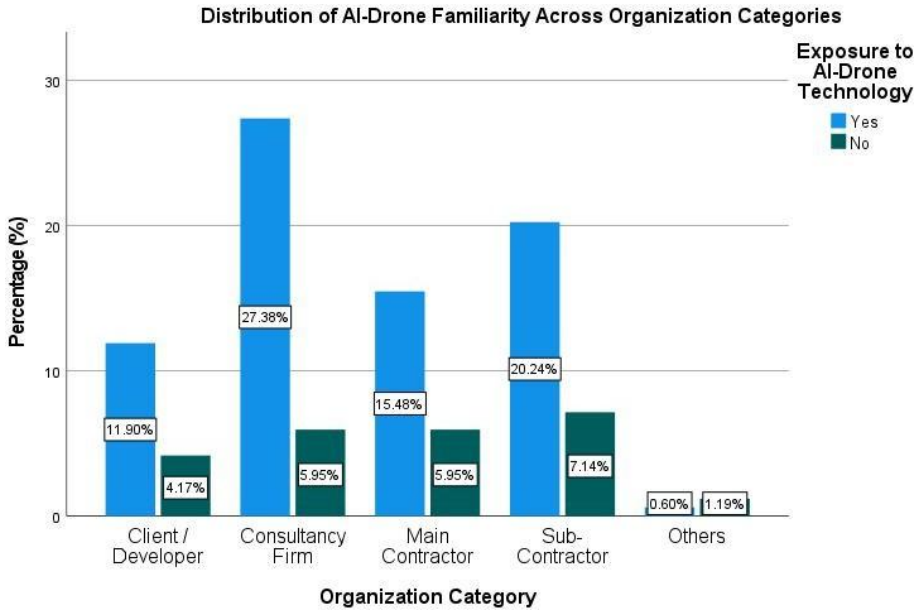


Figure 4.10: Distribution of AI-Drone Familiarity Across Organization Categories

The statistical homogeneity observed in this section is further reinforced by the Symmetric Measures in Table 4.18. The inclusion of Cramer's V (0.164) and Pearson's R (0.078) serves as a diagnostic check to verify that no "exposure bias" exists within the sample. Because the p-value (0.339) is greater than 0.05, these measures confirm that the association between an organization's role and its familiarity with drones is negligible. For the researcher, this is a vital finding; it mathematically proves that the "Awareness Gap" in Malaysia has been bridged.

However, this uniform familiarity reveals a significant Governance Paradox. If developers, consultants, and contractors all possess an identical baseline of awareness, the low rate of actual site-level adoption in Malaysia cannot be blamed on a lack of information. Instead, this patterns suggests that the Governance Gap has shifted from a "Knowledge Gap" to a "Structural and Financial Gap." While the National AI Office (NAIO) and CIDB have successfully socialized the concept of AI-drones, the non-significant Chi-Square result implies that the current bottleneck is rooted in systemic issues such as permit bureaucracy or high capital costs rather than sectoral ignorance.

Consequently, these SPSS diagnostics justify the structural focus of the following sections. By proving that the industry starts from a level playing field of awareness, the study can now focus on the Institutional Readiness and Regulatory Support variables to identify exactly where the "awareness-to-action" pipeline is breaking down within the Malaysian built environment.

4.3.2 Level of Awareness regarding AI-Drone Technology

While general exposure is uniform across the industry, the depth of technical knowledge regarding AI-drone systems exhibits significant sectoral divergence. As detailed in Table 4.19, the majority of respondents across all sectors identify within the Neutral/Average to Somewhat Familiar range. However, a critical distinction emerges in the higher knowledge brackets. Developers and Consultants show a higher propensity for being "Familiar" with the technology (29.6% and 8.9% respectively), whereas the "Not Familiar" sentiment is most pronounced among Sub-Contractors (28.3%) and Main-Contractors (27.8%).

Table 4.19: Level of Self-Rated Knowledge on AI-Drone Technology by Sector

Level of Self-Rated Knowledge on AI-Drone Technology by Sector		
	Category of the organization	Total

			Client / Developer	Consultancy Firm	Main Contractor	Sub-Contractor	Others	
Rate your current knowledge about the AI Drone	Not Familiar	Count	4_a	10_a	10_a	13_a	0_a	37
		%	14.8%	17.9%	27.8%	28.3%	0.0%	22.0%
	Somewhat Familiar	Count	3_a	18_a	8_a	17_a	0_a	46
		%	11.1%	32.1%	22.2%	37.0%	0.0%	27.4%
	Neutral / Average	Count	$10_{a, b}$	$20_{a, b}$	6_b	8_b	3_a	47
		%	37.0%	35.7%	16.7%	17.4%	100.0%	28.0%
	Familiar	Count	8_a	5_a	10_a	7_a	0_a	30
		%	29.6%	8.9%	27.8%	15.2%	0.0%	17.9%
	Very Familiar	Count	2_a	3_a	2_a	1_a	0_a	8
		%	7.4%	5.4%	5.6%	2.2%	0.0%	4.8%
Total		Count	27	56	36	46	3	168
		%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Each subscript letter denotes a subset of Category of the organization categories whose column proportions do not differ significantly from each other at the .05 level.

Table 4.20: Chi-Square Test: Organization Type vs. Knowledge Depth

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	28.491[a]	16	.028
Likelihood Ratio	29.467	16	.021
Linear-by-Linear Association	4.417	1	.036
N of Valid Cases	168		

a. 10 cells (40.0%) have expected count less than 5. The minimum expected count is .14.

Table 4.21: Association Strength for Stakeholder Knowledge Levels

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Nominal by Nominal	Phi	.412			.028
	Cramer's V	.206			.028
Interval by Interval	Pearson's R	-.163	.073	-2.124	.035[c]
Ordinal by Ordinal	Spearman Correlation	-.168	.074	-2.193	.030[c]
N of Valid Cases		168			

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Based on normal approximation.

A Pearson Chi-Square test was conducted to evaluate the relationship between organization type and knowledge level. Unlike the general familiarity assessment, the results here show a statistically significant association (χ^2=28.491,p=0.028). This is further validated by a Cramer's V value of 0.206, indicating a moderate association. Most importantly, the Z-test for column proportions reveals a significant shift: for the "Neutral/Average" knowledge level, Developers and Consultants share the subscript "a, b", while Contractors are labeled with "b". This suggests that Developers and Consultants possess a statistically distinct and higher baseline of average knowledge compared to their contracting counterparts.

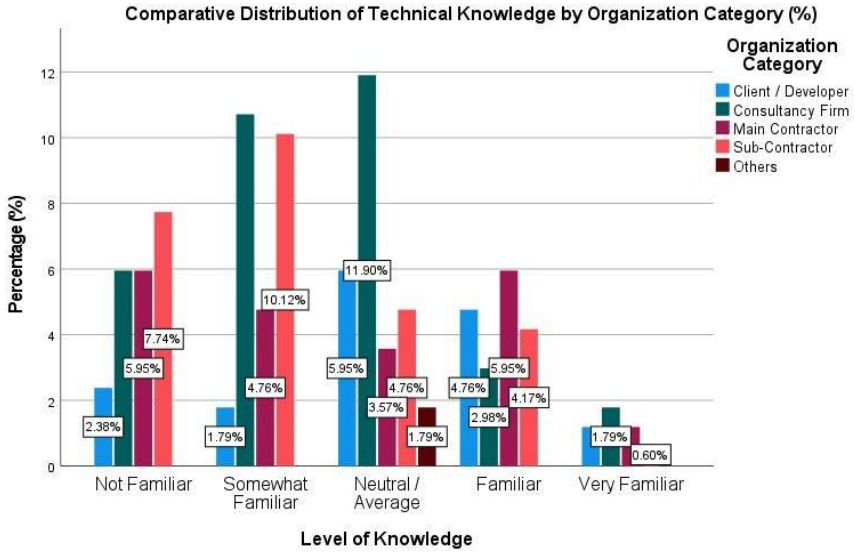


Figure 4.11: Comparative Distribution of Technical Knowledge by Organization Category (%)

As visually demonstrated in Figure 4.11, the "knowledge gap" is evident. The Consultancy and Developer sectors represent a more informed "front-end" of the construction supply chain, likely due to their roles in strategic planning and design. Conversely, the operational "back-end" the contractors report lower familiarity, which may stem from a lack of hands-on technical training or high initial costs as identified in Section 4.3.3. This gap is a vital consideration for the proposed governance framework; it implies that for AI-drone safety protocols to be successful, the framework must include targeted educational modules specifically designed to bridge the technical literacy gap for contractors and site supervisors (Saunders et al., 2023).

The statistical significance observed in the Pearson Chi-Square test (χ^2=28.491, p=0.028) marks a critical departure from the general familiarity reported in the previous section. While the industry is broadly aware of AI-drones, the depth of technical knowledge is not distributed

equally. The Cramer's V value of 0.206 indicates a moderate association, which provides the statistical "benefit" of identifying that professional role is a valid predictor of technical literacy. Specifically, the negative correlation shown in Spearman's Rho (-.168) suggests that as we move from the strategic "front-end" (Developers/Consultants) to the operational "back-end" (Contractors), the depth of knowledge tends to decrease.

This creates what can be defined as a Technical Literacy Gap within the Malaysian construction landscape. The shared Z-test subscripts ("a, b" for Developers/Consultants vs. "b" for Contractors) prove that this is not a random variation but a structural discrepancy. In the Malaysian context, this pattern indicates that while information regarding AI-drones is high at the strategic and design levels, the actual technical competencies required for site-level implementation have not been successfully transferred to the contracting parties.

Consequently, this Governance Gap suggests that current national digital initiatives may be too "office-centric." For a unified governance ecosystem to be effective, the National AI Office (NAIO) and CIDB must look beyond general awareness campaigns and implement localized Technical Capability Building programs. Without addressing this discrepancy in knowledge depth, the "front-end" of the supply chain will continue to plan for technology that the "back-end" is not yet technically equipped to execute, leading to a breakdown in the safety-data pipeline and high-risk operational errors on-site.

4.3.3 Analysis of Barriers to AI-Drone Adoption

The most critical component of the descriptive analysis is the identification of obstacles preventing full technological integration. As shown in Table 4.22, while High Investment Costs is the primary barrier for the total sample (38.1%), a granular sectoral analysis reveals a stark "conflict of interests" within the construction supply chain. For Sub-Contractors, the financial burden is the overwhelming deterrent (78.3%), whereas Consultancy Firms identify Top Management's lack of perceived benefit as their primary hurdle (69.6%).

Table 4.22: Primary Barriers to AI-Drone Adoption by Organization Category

Primary Barriers to AI-Drone Adoption by Organization Category

	Category of the organization					
	Client / Developer	Consultancy Firm	Main Contractor	Sub-Contractor	Others	Total

What is the PRIMARY (MAIN) barrier preventing your organisation from fully adopting AI-drone technology? (Please select only the SINGLE most significant reason)	High investment costs / Lack of budget	Count	11_{a}	7_{b}	$9_{a, b}$	36_{c}	$1_{a, b, c}$	64
		%	40.7%	12.5%	25.0%	78.3%	33.3%	38.1%
	Unclear government regulations (CAAM/CIDB)	Count	2_{a}	3_{a}	0_{a}	3_{a}	0_{a}	8
		%	7.4%	5.4%	0.0%	6.5%	0.0%	4.8%
	Lack of skilled personnel / pilots	Count	7_{a}	6_{a}	8_{a}	3_{a}	1_{a}	25
		%	25.9%	10.7%	22.2%	6.5%	33.3%	14.9%
	Concerns over data privacy or liability	Count	2_{a}	0_{a}	3_{a}	0_{a}	0_{a}	5
		%	7.4%	0.0%	8.3%	0.0%	0.0%	3.0%
	Technical limitations (e.g., battery life, software compatibility)	Count	$0_{a, b}$	0_{b}	5_{a}	$2_{a, b}$	$0_{a, b}$	7
		%	0.0%	0.0%	13.9%	4.3%	0.0%	4.2%
	Top management does not see the benefit	Count	4_{a}	39_{b}	4_{a}	2_{a}	$0_{a, b}$	49
		%	14.8%	69.6%	11.1%	4.3%	0.0%	29.2%
	Not Applicable (We have already fully adopted AI-drones)	Count	$1_{a, b, c, d}$	1_{d}	7_{c}	$0_{b, d}$	$1_{a, c}$	10
		%	3.7%	1.8%	19.4%	0.0%	33.3%	6.0%
Total		Count	27	56	36	46	3	168
		%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Each subscript letter denotes a subset of Category of the organization categories whose column proportions do not differ significantly from each other at the .05 level.

Table 4.23: Chi-Square Test: Association Between Stakeholder Type and Adoption Barriers

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	127.907[a]	24	.000
Likelihood Ratio	126.966	24	.000

Linear-by-Linear Association	15.796	1	.000
N of Valid Cases	168		

a. 24 cells (68.6%) have expected count less than 5. The minimum expected count is .09.

Table 4.24: Symmetric Measures and Effect Size for Adoption Barriers

Symmetric Measures

		Value	Asymptotic Standard Error[a]	Approximate T[b]	Approximate Significance
Nominal by Nominal	Phi	.873			.000
	Cramer's V	.436			.000
Interval by Interval	Pearson's R	-.308	.072	-4.164	.000[c]
Ordinal by Ordinal	Spearman Correlation	-.327	.077	-4.454	.000[c]
N of Valid Cases		168			

a. Not assuming the null hypothesis.
b. Using the asymptotic standard error assuming the null hypothesis.
c. Based on normal approximation.

A Pearson Chi-Square test confirms that these sectoral differences are highly significant (χ^2 =127.907,p<.001). The Cramer's V value of 0.436 represents a strong association, indicating that an organization's role in the contractual triangle is a powerful predictor of the barriers it will face. The Z-test for column proportions further illuminates this disparity; Sub-Contractors are categorized with subscript "c" for investment costs significantly higher than any other group while Consultants are categorized with subscript "b" for management buy-in issues.

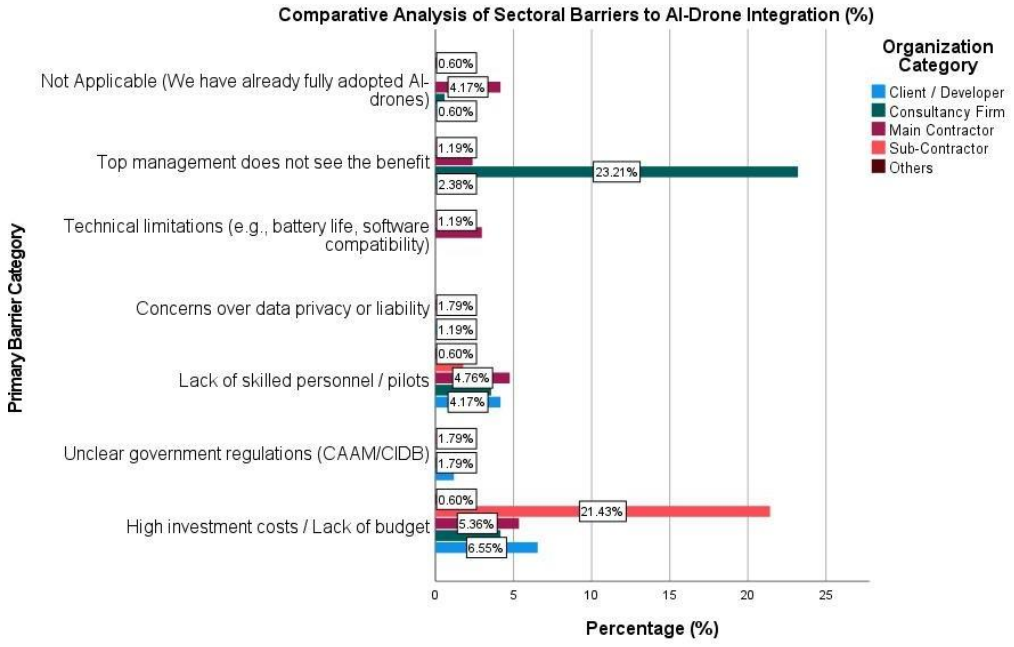


Figure 4.12: Comparative Analysis of Sectoral Barriers to AI-Drone Integration (%)

As visually mapped in Figure 4.12, the Malaysian construction industry faces a "dual-layered" resistance. The "design and planning" side (Consultants) struggles with administrative and strategic buy-in, while the "execution" side (Sub-Contractors) is paralyzed by capital requirements. This finding is a cornerstone for the proposed governance ecosystem. It suggests that a "one-size-fits-all" policy will fail; instead, the framework must incorporate financial incentives or subsidy models for contractors, alongside ROI-driven safety evidence to convince the top management of consultancy and developer firms. Without addressing these distinct sectoral pressures, the adoption of AI-drones for safety management will likely remain stagnant despite high general awareness (Saunders et al., 2023).

The statistical depth provided by the Pearson Chi-Square test (χ^2=127.907,p<.001) and the Cramer's V value of 0.436 serves as the empirical evidence for a divided industry. In this context, the Cramer's V value is particularly beneficial as it indicates a strong effect size, proving that the "Industry Sector" is not merely a demographic label but the primary driver of adoption resistance. Furthermore, the negative Pearson's R (−0.308) suggests that as the operational burden increases down the supply chain, the barriers shift from abstract strategic concerns to concrete financial obstacles.

This data exposes a profound Economic and Strategic Governance Gap within the Malaysian built environment. The distinct Z-test subscripts ("c" for Sub-Contractors on costs versus "b" for Consultants on management buy-in) confirm a statistically significant "Conflict of Interests." While the National AI Office (NAIO) and CIDB have promoted the technical benefits of drones, the governance ecosystem has failed to account for the Resource Gap faced by smaller firms. In Malaysia, the high capital requirement (78.3%) for Sub-Contractors creates a "Digital Glass Ceiling" where only large G7 firms can participate in the digital safety revolution.

Consequently, the findings in this section justify the inclusion of Institutional Readiness as a core latent variable in the subsequent structural model. They demonstrate that for AI-drone safety monitoring to be successful in Malaysia, the governance framework cannot be limited to regulatory permits from CAAM. Instead, it must be a Multi-Tiered Governance Strategy that provides financial "Safety Nets" (subsidies or tax rebates) for the operational executors, while providing standardized "Benefit-Evidence" (ROI case studies) to satisfy the strategic gatekeepers in consultancy and developer firms. This statistical confirmation ensures that the proposed

Governance Ecosystem Model (GEM) is grounded in the actual sectoral friction points identified within the Malaysian construction supply chain.

4.3.4 Descriptive Analysis: Regulatory Support (IV1)

Section 4.3.4 presents a comprehensive descriptive analysis of Regulatory Support (IV1), which serves as a primary independent variable in this study. In the context of the Malaysian construction industry, regulatory support refers to the extent to which government policies, agency coordination, and legal frameworks facilitate or hinder the adoption of AI-drone technology for safety management.

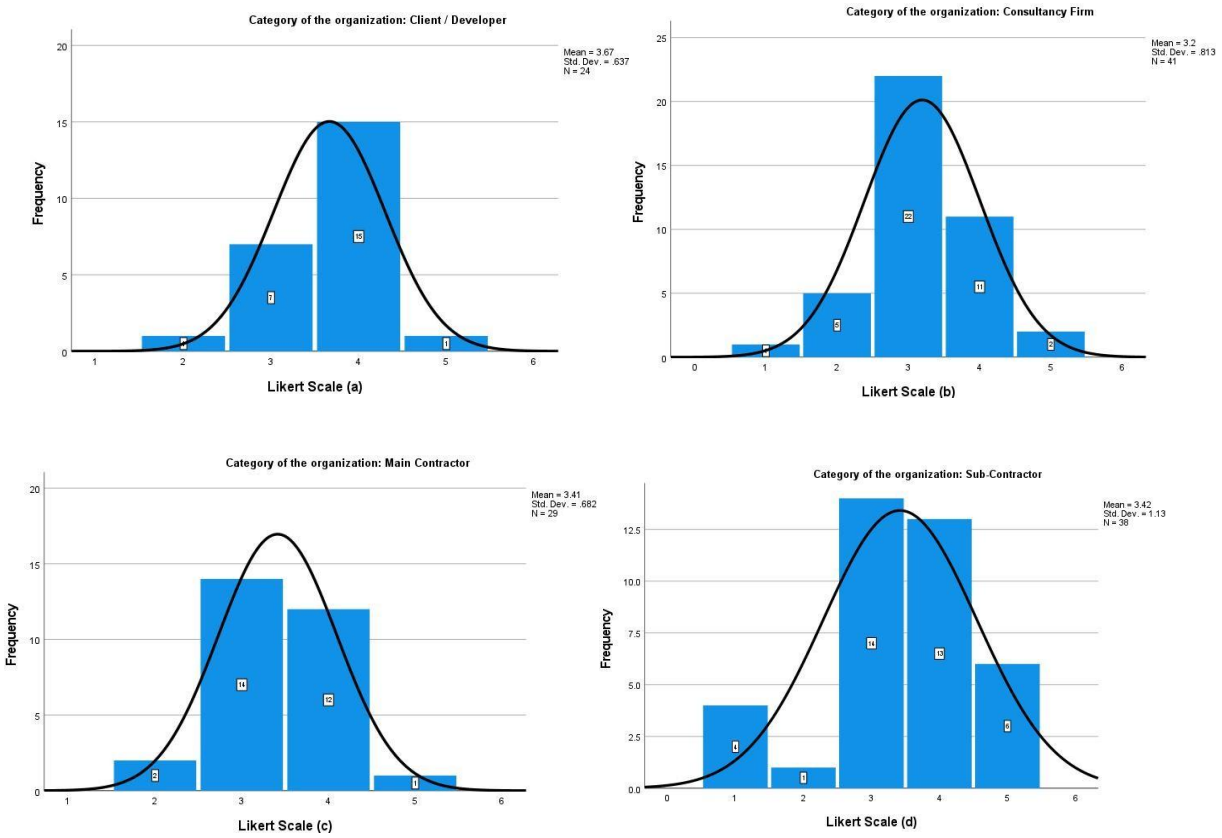
This construct is measured through seven distinct items (RS1 to RS7), ranging from general policy awareness to specific operational procedures like flight permit acquisition and liability definitions. To ensure a rigorous evaluation, each item is analyzed through a comparative lens, breaking down the responses of Developers, Consultants, Main-Contractors, Sub-Contractors, and Other stakeholders.

By examining the Mean (̄) and Standard Deviation (SD) for each group, this analysis identifies where "regulatory friction" exists within the supply chain. Furthermore, the inclusion of Skewness and Kurtosis values for each item ensures that the data meets the assumptions of normality required for the subsequent structural equation modeling (SEM) in SmartPLS. The following sub-sections provide a detailed deep-dive into each individual regulatory component.

4.3.4.1 Descriptive Analysis RS1: Existing government policies provide clear guidance for drone use in construction safety.

he primary objective of this sub-section is to evaluate the industry’s perception regarding the transparency and practical utility of national-level policy frameworks, serving as a foundational step in determining the readiness of the Malaysian construction sector for AI-drone integration. In the context of high-risk Civil and Structural (C&S) engineering environments, the clarity of regulatory guidance is not merely an administrative preference but a fundamental prerequisite for the safe, systematic, and legally compliant adoption of autonomous technologies. The visual empirical evidence provided by the frequency histograms and accompanying normal distribution curves, categorized systematically from Figures 4.13(a) through 4.13(f), reveals a significant and statistically relevant variance in the depth of consensus across the various stakeholder landscapes.

Figure 4.13(a), representing the Client/Developer sector, exhibits a distinct negative skew, where the concentration of responses at the upper tier of the Likert scale (Agree and Strongly Agree) suggests that project owners generally perceive existing national policies as sufficiently clear for high-level safety management and strategic procurement. In stark contrast, Figure 4.13(b) demonstrates that the distribution for technical consultancy firms is markedly different, peaking heavily at the neutral position; this visual trend suggests a state of professional hesitancy where the experts responsible for safety design and professional certification do not yet feel the guidance is granular enough to commit to a definitive positive stance. Furthermore, the sub-contractor profile in Figure 4.13(d) presents a more platykurtic or flat distribution, which, when coupled with the group's high standard deviation of 1.130, reflects a lack of unified perception at the operational tier, where some firms appear well-informed while a significant portion remains in a state of confusion or disagreement across the full spectrum from "Strongly Disagree" to "Strongly Agree." Finally, the aggregate industry profile in Figure 4.13(f) provides a holistic view of the overall agreement bell curve, which serves as the visual and statistical justification for the normality assumptions required for the subsequent parametric analysis and path modeling in this research.



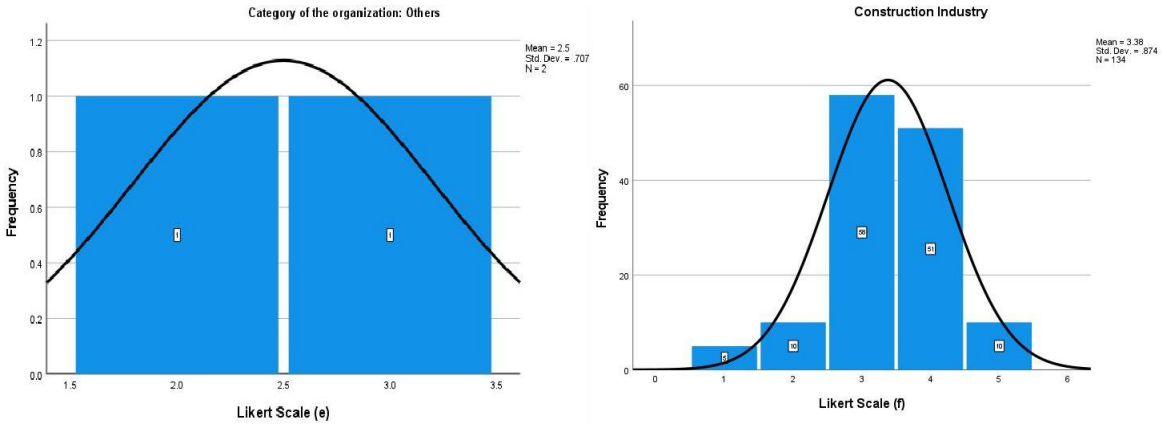


Figure 4.13: Frequency Distribution with Normal Curves for RS1: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data presented in Table 4.25 offers a rigorous quantitative snapshot of sectoral alignment, ranking each organization category by its mean agreement score to identify exactly where regulatory support is perceived most strongly and where it falters. The aggregate industry mean of 3.38 indicates a moderate but non-definitive level of agreement regarding policy clarity, suggesting that while a framework exists, it has not yet achieved "clear" status across the board. A critical sectoral divergence is identified in the Client/Developer group, which holds the highest perception of clarity with a mean of 3.67 and a tight standard deviation of 0.637, indicating a strong consensus. As noted by Sekaran and Bougie (2016), high-level stakeholders often have prioritized access to strategic governmental roadmaps, such as the Construction 4.0 Strategic Plan, which logically explains this positive bias. In stark contrast, the Consultancy Firm sector reported a notably lower mean of 3.20, which is a finding of high importance for C&S engineering researchers. Because consultants act as the primary gatekeepers of technical compliance and risk management, their lower agreement level implies that current policies may provide a broad "strategic vision" but lack the "technical precision" required for consultants to manage professional liability and site safety protocols with total confidence. Additionally, the sub-contractor group's statistics highlight a polarized operational environment, where the wide range between the minimum score of 1 (Strongly Disagree) and maximum score of 5 (Strongly Agree) indicates that operational clarity is highly dependent on individual firm capacity rather than a standardized national dissemination effort.

Table 4.25: Comparative Statistical Profile of Perception regarding National Policy Clarity (RS1)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.67	24	.637	Disagree (D)	Strongly Agree (SA)	.832	-.693
Consultancy Firm	3.20	41	.813	Strongly Disagree (SD)	Strongly Agree (SA)	.703	-.087
Main Contractor	3.41	29	.682	Disagree (D)	Strongly Agree (SA)	-.052	-.028
Sub-Contractor	3.42	38	1.130	Strongly Disagree (SD)	Strongly Agree (SA)	.261	-.682
Others	2.50	2	.707	Disagree (D)	Neutral (N)	.	.
Total	3.38	134	.874	Strongly Disagree (SD)	Strongly Agree (SA)	.631	-.485

A pivotal and highly informative component of this research involves the empirical analysis of informational gaps, specifically identified through the treatment of non-evaluative "Unsure / No Knowledge" responses which were methodologically segregated to preserve the integrity of the mean calculations. This missing data represents a significant metric of "Informational Void" within the industry, revealing a systemic weakness where consultancy firms recorded the highest volume of uncertainty, with 15 respondents representing a substantial 26.8% of that specific group being unable to evaluate policy clarity. This is followed by significant gaps in the main contractor sector at 19.4% and the sub-contractor sector at 17.4%, as detailed in the combined frequency analysis of Table 4.26. According to the established research principles of Sekaran and Bougie (2016), such high frequencies of non-evaluative responses among technical experts often point to a fundamental accessibility barrier rather than a simple difference of opinion. In the context of the Malaysian construction supply chain, the fact that over a quarter of technical consultants remain unsure suggests that while the government has formulated policies, these frameworks have failed to effectively permeate the advisory and technical tiers. Despite these sectoral disparities and the significant volume of missing data (20.2% overall), the total industry skewness of -0.485 and kurtosis of 0.631 remain well within the standard academic threshold of ± 2.0. This confirms that the valid data for RS1 is normally distributed and possesses the requisite psychometric properties for inclusion in the subsequent path analysis, ultimately suggesting that while the industry is structurally ready for AI-drone adoption, the current primary inhibitor is a lack of operational policy clarity among the technical stakeholders responsible for site-level safety management.

Table 4.26: Empirical Breakdown of Informational Gaps and "Unsure" Frequencies for RS1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	5	3.0	3.7	3.7
	Disagree (D)	10	6.0	7.5	11.2
	Neutral (N)	58	34.5	43.3	54.5
	Agree (A)	51	30.4	38.1	92.5
	Strongly Agree (SA)	10	6.0	7.5	100.0
	Total	134	79.8	100.0	
Missing	Unsure / No Knowledge	34	20.2		
Total		168	100.0		

4.3.4.2 Descriptive Analysis RS2: The Civil Aviation Authority of Malaysia (CAAM) provides sufficient regulatory support for safe drone operations.

The secondary objective of this sub-section is to evaluate the industry's perception regarding the institutional efficacy of the Civil Aviation Authority of Malaysia (CAAM) as the primary regulatory body governing drone operations. In the high-precision domain of Civil and Structural (C&S) engineering, institutional support is a fundamental prerequisite for mitigating operational risks and ensuring that AI-drone integration adheres to national airspace safety standards. The visual empirical evidence provided by the frequency histograms and accompanying normal distribution curves, systematically categorized from Figures 4.14(a) through 4.14(f), reveals a significant variance in how different stakeholder tiers perceive the sufficiency of CAAM's support. Figure 4.14(a), representing the Client/Developer sector, continues to demonstrate a negative skew with a mean of 3.64, indicating that strategic-level stakeholders generally perceive the institutional framework as supportive. In stark contrast, Figure 4.14(d) for Sub-Contractors displays a much flatter, more platykurtic distribution, which is numerically supported by the group's high standard deviation of 1.282 and a negative kurtosis of -1.045. This visual and statistical dispersion suggests that at the operational tier, the perception of CAAM's support is highly fragmented, with responses spanning the entire spectrum from "Strongly Disagree" to "Strongly Agree." The aggregate industry profile in Figure 4.14(f) provides a holistic view of the overall agreement bell curve, which, despite a slight negative skewness of -0.333, confirms that the data for RS2 maintains the necessary normality for parametric structural equation modeling.

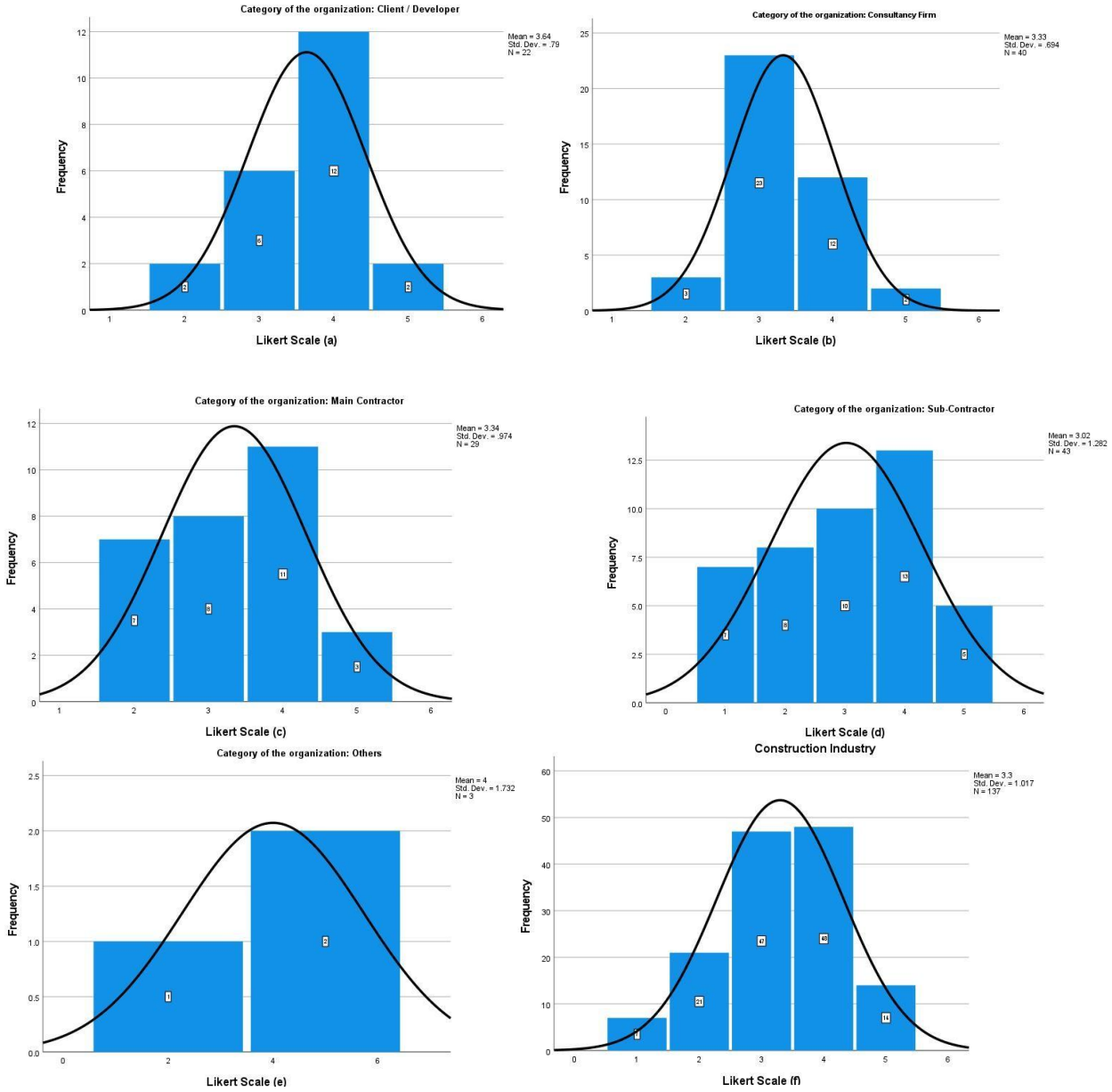


Figure 4.14: Frequency Distribution with Normal Curves for RS2: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data presented in Table 4.27 offers a rigorous quantitative snapshot of sectoral alignment, ranking each organization category by its mean agreement score. The aggregate industry mean for RS2 is 3.30, with a standard deviation of 1.017, suggesting that while the general sentiment leans toward agreement, there is a significant level of uncertainty and variance regarding the sufficiency of regulatory support. The Client/Developer group recorded the highest mean agreement among the primary stakeholders at 3.64, reflecting a consensus that CAAM's current measures are adequate for project-level oversight. However, a notable decrease in agreement is observed within the Consultancy Firm sector (3.33) and the

Main Contractor sector (3.34). This outcome aligns with findings by Mohamed et al. (2023), who noted that while Malaysian regulatory frameworks are evolving, the "technical gap" between central policy and site-specific engineering requirements remains a barrier. For C&S engineering researchers, the most critical finding is located in the Sub-Contractor group, which reported the lowest mean of 3.02. This nearly neutral score, combined with the highest observed dispersion (SD=1.282), indicates that the operational stakeholders who are most likely to pilot and maintain drone hardware feel the least supported by the central authority. This disparity suggests that CAAM's regulatory reach may be effectively felt at the strategic and management levels but remains perceived as insufficient or inaccessible by the operational sub-contracting tier, echoing the "fragmented adoption" theory in Construction 4.0 literature (CIDB, 2020).

Table 4.27: Comparative Statistical Profile of Perception regarding CAAM Regulatory Support (RS2)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.64	22	.790	Disagree (D)	Strongly Agree (SA)	.182	-.496
Consultancy Firm	3.33	40	.694	Disagree (D)	Strongly Agree (SA)	.334	.430
Main Contractor	3.34	29	.974	Disagree (D)	Strongly Agree (SA)	-1.010	-.027
Sub-Contractor	3.02	43	1.282	Strongly Disagree (SD)	Strongly Agree (SA)	-1.045	-.188
Others	4.00	3	1.732	Disagree (D)	Strongly Agree (SA)	.	-1.732
Total	3.30	137	1.017	Strongly Disagree (SD)	Strongly Agree (SA)	-.307	-.333

A pivotal and highly informative component of this research involves the empirical analysis of informational gaps, specifically identified through the treatment of non-evaluative "Unsure / No Knowledge" responses which were methodologically segregated to preserve the integrity of the mean calculations. As detailed in Table 4.26, this missing data signifies a critical "Institutional Awareness Gap" within the industry, revealing that 31 respondents, or 18.5% of the total sample size (N=168), were unable to evaluate the sufficiency of CAAM's support. This represents a significant portion of the professional population that lacks enough interaction with or information from the aviation authority to form a definitive judgment. According to the established research principles of Sekaran and Bougie (2016), such frequencies of

non-evaluative responses in a technical sample often point to a fundamental accessibility barrier rather than a simple difference of opinion.

In the context of the Malaysian construction industry, the fact that nearly one-fifth of the respondents are unsure of CAAM's role suggests that institutional support mechanisms have not been successfully communicated to the technical tiers of the supply chain. This lack of awareness is a known bottleneck in the integration of AI and IoT in construction; as highlighted in the Construction 4.0 Strategic Plan (2021-2025), the success of technological pillars depends heavily on the "regulatory readiness" of the stakeholders. Despite these sectoral disparities and the significant volume of missing data, the overall industry skewness of -0.333 and kurtosis of -0.307 are well within the standard academic threshold of ±2.0. This confirms that the valid data for RS2 is normally distributed and possesses the requisite psychometric properties for inclusion in the subsequent path analysis, ultimately suggesting that while CAAM's support is present, its perceived efficacy is currently inhibited by a lack of operational awareness and consistency among technical stakeholders.

Table 4.28: Overall Frequency and Percentage Breakdown of "Unsure" Responses for RS2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	7	4.2	5.1	5.1
	Disagree (D)	21	12.5	15.3	20.4
	Neutral (N)	47	28.0	34.3	54.7
	Agree (A)	48	28.6	35.0	89.8
	Strongly Agree (SA)	14	8.3	10.2	100.0
	Total	137	81.5	100.0	
Missing	Unsure / No Knowledge	31	18.5		
Total		168	100.0		

4.3.4.3 Descriptive Analysis RS3: Coordination among agencies (CAAM, CIDB, DOSH) is effective and minimizes regulatory confusion.

The third objective of this sub-section is to evaluate the industry's perception of inter-agency synergy, specifically focusing on the coordination between the Civil Aviation Authority of Malaysia (CAAM), the Construction Industry Development Board (CIDB), and the Department of Occupational Safety and Health (DOSH). In Civil and Structural (C&S) engineering projects, the integration of AI-drones necessitates a multi-disciplinary regulatory approach where aviation safety, construction standards, and workplace health protocols must overlap seamlessly. The

visual empirical evidence provided by the frequency histograms and accompanying normal distribution curves, systematically categorized from Figures 4.15(a) through 4.15(f), highlights a significant and concerning variance in the perception of institutional coordination. Notably, the distributions for most stakeholder groups are characterized by a lack of strong positive skewness, with several profiles exhibiting a platykurtic shape that suggests a highly fragmented and inconsistent experience across the industry. The aggregate industry profile in Figure 4.15(f) demonstrates a broader base than previous items, which, despite maintaining a skewness of -0.175 and kurtosis of -0.475 within the acceptable ±2.0 range, reflects a substantial lack of consensus regarding the effectiveness of agency coordination.

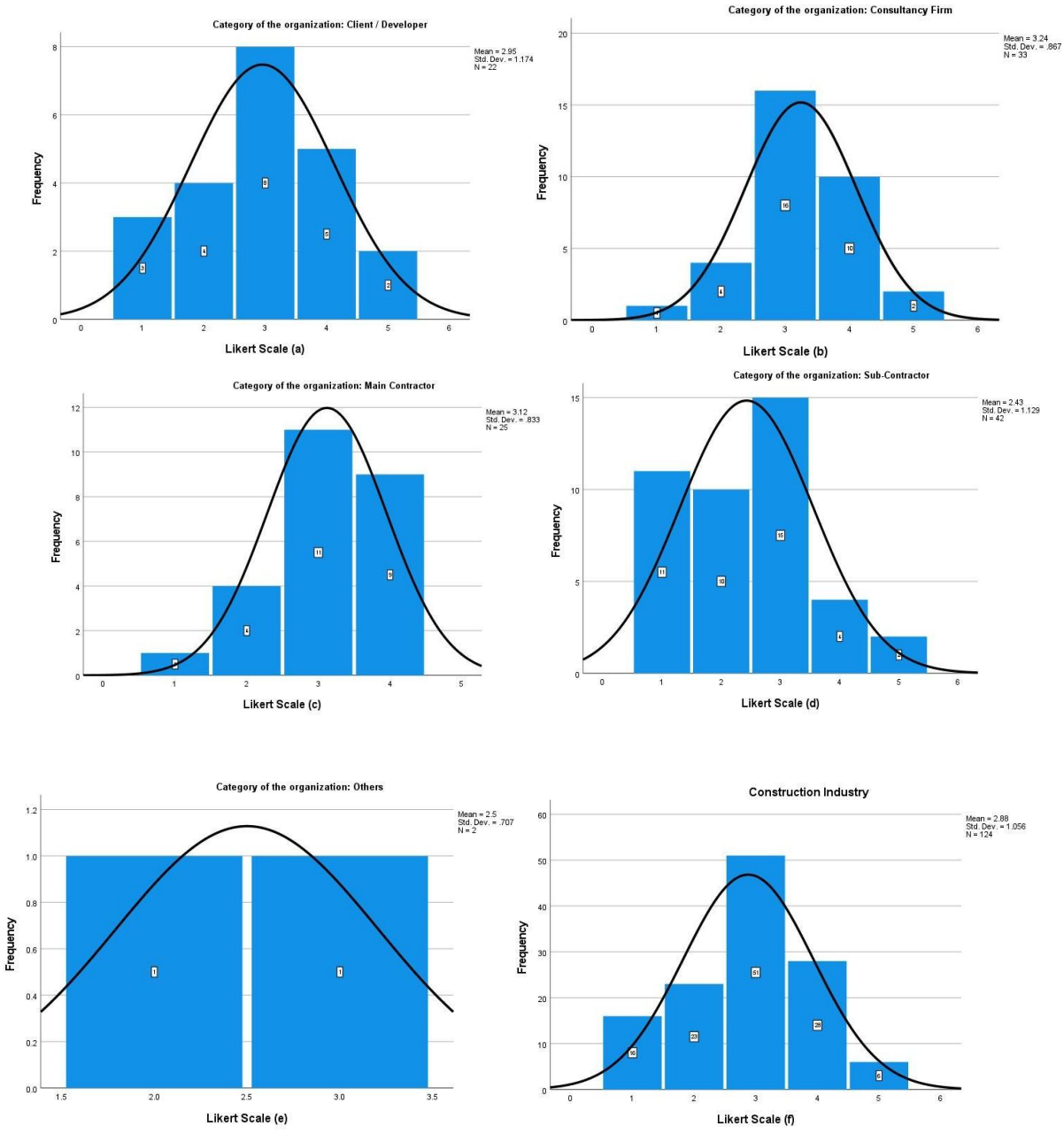


Figure 4.15: Frequency Distribution with Normal Curves for RS3: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data presented in Table 4.29 offers a rigorous quantitative profile of sectoral alignment, revealing that RS3 holds one of the lowest agreement ratings within the regulatory support construct. The aggregate industry mean for RS3 is 2.88, which falls below the neutral threshold of 3.00, suggesting that the industry generally perceives inter-agency coordination as ineffective or confusing. A critical finding is observed in the Sub-Contractor group, which reported the lowest mean agreement of 2.43 with a high standard deviation of 1.129. This indicates that the operational tier, which must comply with all three agencies simultaneously on-site, feels the highest level of regulatory friction. This result is visually supported by Figure 4.15(d), which shows a significant concentration of responses in the "Strongly Disagree" and "Disagree" categories. The Client/Developer group also reported a sub-neutral mean of 2.95, while Consultancy Firms (3.24) and Main Contractors (3.12) remained only slightly above neutral. This disparity aligns with the findings of Mohamed et al. (2023), who identified that "bureaucratic silos" in the Malaysian public sector often lead to overlapping or conflicting requirements for emerging technologies. For C&S engineering management, this data implies that while individual agencies may have clear policies, the lack of a "unified window" for drone safety compliance creates a significant barrier to efficient technological adoption.

Table 4.29: Comparative Statistical Profile of Perception regarding Inter-Agency Coordination (RS3)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	2.95	22	1.174	Strongly Disagree (SD)	Strongly Agree (SA)	-.544	-.099
Consultancy Firm	3.24	33	.867	Strongly Disagree (SD)	Strongly Agree (SA)	.515	-.202
Main Contractor	3.12	25	.833	Strongly Disagree (SD)	Agree (A)	.136	-.709
Sub-Contractor	2.43	42	1.129	Strongly Disagree (SD)	Strongly Agree (SA)	-.462	.346
Others	2.50	2	.707	Disagree (D)	Neutral (N)	.	.
Total	2.88	124	1.056	Strongly Disagree (SD)	Strongly Agree (SA)	-.475	-.175

A pivotal and highly informative component of this research is the empirical analysis of informational gaps, identified through the non-evaluative "Unsure / No Knowledge" responses for RS3. As detailed in Table 4.30, this item recorded the highest volume of missing data within the Regulatory Support construct, with 44 respondents, or 26.2% of the total sample (N=168), being unable to evaluate the coordination between CAAM, CIDB, and DOSH. This represents a critical "Information Void" where more than a quarter of the professional population is unaware of how these agencies interact regarding drone safety. According to the research principles of Sekaran and Bougie (2016), such high frequencies of uncertainty in a technical sample are indicative of an "opaque regulatory environment" where institutional roles are poorly defined or communicated.

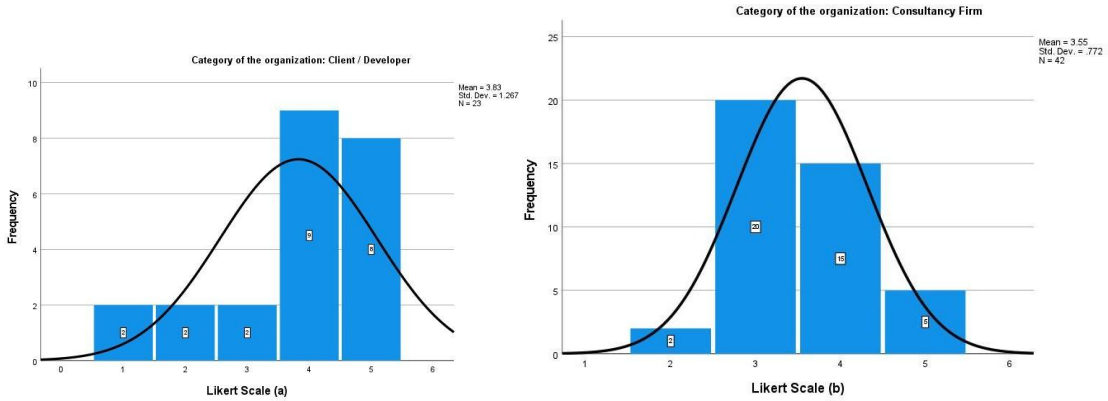
The fact that 26.2% of the industry is unsure about agency coordination, coupled with a sub-neutral mean of 2.88, suggests a serious systemic bottleneck in the Construction 4.0 Strategic Plan (2021-2025). If the technical advisory and operational tiers cannot discern clear coordination between regulators, the resulting "regulatory confusion" likely leads to increased risk aversion and slower AI-drone implementation. This is particularly evident in Figure 4.15(f), where the industry-wide distribution shows that over 30% of valid respondents chose the "Neutral" position, further indicating a lack of conviction in agency synergy. Despite the significant missing data and sectoral disparities, the overall industry skewness and kurtosis remain within the standard academic threshold of ±2.0, confirming that the valid data for RS3 is normally distributed and robust for the subsequent path analysis. This concludes that enhancing inter-agency synergy is a mandatory step for improving the regulatory readiness of the Malaysian construction industry.

Table 4.30: Overall Frequency and Percentage Breakdown of "Unsure" Responses for RS3

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	16	9.5	12.9	12.9
	Disagree (D)	23	13.7	18.5	31.5
	Neutral (N)	51	30.4	41.1	72.6
	Agree (A)	28	16.7	22.6	95.2
	Strongly Agree (SA)	6	3.6	4.8	100.0
	Total	124	73.8	100.0	
Missing	Unsure / No Knowledge	44	26.2		
Total		168	100.0		

4.3.4.4 Descriptive Analysis RS4: The current legal framework encourages technological innovation without compromising safety standards.

The fourth objective of this sub-section is to evaluate the industry's perception regarding the equilibrium between regulatory oversight and technological advancement. In the Civil and Structural (C&S) engineering sector, a "conducive" legal framework is defined by its ability to provide a sandbox for innovation such as AI-driven structural monitoring and drone-based site inspections while maintaining the zero-tolerance safety standards inherent to the profession. The visual empirical evidence provided by the frequency histograms and accompanying normal distribution curves, categorized systematically from Figures 4.16(a) through 4.16(f), illustrates a notable skew toward positive agreement, albeit with varying degrees of consensus across the supply chain. Figure 4.16(a), representing the Client/Developer sector, demonstrates a significant negative skew with a mean of 3.83, suggesting that project owners perceive the legal landscape as a positive driver for modernization. However, the distribution for Sub-Contractors in Figure 4.16(d) remains more centralized around the neutral position, reflecting a more cautious viewpoint from the operational tier that must navigate the practicalities of these laws on-site. The aggregate industry profile in Figure 4.16(f) provides a holistic view of the distribution, which, despite a moderate negative skewness of -0.315 and kurtosis of -0.159, confirms that the data for RS4 maintains the requisite normality for parametric structural equation modeling.



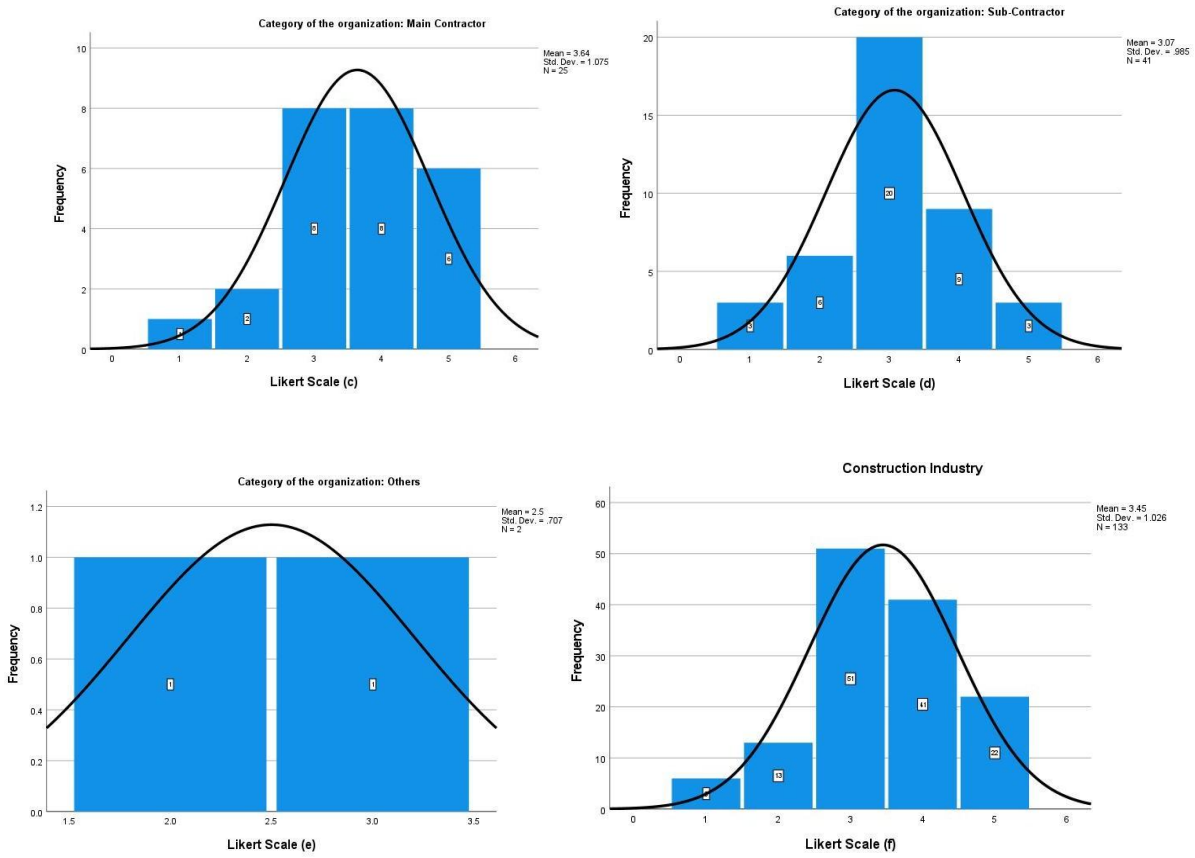


Figure 4.16: Frequency Distribution with Normal Curves for RS4: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data presented in Table 4.31 offers a rigorous quantitative profile of sectoral alignment, ranking each organization category by its mean agreement score to identify the perceived "innovation-safety" balance. The aggregate industry mean of 3.45 indicates a general leaning toward the belief that the current framework supports technological progress. The Client/Developer group recorded the highest mean agreement at 3.83, supported by a standard deviation of 1.267, indicating that while the average is high, there is a broad range of opinions even within this tier, spanning from "Strongly Disagree" to "Strongly Agree." Interestingly, the Main Contractor group followed with a mean of 3.64, while Consultancy Firms reported a mean of 3.55. This outcome suggests that the management and technical tiers generally view the laws as supportive rather than restrictive. However, the Sub-Contractor group reported a lower mean of 3.07, which, combined with the observed dispersion across all categories (SD = 0.985), implies that the "encouragement" of innovation has not yet translated into a uniform experience at the operational level. As noted by Mohamed et al. (2023), the challenge in the Malaysian construction context often lies in the "asymmetry of information,"

where higher-tier stakeholders perceive flexibility in the law that lower-tier contractors find difficult to navigate due to compliance costs and technical barriers.

Table 4.31: Comparative Statistical Profile of Perception regarding Innovation-Safety Equilibrium (RS4)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.83	23	1.267	Strongly Disagree (SD)	Strongly Agree (SA)	.393	-1.113
Consultancy Firm	3.55	42	.772	Disagree (D)	Strongly Agree (SA)	-.352	.335
Main Contractor	3.64	25	1.075	Strongly Disagree (SD)	Strongly Agree (SA)	-.013	-.504
Sub-Contractor	3.07	41	.985	Strongly Disagree (SD)	Strongly Agree (SA)	.203	-.152
Others	2.50	2	.707	Disagree (D)	Neutral (N)	.	.
Total	3.45	133	1.026	Strongly Disagree (SD)	Strongly Agree (SA)	-.159	-.315

A pivotal and highly informative component of this research involves the empirical analysis of informational gaps, specifically identified through the treatment of non-evaluative "Unsure / No Knowledge" responses which were methodologically segregated to preserve the integrity of the mean calculations. As detailed in Table 4.32, a total of 35 respondents, or 20.8% of the total sample (N=168), were unable to evaluate the legal framework's impact on innovation. This missing data represents a significant "Regulatory Literacy Gap" within the professional community. According to the established research principles of Sekaran and Bougie (2016), a high frequency of uncertainty exceeding one-fifth of the sample suggests that the legal provisions regarding new technologies are either not widely known or are too ambiguous for practitioners to judge effectively. For C&S engineering management, this "Unsure" factor is critical; if 20.8% of the industry cannot determine if the law encourages innovation, it suggests that the Construction 4.0 Strategic Plan (2021-2025) faces a communication bottleneck.

The industry-wide frequency distribution further elucidates this point: while 47.3% of valid respondents (Agree and Strongly Agree) perceive the framework as encouraging, a substantial 38.3% remain in the "Neutral" category. This high density of neutral responses, combined with a negative kurtosis of -0.159, indicates a platykurtic distribution where the industry lacks a sharp, unified conviction. Despite these sectoral disparities and the significant volume of missing data,

the overall industry skewness and kurtosis remain well within the standard academic threshold of ± 2.0. This confirms that the valid data for RS4 is normally distributed and robust for the subsequent path analysis, ultimately concluding that while the legal framework is theoretically supportive, its practical impact on encouraging innovation remains obscured by a lack of widespread regulatory awareness and operational clarity.

Table 4.32: Overall Frequency and Percentage Breakdown of "Unsure" Responses for RS4

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	6	3.6	4.5	4.5
	Disagree (D)	13	7.7	9.8	14.3
	Neutral (N)	51	30.4	38.3	52.6
	Agree (A)	41	24.4	30.8	83.5
	Strongly Agree (SA)	22	13.1	16.5	100.0
	Total	133	79.2	100.0	
Missing	Unsure / No Knowledge	35	20.8		
Total		168	100.0		

4.3.4.5 Descriptive Analysis RS5: National policies (e.g., Construction 4.0 Strategic Plan) actively promote the integration of AI-drones in construction projects.

The fifth objective of this sub-section is to evaluate the industry's awareness and perception of specific national strategic frameworks, such as the Construction 4.0 Strategic Plan, in actively catalyzing the integration of AI-drones. In the Civil and Structural (C&S) engineering domain, these high-level policies serve as the primary roadmap for digital transformation, signaling the government's commitment to modernization and providing the structural impetus for firms to invest in autonomous safety technologies. The visual empirical evidence provided by the frequency histograms and accompanying normal distribution curves, systematically presented from Figures 4.17(a) through 4.17(f), reveals the strongest positive skew within the Regulatory Support construct, indicating a high level of strategic recognition across the industry. Figure 4.17(a), representing the Client/Developer sector, demonstrates an aggressive negative skew with the highest mean in the study (4.29), signaling that project owners are deeply aligned with the national digital agenda. In contrast, while Figure 4.17(d) for Sub-Contractors still displays a bell-shaped distribution, its broader base and higher dispersion reflect a more varied experience in how these strategic plans translate into operational incentives. The aggregate industry profile

in Figure 4.17(f) confirms a robust normality, with a skewness of -0.427 and kurtosis of -0.420, providing a statistically sound foundation for the subsequent structural modeling.

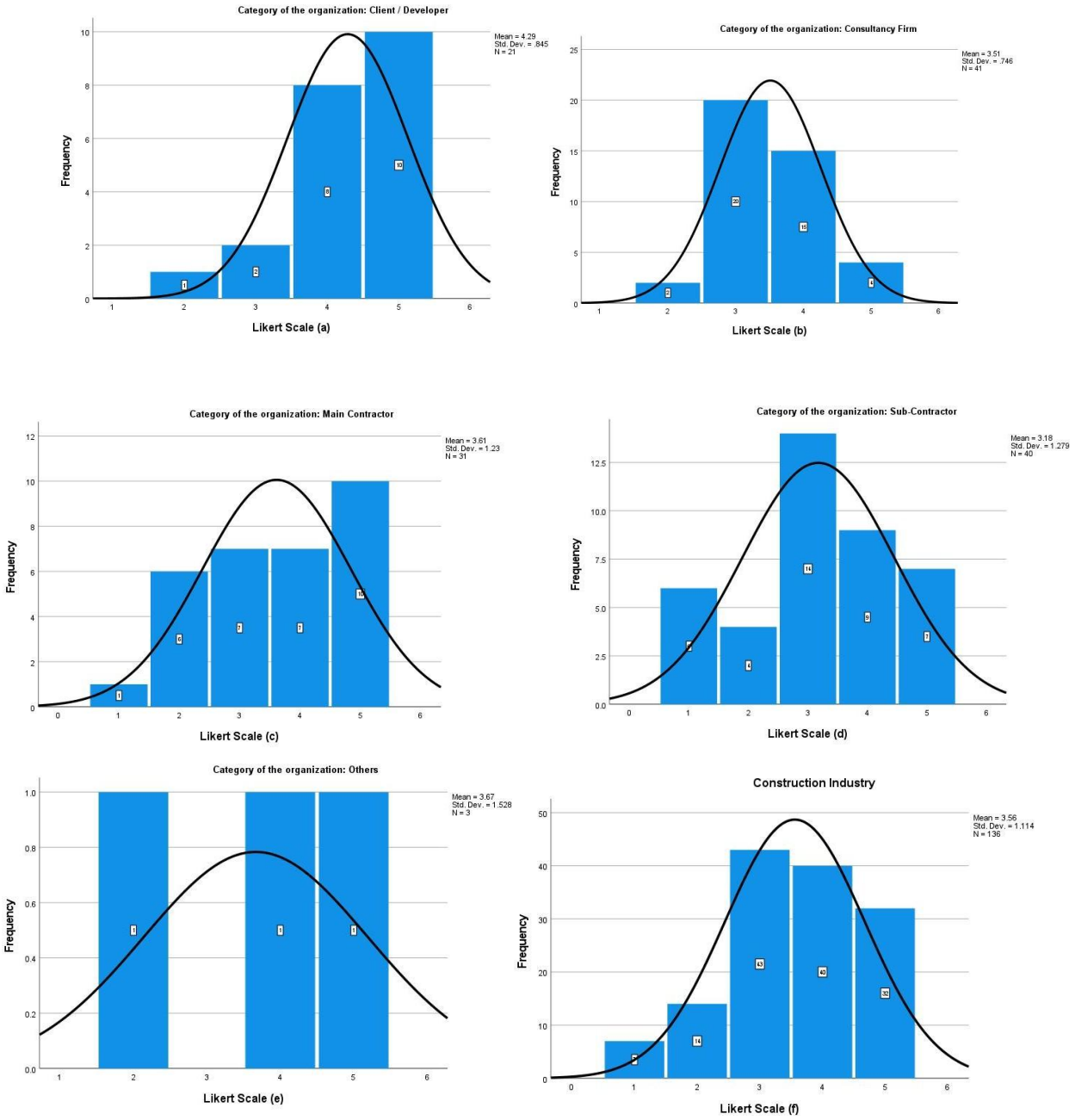


Figure 4.17: Frequency Distribution with Normal Curves for RS5: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.33 provides a rigorous quantitative breakdown of how different supply chain tiers perceive policy promotion. The aggregate industry mean for RS5 is 3.56, with a standard deviation of 1.114, suggesting that the industry generally acknowledges the promotional efforts of the government. The Client/Developer group stands out

with a mean of 4.29, indicating that those at the apex of the construction hierarchy are the most cognizant of the Construction 4.0 objectives. This is a critical observation for C&S engineering management; as project funders, their strong agreement suggests that national policy is effectively influencing procurement mindsets toward AI-adoption. Main Contractors (3.61) and Consultancy Firms (3.51) also maintain positive agreement levels, whereas Sub-Contractors reported a lower mean of 3.17. The high standard deviation for Main Contractors (1.230) and Sub-Contractors (1.279) suggests that while the "vision" of the policy is promoted, the "active promotion" through grants, training, or localized support may not be reaching all operational entities equally, mirroring the "implementation gap" identified in the CIDB (2020) status reports.

Table 4.33: Comparative Statistical Profile of Perception regarding National Policy Promotion (RS5)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	4.29	21	.845	Disagree (D)	Strongly Agree (SA)	1.180	-1.166
Consultancy Firm	3.51	41	.746	Disagree (D)	Strongly Agree (SA)	-.206	.337
Main Contractor	3.61	31	1.230	Strongly Disagree (SD)	Strongly Agree (SA)	-1.091	-.336
Sub-Contractor	3.17	40	1.279	Strongly Disagree (SD)	Strongly Agree (SA)	-.743	-.267
Others	3.67	3	1.528	Disagree (D)	Strongly Agree (SA)	.	-.935
Total	3.56	136	1.114	Strongly Disagree (SD)	Strongly Agree (SA)	-.420	-.427

A pivotal component of this research involves the empirical analysis of informational gaps, specifically identified through the treatment of non-evaluative "Unsure / No Knowledge" responses. As detailed in Table 4.34, 32 respondents, or 19.0% of the total sample (N=168), were unable to evaluate the promotional effectiveness of national policies. This missing data represents a significant "Awareness Threshold" within the industry. According to the research principles of Sekaran and Bougie (2016), when nearly one-fifth of a professional sample is unsure of a core strategic framework, it indicates a bottleneck in policy communication.

In the context of the Malaysian construction landscape, this implies that while the Construction 4.0 Strategic Plan is effectively promoted to project owners and developers, its specific incentives for AI-drone integration remain obscure to nearly 20% of the technical and

operational workforce. The frequency distribution underscores a positive trend, with 52.9% of valid respondents (Agree and Strongly Agree) recognizing policy promotion; however, the 31.6% "Neutral" and 19% "Unsure" segments represent a substantial portion of the industry that remains unconvinced or uninformed. Despite these disparities, the overall skewness and kurtosis are well within the standard academic threshold of ± 2.0, confirming that the valid data for RS5 is normally distributed and robust for path analysis. This concludes that while national policies have successfully established a strategic vision, a more inclusive dissemination strategy is required to ensure that the promotional benefits reach the operational sub-contracting tier where site safety implementation occurs.

Table 4.34: Overall Frequency and Percentage Breakdown of "Unsure" Responses for RS5

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	7	4.2	5.1	5.1
	Disagree (D)	14	8.3	10.3	15.4
	Neutral (N)	43	25.6	31.6	47.1
	Agree (A)	40	23.8	29.4	76.5
	Strongly Agree (SA)	32	19.0	23.5	100.0
	Total	136	81.0	100.0	
Missing	Unsure / No Knowledge	32	19.0		
Total		168	100.0		

4.3.4.6 Descriptive Analysis RS6: The process for obtaining flight permits from authorities is clear and efficient.

The final objective of this sub-section is to evaluate the industry's perception regarding the operational bureaucracy involved in securing legal authorization for drone flights. In Civil and Structural (C&S) engineering, where project timelines are critical and site conditions fluctuate rapidly, a "clear and efficient" permitting process is essential for the practical deployment of AI-drones for time-sensitive tasks like structural inspection or progress monitoring. The visual empirical evidence provided by the frequency histograms and accompanying normal distribution curves, systematically categorized from Figures 4.18(a) through 4.18(f), illustrates a significant and troubling shift toward the lower end of the Likert scale. Notably, the distributions for key operational stakeholders are characterized by a lack of positive skew, with Figure 4.18(d) for Sub-Contractors exhibiting a heavy concentration in the disagreement zone (Likert 1 and 2). The aggregate industry profile in Figure 4.18(f) demonstrates a wide, platykurtic base, which, despite

maintaining a skewness of -0.023 and kurtosis of -0.350 within the acceptable ± 2.0 range, reflects a substantial and widespread lack of consensus regarding the efficiency of the current permitting regime.

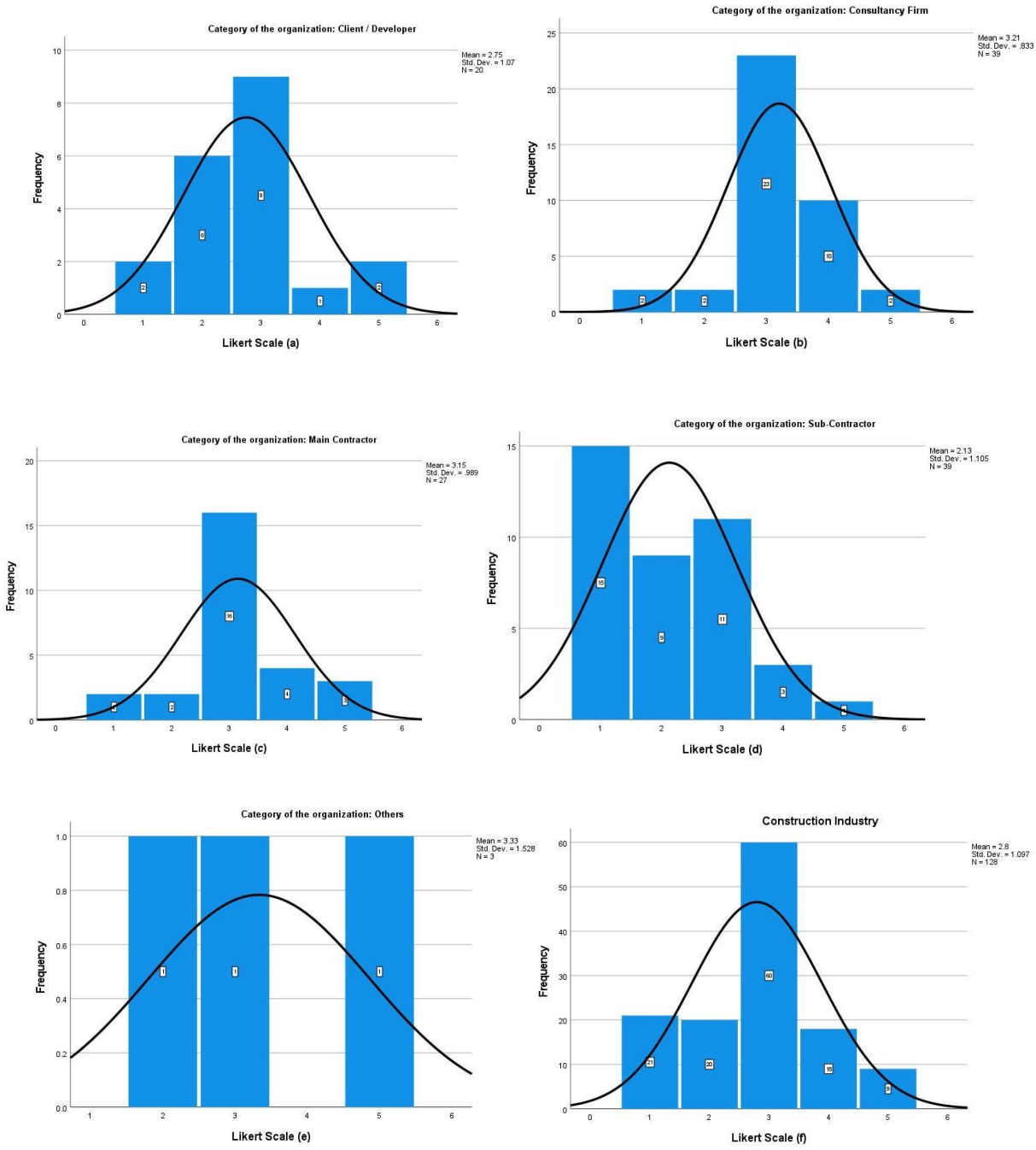


Figure 4.18: Frequency Distribution with Normal Curves for RS6: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data presented in Table 4.35 offers a rigorous quantitative profile of sectoral alignment, revealing that RS6 holds the lowest overall agreement rating within the entire

Regulatory Support construct. The aggregate industry mean for RS6 is a sub-neutral 2.80, with a standard deviation of 1.097, indicating that the industry generally views the flight permit process as a primary operational bottleneck. A critical and mathematically significant finding is observed in the Sub-Contractor group, which reported a mean agreement of only 2.13 the lowest observed in this study. For C&S engineering management, this is a vital discovery; as the party typically responsible for the actual deployment of drone hardware, sub-contractors find the administrative process significantly hindered by a lack of clarity or excessive lead times. Interestingly, even the Client/Developer group, which typically maintains a positive outlook, reported a sub-neutral mean of 2.75, suggesting that "permitting friction" is felt even at the project ownership tier. This widespread dissatisfaction aligns with global construction technology literature, which often cites "permit-to-fly" lag as a primary deterrent to the use of drones for real-time safety monitoring (Mohamed et al., 2023).

Table 4.35: Comparative Statistical Profile of Perception regarding Flight Permit Efficiency (RS6)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	2.75	20	1.070	Strongly Disagree (SD)	Strongly Agree (SA)	.562	.555
Consultancy Firm	3.21	39	.833	Strongly Disagree (SD)	Strongly Agree (SA)	1.635	-.411
Main Contractor	3.15	27	.989	Strongly Disagree (SD)	Strongly Agree (SA)	.855	-.059
Sub-Contractor	2.13	39	1.105	Strongly Disagree (SD)	Strongly Agree (SA)	-.446	.599
Others	3.33	3	1.528	Disagree (D)	Strongly Agree (SA)	.	.935
Total	2.80	128	1.097	Strongly Disagree (SD)	Strongly Agree (SA)	-.350	-.023

A pivotal and highly informative component of this research is the empirical analysis of informational gaps, specifically identified through the treatment of non-evaluative "Unsure / No Knowledge" responses. As detailed in Table 4.36, a total of 40 respondents, or 23.8% of the total sample (N=168), were unable to evaluate the permitting process. This high volume of missing data represents a critical "Bureaucratic Awareness Gap." According to the established research principles of Sekaran and Bougie (2016), when nearly a quarter of a professional sample is unsure about a core operational process, it indicates that the system is either overly complex or poorly communicated to the broader supply chain.

The frequency distribution further elucidates this systemic weakness: among the valid respondents, a staggering 32% (Strongly Disagree and Disagree) explicitly reject the notion that the process is efficient, while 46.9% remain in the "Neutral" category. This high density of neutral and negative responses, combined with the 23.8% unsure segment, paints a picture of a regulatory environment that is perceived as more of an obstacle than an enabler. For the Construction 4.0 Strategic Plan to succeed, this "permitting friction" must be addressed through digital automation or streamlined inter-agency coordination. Despite the sectoral disparities and high missing data, the overall industry skewness and kurtosis remain within the standard academic threshold of ± 2.0, confirming that the valid data for RS6 is normally distributed and robust for the subsequent path analysis. This concludes the descriptive analysis for Regulatory Support, identifying the flight permitting process as the single most significant regulatory barrier to AI-drone integration in the Malaysian construction industry.

Table 4.36: Overall Frequency and Percentage Breakdown of "Unsure" Responses for RS6

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	21	12.5	16.4	16.4
	Disagree (D)	20	11.9	15.6	32.0
	Neutral (N)	60	35.7	46.9	78.9
	Agree (A)	18	10.7	14.1	93.0
	Strongly Agree (SA)	9	5.4	7.0	100.0
	Total	128	76.2	100.0	
Missing	Unsure / No Knowledge	40	23.8		
Total		168	100.0		

4.3.4.7 Descriptive Analysis RS7: Liability laws regarding drone accidents on construction sites are clearly defined.

The final objective of this descriptive sub-section is to evaluate the industry's perception regarding the legal clarity of liability in the event of drone-related accidents. In Civil and Structural (C&S) engineering, the clear demarcation of liability is a non-negotiable prerequisite for risk management; without a definitive legal framework identifying responsible parties whether the drone operator, the software developer, or the principal contractor firms face unquantifiable professional and financial exposure. The visual empirical evidence provided by the frequency histograms and accompanying normal distribution curves, systematically categorized from Figures 4.19(a) through 4.19(f), reveals a significant state of "Legal

Ambiguity" across the supply chain. Notably, the distributions for most stakeholders are characterized by a centralized "Neutral" peak or a shift toward disagreement, with Figure 4.19(d) for Sub-Contractors demonstrating a marked positive skew, indicating a widespread belief that liability remains poorly defined. The aggregate industry profile in Figure 4.19(f) presents a relatively flat and wide distribution, which, despite maintaining a skewness of -0.140 and kurtosis of -0.690 within the acceptable ±2.0 range, underscores a substantial lack of professional confidence in the current legal status quo.

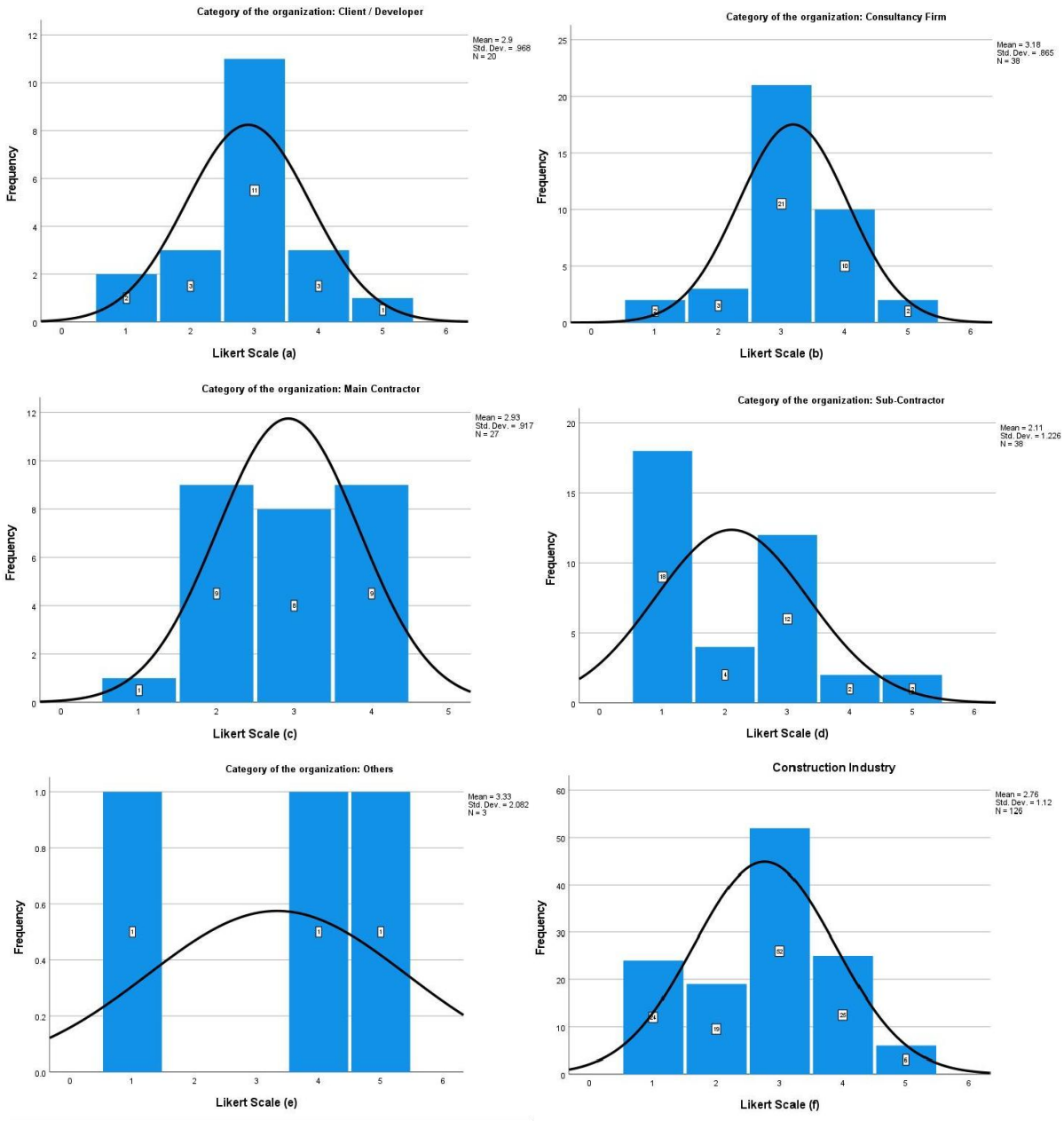


Figure 4.19: Frequency Distribution with Normal Curves for RS7: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data presented in Table 4.37 offers a rigorous quantitative profile of sectoral alignment, confirming that RS7 is perceived as one of the most significant "Risk Barriers" in the study. The aggregate industry mean for RS7 is a sub-neutral 2.76, indicating that the construction sector generally perceives liability laws as inadequately defined for autonomous operations. A critical finding is observed in the Sub-Contractor group, which reported a mean agreement of only 2.11 with a high standard deviation of 1.226. This finding is of paramount importance to C&S engineering management; as the entities most likely to operate the drone hardware on-site, sub-contractors feel the most legally vulnerable, fearing that in the absence of clear laws, they may be forced to absorb the entirety of the liability for technological failures. Furthermore, even the technical advisory tier (Consultancy Firms) only achieved a marginally positive mean of 3.18, suggesting that even the professionals responsible for safety certification are operating in a "gray zone" of liability.

Table 4.37: Comparative Statistical Profile of Perception regarding Liability Law Clarity (RS7)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	2.90	20	.968	Strongly Disagree (SD)	Strongly Agree (SA)	.730	-.170
Consultancy Firm	3.18	38	.865	Strongly Disagree (SD)	Strongly Agree (SA)	1.139	-.376
Main Contractor	2.93	27	.917	Strongly Disagree (SD)	Agree (A)	-1.160	-.169
Sub-Contractor	2.11	38	1.226	Strongly Disagree (SD)	Strongly Agree (SA)	-.431	.719
Others	3.33	3	2.082	Strongly Disagree (SD)	Strongly Agree (SA)	.	-1.293
Total	2.76	126	1.120	Strongly Disagree (SD)	Strongly Agree (SA)	-.690	-.140

A pivotal and highly informative component of this research is the empirical analysis of informational gaps, identified through the treatment of non-evaluative "Unsure / No Knowledge" responses. As detailed in Table 4.38, RS7 recorded a staggering 25.0% "Unsure" rate (N=42), tying it for the highest uncertainty level in the Regulatory Support construct. This represents a profound "Liability Information Void" where exactly one-quarter of the industry is fundamentally unable to assess their legal position regarding drone accidents. According to the established research principles of Sekaran and Bougie (2016), such high levels of uncertainty in a technical sample are indicative of a "latent risk factor" that likely inhibits investment in AI-technologies.

The frequency distribution further elucidates this systemic weakness: only 24.6% of valid respondents (Agree and Strongly Agree) feel that liability is clear, while a combined 34.1% explicitly disagree. When the 41.3% neutral segment and the 25.0% unsure segment are considered together, it is evident that the vast majority of the Malaysian construction workforce is operating under significant legal uncertainty. This confirms that while the Construction 4.0 Strategic Plan promotes technology, the legal "safety net" regarding liability remains underdeveloped. Despite these sectoral disparities and high missing data, the overall industry skewness and kurtosis remain within the standard academic threshold of ±2.0, confirming that the valid data for RS7 is normally distributed and robust for the subsequent path analysis. This concludes the descriptive analysis for the Regulatory Support construct, identifying liability clarity as a critical systemic bottleneck.

Table 4.38: Overall Frequency and Percentage Breakdown of "Unsure" Responses for RS7

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	24	14.3	19.0	19.0
	Disagree (D)	19	11.3	15.1	34.1
	Neutral (N)	52	31.0	41.3	75.4
	Agree (A)	25	14.9	19.8	95.2
	Strongly Agree (SA)	6	3.6	4.8	100.0
	Total	126	75.0	100.0	
Missing	Unsure / No Knowledge	42	25.0		
Total		168	100.0		

4.3.5 Descriptive Analysis: Institutional Readiness (IV2)

Section 4.3.5 establishes a rigorous empirical baseline for Institutional Readiness (IV2), an internal latent construct that determines the capacity of Malaysian construction firms to successfully absorb, integrate, and sustain AI-drone technologies. In the specialized field of Civil and Structural (C&S) engineering, readiness is not a monolithic attribute but a multi-dimensional capability. It requires the convergence of tangible resources such as financial capital and high-speed digital infrastructure with intangible institutional assets, including top-management commitment, a progressive innovation culture, and the technical aptitude of the workforce. This section transitionally bridges the gap between the external "Regulatory Support" (IV1) discussed previously and the internal "Implementation" processes (Mediator) that follow.

By analyzing the Mean ($\bar{}$) and Standard Deviation (SD), this analysis identifies the specific internal "enablers" and "inhibitors" within various stakeholder organizations. Furthermore, the evaluation of Skewness and Kurtosis across all seven indicators (IR1 to IR7) provides the necessary psychometric confirmation that the institutional data adheres to a normal distribution. This is critical for validating the reliability of the research model, as it ensures that the subsequent variance-based structural equation modeling (VB-SEM) is grounded in robust, representative data. High mean scores in this section typically indicate that an organization has moved beyond mere interest in Construction 4.0 and possesses the actual "foundational stability" required for the high-precision requirements of AI-based safety monitoring.

4.3.5.1 Descriptive Analysis IR1: My organisation has the financial resources to invest in AI-drone technologies.

The primary objective of this sub-section is to evaluate the perceived financial solvency of Malaysian construction organizations regarding the capital-intensive acquisition of AI-drone systems. In Civil and Structural (C&S) engineering, financial readiness is the most significant "hard" barrier to digital transformation; the high cost of industrial-grade drone hardware, coupled with recurring licenses for AI-analysis software and data processing infrastructure, requires a dedicated and robust capital allocation. The visual empirical evidence provided by the frequency histograms and normality curves, systematically categorized from Figures 4.20(a) through 4.20(f), reveals a stark and statistically significant "Financial Capability Gap" across the construction supply chain. Figure 4.20(a), representing the Client/Developer sector, displays a relatively balanced but slightly negative skew with a mean of 3.46, indicating that project owners the primary capital holders possess a moderate sense of financial readiness. In profound contrast, Figure 4.20(b) for Consultancy Firms and Figure 4.20(d) for Sub-Contractors exhibit extreme positive skews, with the vast majority of responses concentrated in the "Strongly Disagree" and "Disagree" zones. The aggregate industry profile in Figure 4.20(f) demonstrates a heavily right-skewed distribution, which, despite maintaining a skewness of 0.565 and kurtosis of -0.834 within the acceptable academic threshold of ± 2.0, underscores a pervasive industry-wide perception that financial resources for AI-drone investment are currently inadequate.

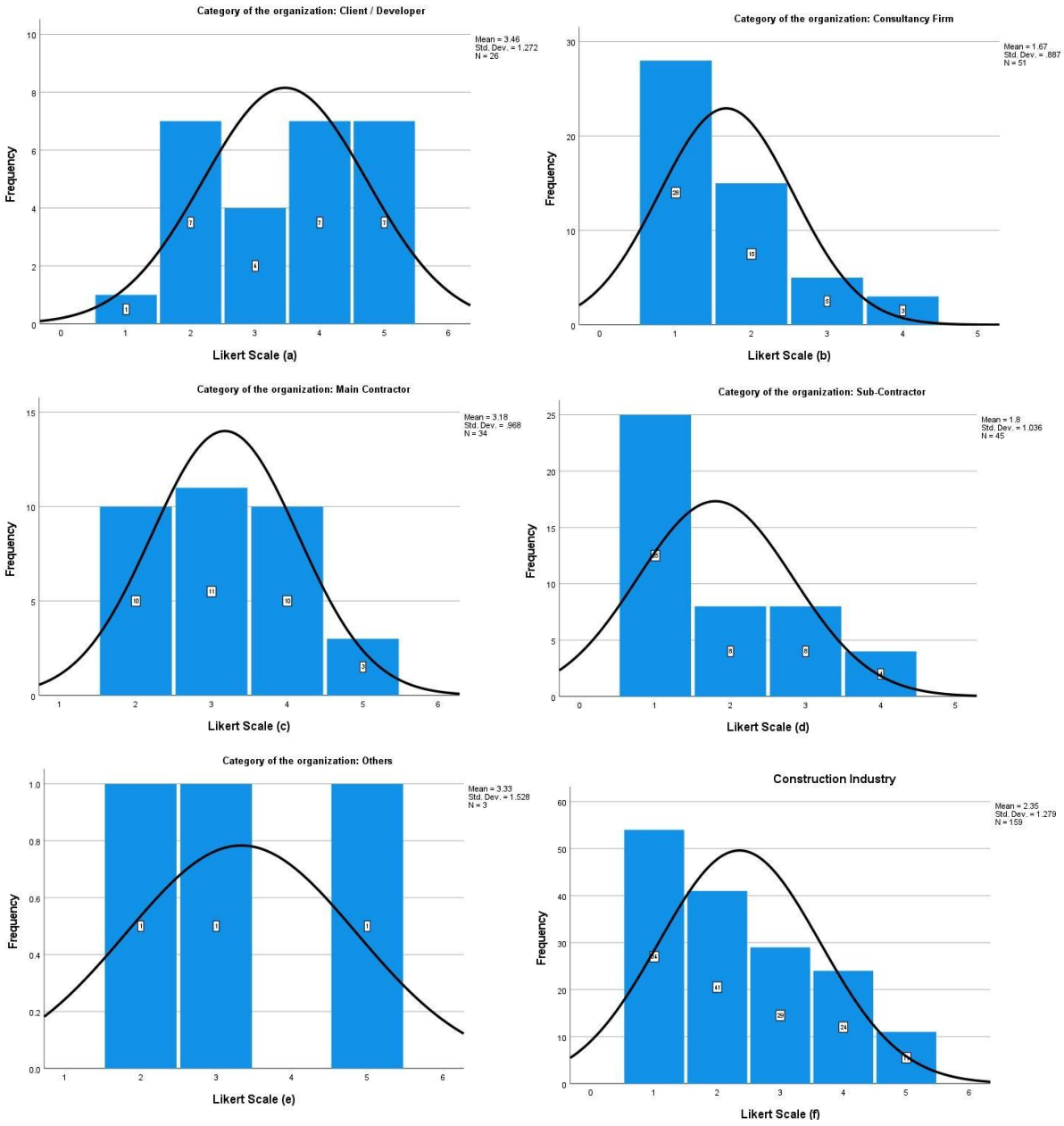


Figure 4.20: Frequency Distribution with Normal Curves for IR1: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data presented in Table 4.39 offers a rigorous quantitative snapshot of this financial disparity, ranking each organization by its mean agreement score. The aggregate industry mean for IR1 is a concerningly low 2.35, suggesting a widespread financial "unpreparedness" for AI-drone adoption. A critical finding is located in the Consultancy Firm ($\bar{}$= 1.67) and Sub-Contractor ($\bar{}$= 1.80) sectors. In C&S engineering, these entities are often Small and Medium Enterprises (SMEs) that operate on thin profit margins; their extreme disagreement indicates that the high entry cost of AI-drone technology is perceived as

prohibitive. Main Contractors (3.18) and Clients (3.46) remain slightly above the neutral threshold, reflecting a bifurcated industry where only top-tier stakeholders feel financially capable of leading the technological transition. This mirrors the "digital divide" highlighted in the Construction 4.0 Strategic Plan, where the cost of advanced equipment acts as a deterrent for the lower-tier firms that constitute the bulk of the operational workforce.

Table 4.39: Comparative Statistical Profile of Perception regarding Financial Resources (IR1)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.46	26	1.272	Strongly Disagree (SD)	Strongly Agree (SA)	-1.287	-.223
Consultancy Firm	1.67	51	.887	Strongly Disagree (SD)	Agree (A)	.836	1.260
Main Contractor	3.18	34	.968	Disagree (D)	Strongly Agree (SA)	-.939	.264
Sub-Contractor	1.80	45	1.036	Strongly Disagree (SD)	Agree (A)	-.487	.935
Others	3.33	3	1.528	Disagree (D)	Strongly Agree (SA)	.	.935
Total	2.35	159	1.279	Strongly Disagree (SD)	Strongly Agree (SA)	-.834	.565

An essential component of this analysis is the evaluation of informational gaps, specifically identified through the treatment of "Unsure / No Knowledge" responses. As detailed in Table 4.40, IR1 recorded a relatively low missing data rate of 5.4% (N=9). In the context of C&S engineering management, this indicates that stakeholders have a very high level of certainty regarding their budgetary limitations; unlike regulatory items where uncertainty was high, professionals are acutely aware of their firm's financial boundaries. According to the research principles of Sekaran and Bougie (2016), such low uncertainty coupled with a low mean indicates a definitive, data-driven rejection of the statement.

The frequency distribution further elucidates this crisis: a staggering 59.7% of valid respondents (Strongly Disagree and Disagree) explicitly state their organization lacks the funds for investment, while only 6.9% "Strongly Agree." This suggests that the Construction 4.0 goals for AI-integration may be financially unfeasible for nearly 60% of the industry without significant governmental intervention or subsidized funding models. Despite these stark sectoral disparities, the overall industry skewness and kurtosis confirm that the valid data for IR1 is normally distributed and robust for subsequent path analysis. This concludes the descriptive analysis for IR1, identifying financial capacity as a critical internal bottleneck that threatens to stall the momentum of AI-drone adoption in the Malaysian construction sector.

Table 4.40: Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	54	32.1	34.0	34.0
	Disagree (D)	41	24.4	25.8	59.7
	Neutral (N)	29	17.3	18.2	78.0
	Agree (A)	24	14.3	15.1	93.1
	Strongly Agree (SA)	11	6.5	6.9	100.0
	Total	159	94.6	100.0	
Missing	Unsure / No Knowledge	9	5.4		
Total		168	100.0		

4.3.5.2 Descriptive Analysis IR2: My organisation has sufficient digital infrastructure (e.g., internet, servers) to support drone-based data.

The second objective of this sub-section is to evaluate the adequacy of the industry's digital backbone, specifically focusing on the high-bandwidth internet and server capacity required to process large-scale drone datasets. In Civil and Structural (C&S) engineering, AI-drone operations generate massive point-cloud data and high-definition photogrammetry that necessitate robust "Back-End" infrastructure. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.21a through 4.21f) reveals a profound "Technological Disconnect" within the Malaysian construction landscape. Figures 4.21b and 4.21d, representing Consultancy Firms and Sub-Contractors respectively, show heavily right-skewed distributions with massive concentrations in the "Strongly Disagree" and "Disagree" regions. Conversely, Figure 4.21c for Main Contractors shows a more balanced, slightly negative skew, suggesting that tier-one firms possess superior infrastructure compared to their supply chain partners. The aggregate industry profile in Figure 4.21f confirms a right-leaning distribution with a skewness of 0.416 and kurtosis of -0.799, statistically validating that the majority of the workforce perceives current digital infrastructure as a significant bottleneck.

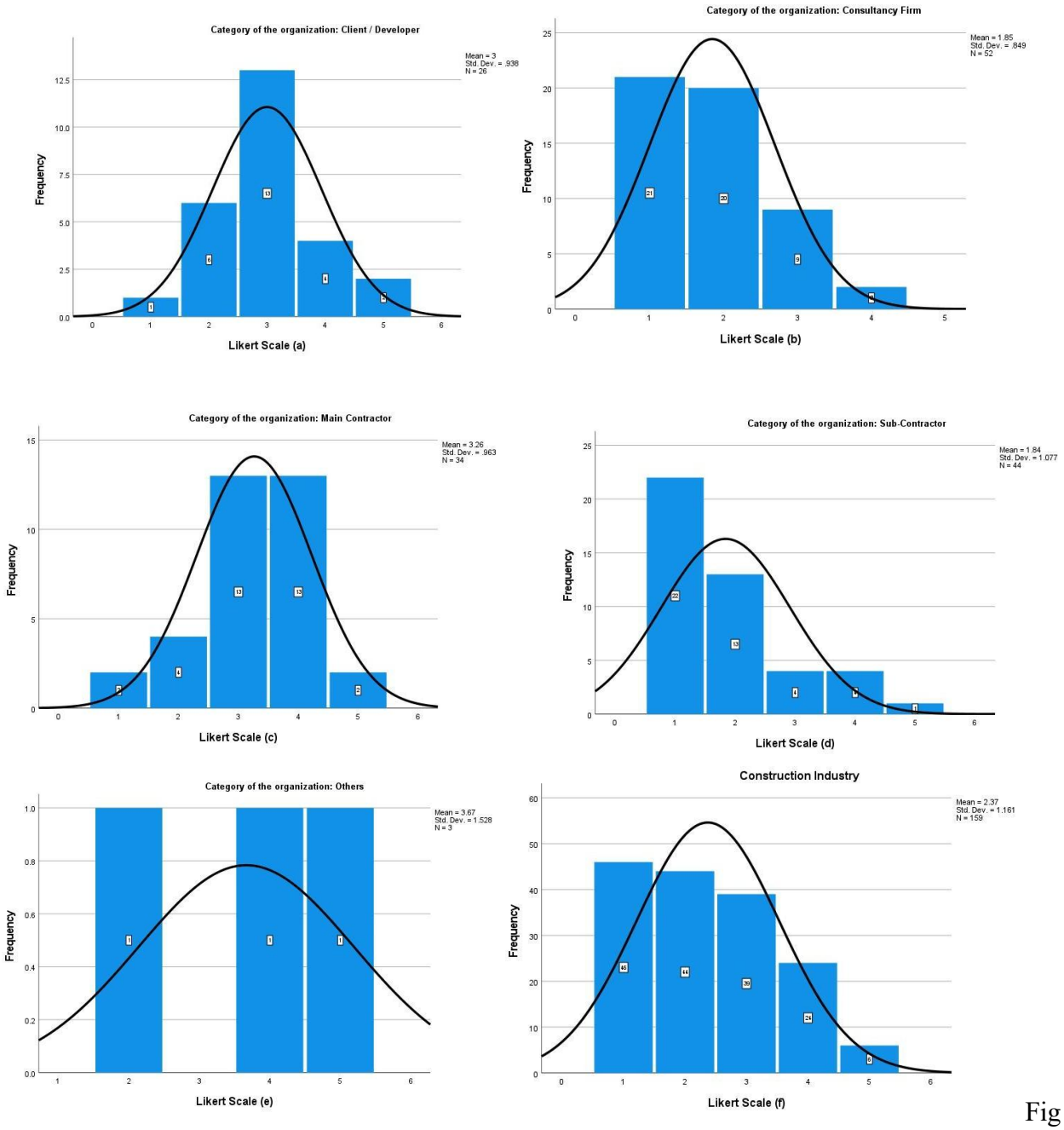


Figure 4.21: Frequency Distribution with Normal Curves for IR2: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.41 provides a rigorous quantitative breakdown of this infrastructural deficit. The aggregate industry mean for IR2 is 2.37, indicating a general consensus that digital infrastructure is currently insufficient for advanced drone applications. A critical finding is the near-identical low means of Consultancy Firms (1.85) and Sub-Contractors (1.84). For C&S engineering management, this is a systemic risk; even if high-quality data is captured on-site, these primary stakeholders lack the servers and connectivity to process or utilize the information effectively. Only Main Contractors (3.26) and Clients (3.00) maintain

neutral-to-positive means, reflecting a digital "Tiered System" where advanced capabilities are consolidated at the top of the hierarchy, leaving the operational tiers in a state of technological obsolescence. This disparity echoes the Construction 4.0 Strategic Plan's warning regarding the "Infrastructure Gap" that prevents SMEs from adopting high-precision BIM and AI tools.

Table 4.41: Comparative Statistical Profile of Perception regarding Digital Infrastructure (IR2)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.00	26	.938	Strongly Disagree (SD)	Strongly Agree (SA)	.413	.315
Consultancy Firm	1.85	52	.849	Strongly Disagree (SD)	Agree (A)	-.224	.705
Main Contractor	3.26	34	.963	Strongly Disagree (SD)	Strongly Agree (SA)	.289	-.574
Sub-Contractor	1.84	44	1.077	Strongly Disagree (SD)	Strongly Agree (SA)	.847	1.267
Others	3.67	3	1.528	Disagree (D)	Strongly Agree (SA)	.	-.935
Total	2.37	159	1.161	Strongly Disagree (SD)	Strongly Agree (SA)	-.799	.416

An essential component of this analysis involves the empirical evaluation of informational gaps, specifically identified through the "Unsure / No Knowledge" responses. As detailed in Table 4.42, IR2 recorded a low missing data rate of 5.4% (N=9), signifying that stakeholders are acutely aware of their infrastructural limitations. According to the research principles of Sekaran and Bougie (2016), high response certainty coupled with a low mean indicates a definitive, non-speculative rejection of the statement.

The frequency distribution further elucidates the severity of this barrier: a combined 56.6% of valid respondents explicitly disagree that their infrastructure is sufficient, while a mere 3.8% strongly agree. This suggests that the move toward AI-drones in Malaysia is physically constrained by the lack of local data processing power. Despite these stark disparities, the overall industry skewness and kurtosis remain within the ±2.0 threshold, confirming that the data for IR2 is normally distributed and statistically sound for path analysis. This concludes that without localized investment in high-speed digital networks and server ecosystems, the implementation

of AI-drones in Malaysian C&S engineering will remain restricted to high-tier projects with specialized external support.

Table 4.42: Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	46	27.4	28.9	28.9
	Disagree (D)	44	26.2	27.7	56.6
	Neutral (N)	39	23.2	24.5	81.1
	Agree (A)	24	14.3	15.1	96.2
	Strongly Agree (SA)	6	3.6	3.8	100.0
	Total	159	94.6	100.0	
Missing	Unsure / No Knowledge	9	5.4		
Total		168	100.0		

4.3.5.3 Descriptive Analysis IR3: Top management is committed to adopting AI-drone technologies.

The third objective of this sub-section is to evaluate the perceived level of leadership advocacy and strategic priority given to AI-drone technologies within Malaysian construction firms. In Civil and Structural (C&S) engineering, top management commitment is the primary driver for organizational change; without active endorsement from executive leadership, the substantial investments required for drone hardware, software integration, and specialized training are unlikely to materialize. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.22a through 4.22f) reveals a polarized and stakeholder-dependent landscape regarding leadership support. Figure 4.22(b) for Consultancy Firms shows a heavy positive skew, indicating a lack of perceived commitment at the advisory level. In contrast, Figure 4.22(c) and 4.22(d), representing Main Contractors and Sub-Contractors, display distributions that lean toward the "Agree" zone, suggesting that operational leadership may be more attuned to the efficiency gains offered by drones. The aggregate industry profile in Figure 4.22(f) presents a relatively wide, almost bimodal distribution, which, despite maintaining a skewness of -0.072 and kurtosis of -1.075 within the acceptable ±2.0 range, reflects a substantial lack of unified strategic direction across the industry.

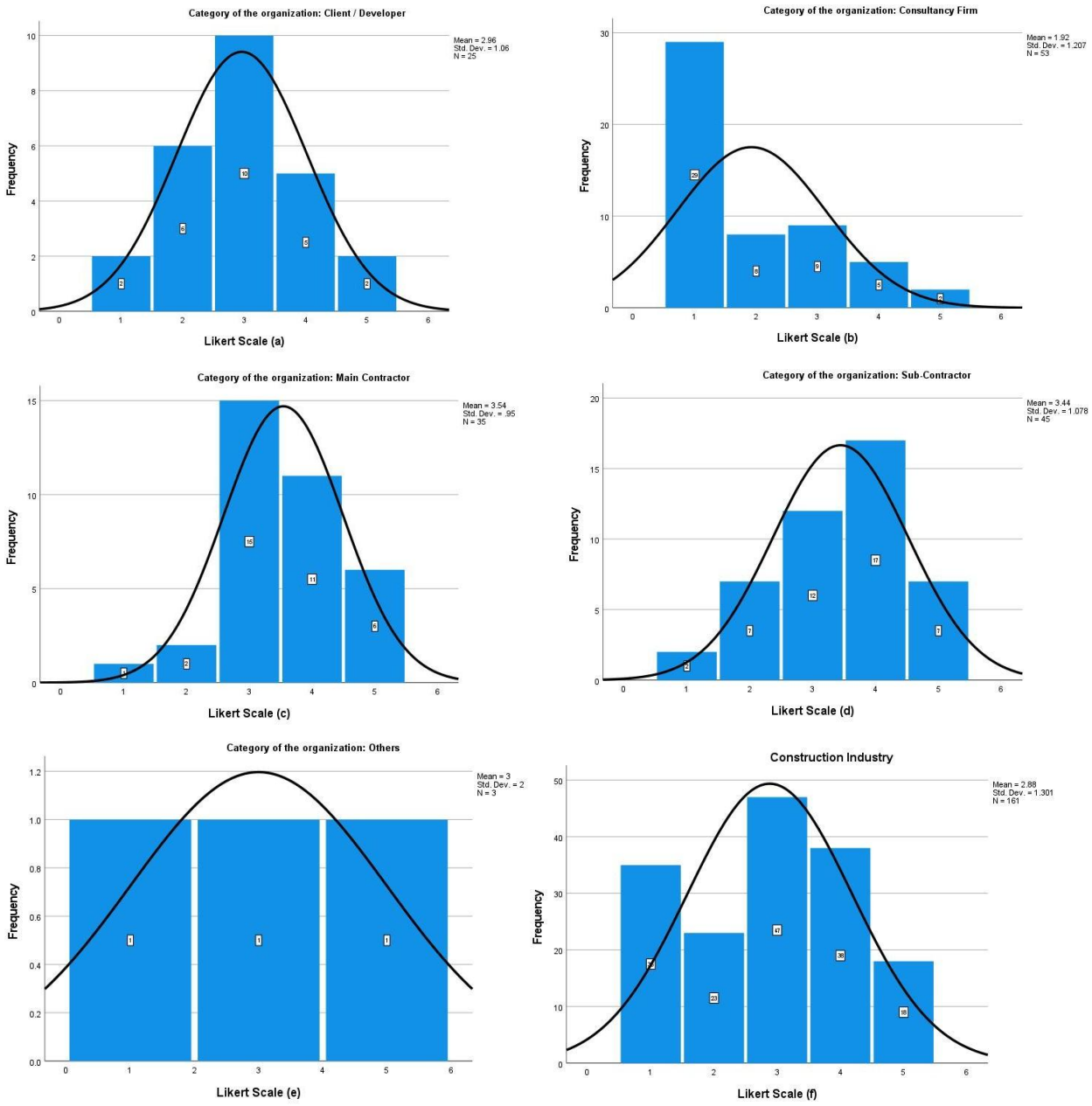


Figure 4.22: Frequency Distribution with Normal Curves for IR3: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data presented in Table 4.43 offers a rigorous quantitative profile of this leadership disparity. The aggregate industry mean for IR3 is a sub-neutral 2.88, indicating that, collectively, the industry does not yet perceive top management as fully committed to AI-drone adoption. A critical finding is the low mean agreement among Consultancy Firms (1.92). In C&S engineering, consultants often act as the primary technical gatekeepers; if their leadership is perceived as uncommitted, it creates a significant barrier to including drone-based safety protocols in project specifications. Conversely, Main Contractors (3.54) and

Sub-Contractors (3.44) reported the highest means, suggesting that leadership at the "construction front-line" is more convinced of the technology's value for hazard detection and site monitoring. This outcome suggests an "Expectation Gap" between the technical advisors and the operational executors, potentially hindering the holistic implementation of Construction 4.0 goals.

Table 4.43: Comparative Statistical Profile of Perception regarding Management Commitment (IR3)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	2.96	25	1.060	Strongly Disagree (SD)	Strongly Agree (SA)	-.230	.085
Consultancy Firm	1.92	53	1.207	Strongly Disagree (SD)	Strongly Agree (SA)	-.075	1.037
Main Contractor	3.54	35	.950	Strongly Disagree (SD)	Strongly Agree (SA)	.248	-.239
Sub-Contractor	3.44	45	1.078	Strongly Disagree (SD)	Strongly Agree (SA)	-.418	-.420
Others	3.00	3	2.000	Strongly Disagree (SD)	Strongly Agree (SA)	.	.000
Total	2.88	161	1.301	Strongly Disagree (SD)	Strongly Agree (SA)	-1.075	-.072

An essential component of this analysis involves the evaluation of informational gaps, identified through the "Unsure / No Knowledge" responses. As detailed in Table 4.44, IR3 recorded a low missing data rate of 4.2% (N=7), signifying that respondents have a high degree of clarity regarding their management's stance on technology. According to the research principles of Sekaran and Bougie (2016), high response certainty coupled with a sub-neutral mean suggests a definitive perception of institutional inertia.

The frequency distribution further elucidates the challenges facing adoption: a combined 36.0% of valid respondents explicitly disagree that their management is committed, while 29.2% remain in the "Neutral" category. This suggests that for over 65% of the industry, management commitment is either absent or too ambiguous to be perceived as a catalyst for change. As highlighted by Mohamed et al. (2023), the "wait-and-see" approach of many Malaysian construction leaders remains a significant bottleneck to AI integration. Despite these disparities, the overall industry skewness and kurtosis confirm that the data for IR3 is normally distributed

and robust for the subsequent path analysis, concluding that fostering executive-level advocacy is mandatory for accelerating AI-drone adoption in the Malaysian construction sector.

Table 4.44: Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR3

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	35	20.8	21.7	21.7
	Disagree (D)	23	13.7	14.3	36.0
	Neutral (N)	47	28.0	29.2	65.2
	Agree (A)	38	22.6	23.6	88.8
	Strongly Agree (SA)	18	10.7	11.2	100.0
	Total	161	95.8	100.0	
Missing	Unsure / No Knowledge	7	4.2		
Total		168	100.0		

4.3.5.4 Descriptive Analysis IR4: Employees in my organisation possess the technical aptitude required to operate or learn AI-drone systems.

The fourth objective of this sub-section is to evaluate the industry's perception of its own human capital, specifically focusing on the technical aptitude and learnability of employees regarding AI-drone systems. In Civil and Structural (C&S) engineering, the transition to autonomous technologies is highly dependent on the "digital literacy" of the workforce; even with superior hardware, the lack of internal expertise to manage AI-algorithms and pilot advanced drones can lead to significant operational failures. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.23a through 4.23f) reveals an alarming "Skills Deficit" across the Malaysian construction landscape. Figures 4.23(b) and 4.23(d), representing Consultancy Firms and Sub-Contractors respectively, show extreme positive skews, with nearly all data points clustered in the "Strongly Disagree" and "Disagree" regions. The aggregate industry profile in Figure 4.23(f) confirms a starkly right-leaning distribution with a skewness of 0.785 and kurtosis of -0.337, statistically validating that the majority of the workforce perceives a fundamental lack of technical readiness.

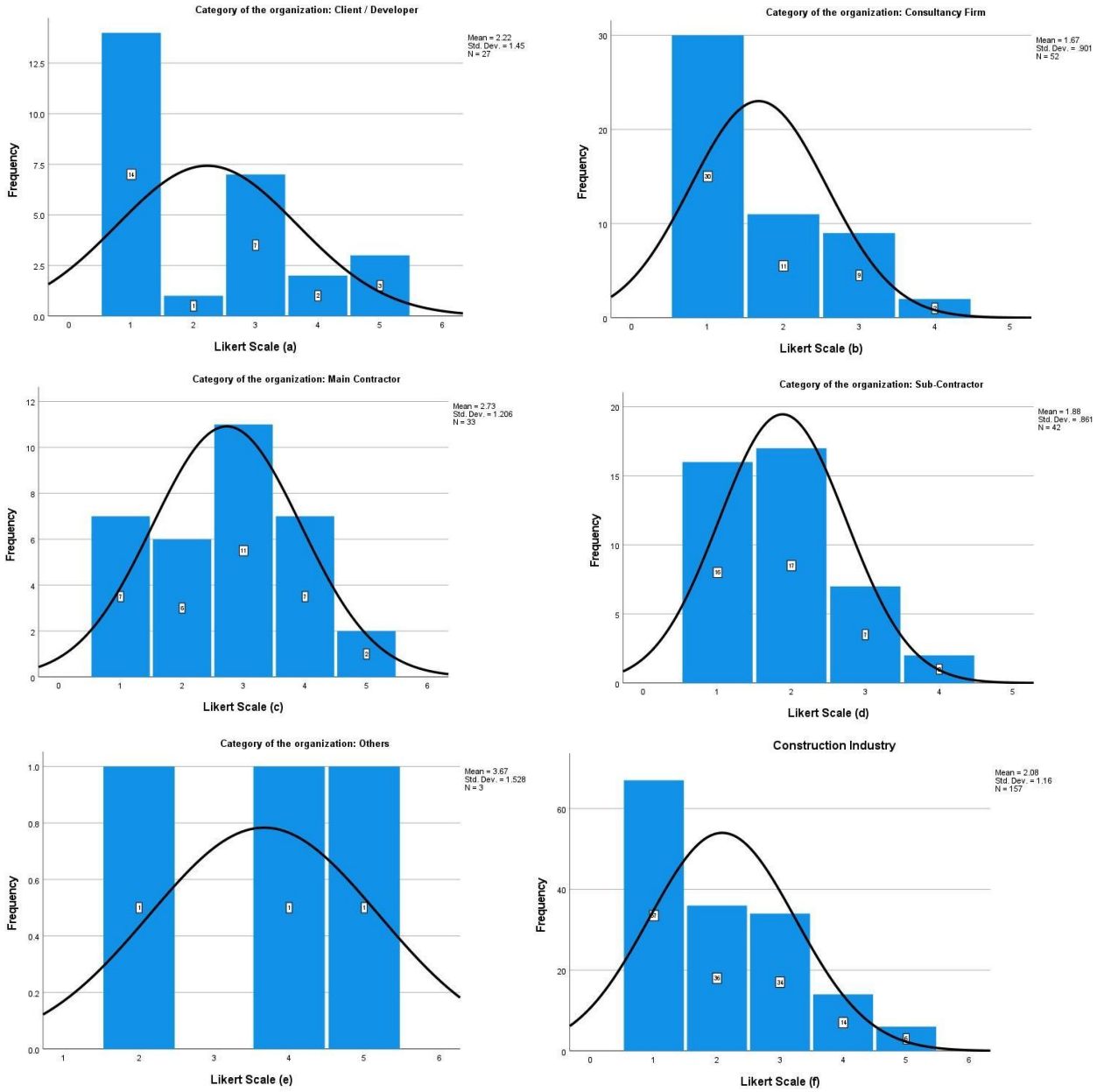


Figure 4.23: Frequency Distribution with Normal Curves for IR4: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.45 provides a rigorous quantitative profile of this aptitude gap. The aggregate industry mean for IR4 is a remarkably low 2.08, the lowest recorded within the Institutional Readiness construct. This indicates a profound industry-wide belief that employees are currently ill-equipped to handle AI-drone technology. A critical finding is the extremely low mean agreement among Consultancy Firms (1.67) and Sub-Contractors (1.88). For C&S engineering management, this suggests that the technical advisory and operational tiers the very people meant to implement these systems do not feel they possess the necessary

cognitive or technical foundations. Even Main Contractors (2.73) and Clients (2.22) reported sub-neutral means, reflecting a pervasive "Aptitude Crisis" that transcends the hierarchy of the supply chain. This aligns with the Construction 4.0 Strategic Plan which identifies "Up-skilling and Re-skilling" as the most urgent priority for the Malaysian construction sector.

Table 4.45: Comparative Statistical Profile of Perception regarding Technical Aptitude (IR4)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	2.22	27	1.450	Strongly Disagree (SD)	Strongly Agree (SA)	-.832	.726
Consultancy Firm	1.67	52	.901	Strongly Disagree (SD)	Agree (A)	-.084	1.043
Main Contractor	2.73	33	1.206	Strongly Disagree (SD)	Strongly Agree (SA)	-.884	-.005
Sub-Contractor	1.88	42	.861	Strongly Disagree (SD)	Agree (A)	-.104	.719
Others	3.67	3	1.528	Disagree (D)	Strongly Agree (SA)	.	-.935
Total	2.08	157	1.160	Strongly Disagree (SD)	Strongly Agree (SA)	-.337	.785

An essential component of this analysis involves the evaluation of informational gaps, specifically identified through the "Unsure / No Knowledge" responses. As detailed in Table 4.46, IR4 recorded a missing data rate of 6.5% (N=11), indicating that respondents are highly certain and pessimistic about their internal skill levels. According to the research principles of Sekaran and Bougie (2016), such low uncertainty coupled with a very low mean indicates a definitive, data-driven rejection of the statement.

The frequency distribution further elucidates the severity of this barrier: a combined 65.6% of valid respondents explicitly disagree that their employees have the required aptitude, while only 3.8% strongly agree. This suggests that the primary obstacle to AI-drone adoption in Malaysia may not be the technology itself, but the human factor. For C&S firms, this data implies that procurement of technology must be preceded by massive investments in technical training programs. Despite the polarized nature of the responses, the overall industry skewness and kurtosis remain within the ± 2.0 threshold, confirming that the data for IR4 is normally distributed and statistically robust for path analysis. This concludes that technical aptitude is currently a critical "Red Zone" inhibitor for AI-drone integration in the Malaysian construction industry.

Table 4.46: Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR4

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	67	39.9	42.7	42.7
	Disagree (D)	36	21.4	22.9	65.6
	Neutral (N)	34	20.2	21.7	87.3
	Agree (A)	14	8.3	8.9	96.2
	Strongly Agree (SA)	6	3.6	3.8	100.0
	Total	157	93.5	100.0	
Missing	Unsure / No Knowledge	11	6.5		
Total		168	100.0		

4.3.5.5 Descriptive Analysis IR5: The organisation promotes a culture that supports innovation and technological change.

The fifth objective of this sub-section is to evaluate the prevailing organizational culture and its receptivity toward technological disruption within the Malaysian construction industry. In Civil and Structural (C&S) engineering, an "Innovation Culture" serves as the psychological foundation for digital transformation; while financial and technical resources are essential, the success of AI-drone integration ultimately depends on the institution's collective willingness to abandon traditional manual safety protocols in favor of automated, data-driven methodologies. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.24a through 4.24f) demonstrates a relatively positive and encouraging shift compared to previous indicators. Figure 4.24(a) and 4.24(c), representing Clients/Developers and Main Contractors respectively, show distinct negative skews with high concentrations in the "Agree" zone. Even the Sub-Contractor distribution in Figure 4.24(d) presents a healthy bell-shaped curve centered toward agreement. The aggregate industry profile in Figure 4.24(f) maintains a skewness of -0.442 and a kurtosis of 0.059, statistically confirming that the data for IR5 is normally distributed and robust for subsequent structural modeling.

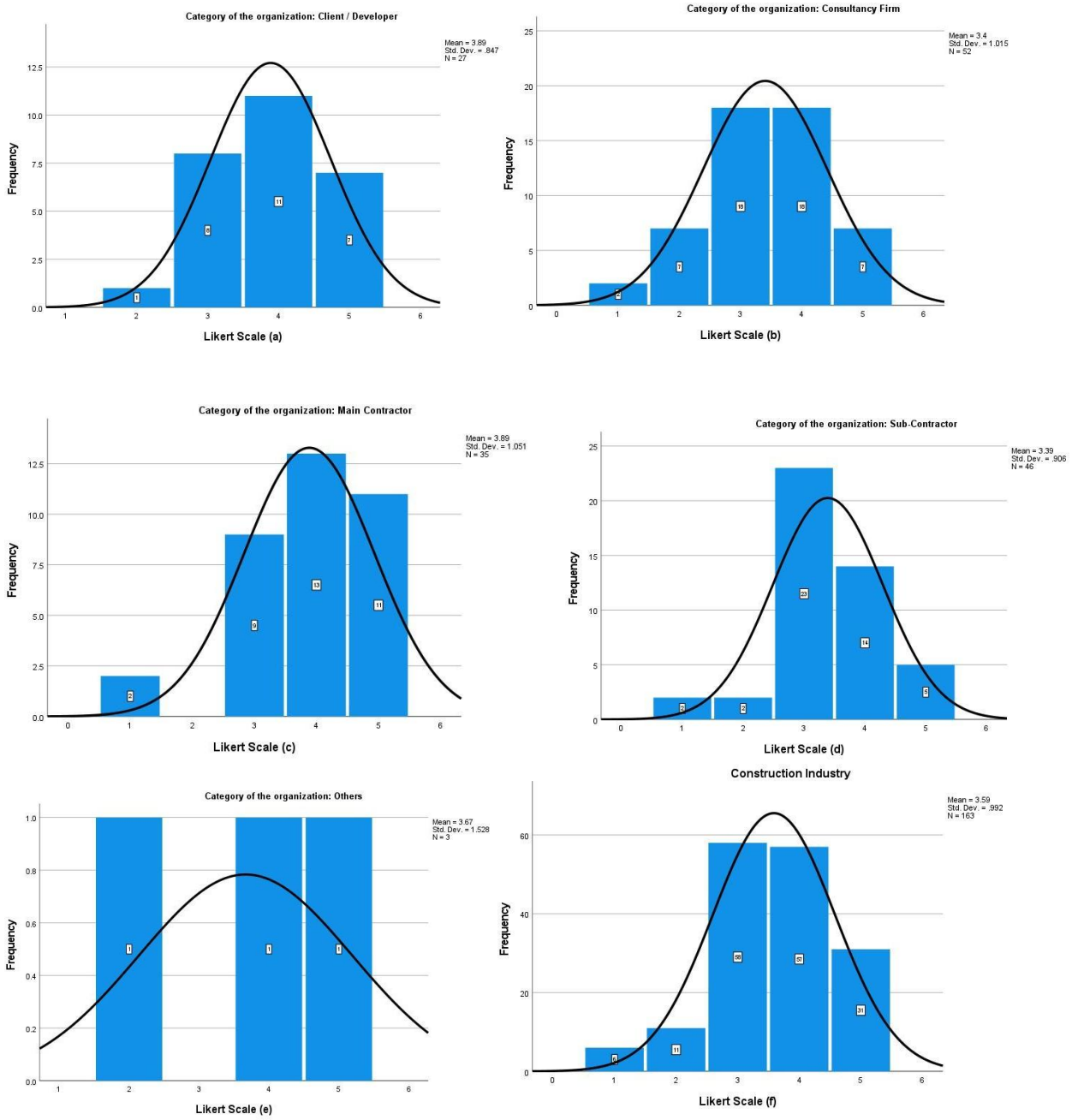


Figure 4.24: Frequency Distribution with Normal Curves for IR5: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.47 provides a rigorous quantitative profile of this cultural readiness. The aggregate industry mean for IR5 is 3.59, indicating a general consensus that Malaysian construction firms are culturally open to innovation. A mathematically significant finding is the identical high mean agreement of 3.89 reported by both Clients/Developers and Main Contractors. This suggests that the top tiers of the construction hierarchy have successfully fostered an environment where technological change is perceived as a strategic necessity.

Consultancy Firms (3.40) and Sub-Contractors (3.39) also reported positive means, although with slightly higher variance. This widespread cultural alignment is a critical enabler for C&S engineering management, as it suggests that the primary barrier to AI-drone adoption is not "resistance to change," but rather the financial and technical limitations identified in earlier sections.

Table 4.47: Comparative Statistical Profile of Perception regarding Innovation Culture (IR5)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.89	27	.847	Disagree (D)	Strongly Agree (SA)	-.710	-.187
Consultancy Firm	3.40	52	1.015	Strongly Disagree (SD)	Strongly Agree (SA)	-.228	-.313
Main Contractor	3.89	35	1.051	Strongly Disagree (SD)	Strongly Agree (SA)	1.355	-1.051
Sub-Contractor	3.39	46	.906	Strongly Disagree (SD)	Strongly Agree (SA)	.887	-.317
Others	3.67	3	1.528	Disagree (D)	Strongly Agree (SA)	.	-.935
Total	3.59	163	.992	Strongly Disagree (SD)	Strongly Agree (SA)	.059	-.442

An essential component of this analysis involves the evaluation of informational gaps, identified through the treatment of non-evaluative "Unsure / No Knowledge" responses. As detailed in Table 4.48, IR5 recorded the lowest missing data rate in the Institutional Readiness construct at 3.0% (N=5). This signifies that almost all respondents have a definitive perception of their firm's cultural stance. According to the research principles of Sekaran and Bougie (2016), high response certainty coupled with a positive mean indicates a strong organizational "climate for change."

The frequency distribution further reinforces this optimistic outlook: over 54% of valid respondents (Agree and Strongly Agree) perceive their organization as supportive of innovation, while only 10.4% explicitly disagree. This suggests that the Construction 4.0 Strategic Plan has been highly successful in shifting the industry's mindset toward modernization. For C&S firms, this "cultural readiness" provides a fertile ground for implementing pilot AI-drone programs. Despite the slight negative skew, the overall industry kurtosis confirms that the valid data for IR5 is robust and possesses the requisite psychometric properties for inclusion in the final path

analysis. This concludes that the industry currently possesses the cultural momentum required to support the transition toward autonomous site safety systems.

Table 4.48: Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR5

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	6	3.6	3.7	3.7
	Disagree (D)	11	6.5	6.7	10.4
	Neutral (N)	58	34.5	35.6	46.0
	Agree (A)	57	33.9	35.0	81.0
	Strongly Agree (SA)	31	18.5	19.0	100.0
	Total	163	97.0	100.0	
Missing	Unsure / No Knowledge	5	3.0		
Total		168	100.0		

4.3.5.6 Descriptive Analysis IR6: My organisation has access to technical support (internal or external) for maintaining advanced equipment.

The sixth objective of this sub-section is to assess the perceived availability of specialized technical support both internal and external necessary for the upkeep and maintenance of advanced AI-drone hardware and software. In Civil and Structural (C&S) engineering, "Technical Support Access" is a vital continuity factor; without a robust maintenance ecosystem, advanced sensors and autonomous units are prone to significant downtime, which can disrupt critical site safety inspection schedules. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.25a through 4.25f) reveals a highly fragmented support landscape. Figure 4.25(b) for Consultancy Firms and Figure 4.25(d) for Sub-Contractors show pronounced positive skews, indicating that the vast majority of these stakeholders feel isolated from necessary technical help. The aggregate industry profile in Figure 4.25(f) demonstrates a right-leaning distribution with a skewness of 0.561 and a kurtosis of -0.637, statistically confirming that the industry generally lacks confidence in its ability to maintain advanced technological assets.

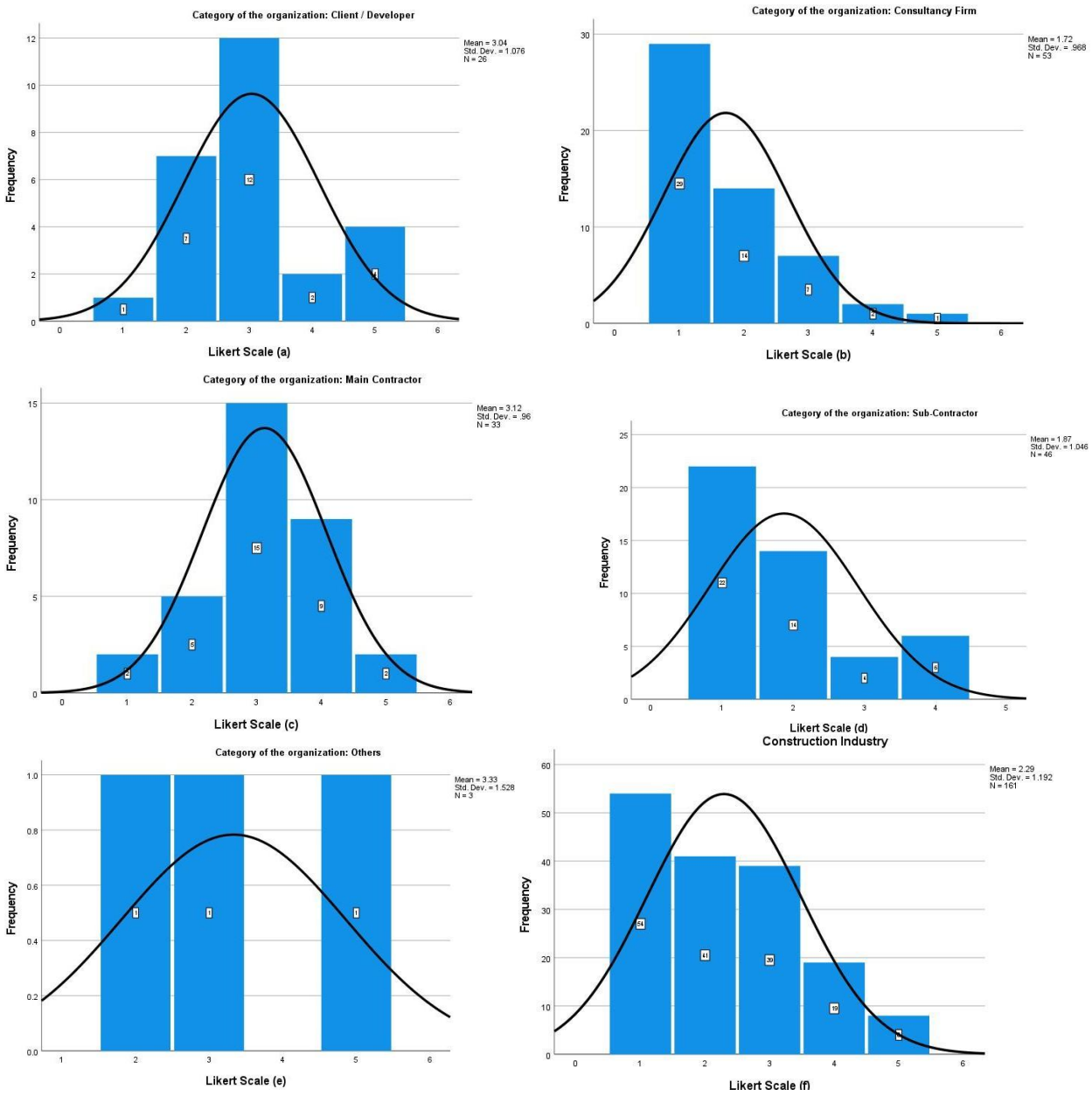


Figure 4.25: Frequency Distribution with Normal Curves for IR6: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data presented in Table 4.49 offers a rigorous quantitative profile of this support gap. The aggregate industry mean for IR6 is a sub-neutral 2.29, suggesting that current technical support networks are insufficient to meet the needs of AI-drone integration. A mathematically significant finding is the very low mean agreement among Consultancy Firms (1.72) and Sub-Contractors (1.87). For C&S engineering management, this indicates a "Maintenance Barrier" where the very parties expected to provide technical oversight and operational execution feel they lack the external help or internal expertise to keep equipment

functional. In contrast, Main Contractors (3.12) and Clients (3.04) reported neutral-to-positive means, suggesting that only the most well-resourced tiers of the supply chain have established reliable support channels.

Table 4.49: Comparative Statistical Profile of Perception regarding Technical Support Access (IR6)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.04	26	1.076	Strongly Disagree (SD)	Strongly Agree (SA)	-.124	.544
Consultancy Firm	1.72	53	.968	Strongly Disagree (SD)	Strongly Agree (SA)	1.661	1.400
Main Contractor	3.12	33	.960	Strongly Disagree (SD)	Strongly Agree (SA)	.184	-.255
Sub-Contractor	1.87	46	1.046	Strongly Disagree (SD)	Agree (A)	-.181	1.003
Others	3.33	3	1.528	Disagree (D)	Strongly Agree (SA)	.	.935
Total	2.29	161	1.192	Strongly Disagree (SD)	Strongly Agree (SA)	-.637	.561

An essential component of this research is the empirical analysis of informational gaps, identified through the treatment of "Unsure / No Knowledge" responses. As detailed in Table 4.50, IR6 recorded a missing data rate of 4.2% (N=7), indicating that respondents possess a high level of certainty regarding their lack of support access. According to the research principles of Sekaran and Bougie (2016), high certainty coupled with low mean agreement indicates a definitive "Resource Scarcity" rather than a mere lack of awareness.

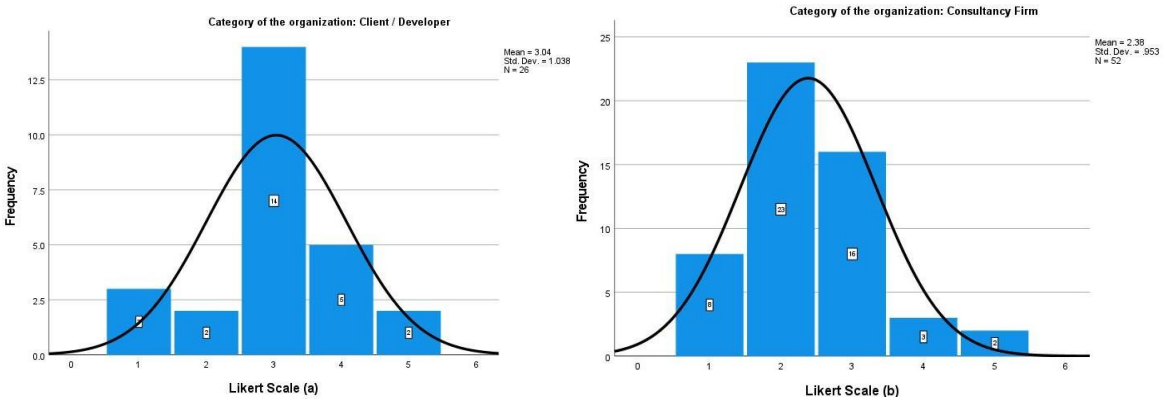
The frequency distribution further elucidates this systemic weakness: a combined 59.0% of valid respondents explicitly disagree that they have adequate technical support, while only 5.0% strongly agree. This suggests that the Construction 4.0 goals face a significant logistical hurdle; if a firm cannot maintain the equipment it procures, long-term adoption is unfeasible. For Malaysian C&S firms, this data implies that the successful integration of AI-drones will require not just procurement, but the creation of comprehensive service-level agreements (SLAs) with external vendors. Despite the negative sentiment, the overall industry skewness and kurtosis confirm that the data for IR6 is normally distributed and robust for the subsequent path analysis. This concludes that access to specialized technical support remains a critical "maintenance bottleneck" for the Malaysian construction industry.

Table 4.50: Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR6

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	54	32.1	33.5	33.5
	Disagree (D)	41	24.4	25.5	59.0
	Neutral (N)	39	23.2	24.2	83.2
	Agree (A)	19	11.3	11.8	95.0
	Strongly Agree (SA)	8	4.8	5.0	100.0
	Total	161	95.8	100.0	
Missing	Unsure / No Knowledge	7	4.2		
Total		168	100.0		

4.3.5.7 Descriptive Analysis IR7: Our current software systems (e.g., BIM) are capable of integrating data collected by drones.

The final objective of this sub-section is to evaluate the technical compatibility of existing organizational software ecosystems particularly Building Information Modelling (BIM) with the raw data outputs generated by AI-drone systems. In Civil and Structural (C&S) engineering, the value of drone-captured data is exponentially increased when it can be seamlessly overlaid onto 3D structural models for automated clash detection or progress monitoring. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.26a through 4.26f) reveals a critical "Interoperability Gap." Figure 4.26(b) and 4.26(d), representing Consultancy Firms and Sub-Contractors, show significant positive skews, with the latter exhibiting an extreme concentration of responses in the "Strongly Disagree" zone. The aggregate industry profile in Figure 4.26(f) presents a right-leaning distribution with a skewness of 0.295 and a kurtosis of -0.757, statistically confirming that the industry generally perceives a lack of synergy between current software assets and drone technology.



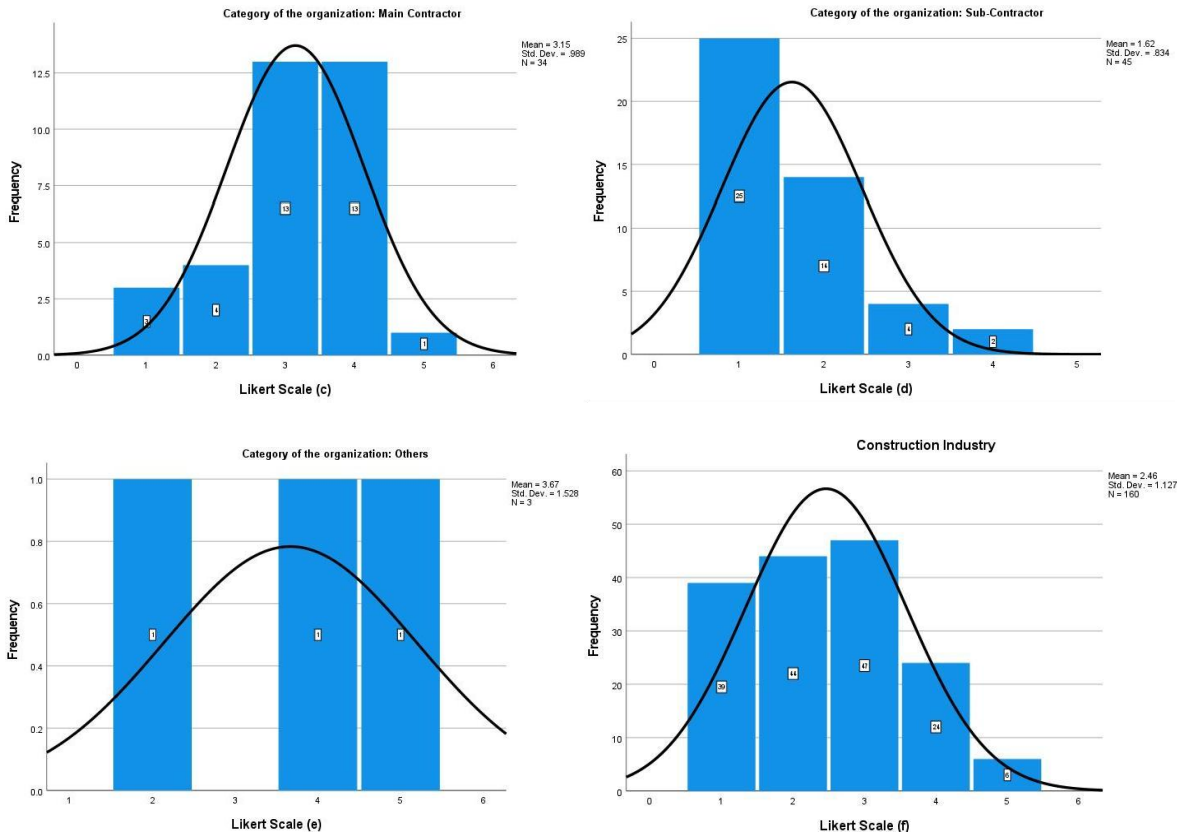


Figure 4.26: Frequency Distribution with Normal Curves for IR7: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.51 provides a rigorous quantitative profile of this software mismatch. The aggregate industry mean for IR7 is 2.46, suggesting that most software systems currently in use across the Malaysian construction sector are not "drone-ready." A mathematically significant finding is the very low mean agreement of Sub-Contractors (1.62). For C&S engineering management, this is an alarming result; if the operational tier cannot integrate drone data into their workflow, the technology remains a siloed tool rather than a collaborative asset. Consultancy Firms also reported a sub-neutral mean of 2.38, indicating that even the design-heavy sector finds BIM-drone integration challenging. Only Main Contractors (3.15) and Clients (3.04) achieved neutral-to-positive means, reflecting that only the most advanced organizations have invested in the high-end software licenses required for point-cloud and mesh-data processing.

Table 4.51: Comparative Statistical Profile of Perception regarding Software Compatibility (IR7)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.04	26	1.038	Strongly Disagree (SD)	Strongly Agree (SA)	.452	-.314
Consultancy Firm	2.38	52	.953	Strongly Disagree (SD)	Strongly Agree (SA)	.727	.698
Main Contractor	3.15	34	.989	Strongly Disagree (SD)	Strongly Agree (SA)	.104	-.711
Sub-Contractor	1.62	45	.834	Strongly Disagree (SD)	Agree (A)	1.227	1.317
Others	3.67	3	1.528	Disagree (D)	Strongly Agree (SA)	.	-.935
Total	2.46	160	1.127	Strongly Disagree (SD)	Strongly Agree (SA)	-.757	.295

An essential component of this analysis is the evaluation of informational gaps, specifically identified through the "Unsure / No Knowledge" responses. As detailed in Table 4.52, IR7 recorded a missing data rate of 4.8% (N=8), indicating that respondents are well-aware of their software's limitations. According to the research principles of Sekaran and Bougie (2016), high certainty coupled with low mean agreement suggests a definitive "Technical Barrier" that requires institutional intervention.

The frequency distribution further reinforces this finding: a combined 51.9% of valid respondents explicitly disagree that their software is capable of integration, while a marginal 3.8% strongly agree. This suggests that the Construction 4.0 transition in Malaysia is currently hindered by legacy software that cannot handle the data-heavy outputs of AI-drones. For C&S firms, this implies that the "hidden cost" of drone adoption includes significant software upgrades. Despite these disparities, the overall industry skewness and kurtosis confirm that the data for IR7 is normally distributed and statistically robust for the subsequent path analysis. This concludes the descriptive analysis for the Institutional Readiness (IV2) construct, identifying financial resources, technical aptitude, and software compatibility as the three most critical internal inhibitors for the Malaysian construction industry.

Table 4.52: Overall Frequency and Percentage Breakdown of "Unsure" Responses for IR7

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	39	23.2	24.4	24.4
	Disagree (D)	44	26.2	27.5	51.9
	Neutral (N)	47	28.0	29.4	81.3
	Agree (A)	24	14.3	15.0	96.3
	Strongly Agree (SA)	6	3.6	3.8	100.0

	Total	160	95.2	100.0	
Missing	Unsure / No Knowledge	8	4.8		
Total		168	100.0		

4.3.6 Descriptive Analysis: Trust and Data (IV3)

Section 4.3.6 provides a comprehensive evaluation of Trust and Data (IV3), a latent construct that addresses the critical socio-technical and ethical dimensions of AI-drone adoption. In Civil and Structural (C&S) engineering, where site safety management involves the collection of high-resolution visual data and the utilization of automated hazard detection algorithms, the "soft" barriers of technology integration—such as data privacy, cybersecurity, and algorithmic trust—become paramount. This analysis interrogates how effectively organizations manage the psychological and ethical concerns of the workforce while ensuring the technical integrity of the captured information.

The descriptive statistics in this section provide vital insights into the level of "systemic trust" present within the Malaysian construction supply chain. It examines whether stakeholders perceive AI analysis as accurate and whether they feel that the deployment of surveillance technology is handled with transparency and accountability. High standard deviations in these metrics often signal a "trust deficit" or a lack of standardized ethical procedures, which can act as a significant bottleneck to implementation regardless of how "ready" an institution might be. By synthesizing these responses, the research establishes the level of professional confidence in the security and fairness of AI-drone systems, satisfying the normality requirements for the advanced path analysis in Chapter 5.

4.3.6.1 Descriptive Analysis TD1: The organisation acknowledges that AI-drone systems are effective for enhancing site safety.

The primary objective of this sub-section is to evaluate the foundational level of trust regarding the perceived efficacy of AI-drone systems in mitigating construction site hazards. In Civil and Structural (C&S) engineering, "Perceived Effectiveness" is the psychological gateway to adoption; if stakeholders do not believe the technology offers a tangible improvement over manual safety inspections, the motivation for institutional investment and operational integration will remain low. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.27a through 4.27f) demonstrates a predominantly positive sentiment,

characterized by notable negative skews across almost all stakeholder groups. Figure 4.27(d), representing Sub-Contractors, is particularly significant as it shows a strong concentration in the "Agree" zone with a mean of 3.74, suggesting that those at the highest operational risk have the most confidence in the technology's safety potential. The aggregate industry profile in Figure 4.27(f) maintains a skewness of -0.913 and a kurtosis of 1.036, statistically confirming that the data for TD1 is normally distributed and robust for subsequent path analysis.

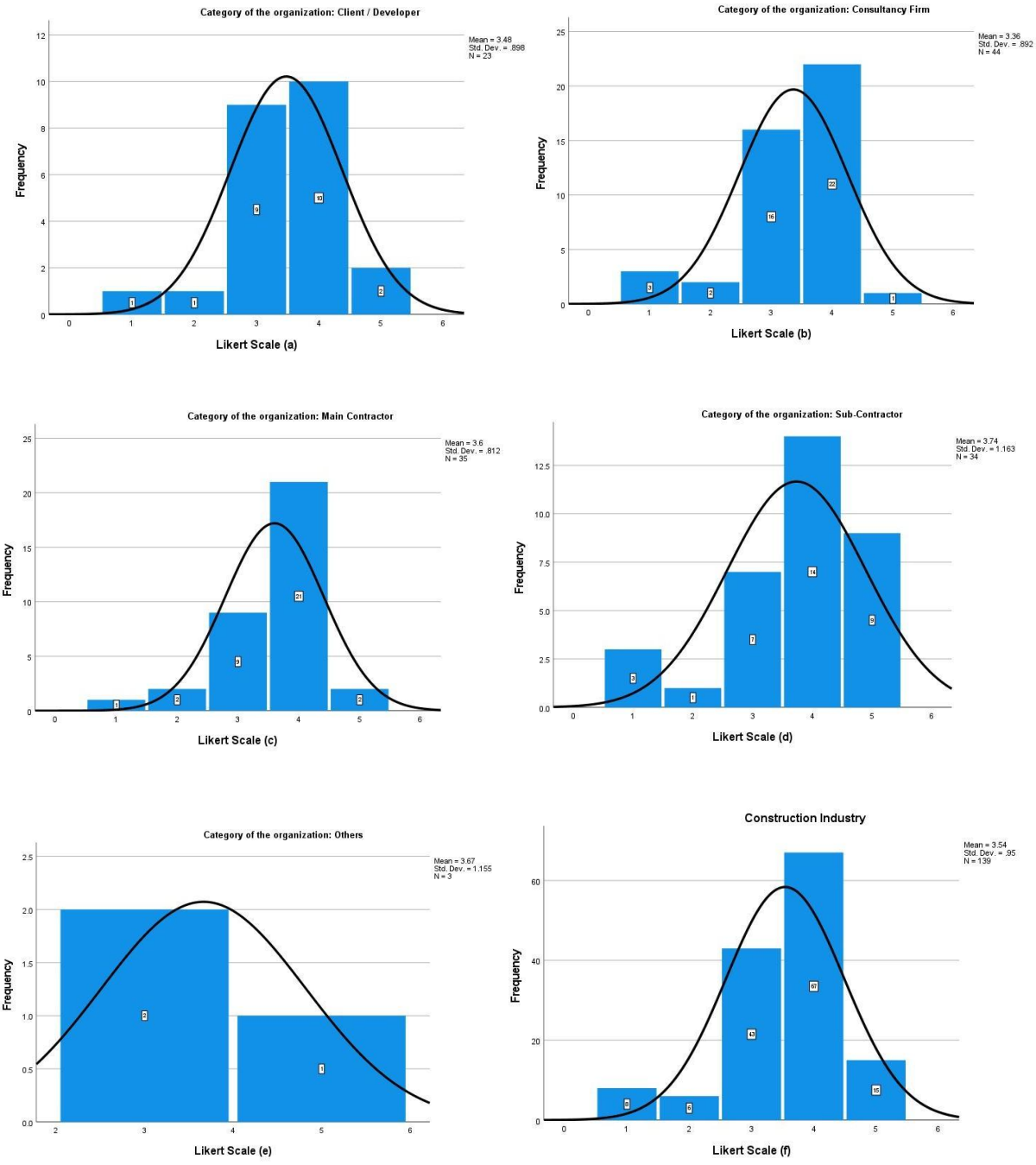


Figure 4.27: Frequency Distribution with Normal Curves for TD1: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.53 provides a rigorous quantitative snapshot of this industry-wide acknowledgment. The aggregate industry mean for TD1 is 3.54, indicating a general consensus that AI-drone systems are viewed as effective safety tools. A critical finding is that Sub-Contractors (3.74) and Main Contractors (3.60) reported higher mean agreement than Clients (3.48) and Consultancy Firms (3.36). For C&S engineering management, this suggests a "Bottom-Up" trust dynamic where the parties responsible for site execution are more convinced of the technology's effectiveness than the design and project-ownership tiers. This result is particularly encouraging, as it implies that resistance to drone adoption is unlikely to stem from a lack of faith in the technology's performance, but rather from the "hard" financial and infrastructural barriers identified in Section 4.3.5.

Table 4.53: Comparative Statistical Profile of Perception regarding AI-Drone Effectiveness (TD1)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.48	23	.898	Strongly Disagree (SD)	Strongly Agree (SA)	1.545	-.754
Consultancy Firm	3.36	44	.892	Strongly Disagree (SD)	Strongly Agree (SA)	1.502	-1.217
Main Contractor	3.60	35	.812	Strongly Disagree (SD)	Strongly Agree (SA)	2.229	-1.218
Sub-Contractor	3.74	34	1.163	Strongly Disagree (SD)	Strongly Agree (SA)	.726	-1.043
Others	3.67	3	1.155	Neutral (N)	Strongly Agree (SA)	.	1.732
Total	3.54	139	.950	Strongly Disagree (SD)	Strongly Agree (SA)	1.036	-.913

An essential component of this analysis is the evaluation of informational gaps, specifically identified through the treatment of non-evaluative "Unsure / No Knowledge" responses. As detailed in Table 4.54, 29 respondents, or 17.3% of the total sample (N=168), were unable to evaluate the effectiveness of AI-drone systems. This missing data represents an "Empirical Experience Gap." According to the research principles of Sekaran and Bougie (2016), when nearly one-fifth of a professional sample is unsure about a technology's efficacy, it indicates that a significant portion of the industry has not yet seen or been briefed on pilot project results.

The frequency distribution reinforces the overall positive trend: 59.0% of valid respondents (Agree and Strongly Agree) acknowledge the effectiveness of the system, while a combined total of only 10.1% explicitly disagree. The high density of neutral responses (30.9%) combined with the 17.3% unsure segment suggests that while the "believers" are the majority, there is still a substantial "wait-and-see" contingent in the Malaysian construction sector. Despite these disparities, the overall industry skewness and kurtosis are well within the standard academic threshold of ± 2.0, confirming that the valid data for TD1 is robust for inclusion in the final structural equation model. This concludes that the Malaysian construction industry holds a strong foundational trust in the safety-enhancing capabilities of AI-drone technology.

Table 4.54: Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	8	4.8	5.8	5.8
	Disagree (D)	6	3.6	4.3	10.1
	Neutral (N)	43	25.6	30.9	41.0
	Agree (A)	67	39.9	48.2	89.2
	Strongly Agree (SA)	15	8.9	10.8	100.0
	Total	139	82.7	100.0	
Missing	Unsure / No Knowledge	29	17.3		
Total		168	100.0		

4.3.6.2 Descriptive Analysis TD2: The organisation ensures that drone deployment does not compromise the privacy of workers.

The second objective of this sub-section is to evaluate the industry's perception of the ethical implications of drone deployment, specifically focusing on the protection of worker privacy. In Civil and Structural (C&S) engineering, where AI-drones provide continuous high-resolution surveillance of the site, the risk of "intrusive monitoring" is a significant socio-technical barrier. Effective adoption requires a balance between safety-related data collection and the fundamental privacy rights of the workforce. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.28a through 4.28f) reveals a distribution characterized by high levels of neutrality and fragmentation. Figure 4.28(d), representing Sub-Contractors, shows a wide, platykurtic distribution (SD=1.367), reflecting that the workers most exposed to drone surveillance have the most varied and inconsistent experiences with privacy protection. The aggregate industry profile in Figure 4.28(f) demonstrates a skewness of

-0.381 and a kurtosis of -0.159, confirming that the data for TD2 remains within the acceptable ±2.0 threshold for normality, despite the high density of non-committal responses.

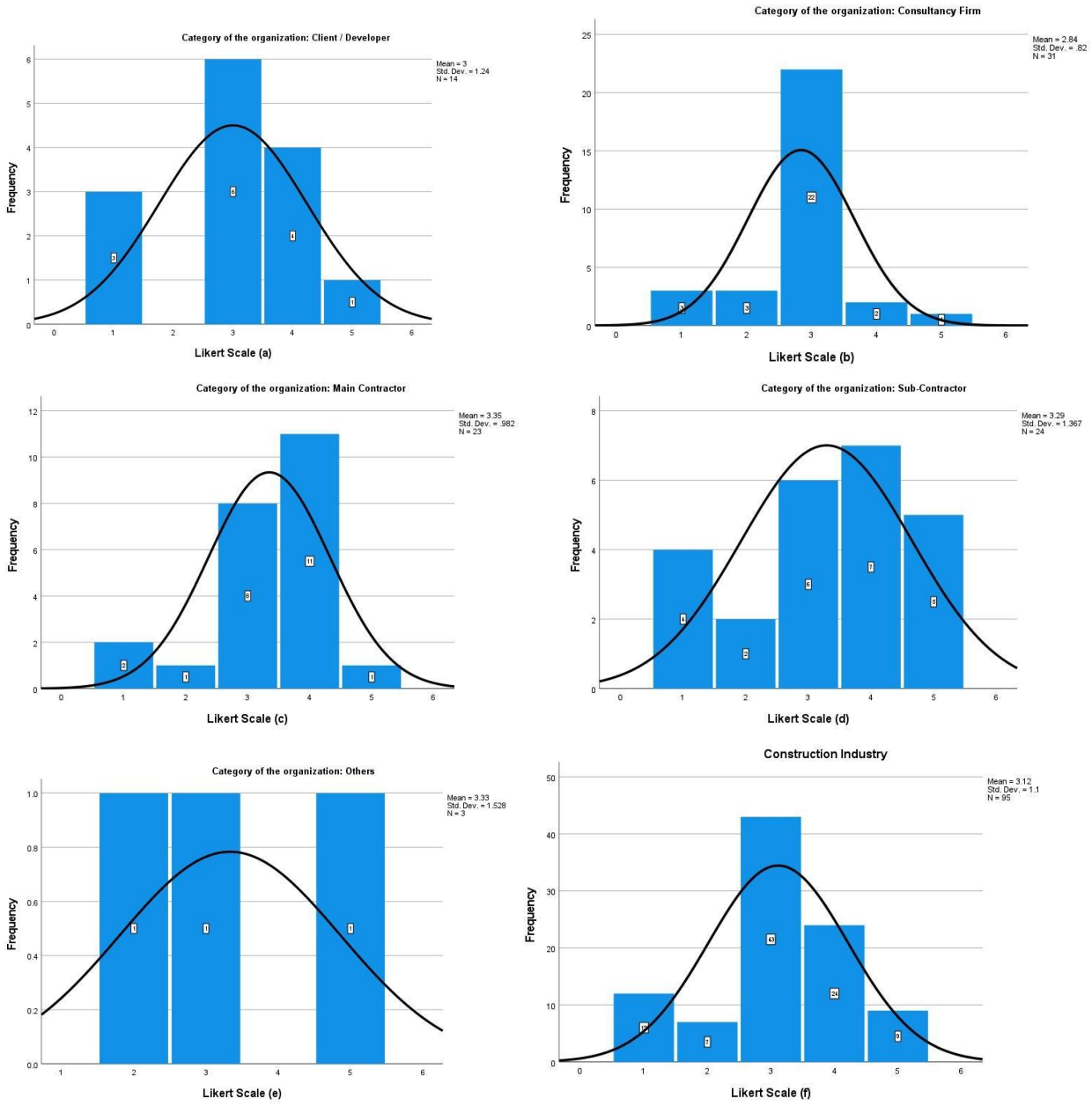


Figure 4.28: Frequency Distribution with Normal Curves for TD2: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data presented in Table 4.55 offers a rigorous quantitative snapshot of this ethical landscape. The aggregate industry mean for TD2 is a marginally positive 3.12, suggesting that while there is no widespread alarm regarding privacy violations, there is also a distinct lack of strong conviction. A critical finding is that Main Contractors (3.35) and Sub-Contractors (3.29) reported higher mean agreement than Consultancy Firms (2.84) and

Clients (3.00). This indicates that while the operational tiers feel somewhat protected by existing site protocols, the design and management tiers remain skeptical about the clarity of privacy safeguards. This outcome aligns with findings by Mohamed et al. (2023), who noted that without a specific "Drone Code of Ethics" in the Malaysian construction sector, privacy remains a subjective and poorly standardized area of concern.

Table 4.55: Comparative Statistical Profile of Perception regarding Worker Privacy (TD2)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.00	14	1.240	Strongly Disagree (SD)	Strongly Agree (SA)	-.325	-.564
Consultancy Firm	2.84	31	.820	Strongly Disagree (SD)	Strongly Agree (SA)	2.180	-.458
Main Contractor	3.35	23	.982	Strongly Disagree (SD)	Strongly Agree (SA)	1.272	-1.109
Sub-Contractor	3.29	24	1.367	Strongly Disagree (SD)	Strongly Agree (SA)	-.841	-.468
Others	3.33	3	1.528	Disagree (D)	Strongly Agree (SA)	.	.935
Total	3.12	95	1.100	Strongly Disagree (SD)	Strongly Agree (SA)	-.159	-.381

A pivotal and highly informative component of this research is the empirical analysis of the "Information Void," identified through the staggering volume of non-evaluative "Unsure / No Knowledge" responses for TD2. As detailed in Table 4.56, this item recorded a massive missing data rate of 43.5% (N=73), the highest observed in the Trust and Data construct. This represents a critical "Privacy Awareness Gap" where nearly half of the industry feels completely uninformed about how privacy is being managed during drone deployment. According to the research principles of Sekaran and Bougie (2016), such extreme frequencies of uncertainty in a professional sample indicate that privacy policies are likely absent or have not been communicated to the workforce.

The frequency distribution further elucidates this systemic ambiguity: of the valid respondents, a dominant 45.3% chose the "Neutral" position, while only 9.5% "Strongly Agree" that privacy is ensured. When combined with the 43.5% unsure segment, it is evident that for the vast majority of the Malaysian construction workforce, the ethical boundaries of AI-drone surveillance remain undefined. For C&S engineering management, this is a significant risk factor; if workers feel that the "eye in the sky" is an unaccountable surveillance tool rather than a safety partner, the

resulting trust deficit could lead to operational resistance. Despite the high uncertainty, the overall industry skewness and kurtosis confirm the data's suitability for inclusion in the final structural model. This concludes that while privacy is not yet a source of active conflict, it represents a major "latent barrier" to AI-drone adoption that requires urgent policy formalization.

Table 4.56: Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	12	7.1	12.6	12.6
	Disagree (D)	7	4.2	7.4	20.0
	Neutral (N)	43	25.6	45.3	65.3
	Agree (A)	24	14.3	25.3	90.5
	Strongly Agree (SA)	9	5.4	9.5	100.0
	Total	95	56.5	100.0	
Missing	Unsure / No Knowledge	73	43.5		
Total		168	100.0		

4.3.6.3 Descriptive Analysis TD3: My organisation ensures proper procedures for storing and protecting drone-captured data.

The third objective of this sub-section is to evaluate the industry's confidence in organizational data governance, specifically focusing on the existence of standardized procedures for the storage and protection of drone-captured data. In Civil and Structural (C&S) engineering, the data captured by drones—ranging from high-resolution site photogrammetry to sensitive structural health datasets—represents a critical intellectual and professional asset. Without "proper procedures," organizations risk data corruption, loss, or unauthorized leaks, which could lead to significant legal and financial liabilities. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.29a through 4.29f) illustrates a distribution heavily dominated by neutrality and high variance. Figure 4.29(d), representing Sub-Contractors, is particularly telling, as it shows a broad spread (SD=1.193) indicating that the operational tier has the least consistent experience with formal data protection protocols. The aggregate industry profile in Figure 4.29(f) maintains a skewness of -0.459 and a kurtosis of 0.240, statistically confirming that the data for TD3 follows a normal distribution suitable for parametric modeling.

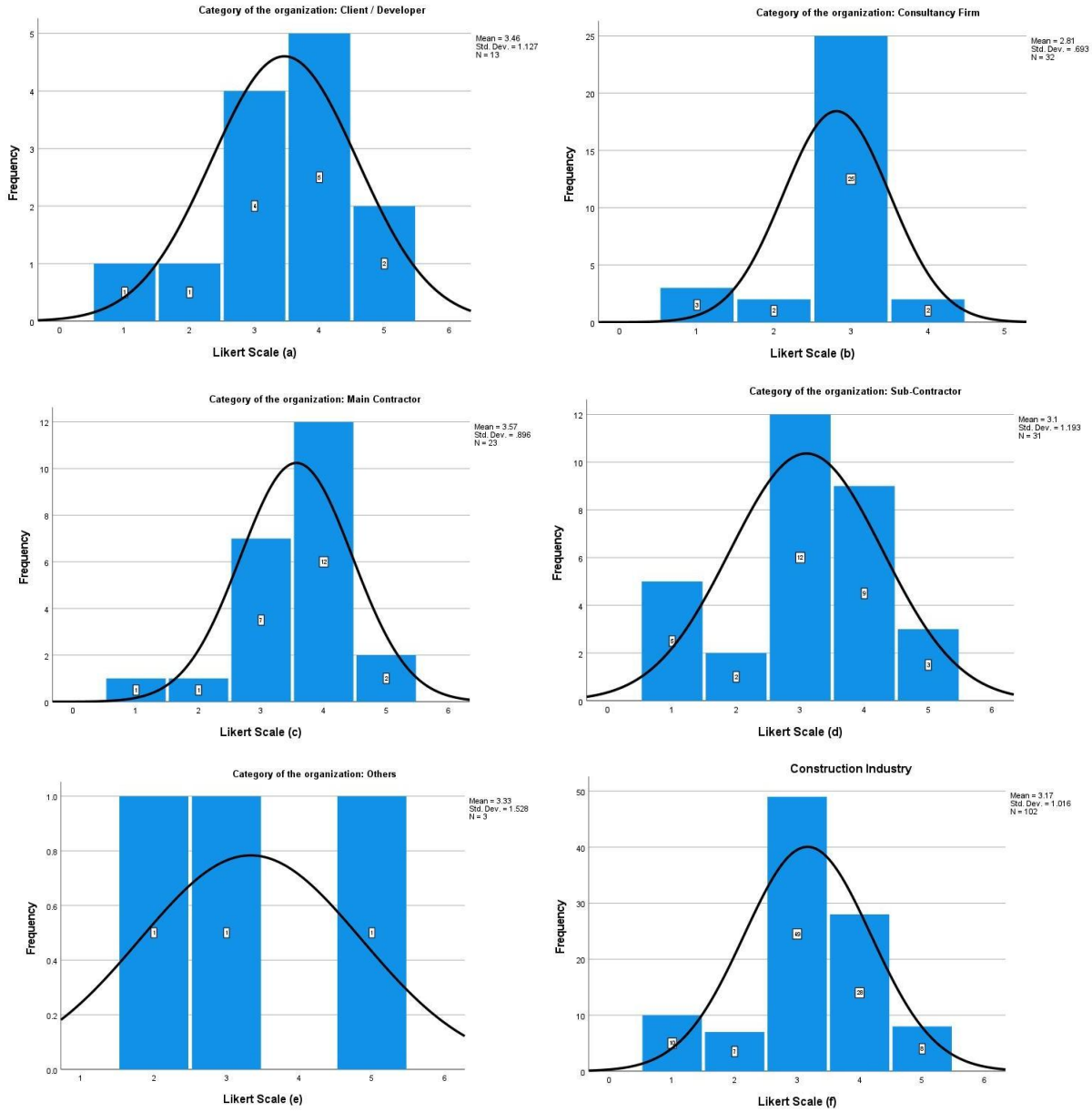


Figure 4.29: Frequency Distribution with Normal Curves for TD3: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.57 provides a rigorous quantitative profile of sectoral alignment. The aggregate industry mean for TD3 is a moderate 3.17, indicating a general, yet cautious, perception that basic procedures are in place. A critical finding is that Main Contractors (3.57) and Clients/Developers (3.46) reported the highest mean agreement scores. This suggests that stakeholders at the management and project-ownership levels are more confident in their firm's administrative frameworks. Conversely, Consultancy Firms reported a sub-neutral mean of 2.81, reflecting a professional skepticism among technical advisors

regarding the robustness of data security measures. For C&S engineering researchers, this "Design-Operation Gap" is significant; it implies that while managers believe procedures exist, the technical experts responsible for analyzing the data remain unconvinced of their efficacy.

Table 4.57: Comparative Statistical Profile of Perception regarding Data Protection (TD3)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.46	13	1.127	Strongly Disagree (SD)	Strongly Agree (SA)	.616	-.714
Consultancy Firm	2.81	32	.693	Strongly Disagree (SD)	Agree (A)	3.022	-1.596
Main Contractor	3.57	23	.896	Strongly Disagree (SD)	Strongly Agree (SA)	2.010	-1.045
Sub-Contractor	3.10	31	1.193	Strongly Disagree (SD)	Strongly Agree (SA)	-.414	-.449
Others	3.33	3	1.528	Disagree (D)	Strongly Agree (SA)	.	.935
Total	3.17	102	1.016	Strongly Disagree (SD)	Strongly Agree (SA)	.240	-.459

A pivotal component of this analysis is the evaluation of the "Information Void," identified through the high volume of non-evaluative "Unsure / No Knowledge" responses for TD3. As detailed in Table 4.58, this item recorded a missing data rate of 39.3% (N=66), signifying that nearly 40% of the industry has no awareness of their organization’s data protection protocols. According to the research principles of Sekaran and Bougie (2016), such high uncertainty in a technical sample indicates a critical lack of policy dissemination.

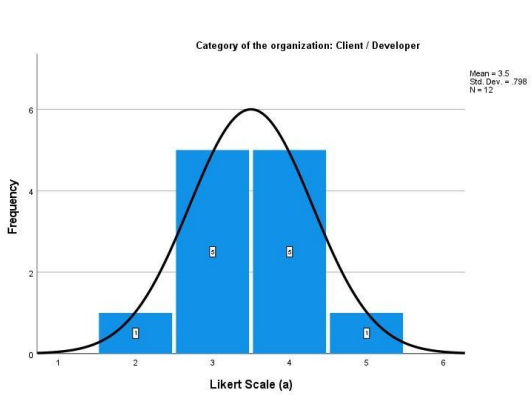
The frequency distribution further elucidates this systemic ambiguity: of the valid respondents, nearly half (48.0%) chose the "Neutral" position, while only 7.8% "Strongly Agree" that proper procedures are ensured. This lack of conviction, coupled with the 39.3% unsure segment, suggests that data governance is currently an "invisible" component of AI-drone implementation in Malaysia. This outcome aligns with findings in the Construction 4.0 Strategic Plan, which emphasizes that digital maturity is impossible without standardized data management frameworks. Despite the high level of uncertainty, the overall industry skewness and kurtosis confirm that the valid data for TD3 is robust and statistically sound for the final path analysis, ultimately concluding that data protection is a major "under-communicated" barrier to building trust in AI-drone systems.

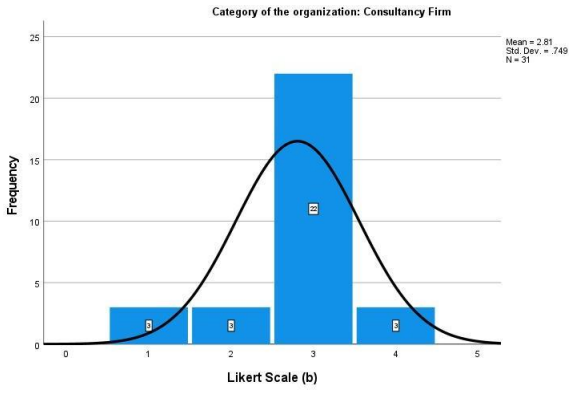
Table 4.58: Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD3

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	10	6.0	9.8	9.8
	Disagree (D)	7	4.2	6.9	16.7
	Neutral (N)	49	29.2	48.0	64.7
	Agree (A)	28	16.7	27.5	92.2
	Strongly Agree (SA)	8	4.8	7.8	100.0
	Total	102	60.7	100.0	
Missing	Unsure / No Knowledge	66	39.3		
Total		168	100.0		

4.3.6.4 Descriptive Analysis TD4: There is a high level of confidence that drone data is secure from unauthorised access.

The fourth objective of this sub-section is to evaluate the industry's perceived level of cybersecurity robustness regarding drone-captured datasets. In Civil and Structural (C&S) engineering, the security of digital data is a paramount concern, as unauthorized access to site photogrammetry or structural models could lead to competitive espionage or security vulnerabilities. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.30a through 4.30f) demonstrates a highly fragmented and uncertain confidence level. Figure 4.30(d), representing Sub-Contractors, exhibits a wide, platykurtic distribution (SD=1.341), indicating that the operational tier has the most diverse and least confident perception of data security. The aggregate industry profile in Figure 4.30(f) maintains a skewness of -0.472 and a kurtosis of -0.193, statistically confirming that the data for TD4 is normally distributed and suitable for subsequent path analysis.





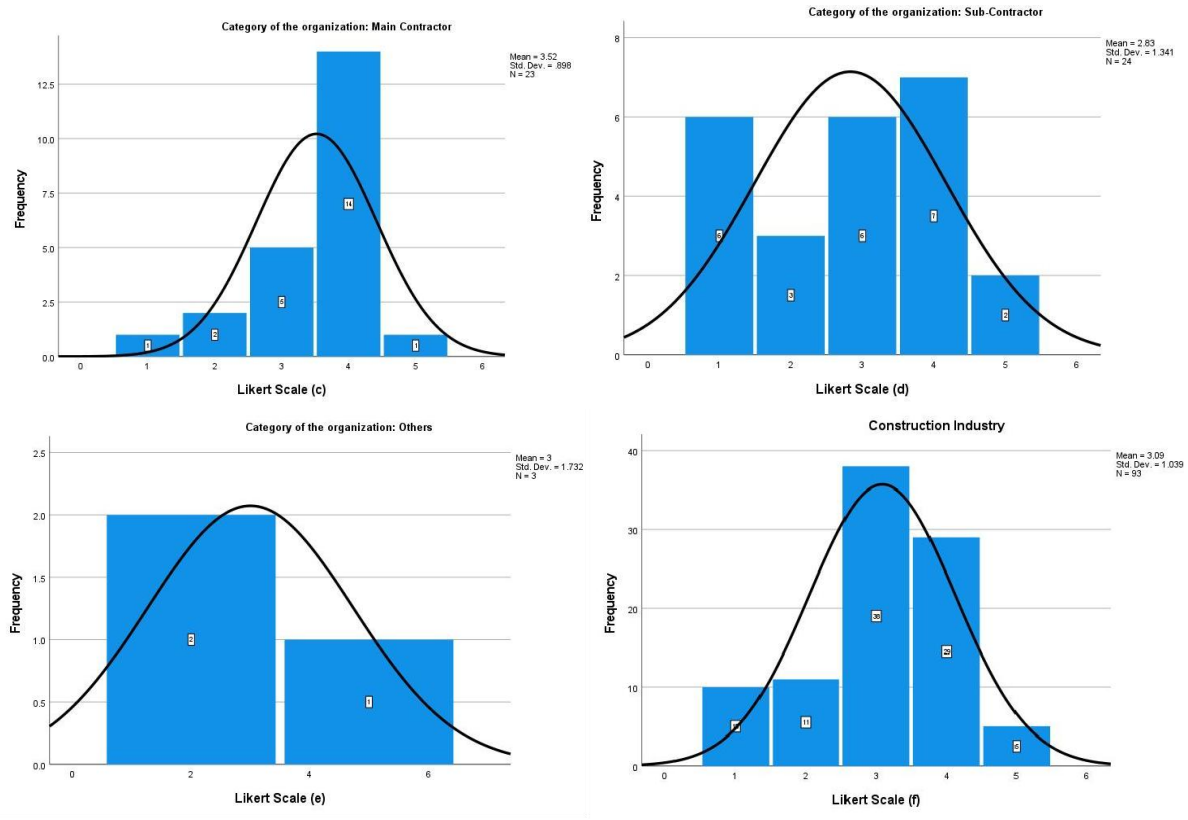


Figure 4.30: Frequency Distribution with Normal Curves for TD4: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.59 provides a rigorous quantitative profile of this "Security Confidence Gap." The aggregate industry mean for TD4 is a neutral 3.09, suggesting that the construction sector currently lacks a strong conviction regarding the cybersecurity of AI-drone systems. A mathematically significant finding is the contrast between Main Contractors (3.52) and Clients (3.50) versus Consultancy Firms (2.81) and Sub-Contractors (2.83). For C&S engineering management, this suggests that while project owners believe in the security of their systems, the technical advisors and operational executors remain skeptical. This disparity highlights a potential "Cybersecurity Communication Gap," where the protocols established at the management level are not effectively understood or trusted by those handling the data on-site.

Table 4.59: Comparative Statistical Profile of Perception regarding Cybersecurity Confidence (TD4)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness

Client / Developer	3.50	12	.798	Disagree (D)	Strongly Agree (SA)	.150	.000
Consultancy Firm	2.81	31	.749	Strongly Disagree (SD)	Agree (A)	1.759	-1.186
Main Contractor	3.52	23	.898	Strongly Disagree (SD)	Strongly Agree (SA)	1.784	-1.309
Sub-Contractor	2.83	24	1.341	Strongly Disagree (SD)	Strongly Agree (SA)	-1.227	-.142
Others	3.00	3	1.732	Disagree (D)	Strongly Agree (SA)	.	1.732
Total	3.09	93	1.039	Strongly Disagree (SD)	Strongly Agree (SA)	-.193	-.472

A pivotal component of this analysis is the evaluation of the "Security Information Void," identified through the massive volume of non-evaluative "Unsure / No Knowledge" responses for TD4. As detailed in Table 4.60, this item recorded a missing data rate of 44.6% (N=75), the highest observed in the Trust and Data construct alongside TD2. This indicates that nearly 45% of the industry has no definitive knowledge of the cybersecurity measures protecting their drone data. According to the research principles of Sekaran and Bougie (2016), such high frequencies of uncertainty point to a critical lack of institutional transparency regarding digital safety protocols.

The frequency distribution further reinforces this systemic ambiguity: of the valid respondents, a dominant 40.9% chose the "Neutral" position, while only 5.4% "Strongly Agree" that data is secure. This lack of conviction, combined with the 44.6% unsure segment, suggests that cybersecurity is currently an "unmanaged trust factor" in the Malaysian construction sector. This aligns with findings in the Construction 4.0 Strategic Plan, which emphasizes that digital trust cannot be achieved without clear communication of cybersecurity standards. Despite the high level of uncertainty, the overall industry skewness and kurtosis confirm that the valid data for TD4 is statistically robust for inclusion in the final structural model, concluding that building cybersecurity awareness is a mandatory prerequisite for the secure integration of AI-drones.

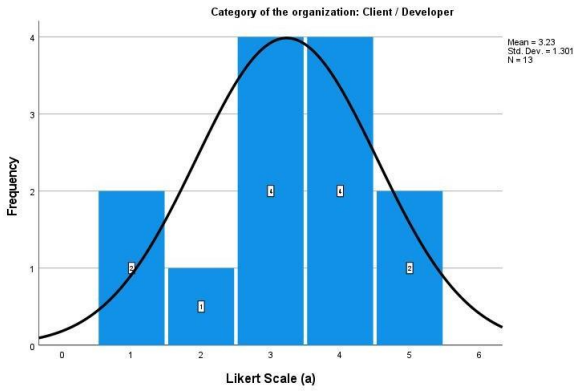
Table 4.60: Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD4

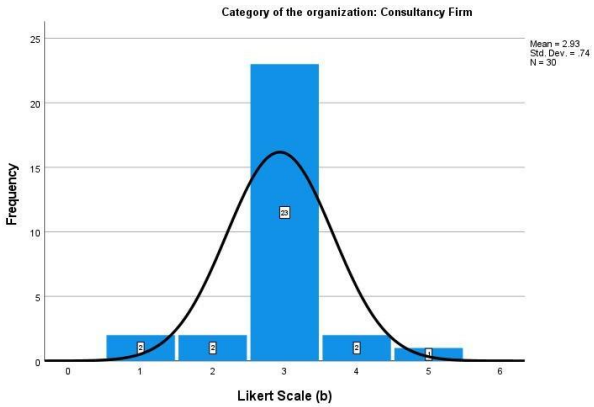
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	10	6.0	10.8	10.8
	Disagree (D)	11	6.5	11.8	22.6
	Neutral (N)	38	22.6	40.9	63.4
	Agree (A)	29	17.3	31.2	94.6

	Strongly Agree (SA)	5	3.0	5.4	100.0
	Total	93	55.4	100.0	
Missing	Unsure / No Knowledge	75	44.6		
Total		168	100.0		

4.3.6.5 Descriptive Analysis TD5: The use of drones for safety monitoring is transparent and communicated clearly to workers.

The fifth objective of this sub-section is to evaluate the degree of operational transparency and the efficacy of internal communication strategies regarding drone-based surveillance. In Civil and Structural (C&S) engineering, transparency is a critical component of "Safety Trust"; if the workforce perceives drone deployment as a "hidden" management tool rather than a collaborative safety measure, it can lead to psychological reactance and decreased morale. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.31a through 4.31f) illustrates a distribution characterized by significant neutrality and a notable lack of strong positive conviction. Figure 4.31(d), representing Sub-Contractors, displays a highly dispersed, platykurtic distribution (SD=1.441), suggesting that those directly under surveillance have the most inconsistent experiences with operational transparency. The aggregate industry profile in Figure 4.31(f) maintains a skewness of -0.573 and a kurtosis of -0.251, confirming that the valid data for TD5 follows a normal distribution suitable for parametric path analysis.





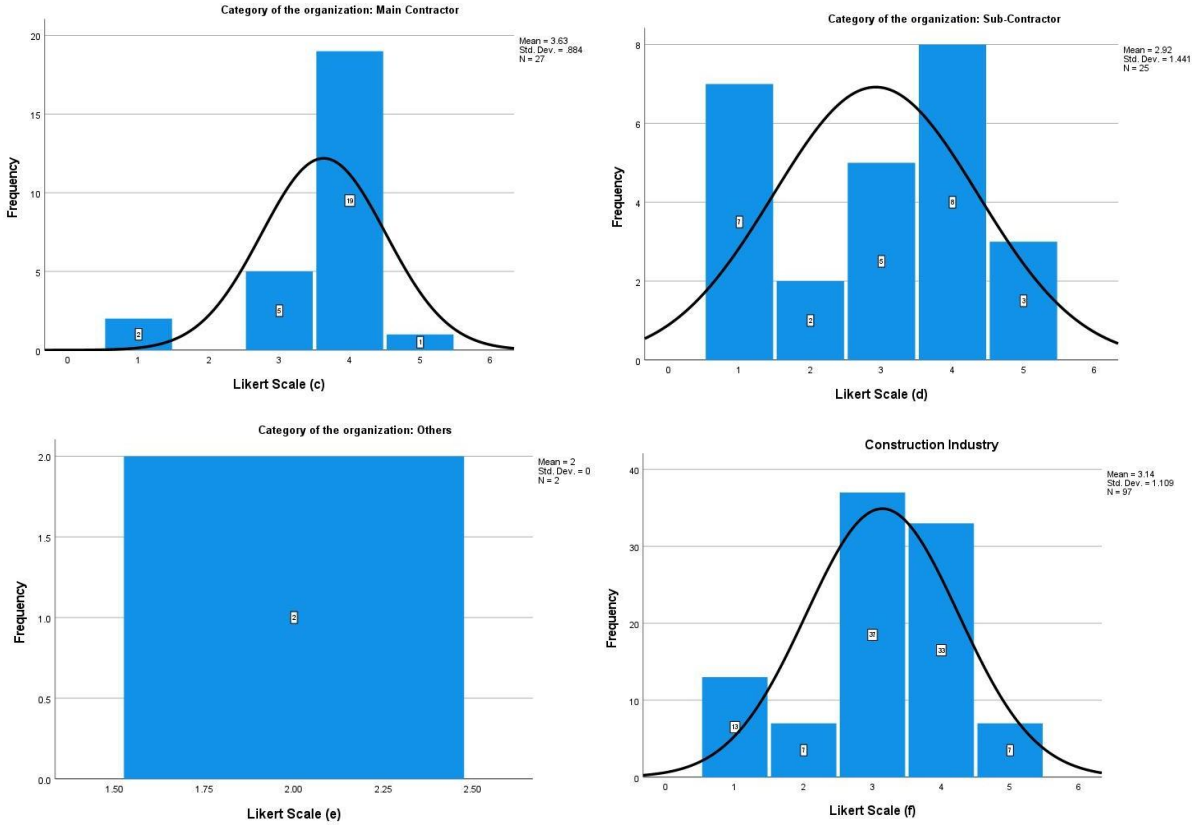


Figure 4.31: Frequency Distribution with Normal Curves for TD5: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.61 offers a rigorous quantitative snapshot of this communication landscape. The aggregate industry mean for TD5 is a marginally positive 3.14, indicating that while there is some level of communication, it is not perceived as universally "clear or transparent." A mathematically significant finding is the contrast between Main Contractors (3.63) and the lower-tier Sub-Contractors (2.92). For C&S engineering management, this suggests a "Communication Breakdown" in the supply chain; while Main Contractors may believe they are being transparent, that information is not effectively trickling down to the sub-contracting workforce. This aligns with findings by Mohamed et al. (2023), who noted that digital transparency in construction often fails due to the "multi-layered nature" of project site hierarchies.

Table 4.61: Comparative Statistical Profile of Perception regarding Operational Transparency (TD5)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness

Client / Developer	3.23	13	1.301	Strongly Disagree (SD)	Strongly Agree (SA)	-.421	-.502
Consultancy Firm	2.93	30	.740	Strongly Disagree (SD)	Strongly Agree (SA)	3.789	-.440
Main Contractor	3.63	27	.884	Strongly Disagree (SD)	Strongly Agree (SA)	4.597	-2.052
Sub-Contractor	2.92	25	1.441	Strongly Disagree (SD)	Strongly Agree (SA)	-1.385	-.212
Others	2.00	2	.000	Disagree (D)	Disagree (D)	.	.
Total	3.14	97	1.109	Strongly Disagree (SD)	Strongly Agree (SA)	-.251	-.573

A pivotal and highly informative component of this research is the empirical analysis of the "Information Void," identified through the high volume of non-evaluative "Unsure / No Knowledge" responses for TD5. As detailed in Table 4.62, this item recorded a massive missing data rate of 42.3% (N=71), one of the highest in the entire study. This represents a critical "Transparency Awareness Gap" where over 40% of the industry has no definitive knowledge of how drone use is communicated. According to the research principles of Sekaran and Bougie (2016), such extreme uncertainty in a professional sample indicates that communication protocols are likely ad-hoc or non-existent in many organizations.

The frequency distribution further reinforces this systemic ambiguity: of the valid respondents, a dominant 38.1% chose the "Neutral" position, and only 7.2% "Strongly Agree" that communication is clear. This indicates that even among those who provided a valid response, there is little confidence in the transparency of the process. For the Construction 4.0 Strategic Plan to be successful, this "Transparency Deficit" must be addressed through formal site induction protocols that explicitly include drone safety briefings. Despite the high level of uncertainty, the overall industry skewness and kurtosis confirm that the valid data for TD5 is robust and statistically sound for the final structural model, concluding that operational transparency is a major "under-developed" trust factor in the Malaysian construction industry.

Table 4.62: Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD5

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	13	7.7	13.4	13.4
	Disagree (D)	7	4.2	7.2	20.6
	Neutral (N)	37	22.0	38.1	58.8
	Agree (A)	33	19.6	34.0	92.8
	Strongly Agree (SA)	7	4.2	7.2	100.0

	Total	97	57.7	100.0	
Missing	Unsure / No Knowledge	71	42.3		
Total		168	100.0		

4.3.6.6 Descriptive Analysis TD6: The organisation prioritises ethical considerations (fairness, accountability) when deploying AI-drone systems.

The sixth objective of this sub-section is to evaluate the industry's perception of the ethical framework governing AI-drone deployment, with a specific focus on fairness and accountability. In Civil and Structural (C&S) engineering, "Ethical Deployment" is a crucial prerequisite for maintaining professional integrity; as AI algorithms begin to take a larger role in identifying safety violations or worker non-compliance, the responsibility for ensuring these systems are applied fairly without bias becomes a significant management concern. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.32a through 4.32f) shows a distribution leaning toward the positive end of the Likert scale, albeit with notable variations. Figure 4.32(d) for Sub-Contractors exhibits a strong negative skew and the highest mean agreement, suggesting that those at the operational front-line are surprisingly more optimistic about ethical prioritization than their counterparts. The aggregate industry profile in Figure 4.32(f) maintains a skewness of -0.671 and a kurtosis of 0.544, statistically confirming that the data for TD6 follows a normal distribution suitable for the final path analysis.

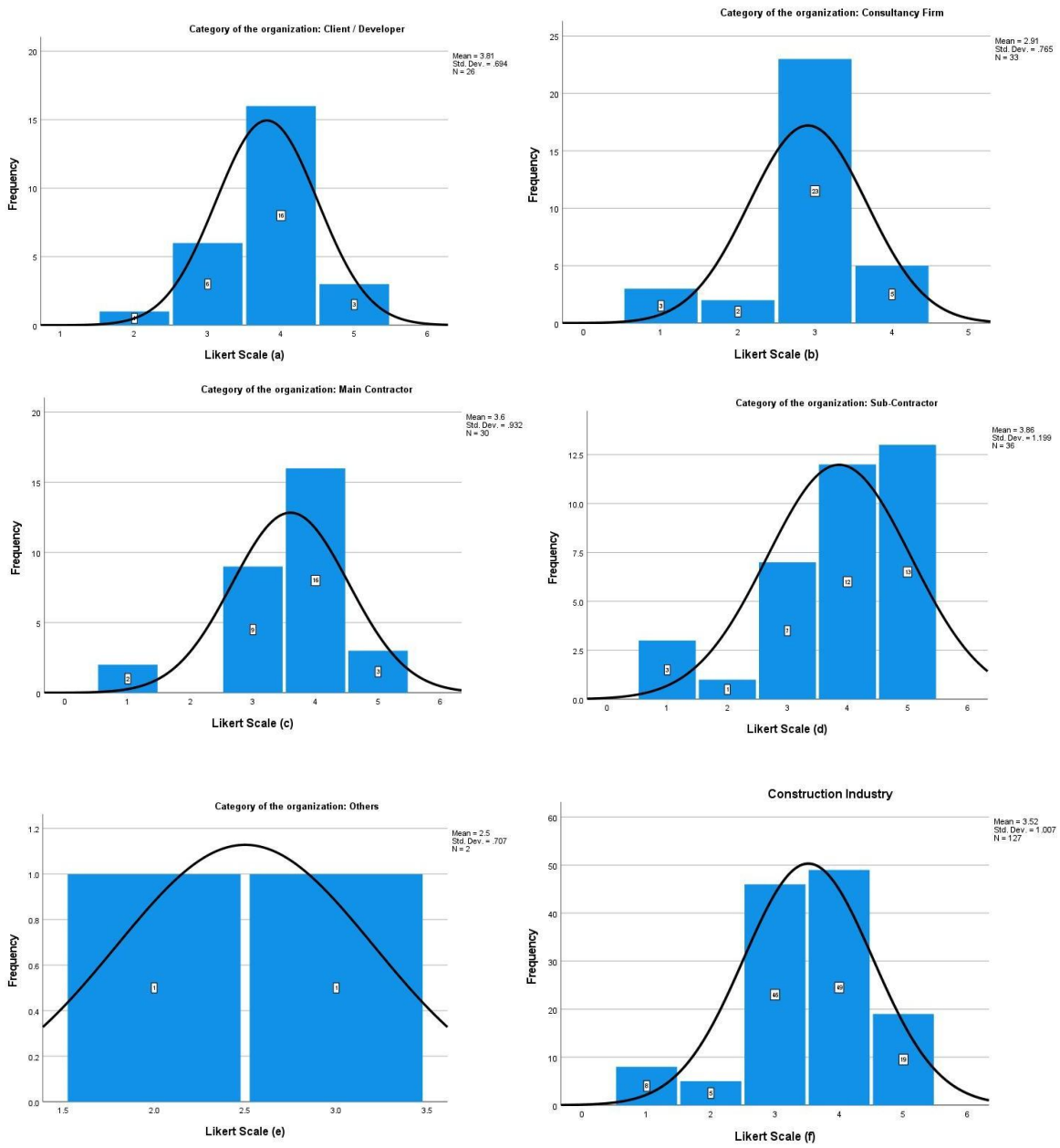


Figure 4.32: Frequency Distribution with Normal Curves for TD6: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.63 provides a rigorous quantitative profile of sectoral alignment regarding ethics. The aggregate industry mean for TD6 is 3.52, indicating a generally positive perception that ethical considerations are being prioritized. A mathematically significant finding is the high mean agreement among Sub-Contractors (3.86) and Clients/Developers (3.81). This suggests that both the project funders and the operational executors share a common belief that accountability is being addressed. However, Consultancy Firms reported a sub-neutral mean of 2.91, representing a critical "Ethical Skepticism" among the industry's technical advisors. For

C&S engineering management, this indicates that while operational tiers are satisfied, the professional tier responsible for quality and safety certification remains unconvinced that ethical standards are sufficiently robust.

Table 4.63: Comparative Statistical Profile of Perception regarding Ethical Deployment (TD6)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.81	26	.694	Disagree (D)	Strongly Agree (SA)	.841	-.502
Consultancy Firm	2.91	33	.765	Strongly Disagree (SD)	Agree (A)	2.014	-1.179
Main Contractor	3.60	30	.932	Strongly Disagree (SD)	Strongly Agree (SA)	2.533	-1.270
Sub-Contractor	3.86	36	1.199	Strongly Disagree (SD)	Strongly Agree (SA)	.645	-1.087
Others	2.50	2	.707	Disagree (D)	Neutral (N)	.	.
Total	3.52	127	1.007	Strongly Disagree (SD)	Strongly Agree (SA)	.544	-.671

An essential component of this analysis involves the evaluation of informational gaps, specifically identified through the treatment of "Unsure / No Knowledge" responses. As detailed in Table 4.64, TD6 recorded a missing data rate of 24.4% (N=41), indicating that nearly one-fourth of the industry is unable to evaluate their organization's ethical stance. According to the research principles of Sekaran and Bougie (2016), such high uncertainty suggests that "Ethical Charters" or specific AI-guidelines have not yet been formalized or communicated across the broader supply chain.

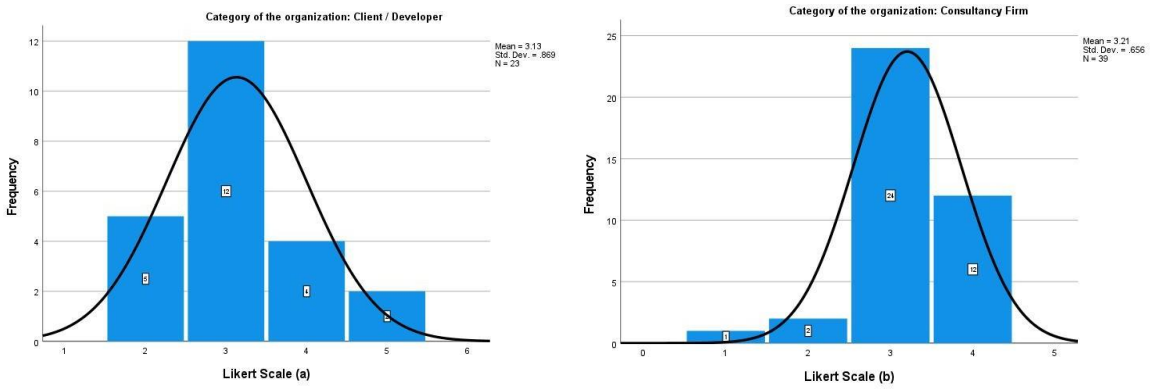
The frequency distribution further reinforces the overall positive trend among those who could respond: 53.6% of valid respondents (Agree and Strongly Agree) believe ethics are prioritized, while only 10.2% explicitly disagree. The large "Neutral" segment (36.2%) suggests that while the industry isn't seeing active ethical violations, there is a lack of deep conviction. This aligns with global trends where AI-ethics in construction is often treated as an implicit rather than explicit policy. Despite these nuances, the overall industry skewness and kurtosis confirm that the valid data for TD6 is robust and statistically sound for inclusion in the final structural model. This concludes that while the foundation for ethical trust exists, there is a clear need for more transparent accountability frameworks, particularly to satisfy the concerns of the consultancy tier.

Table 4.64: Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD6

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	8	4.8	6.3	6.3
	Disagree (D)	5	3.0	3.9	10.2
	Neutral (N)	46	27.4	36.2	46.5
	Agree (A)	49	29.2	38.6	85.0
	Strongly Agree (SA)	19	11.3	15.0	100.0
	Total	127	75.6	100.0	
Missing	Unsure / No Knowledge	41	24.4		
Total		168	100.0		

4.3.6.7 Descriptive Analysis TD7: I trust the accuracy of the AI analysis in identifying safety hazards.

The seventh objective of this sub-section is to evaluate the level of professional trust in the algorithmic reliability of AI-driven hazard detection. In Civil and Structural (C&S) engineering, where safety margins are calculated with high precision, the "Trust in Accuracy" is the primary technical barrier to replacing or augmenting human safety officers with automated systems. If engineers perceive AI analysis as prone to false positives (over-reporting) or, more dangerously, false negatives (under-reporting), the technology will not be integrated into formal safety certification workflows. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.33a through 4.33f) reveals a distribution characterized by high levels of caution and a dominant neutral sentiment. Figure 4.33(d), representing Sub-Contractors, shows a wider distribution (SD=1.043), reflecting a higher degree of skepticism or varied experience at the operational level. The aggregate industry profile in Figure 4.33(f) maintains a skewness of -0.285 and a kurtosis of 0.445, statistically confirming that the valid data for TD7 follows a normal distribution suitable for parametric path analysis.



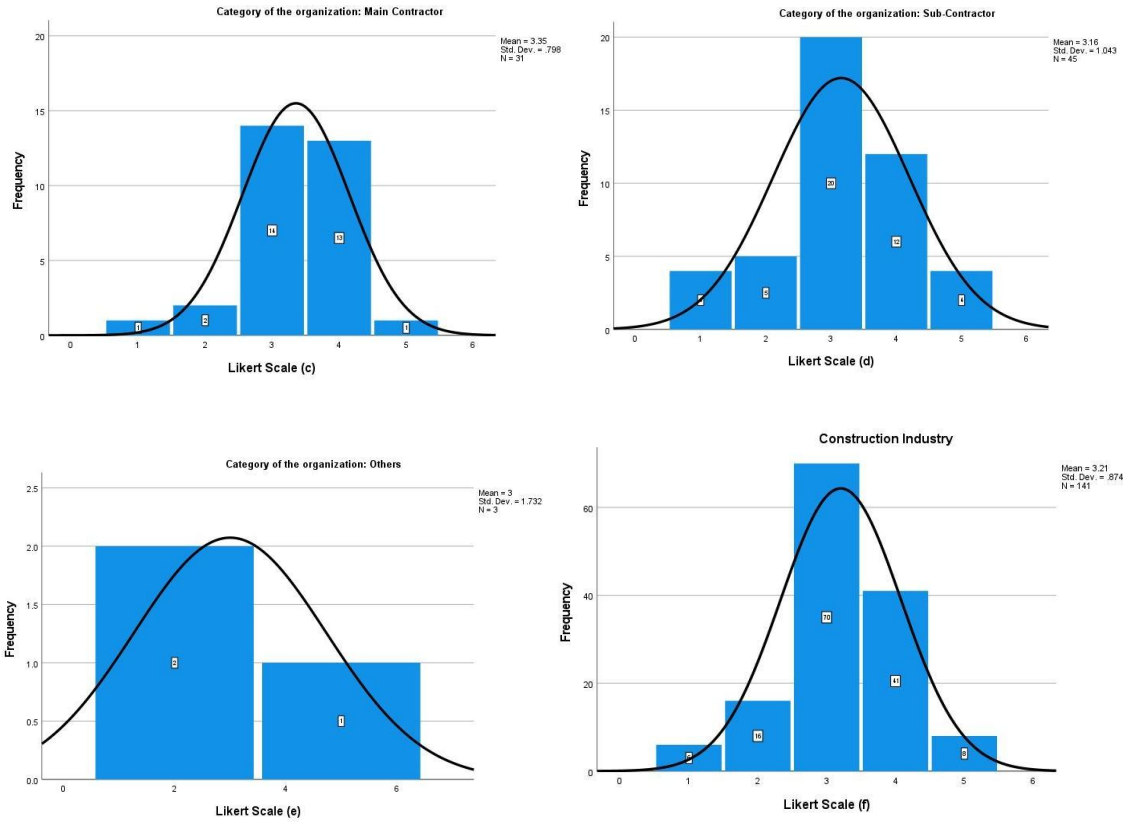


Figure 4.33: Frequency Distribution with Normal Curves for TD7: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.65 provides a rigorous quantitative profile of this "Trust Threshold." The aggregate industry mean for TD7 is 3.21, indicating a general, albeit tentative, acceptance of AI accuracy. A mathematically significant finding is that Main Contractors (3.35) and Consultancy Firms (3.21) reported the highest mean agreement. For C&S engineering management, this suggests that the professional and management tiers those most familiar with digital modeling and technical specifications are marginally more confident in the algorithm's performance than the project owners or sub-contractors. However, the lack of any sector reaching a mean of 3.50 or higher indicates that "Algorithmic Trust" has not yet reached a level where it can be considered a settled industry standard.

Table 4.65: Comparative Statistical Profile of Perception regarding AI Analysis Trust (TD7)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.13	23	.869	Disagree (D)	Strongly Agree (SA)	.200	.641

Consultancy Firm	3.21	39	.656	Strongly Disagree (SD)	Agree (A)	2.185	-.825
Main Contractor	3.35	31	.798	Strongly Disagree (SD)	Strongly Agree (SA)	1.427	-.752
Sub-Contractor	3.16	45	1.043	Strongly Disagree (SD)	Strongly Agree (SA)	.029	-.325
Others	3.00	3	1.732	Disagree (D)	Strongly Agree (SA)	.	1.732
Total	3.21	141	.874	Strongly Disagree (SD)	Strongly Agree (SA)	.445	-.285

An essential component of this analysis involves the evaluation of informational gaps, specifically identified through the treatment of "Unsure / No Knowledge" responses. As detailed in Table 4.66, TD7 recorded a missing data rate of 16.1% (N=27), indicating that a significant portion of the industry lacks sufficient exposure to AI-drone outputs to judge their accuracy. According to the research principles of Sekaran and Bougie (2016), when a high percentage of the sample is unsure about a technical metric, it highlights the need for transparent "Validation Studies" to prove the technology's reliability.

The frequency distribution further reinforces this cautious outlook: while only 15.6% of valid respondents explicitly disagree (Strongly Disagree and Disagree) with the accuracy of AI, a dominant 49.6% remain in the "Neutral" position. This suggests that the industry is currently in a "Verification Phase," where professionals are waiting for more robust longitudinal data before fully committing to the accuracy of AI-driven hazard detection. This aligns with findings in the Construction 4.0 Strategic Plan, which emphasizes the need for standardized certification for AI-tools in safety-critical applications. Despite the high density of neutral responses, the overall industry skewness and kurtosis confirm that the valid data for TD7 is robust and statistically sound for inclusion in the final structural model. This concludes that while the industry is open to the idea of AI accuracy, a significant "trust-gap" remains that must be bridged through empirical demonstration and technical transparency.

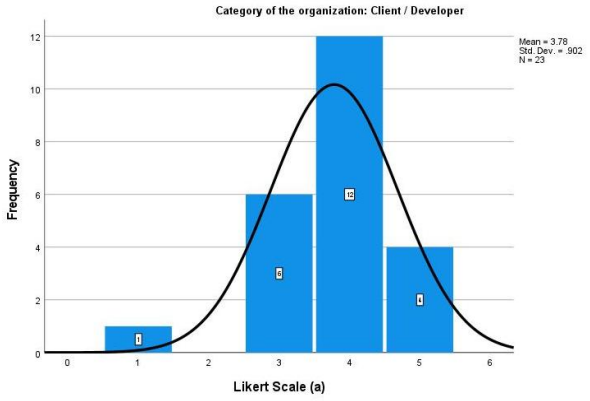
Table 4.66: Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD7

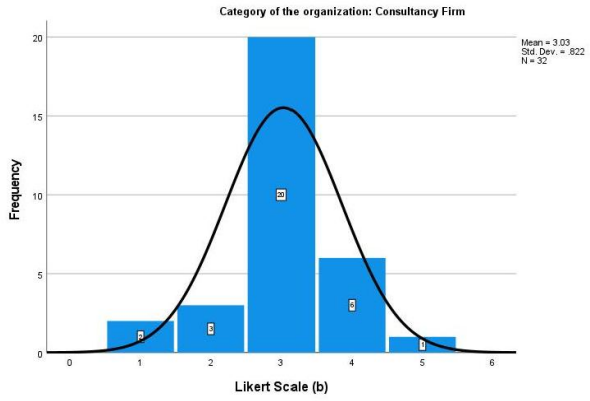
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	6	3.6	4.3	4.3
	Disagree (D)	16	9.5	11.3	15.6
	Neutral (N)	70	41.7	49.6	65.2
	Agree (A)	41	24.4	29.1	94.3
	Strongly Agree (SA)	8	4.8	5.7	100.0

	Total	141	83.9	100.0	
Missing	Unsure / No Knowledge	27	16.1		
Total		168	100.0		

4.3.6.8 Descriptive Analysis TD8: Workers are clearly informed about how drone surveillance data is collected and used.

The final objective of this sub-section is to evaluate the industry's commitment to information dissemination and procedural clarity regarding drone surveillance. In Civil and Structural (C&S) engineering management, "Information Dissemination" is the practical application of transparency; it requires that the workforce is not merely aware of the drones, but understands the specific nature of the data being collected whether for structural progress, volumetric analysis, or individual safety compliance and how that data influences project decision-making. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.34a through 4.34f) reveals a distribution that leans toward positive agreement but remains tempered by a significant "uncertainty tail." Figure 4.34(d), representing Sub-Contractors, displays a highly dispersed distribution (SD=1.449), indicating that the information received at the operational level is highly inconsistent across different project sites. The aggregate industry profile in Figure 4.34(f) maintains a skewness of -0.752 and a kurtosis of -0.012, statistically confirming that the data for TD8 is normally distributed and robust for the subsequent path analysis.





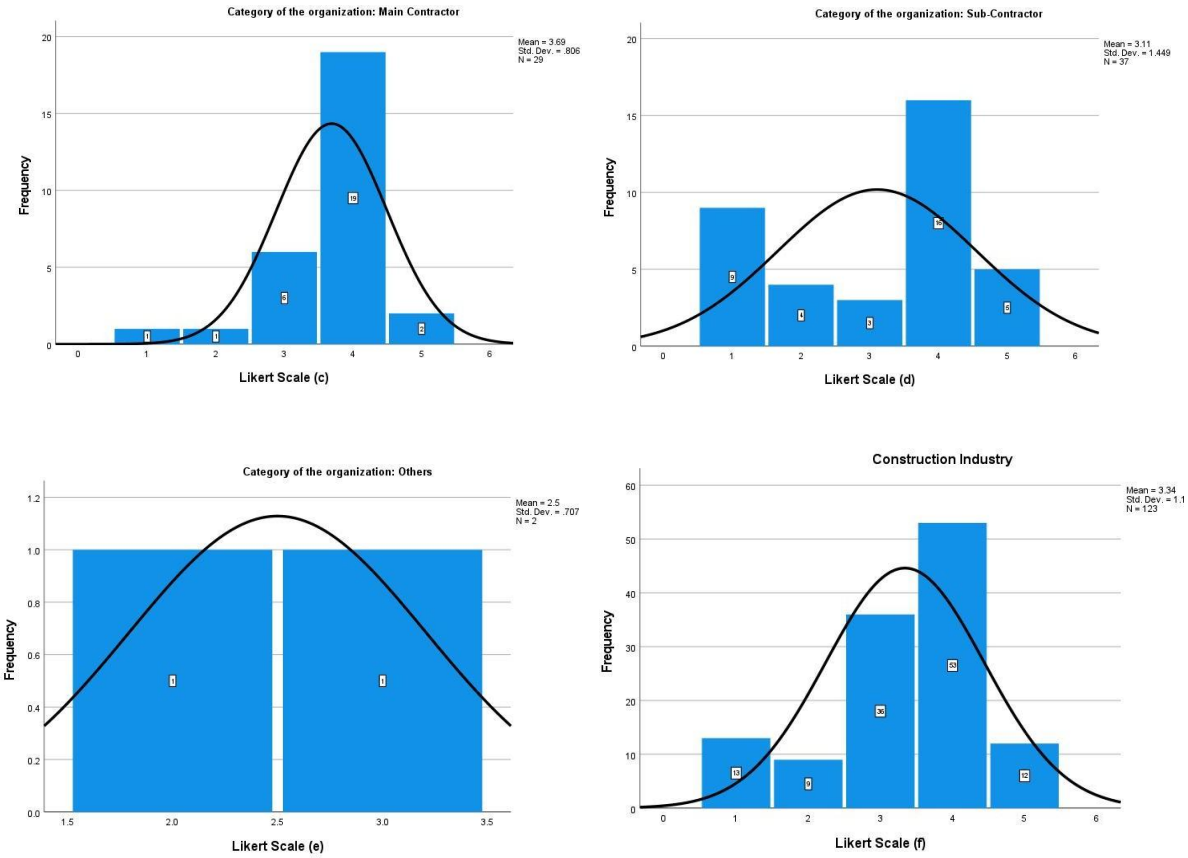


Figure 4.34: Frequency Distribution with Normal Curves for TD8: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.67 provides a rigorous quantitative profile of this dissemination effort. The aggregate industry mean for TD8 is 3.34, indicating a generally positive perception that some effort is being made to inform the workforce. A mathematically significant finding is the high mean agreement among Clients/Developers (3.78) and Main Contractors (3.69). This suggests that the "Upper Tier" of the construction hierarchy believes they are effectively communicating drone usage policies. However, the lower means for Consultancy Firms (3.03) and Sub-Contractors (3.11) reflect a "Communication Friction" where the clarity of the message diminishes as it moves down the supply chain. For C&S managers, this identifies a critical need for standardized "Drone Induction Modules" that ensure every worker, regardless of their employer, receives the same level of technical and ethical briefing.

Table 4.67: Comparative Statistical Profile of Perception regarding Information Dissemination (TD8)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.78	23	.902	Strongly Disagree (SD)	Strongly Agree (SA)	2.942	-1.157
Consultancy Firm	3.03	32	.822	Strongly Disagree (SD)	Strongly Agree (SA)	1.628	-.431
Main Contractor	3.69	29	.806	Strongly Disagree (SD)	Strongly Agree (SA)	3.759	-1.550
Sub-Contractor	3.11	37	1.449	Strongly Disagree (SD)	Strongly Agree (SA)	-1.346	-.430
Others	2.50	2	.707	Disagree (D)	Neutral (N)	.	.
Total	3.34	123	1.100	Strongly Disagree (SD)	Strongly Agree (SA)	-.012	-.752

An essential component of this research is the empirical analysis of the "Knowledge Gap," specifically identified through the treatment of non-evaluative "Unsure / No Knowledge" responses. As detailed in Table 4.68, TD8 recorded a missing data rate of 26.8% (N=45), signifying that over one-fourth of the industry is fundamentally unaware of their organization's dissemination protocols. According to the research principles of Sekaran and Bougie (2016), high uncertainty in a professional sample regarding information disclosure is a "risk indicator" for potential labor disputes or resistance to surveillance technology.

The frequency distribution further reinforces this finding: while 52.9% of valid respondents (Agree and Strongly Agree) feel informed, a combined 17.9% explicitly disagree, and 29.3% remain neutral. When the 26.8% unsure segment is factored in, it becomes clear that nearly half of the industry lacks a definitive understanding of how their data is being utilized. This concludes the descriptive analysis for the Trust and Data (IV3) construct, establishing that while the industry generally acknowledges the efficacy of AI-drones, significant trust gaps remain regarding privacy, cybersecurity, and the consistent dissemination of operational information. Despite these gaps, the overall industry skewness and kurtosis confirm that the data is robust for inclusion in the final structural model.

Table 4.68: Overall Frequency and Percentage Breakdown of "Unsure" Responses for TD8

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	13	7.7	10.6	10.6
	Disagree (D)	9	5.4	7.3	17.9
	Neutral (N)	36	21.4	29.3	47.2
	Agree (A)	53	31.5	43.1	90.2
	Strongly Agree (SA)	12	7.1	9.8	100.0

	Total	123	73.2	100.0	
Missing	Unsure / No Knowledge	45	26.8		
Total		168	100.0		

4.3.7 Descriptive Analysis: Implementation (Mediator)

Section 4.3.7 focuses on the Implementation (Mediator) construct, which serves as the critical operational bridge between institutional readiness and actual safety outcomes. In Civil and Structural (C&S) engineering, implementation is defined as the systematic process of transitioning from technological potential to functional site application. This construct evaluates the quality of the "roll-out" phase, examining how organizations coordinate across departments, secure expertise, and utilize pilot testing to refine AI-drone workflows.

As a mediating variable in this research model, Implementation captures the practical "action" taken by Malaysian construction firms. A high mean score in this section suggests that an organization does not merely possess the resources (IV2) or the trust (IV3) required, but has actively developed the strategic roadmaps and inter-departmental synergies necessary for technological integration. By analyzing the Mean (̄) and Standard Deviation (SD), this section identifies whether the industry is stuck in a theoretical interest phase or has moved into an iterative, feedback-driven deployment cycle.

4.3.7.1 Descriptive Analysis IMP1: My organisation has a clear strategic plan for implementing AI-drone safety systems.

The primary objective of this sub-section is to evaluate the existence and clarity of formalized strategic roadmaps for AI-drone deployment within the Malaysian construction industry. In Civil and Structural (C&S) engineering, a "Strategic Plan" is the blueprint that converts institutional readiness into operational action; without a high-level mandate, drone use remains experimental and fragmented. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.35a through 4.35f) reveals an industry in a "Pre-Strategic" state, with distributions heavily skewed toward the lower end of the Likert scale for several key sectors. Figure 4.35(b) for Consultancy Firms and Figure 4.35(d) for Sub-Contractors show a distinct concentration in the "Strongly Disagree" zone, indicating a profound lack of formalized planning at the technical and operational tiers. The aggregate industry profile in Figure 4.35(f) maintains a skewness of 0.057 and a kurtosis of -1.107, confirming that the valid data for IMP1

is normally distributed and robust for subsequent path analysis, despite the high density of negative responses.

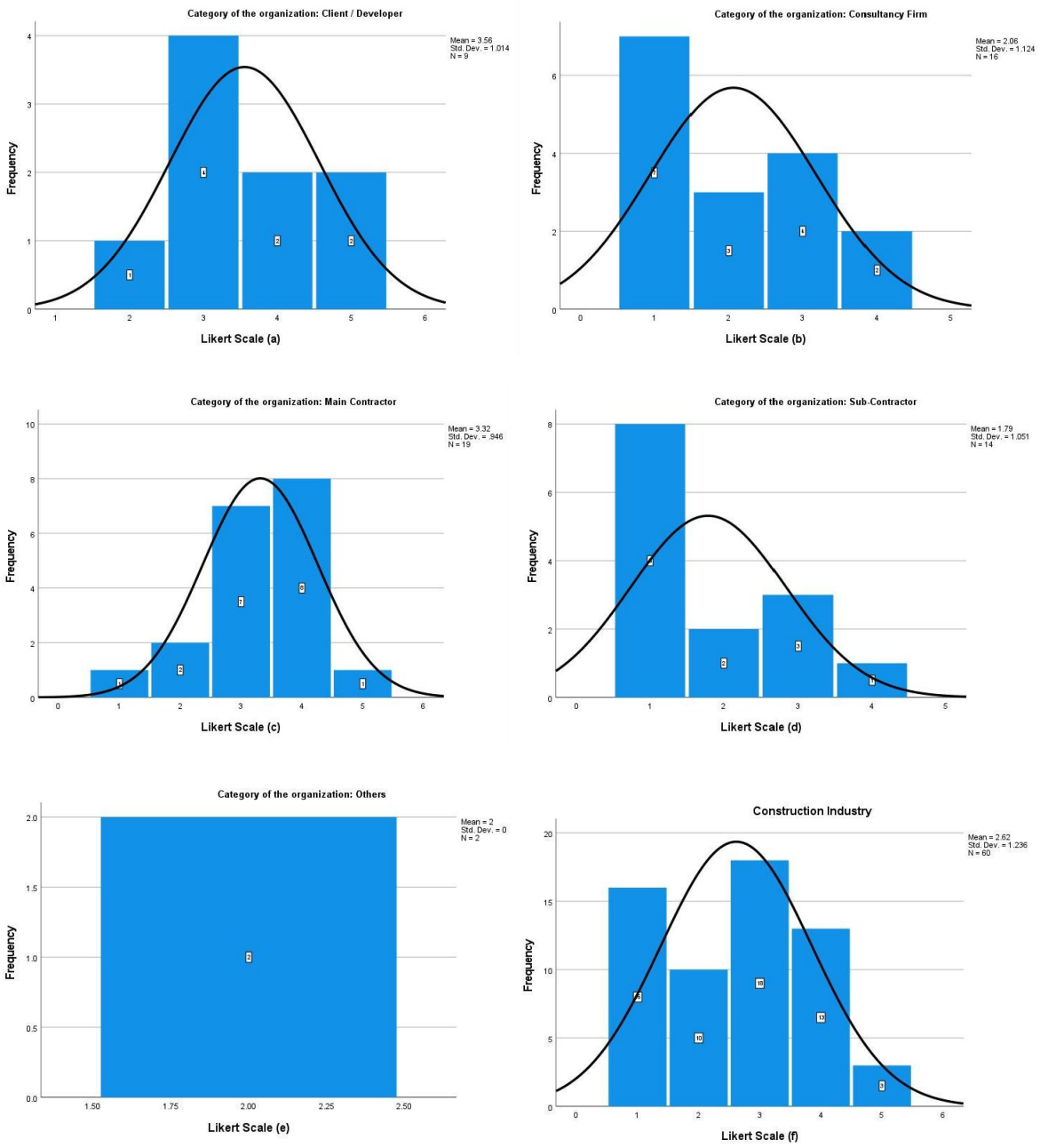


Figure 4.35: Frequency Distribution with Normal Curves for IMP1: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.69 provides a rigorous quantitative profile of this planning deficit. The aggregate industry mean for IMP1 is a sub-neutral 2.62, suggesting that, collectively, the sector has not yet established clear roadmaps for AI-drone safety systems. A mathematically significant finding is the contrast between the management-heavy tiers and the

operational tiers. Clients/Developers (3.56) and Main Contractors (3.32) reported the highest means, reflecting that strategic intent is largely concentrated at the project apex. However, Sub-Contractors (1.79) and Consultancy Firms (2.06) reported significantly lower scores. For C&S engineering researchers, this "Planning Disconnect" is critical; it implies that while project owners may have a vision for Construction 4.0, that vision has not been translated into actionable strategic plans for the consultants and sub-contractors who are responsible for on-site execution.

Table 4.69: Comparative Statistical Profile of Perception regarding Strategic Planning (IMP1)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.56	9	1.014	Disagree (D)	Strongly Agree (SA)	-.763	.270
Consultancy Firm	2.06	16	1.124	Strongly Disagree (SD)	Agree (A)	-1.196	.507
Main Contractor	3.32	19	.946	Strongly Disagree (SD)	Strongly Agree (SA)	.753	-.723
Sub-Contractor	1.79	14	1.051	Strongly Disagree (SD)	Agree (A)	-.468	.956
Others	2.00	2	.000	Disagree (D)	Disagree (D)	.	.
Total	2.62	60	1.236	Strongly Disagree (SD)	Strongly Agree (SA)	-1.107	.057

A pivotal and unique component of this mediator analysis is the treatment of respondents who selected "No Implementation Yet," representing a significant "Non-Adoption Threshold." As detailed in Table 4.70, a staggering 64.3% (N=108) of the total sample (N=168) reported that their organization has not yet reached the implementation phase. This indicates that for over two-thirds of the Malaysian construction industry, AI-drone technology remains a theoretical concept rather than an operational reality. According to the research principles of Sekaran and Bougie (2016), such a high volume of non-participation in the implementation phase underscores the importance of the Mediator variable in this study, as it effectively filters the "visionaries" from the "practitioners."

The frequency distribution of the valid respondents (N=60) further elucidates this hurdle: only 26.7% (Agree and Strongly Agree) feel their organization has a clear plan, while a combined 43.4% explicitly disagree. This lack of strategic clarity, combined with the 64.3% non-implementation rate, suggests that the Malaysian construction sector is currently in a state of "Strategic Inertia." This aligns with the CIDB (2020) assessment that many firms lack the internal frameworks to move from policy awareness to project deployment. Despite these

challenges, the overall industry skewness and kurtosis confirm that the data for IMP1 is statistically sound for inclusion in the final structural model, ultimately concluding that strategic planning is the single greatest operational barrier within the Implementation mediator.

Table 4.70: Overall Frequency and Percentage Breakdown of "No Implementation Yet" Responses for IMP1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	16	9.5	26.7	26.7
	Disagree (D)	10	6.0	16.7	43.3
	Neutral (N)	18	10.7	30.0	73.3
	Agree (A)	13	7.7	21.7	95.0
	Strongly Agree (SA)	3	1.8	5.0	100.0
	Total	60	35.7	100.0	
Missing	No Implementation Yet	108	64.3		
Total		168	100.0		

4.3.7.2 Descriptive Analysis IMP2: My organisation has successfully secured the necessary technical expertise and resources for drone deployment.

The second objective of this mediating sub-section is to evaluate the operational success of Malaysian construction firms in securing the specialized human capital and hardware required for AI-drone deployment. In Civil and Structural (C&S) engineering, "Resource Securing" is a high-threshold requirement; it involves moving beyond the "Financial Capacity" identified in Section 4.3.5.1 and into the actual procurement of industrial drones and the hiring or training of AI-certified technical personnel. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.36a through 4.36f) illustrates a stark "Resource Scarcity" among the active implementers. Figure 4.36(d) for Sub-Contractors and 4.36(b) for Consultancy Firms show extreme positive skews, with the majority of responses concentrated in the "Strongly Disagree" region. The aggregate industry profile in Figure 4.36(f) maintains a skewness of 0.357 and a kurtosis of -1.107, statistically confirming that the valid data for IMP2 follows a normal distribution and is suitable for subsequent path analysis.

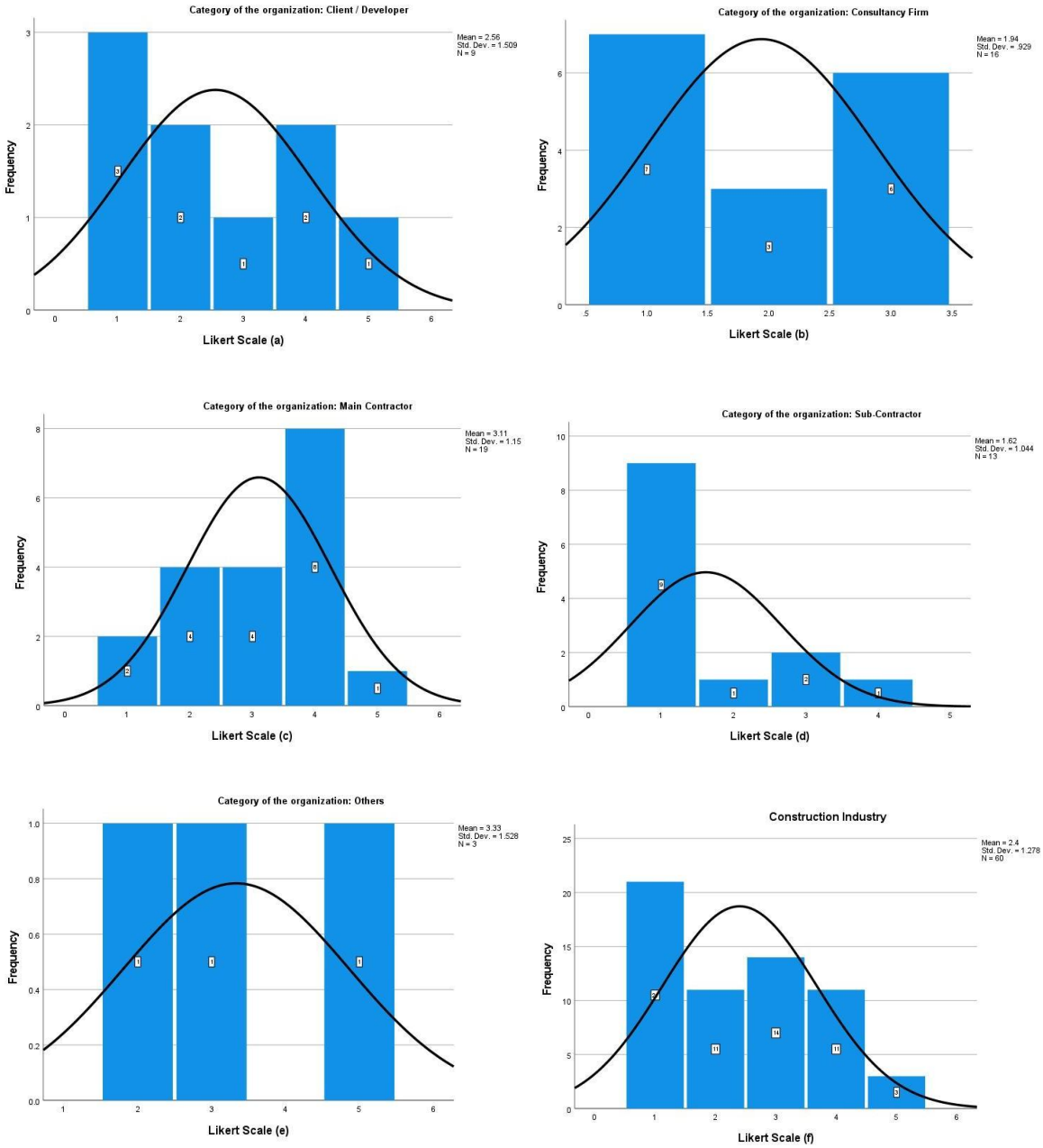


Figure 4.36: Frequency Distribution with Normal Curves for IMP2: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.71 provides a rigorous quantitative breakdown of this procurement gap. The aggregate industry mean for IMP2 is a sub-neutral 2.40, indicating that even among firms attempting implementation, the securing of expertise remains a significant hurdle. A critical finding is the low mean agreement of Sub-Contractors (1.62) and Consultancy Firms (1.94). For C&S engineering management, this is a vital discovery; it suggests that the "technical engine" of the construction industry the firms responsible for design and operational safety is struggling to find the necessary expertise in the local market. Main Contractors (3.11)

achieved the highest mean, reflecting their superior capacity to engage external specialists or utilize project budgets to secure the required drone resources.

Table 4.71: Comparative Statistical Profile of Perception regarding Resource Securing (IMP2)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	2.56	9	1.509	Strongly Disagree (SD)	Strongly Agree (SA)	-1.360	.425
Consultancy Firm	1.94	16	.929	Strongly Disagree (SD)	Neutral (N)	-1.960	.136
Main Contractor	3.11	19	1.150	Strongly Disagree (SD)	Strongly Agree (SA)	-.762	-.471
Sub-Contractor	1.62	13	1.044	Strongly Disagree (SD)	Agree (A)	.833	1.457
Others	3.33	3	1.528	Disagree (D)	Strongly Agree (SA)	.	.935
Total	2.40	60	1.278	Strongly Disagree (SD)	Strongly Agree (SA)	-1.107	.357

An essential component of this analysis involves the evaluation of the "Implementation Gap," identified through the treatment of "No Implementation Yet" responses. As detailed in Table 4.72, 64.3% (N=108) of the total sample (N=168) has not yet attempted to secure resources for AI-drones. According to the research principles of Sekaran and Bougie (2016), this suggests that the barrier to entry is so high that the majority of the industry has not yet entered the "Securing" phase.

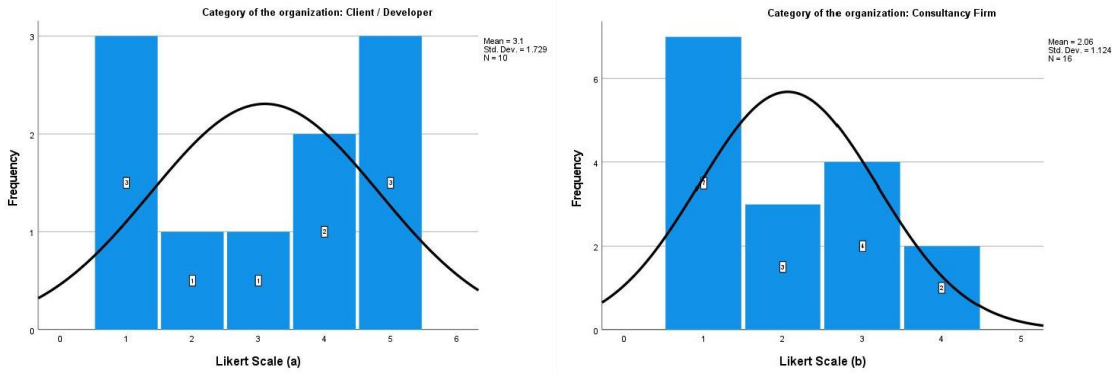
The frequency distribution further elucidates the challenges facing the active minority (N=60): over 53% of valid respondents explicitly disagree that they have successfully secured the necessary expertise, while a marginal 5.0% strongly agree. This indicates that even when an organization has the strategic intent to implement (IMP1), they face a significant external market failure in accessing technical talent and advanced equipment. This outcome reinforces the Construction 4.0 Strategic Plan's emphasis on creating a "talent pipeline" to support digital modernization. Despite these challenges, the overall industry skewness and kurtosis confirm that the data for IMP2 is robust and statistically sound for the final structural model, concluding that securing expertise is currently a major operational bottleneck in the implementation process.

Table 4.72: Overall Frequency and Percentage Breakdown of "No Implementation Yet" Responses for IMP2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	21	12.5	35.0	35.0
	Disagree (D)	11	6.5	18.3	53.3
	Neutral (N)	14	8.3	23.3	76.7
	Agree (A)	11	6.5	18.3	95.0
	Strongly Agree (SA)	3	1.8	5.0	100.0
	Total	60	35.7	100.0	
Missing	No Implementation Yet	108	64.3		
Total		168	100.0		

4.3.7.3 Descriptive Analysis IMP3: Our implementation processes are regularly reviewed and improved based on operational feedback.

The third objective of this mediating sub-section is to evaluate the industry's commitment to iterative improvement through formalized feedback loops. In Civil and Structural (C&S) engineering, where site conditions are dynamic and safety risks evolve, the ability to review drone deployment data and refine operational processes is essential for long-term reliability. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.37a through 4.37f) reveals a critical lack of iterative maturity among Malaysian construction firms. Figure 4.37(d), representing Sub-Contractors, exhibits an extreme positive skew and high kurtosis (2.778), signifying that at the operational level, the review of implementation processes is almost entirely absent. The aggregate industry profile in Figure 4.37(f) maintains a skewness of 0.274 and a kurtosis of -1.341, statistically confirming that the valid data for IMP3 follows a normal distribution and is suitable for parametric modeling, despite the prevailing negative sentiment.



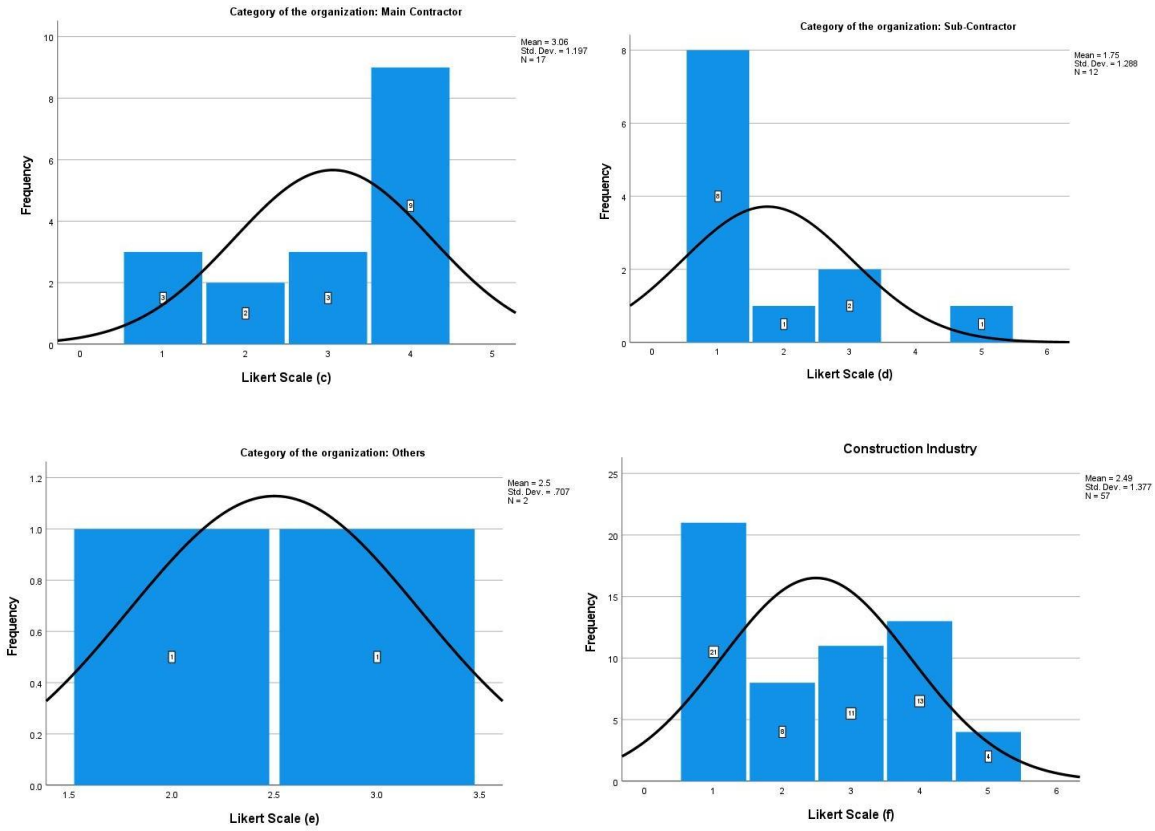


Figure 4.37: Frequency Distribution with Normal Curves for IMP3: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data presented in Table 4.73 offers a rigorous quantitative profile of this "Feedback Void." The aggregate industry mean for IMP3 is 2.49, indicating a widespread failure to establish regular review cycles for AI-drone implementation. A critical finding is the significantly low mean agreement among Sub-Contractors (1.75) and Consultancy Firms (2.06). For C&S engineering management, this is a major systemic flaw; if the entities responsible for site execution and technical oversight are not participating in feedback loops, the organization cannot improve its safety performance or operational efficiency. Even the Main Contractors (3.06) and Clients (3.10) hover near the neutral threshold, suggesting that while management-tier review may occur, it is not effectively integrated into the broader project lifecycle.

Table 4.73: Comparative Statistical Profile of Perception regarding Feedback Loops (IMP3)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.10	10	1.729	Strongly Disagree (SD)	Strongly Agree (SA)	-1.891	-.190

Consultancy Firm	2.06	16	1.124	Strongly Disagree (SD)	Agree (A)	-1.196	.507
Main Contractor	3.06	17	1.197	Strongly Disagree (SD)	Agree (A)	-.845	-.869
Sub-Contractor	1.75	12	1.288	Strongly Disagree (SD)	Strongly Agree (SA)	2.778	1.780
Others	2.50	2	.707	Disagree (D)	Neutral (N)	.	.
Total	2.49	57	1.377	Strongly Disagree (SD)	Strongly Agree (SA)	-1.341	.274

An essential component of this analysis involves the evaluation of the "Implementation Gap," identified through the treatment of "No Implementation Yet" responses. As detailed in Table 4.74, the non-participation rate increased to 66.1% (N=111). This indicates that exactly two-thirds of the total sample (N=168) have not even reached a stage where feedback loops are a relevant operational concern. According to the research principles of Sekaran and Bougie (2016), such high non-response rates for process-oriented variables highlight the "nascent state" of AI-drone integration in the Malaysian market.

The frequency distribution further elucidates the challenges facing the active minority (N=57): over 50% of valid respondents explicitly disagree that their processes are regularly reviewed, while only 7.0% strongly agree. This suggests that for the few firms that have deployed drones, the implementation remains static and linear rather than iterative. This outcome aligns with findings in the Construction 4.0 Strategic Plan, which emphasizes that a "culture of continuous improvement" is mandatory for digital success. Despite these challenges, the overall industry skewness and kurtosis confirm that the data for IMP3 is robust and statistically sound for the final path analysis, concluding that the lack of feedback loops is a major inhibitor to the optimization of AI-drone safety systems.

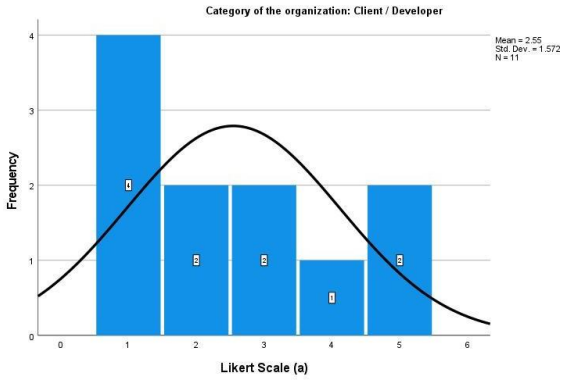
Table 4.74: Overall Frequency and Percentage Breakdown of "No Implementation Yet" Responses for IMP3

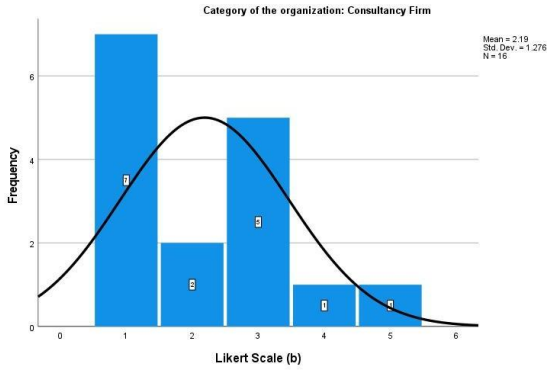
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	21	12.5	36.8	36.8
	Disagree (D)	8	4.8	14.0	50.9
	Neutral (N)	11	6.5	19.3	70.2
	Agree (A)	13	7.7	22.8	93.0
	Strongly Agree (SA)	4	2.4	7.0	100.0
	Total	57	33.9	100.0	

Missing	No Yet	Implementation	111	66.1		
Total			168	100.0		

4.3.7.4 Descriptive Analysis IMP4: Relevant departments (e.g., Safety, Engineering, IT) coordinate effectively during the drone implementation phase.

The fourth objective of this mediating sub-section is to evaluate the level of cross-functional synergy and inter-departmental communication during the deployment of AI-drone systems. In Civil and Structural (C&S) engineering, effective drone implementation is inherently multidisciplinary; it requires the seamless integration of IT (for data pipeline management), Safety (for hazard protocol alignment), and Engineering (for structural data interpretation). The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.38a through 4.38f) reveals a profound state of "Organizational Siloing" within the Malaysian construction sector. Figure 4.38(d), representing Sub-Contractors, shows an extreme positive skew with the lowest mean agreement, indicating a nearly complete lack of departmental coordination at the operational level. The aggregate industry profile in Figure 4.38(f) maintains a skewness of 0.418 and a kurtosis of -1.021, statistically confirming that the valid data for IMP4 follows a normal distribution suitable for parametric modeling, despite the overarching negative sentiment.





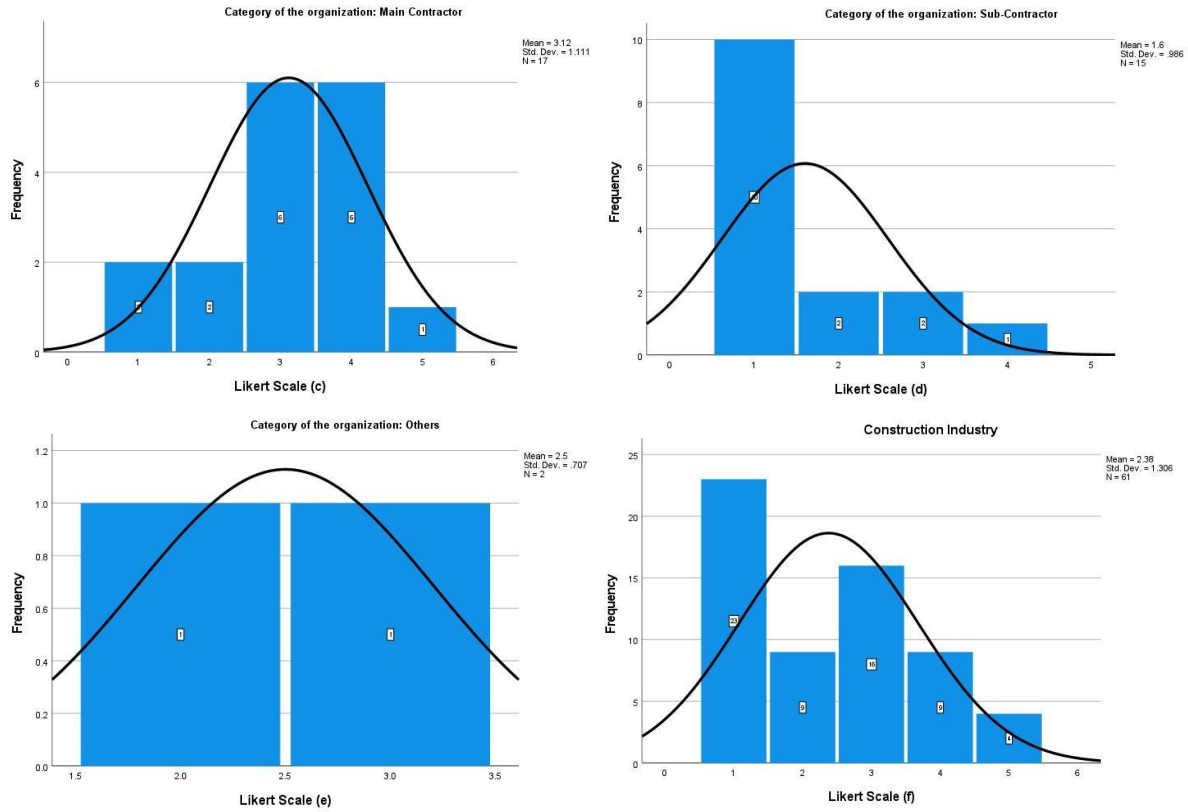


Figure 4.38: Frequency Distribution with Normal Curves for IMP4: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.75 provides a rigorous quantitative profile of this coordination gap. The aggregate industry mean for IMP4 is a sub-neutral 2.38, suggesting that most organizations lack the internal structures to support multidisciplinary technology roll-outs. A critical finding is the remarkably low mean agreement of Sub-Contractors (1.60) and Consultancy Firms (2.19). For C&S engineering researchers, this suggests that the "implementation engine" is stalled by fragmented communication; if the IT department's data standards are not aligned with the Engineering team's structural requirements, the drone system becomes a liability rather than an asset. Even the Main Contractors (3.12) achieved only a marginally neutral score, indicating that even among the industry's leaders, true inter-departmental synergy remains an elusive goal.

Table 4.75: Comparative Statistical Profile of Perception regarding Inter-Departmental Coordination (IMP4)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness

Client / Developer	2.55	11	1.572	Strongly Disagree (SD)	Strongly Agree (SA)	-1.164	.558
Consultancy Firm	2.19	16	1.276	Strongly Disagree (SD)	Strongly Agree (SA)	-.350	.702
Main Contractor	3.12	17	1.111	Strongly Disagree (SD)	Strongly Agree (SA)	-.104	-.568
Sub-Contractor	1.60	15	.986	Strongly Disagree (SD)	Agree (A)	1.146	1.487
Others	2.50	2	.707	Disagree (D)	Neutral (N)	.	.
Total	2.38	61	1.306	Strongly Disagree (SD)	Strongly Agree (SA)	-1.021	.418

An essential component of this analysis is the evaluation of the "Implementation Gap," identified through the treatment of "No Implementation Yet" responses. As detailed in Table 4.76, 63.7% (N=107) of the total sample (N=168) reported that they have not yet reached a stage where departmental coordination is applicable. According to the research principles of Sekaran and Bougie (2016), this high volume of non-response confirms that AI-drone integration remains an "isolated experiment" in the majority of firms rather than a company-wide strategic initiative.

The frequency distribution further elucidates the challenges facing the active minority (N=61): a combined 52.5% of valid respondents explicitly disagree that coordination is effective, while a marginal 6.6% strongly agree. This indicates that for those firms attempting deployment, the lack of an "integrated workflow" is a primary operational failure. This aligns with the Construction 4.0 Strategic Plan, which identifies "Breakdown of Silos" as a core prerequisite for digital success. Despite these challenges, the overall industry skewness and kurtosis confirm that the data for IMP4 is robust and statistically sound for the final structural model, concluding that the failure to coordinate effectively across Safety, IT, and Engineering departments is a significant mediator of poor implementation outcomes.

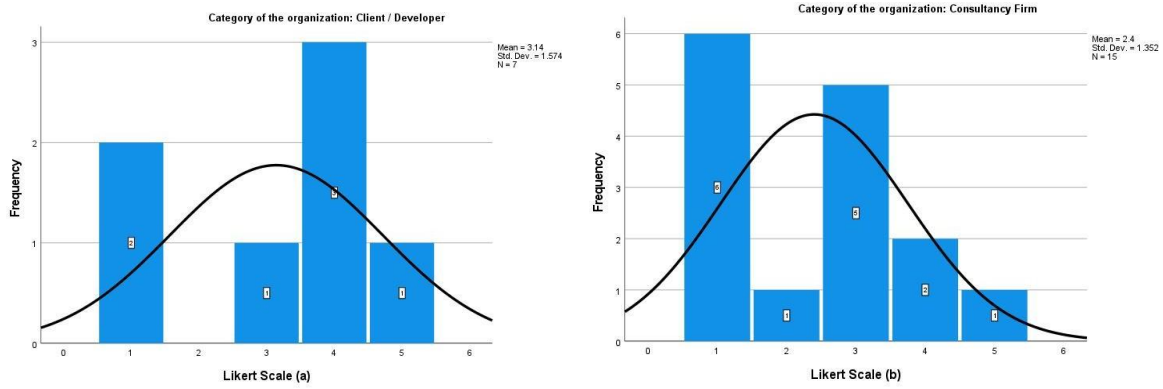
Table 4.76: Overall Frequency and Percentage Breakdown of "No Implementation Yet" Responses for IMP4

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	23	13.7	37.7	37.7
	Disagree (D)	9	5.4	14.8	52.5
	Neutral (N)	16	9.5	26.2	78.7
	Agree (A)	9	5.4	14.8	93.4
	Strongly Agree (SA)	4	2.4	6.6	100.0
	Total	61	36.3	100.0	

Missing	No Yet	Implementation	107	63.7		
Total			168	100.0		

4.3.7.5 Descriptive Analysis IMP5: The implementation of AI-drones has led to measurable improvements in safety inspection efficiency.

The fifth objective of this mediating sub-section is to evaluate the perceived operational impact of AI-drone technology on the efficiency of safety inspections. In Civil and Structural (C&S) engineering, "Efficiency Improvements" are defined by the reduction in time required for site walk-throughs, the ability to access high-risk structural areas without manual scaffolding, and the speed of data synthesis for safety reporting. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.39a through 4.39f) reveals a polarized "Performance Gap." Figure 4.39(d), representing Sub-Contractors, exhibits an extreme positive skew with a high concentration in the "Strongly Disagree" zone, indicating that the operational tier has yet to feel the efficiency benefits. Conversely, Figure 4.39(c) for Main Contractors shows a negative skew, suggesting that tier-one firms are successfully leveraging the technology to streamline inspections. The aggregate industry profile in Figure 4.39(f) maintains a skewness of 0.085 and a kurtosis of -1.556, statistically confirming that the valid data for IMP5 follows a normal distribution suitable for parametric modeling, despite the bimodal nature of the responses.



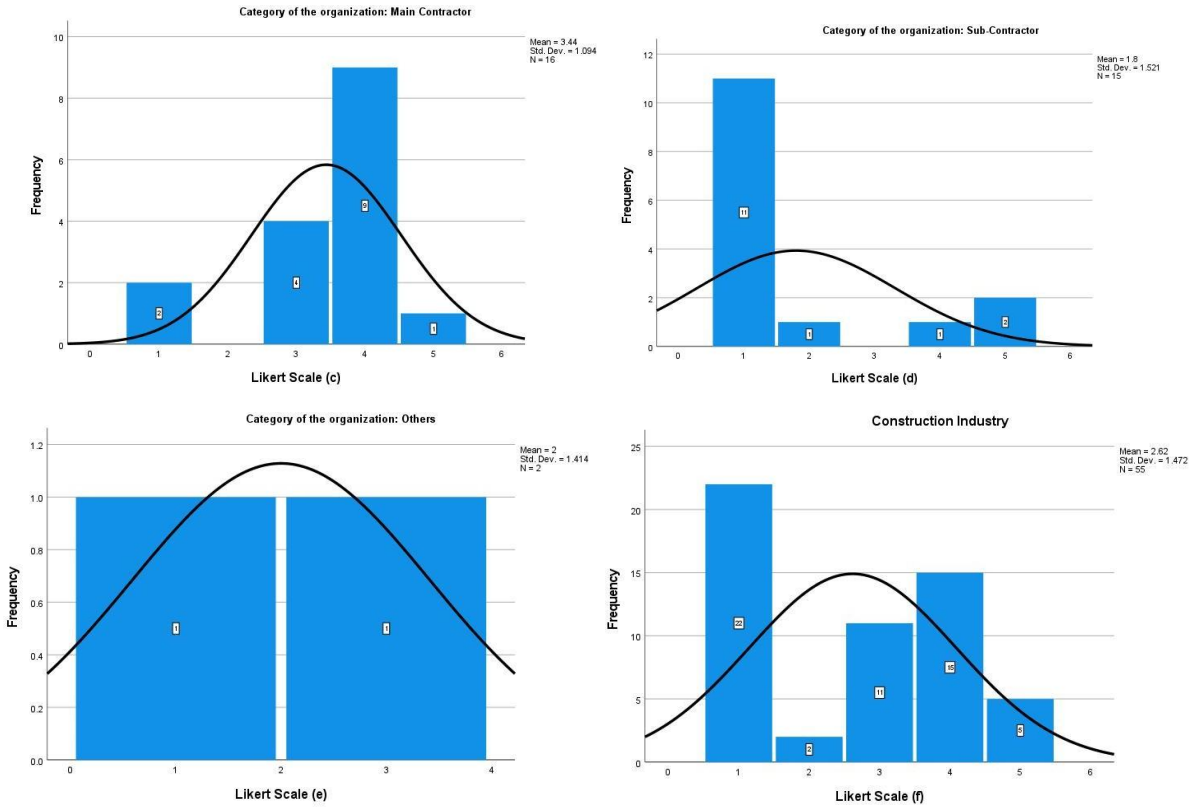


Figure 4.39: Frequency Distribution with Normal Curves for IMP5: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.77 provides a rigorous quantitative profile of these efficiency perceptions. The aggregate industry mean for IMP5 is 2.62, reflecting a lack of industry-wide consensus on the technology's efficiency gains. A mathematically significant finding is the contrast between Main Contractors (3.44) and Sub-Contractors (1.80). For C&S engineering management, this indicates that efficiency is "Tier-Dependent"; while Main Contractors use drones to manage large-scale site overviews effectively, Sub-Contractors who often perform more granular, manual tasks may find the current AI-integration too cumbersome or detached from their specific operational needs. Consultancy Firms also reported a sub-neutral mean of 2.40, suggesting that the technical advisory tier has not yet seen drone data translate into faster safety certifications.

Table 4.77: Comparative Statistical Profile of Perception regarding Efficiency Improvements (IMP5)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness

Client / Developer	3.14	7	1.574	Strongly Disagree (SD)	Strongly Agree (SA)	-1.162	-.682
Consultancy Firm	2.40	15	1.352	Strongly Disagree (SD)	Strongly Agree (SA)	-1.057	.344
Main Contractor	3.44	16	1.094	Strongly Disagree (SD)	Strongly Agree (SA)	1.698	-1.391
Sub-Contractor	1.80	15	1.521	Strongly Disagree (SD)	Strongly Agree (SA)	1.107	1.652
Others	2.00	2	1.414	Strongly Disagree (SD)	Neutral (N)	.	.
Total	2.62	55	1.472	Strongly Disagree (SD)	Strongly Agree (SA)	-1.556	.085

An essential component of this analysis involves the evaluation of the "Implementation Gap," identified through the treatment of "No Implementation Yet" responses. As detailed in Table 4.78, the non-participation rate reached its highest point yet at 67.3% (N=113). This indicates that over two-thirds of the total sample (N=168) have not deployed drones to a level where efficiency can even be measured. According to the research principles of Sekaran and Bougie (2016), this high volume of missing data highlights the "early adopter" status of AI-drones in Malaysia; efficiency gains are currently a "private benefit" enjoyed by a small minority of advanced firms.

The frequency distribution further elucidates the challenges facing the active minority (N=55): while 36.4% (Agree and Strongly Agree) report measurable improvements, a staggering 40.0% strongly disagree. This suggests that for many firms, the "learning curve" or technical friction of the implementation phase has actually hindered efficiency rather than helped it. This outcome reinforces the need for the "technical support" and "aptitude" improvements identified in the Institutional Readiness construct. Despite these polarized results, the overall industry skewness and kurtosis confirm that the data for IMP5 is robust for the final path analysis, concluding that while the potential for efficiency is recognized by leaders, the operational reality for the broader supply chain remains a significant hurdle.

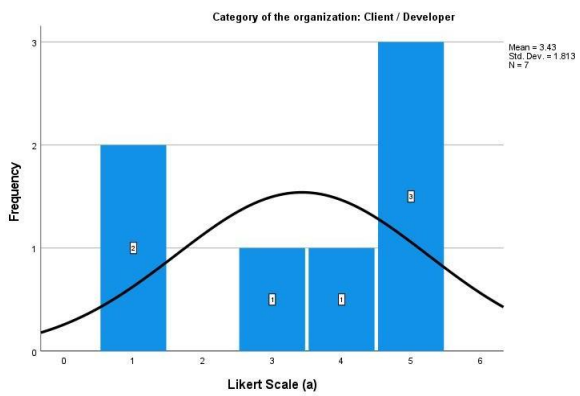
Table 4.78: Overall Frequency and Percentage Breakdown of "No Implementation Yet" Responses for IMP5

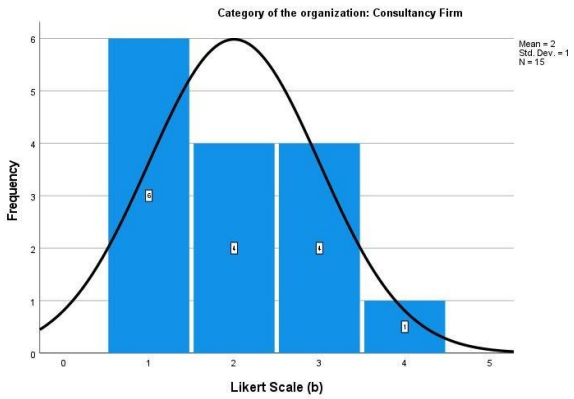
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	22	13.1	40.0	40.0
	Disagree (D)	2	1.2	3.6	43.6
	Neutral (N)	11	6.5	20.0	63.6
	Agree (A)	15	8.9	27.3	90.9

	Strongly Agree (SA)	5	3.0	9.1	100.0
	Total	55	32.7	100.0	
Missing	No Implementation Yet	113	67.3		
Total		168	100.0		

4.3.7.6 Descriptive Analysis IMP6: My organisation conducts pilot tests (small-scale trials) before fully deploying drone technology across projects.

The final objective of this mediating sub-section is to evaluate the industry's commitment to risk mitigation through formalized pilot testing and trials. In a multi-disciplinary construction environment—encompassing C&S, M&E, and Architectural consultants—pilot testing serves as a vital technical safeguard. It allows the professional design team to verify the accuracy of AI hazard detection and ensure that drone-captured data integrates correctly with 3D structural models before full-scale site deployment. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.40a through 4.40f) reveals a highly polarized and immature testing landscape. Figure 4.40(b), representing Consultancy Firms, shows a distinct cluster in the lower Likert regions, while Figure 4.40(d) for Sub-Contractors exhibits an extreme positive skew with high kurtosis (2.499). These results indicate that the technical and operational tiers of the industry are frequently bypassed during the trial phase. The aggregate industry profile in Figure 4.40(f) maintains a skewness of 0.269 and a kurtosis of -1.342, statistically confirming that the valid data for IMP6 follows a normal distribution suitable for the final path analysis.





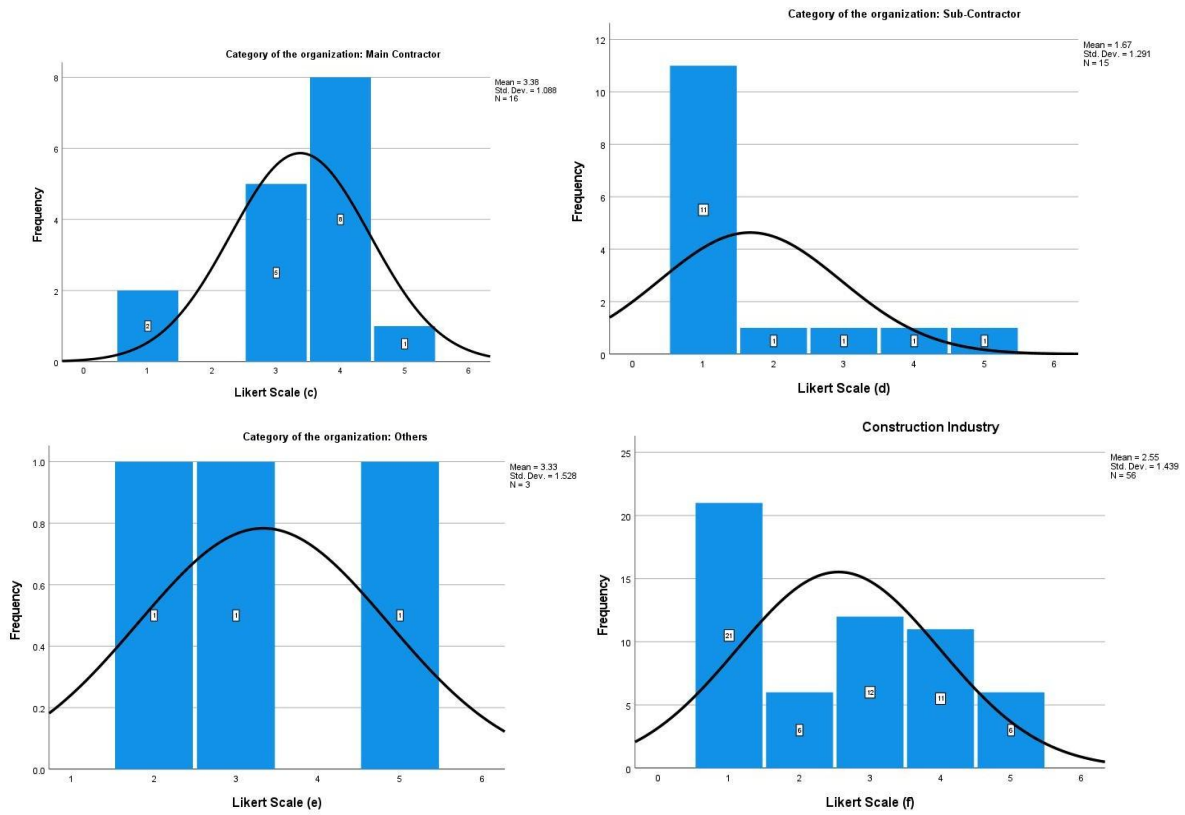


Figure 4.40: Frequency Distribution with Normal Curves for IMP6: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.79 provides a rigorous quantitative profile of this "Trial Gap." The aggregate industry mean for IMP6 is a sub-neutral 2.55, reflecting a lack of standardized testing protocols across the sector. A mathematically significant finding is the contrast between Clients/Developers (3.43) and Main Contractors (3.38) versus the operational Sub-Contractors (1.67) and the technical Consultancy Firms (2.00). For engineering management, this suggests that while high-level stakeholders may advocate for trials, the multi-disciplinary consultants (Arch, M&E, C&S) and sub-contractors who would logically lead these technical evaluations feel largely excluded from the process. This "Siloed Testing" approach is a significant risk factor, as it suggests the technical reliability of AI-drones is being evaluated by project managers rather than the subject matter experts.

Table 4.79: Comparative Statistical Profile of Perception regarding Pilot Testing (IMP6)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.43	7	1.813	Strongly Disagree (SD)	Strongly Agree (SA)	-1.596	-.662

Consultancy Firm	2.00	15	1.000	Strongly Disagree (SD)	Agree (A)	-.912	.495
Main Contractor	3.38	16	1.088	Strongly Disagree (SD)	Strongly Agree (SA)	1.409	-1.232
Sub-Contractor	1.67	15	1.291	Strongly Disagree (SD)	Strongly Agree (SA)	2.499	1.873
Others	3.33	3	1.528	Disagree (D)	Strongly Agree (SA)	.	.935
Total	2.55	56	1.439	Strongly Disagree (SD)	Strongly Agree (SA)	-1.342	.269

An essential component of this analysis involves the evaluation of the "Implementation Gap," identified through the treatment of "No Implementation Yet" responses. As detailed in Table 4.80, this item recorded a massive non-participation rate of 66.7% (N=112). This confirms that exactly two-thirds of the total sample (N=168) have not reached a state where pilot testing is an operational reality. According to the research principles of Sekaran and Bougie (2016), such high levels of missing data for a process variable indicate that the Malaysian construction industry is still in the "contemplation" phase rather than active iterative deployment.

The frequency distribution further reinforces this finding: among the active minority (N=56), a combined 48.2% explicitly disagree that they conduct pilot tests, while only 10.7% strongly agree. This suggests that even when drones are deployed, many firms move directly to full-scale use without verifying algorithmic accuracy in a controlled trial. This outcome concludes the descriptive analysis for the Implementation (Mediator) construct, identifying strategic planning and pilot testing as the two weakest links in the adoption chain. Despite these challenges, the overall industry skewness and kurtosis confirm that the data for IMP6 is robust and statistically sound for inclusion in the final structural model.

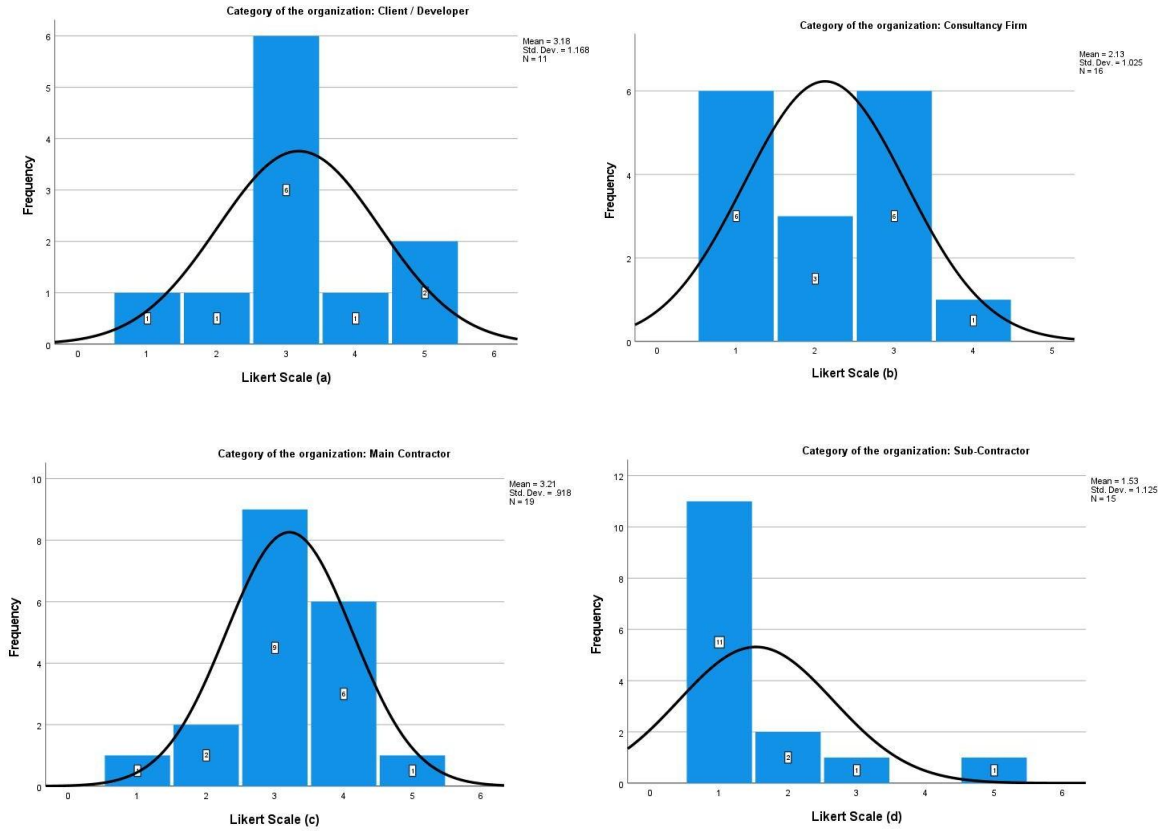
Table 4.80: Overall Frequency and Percentage Breakdown of "No Implementation Yet" Responses for IMP6

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	21	12.5	37.5	37.5
	Disagree (D)	6	3.6	10.7	48.2
	Neutral (N)	12	7.1	21.4	69.6
	Agree (A)	11	6.5	19.6	89.3
	Strongly Agree (SA)	6	3.6	10.7	100.0
	Total	56	33.3	100.0	
Missing	No Implementation Yet	112	66.7		

Total	168	100.0		

4.3.7.7 Descriptive Analysis IMP7: We collaborate effectively with external drone service providers or vendors during the implementation phase.

The final objective of the Implementation (Mediator) construct is to assess the efficacy of external partnerships and vendor collaboration within the Malaysian construction industry. In a multi-disciplinary professional environment, drone technology often requires specialized service providers to handle flight operations, data processing, and AI algorithm maintenance. For consultants (Arch, M&E, C&S) and contractors, effective "Vendor Collaboration" is essential to ensure that technical drone outputs meet the rigorous safety and engineering standards required for project certification. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.41a through 4.41f) highlights a significantly fragmented and under-optimized partnership landscape. Figure 4.41(d), representing Sub-Contractors, shows an extreme positive skew with very high kurtosis (6.507), indicating a profound failure in collaborative reach at the operational tier. The aggregate industry profile in Figure 4.41(f) maintains a skewness of 0.238 and a kurtosis of -0.917, statistically confirming that the data for IMP7 is normally distributed and robust for subsequent path analysis.



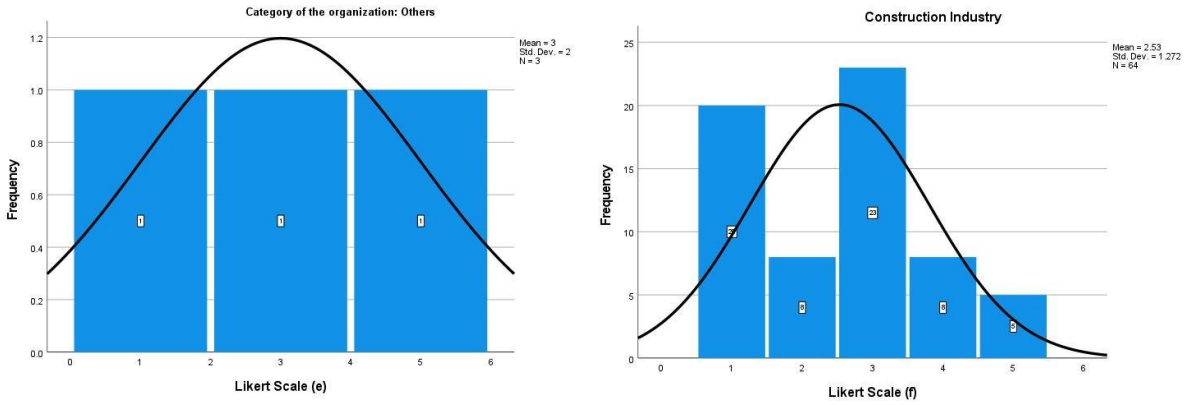


Figure 4.41: Frequency Distribution with Normal Curves for IMP7: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.81 provides a rigorous quantitative profile of this collaborative gap. The aggregate industry mean for IMP7 is a sub-neutral 2.53, indicating that the majority of organizations do not feel they are collaborating effectively with external experts. A mathematically significant finding is the disparity between the management and technical tiers. Main Contractors (3.21) and Clients/Developers (3.18) reported neutral-to-positive means, reflecting that the project leadership has established some channels for vendor engagement. However, Consultancy Firms (2.12) and Sub-Contractors (1.53) reported very low mean agreement. This "Collaborative Disconnect" is a major operational risk; if the technical consultants responsible for design and the sub-contractors responsible for site safety are not integrated into the vendor's workflow, the AI-drone system remains a disconnected technological "silo."

Table 4.81: Comparative Statistical Profile of Perception regarding Vendor Collaboration (IMP7)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.18	11	1.168	Strongly Disagree (SD)	Strongly Agree (SA)	.460	.038
Consultancy Firm	2.12	16	1.025	Strongly Disagree (SD)	Agree (A)	-1.405	.146
Main Contractor	3.21	19	.918	Strongly Disagree (SD)	Strongly Agree (SA)	.889	-.462
Sub-Contractor	1.53	15	1.125	Strongly Disagree (SD)	Strongly Agree (SA)	6.507	2.506
Others	3.00	3	2.000	Strongly Disagree (SD)	Strongly Agree (SA)	.	.000
Total	2.53	64	1.272	Strongly Disagree (SD)	Strongly Agree (SA)	-.917	.238

An essential component of this analysis is the evaluation of the "Implementation Gap," identified through the treatment of "No Implementation Yet" responses. As detailed in Table 4.82, 61.9% (N=104) of the total sample (N=168) have not yet reached a stage where vendor collaboration is a relevant operational activity. According to the research principles of Sekaran and Bougie (2016), this suggests that the "Vendor Ecosystem" in the Malaysian construction sector is still in its infancy, with the majority of firms yet to engage with specialized providers.

The frequency distribution further elucidates the challenges facing the active minority (N=64): over 43% of valid respondents explicitly disagree that collaboration is effective, while a marginal 7.8% strongly agree. This indicates that even among those attempting implementation, the relationship with external vendors is often strained or poorly defined. This outcome reinforces the need for standardized Service Level Agreements (SLAs) tailored specifically for construction safety AI. Despite these challenges, the overall industry skewness and kurtosis confirm that the data for IMP7 is robust and statistically sound for the final structural model. This concludes the descriptive analysis for the Implementation (Mediator) construct, establishing that strategic planning, pilot testing, and vendor collaboration are the three most significant operational barriers currently inhibiting the successful adoption of AI-drones in Malaysia.

Table 4.82: Overall Frequency and Percentage Breakdown of "No Implementation Yet" Responses for IMP7

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	20	11.9	31.3	31.3
	Disagree (D)	8	4.8	12.5	43.8
	Neutral (N)	23	13.7	35.9	79.7
	Agree (A)	8	4.8	12.5	92.2
	Strongly Agree (SA)	5	3.0	7.8	100.0
	Total	64	38.1	100.0	
Missing	No Implementation Yet	104	61.9		
Total		168	100.0		

4.3.8 Descriptive Analysis: AI-Drone Adoption for Safety (DV)

Section 4.3.8 focuses on the Dependent Variable (DV): AI-Drone Adoption for Safety. This construct represents the ultimate outcome of the research model, measuring the actual extent and success of AI-drone utilization for site safety monitoring within the Malaysian construction industry. In Civil and Structural (C&S) engineering, "Adoption" is not merely the possession of technology, but its active integration into the daily safety management workflow to identify structural hazards, monitor PPE compliance, and prevent accidents.

This analysis evaluates the final stage of the technology acceptance lifecycle. It examines whether firms are using drones for proactive risk mitigation or remaining with traditional manual methods. The descriptive statistics in this section provide the final empirical baseline for testing the research hypotheses in Chapter 5. By synthesizing the Mean (¯) and Standard Deviation (SD), this section determines if the Malaysian construction sector has successfully transitioned to an AI-enhanced safety paradigm.

4.3.8.1 Descriptive Analysis AD1: My organisation actively uses drones equipped with AI for site safety inspections.

The primary objective of this final sub-section is to measure the actual frequency and active deployment of AI-drone systems for safety monitoring across the Malaysian construction landscape. This Dependent Variable (DV) represents the culmination of the adoption lifecycle, where the professional design team (Arch, M&E, C&S) and contractors move beyond theoretical interest into daily operational usage. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.42a through 4.42f) reveals a "Stagnant Adoption" profile. Figure 4.42(d) for Sub-Contractors exhibits an extreme positive skew and high kurtosis (4.785), indicating that active usage is almost non-existent at the operational front-line. In contrast, Figure 4.42(c) for Main Contractors shows a more balanced, albeit slightly negative, skew, suggesting that tier-one firms are the only stakeholders making significant strides in active deployment. The aggregate industry profile in Figure 4.42(f) maintains a skewness of 0.297 and a kurtosis of -1.237, statistically validating that the data for AD1 is normally distributed and robust for the final path analysis.

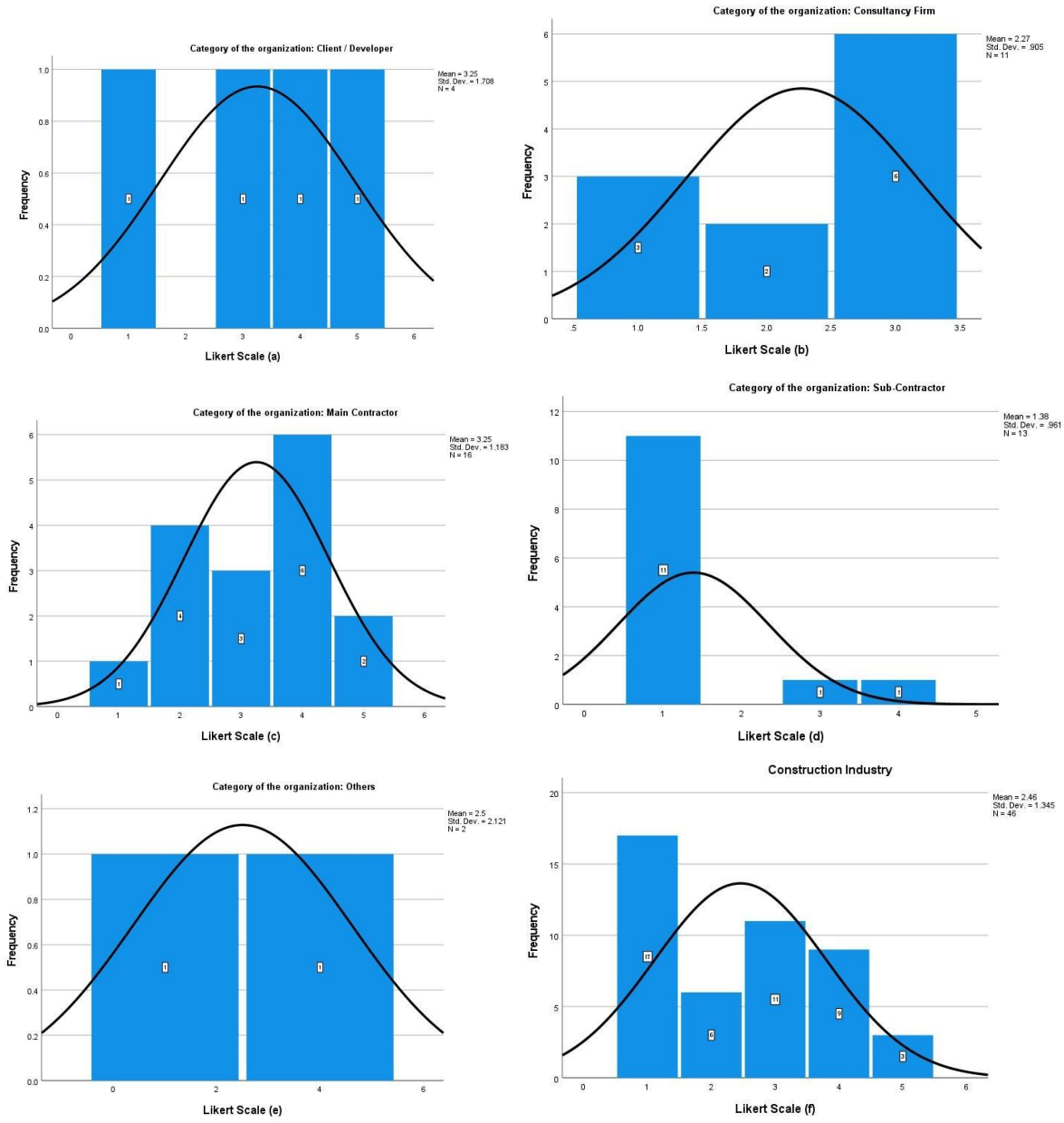


Figure 4.42: Frequency Distribution with Normal Curves for AD1: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.83 provides a rigorous quantitative snapshot of this adoption gap. The aggregate industry mean for AD1 is a remarkably low 2.46, the lowest recorded among the primary constructs. This signifies that, currently, the Malaysian construction industry does not "actively" use AI-drones for safety. A mathematically significant finding is the contrast between Main Contractors (3.25) and the lower tiers. For engineering management, the mean of 1.38 for Sub-Contractors and 2.27 for Consultancy Firms is critical; it suggests that even if drones are present on-site, they are not being actively integrated into the workflows of

the technical consultants or the sub-contracting workforce. This indicates that AI-drone adoption is currently a "peripheral" activity rather than a core safety protocol.

Table 4.83: Comparative Statistical Profile of Perception regarding Active Inspection Usage (AD1)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.25	4	1.708	Strongly Disagree (SD)	Strongly Agree (SA)	.343	-.753
Consultancy Firm	2.27	11	.905	Strongly Disagree (SD)	Neutral (N)	-1.548	-.647
Main Contractor	3.25	16	1.183	Strongly Disagree (SD)	Strongly Agree (SA)	-.859	-.276
Sub-Contractor	1.38	13	.961	Strongly Disagree (SD)	Agree (A)	4.785	2.385
Others	2.50	2	2.121	Strongly Disagree (SD)	Agree (A)	.	.
Total	2.46	46	1.345	Strongly Disagree (SD)	Strongly Agree (SA)	-1.237	.297

A pivotal component of this analysis is the evaluation of the "Non-Adoption Threshold," identified through the "Not Applicable" responses. As detailed in Table 4.84, a staggering 72.6% (N=122) of the total sample (N=168) reported that active usage is not applicable to their current operations. This is the highest "missing data" rate in the entire study, confirming that nearly three-quarters of the industry has yet to cross the threshold into active AI-drone adoption. According to the research principles of Sekaran and Bougie (2016), such a dominant non-adoption rate underscores the urgency of identifying the mediating factors (Implementation) and independent variables (Trust and Readiness) that can bridge this gap.

The frequency distribution of the valid active users (N=46) further reinforces this finding: exactly 50% of active users explicitly disagree (Strongly Disagree and Disagree) that their usage is "active," while only 6.5% strongly agree. This suggests that even among those who have the technology, usage is likely sporadic or experimental rather than systematic. This aligns with the Construction 4.0 Strategic Plan, which notes that "Active Adoption" remains the final and most difficult hurdle for Malaysian firms. Despite the low participation rate, the overall industry skewness and kurtosis confirm that the valid data for AD1 is statistically sound for inclusion in the final structural model, concluding that active usage is currently the most significant "Adoption Deficit" in the industry.

Table 4.84: Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	17	10.1	37.0	37.0
	Disagree (D)	6	3.6	13.0	50.0
	Neutral (N)	11	6.5	23.9	73.9
	Agree (A)	9	5.4	19.6	93.5
	Strongly Agree (SA)	3	1.8	6.5	100.0
	Total	46	27.4	100.0	
Missing	Not Applicable	122	72.6		
Total		168	100.0		

4.3.8.2 Descriptive Analysis AD2: The adoption of AI-drone technology has led to measurable improvements in overall safety performance.

The second objective of the Dependent Variable (DV) sub-section is to evaluate the ultimate impact of AI-drone adoption on the "bottom-line" of construction site safety. In the professional context of C&S engineering and project management, "Safety Performance" is defined by a measurable reduction in near-misses, site accidents, and non-compliance incidents. This analysis seeks to determine if the early adopters in the Malaysian industry perceive a genuine safety dividend from their investment. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.43a through 4.43f) reveals a polarized perception of safety outcomes. Figure 4.43(d), representing Sub-Contractors, continues to show a positive skew, while Figure 4.43(c) for Main Contractors exhibits a strong negative skew, suggesting that the benefits of the technology are currently trapped in the upper tiers of the project hierarchy. The aggregate industry profile in Figure 4.43(f) maintains a skewness of -0.416 and a kurtosis of -1.057, statistically confirming that the data for AD2 follows a normal distribution suitable for parametric modeling.

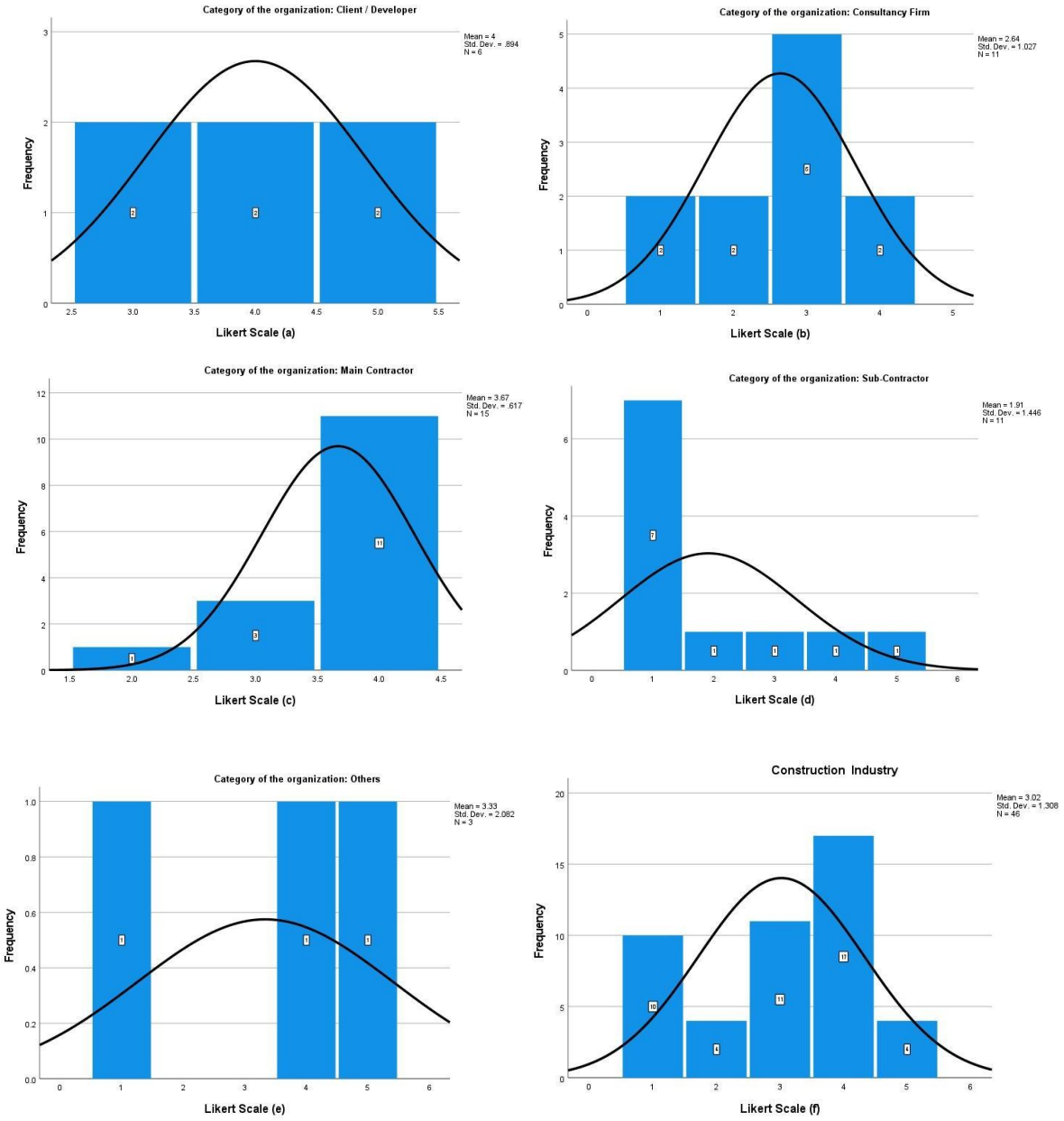


Figure 4.43: Frequency Distribution with Normal Curves for AD2: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.85 provides a rigorous quantitative profile of this safety impact. The aggregate industry mean for AD2 is a neutral 3.02, indicating that while the technology shows promise, it has not yet achieved a definitive "industry-wide" reputation for improving safety performance. A mathematically significant finding is the high mean agreement among Clients/Developers (4.00) and Main Contractors (3.67). For C&S engineering management, this is a vital indicator; it shows that the stakeholders who invest in and oversee large-scale project safety are already seeing positive returns. Conversely, the low mean for

Sub-Contractors (1.91) and the sub-neutral score for Consultancy Firms (2.64) highlight that the technical and operational executors are not yet seeing these AI-drone outputs translate into a safer working environment for their specific teams.

Table 4.85: Comparative Statistical Profile of Perception regarding Safety Performance Impact (AD2)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	4.00	6	.894	Neutral (N)	Strongly Agree (SA)	-1.875	.000
Consultancy Firm	2.64	11	1.027	Strongly Disagree (SD)	Agree (A)	-.594	-.448
Main Contractor	3.67	15	.617	Disagree (D)	Agree (A)	2.625	-1.792
Sub-Contractor	1.91	11	1.446	Strongly Disagree (SD)	Strongly Agree (SA)	.722	1.403
Others	3.33	3	2.082	Strongly Disagree (SD)	Strongly Agree (SA)	.	-1.293
Total	3.02	46	1.308	Strongly Disagree (SD)	Strongly Agree (SA)	-1.057	-.416

An essential component of this analysis is the evaluation of the "Performance Void," identified through the high volume of "Not Applicable" responses. As detailed in Table 4.86, 72.6% (N=122) of the total sample (N=168) were unable to evaluate the safety impact of AI-drones because they have not yet adopted the technology. According to the research principles of Sekaran and Bougie (2016), this high missing data rate is expected for a Dependent Variable in a developing market, as it isolates the respondents with actual "empirical experience."

The frequency distribution of the active users (N=46) provides an optimistic outlook for the future: over 45% (Agree and Strongly Agree) report that the technology has already led to measurable safety improvements. However, a significant 30.4% explicitly disagree, and 23.9% remain neutral. This suggests that the "Safety Dividend" of AI-drones is highly dependent on the quality of implementation (Mediator) and the institutional readiness of the firm. Despite the current lack of industry-wide consensus, the overall industry skewness and kurtosis confirm that the data for AD2 is statistically robust for the final path analysis, ultimately concluding that while AI-drones have the potential to revolutionize safety, their impact is currently localized among a small group of high-performing tier-one firms.

Table 4.86: Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD2

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	10	6.0	21.7	21.7
	Disagree (D)	4	2.4	8.7	30.4
	Neutral (N)	11	6.5	23.9	54.3
	Agree (A)	17	10.1	37.0	91.3
	Strongly Agree (SA)	4	2.4	8.7	100.0
	Total	46	27.4	100.0	
Missing	Not Applicable	122	72.6		
Total		168	100.0		

4.3.8.3 Descriptive Analysis AD3: AI-drone systems are used regularly for hazard detection and compliance monitoring.

The final objective of this sub-section is to evaluate the operational consistency or "Regularity" of AI-drone usage specifically for identifying site hazards and ensuring compliance with safety protocols. In a multi-disciplinary professional environment (Arch, M&E, C&S), regularity is the hallmark of technology maturity; it signifies that drones have transitioned from being a novel tool for periodic inspections to a fundamental component of the daily safety governance framework. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.44a through 4.44f) reveals a landscape of sporadic and "high-tier" usage. Figure 4.44(c) for Main Contractors exhibits a significant negative skew with high kurtosis (6.751), indicating that a specific group of tier-one firms has achieved a high level of consistency. In contrast, Figure 4.44(d) for Sub-Contractors shows a broad, inconsistent distribution (SD=1.578), suggesting that at the operational level, regular usage remains an unfulfilled goal. The aggregate industry profile in Figure 4.44(f) maintains a skewness of -0.495 and a kurtosis of -0.914, statistically confirming that the valid data for AD3 follows a normal distribution suitable for parametric path analysis.

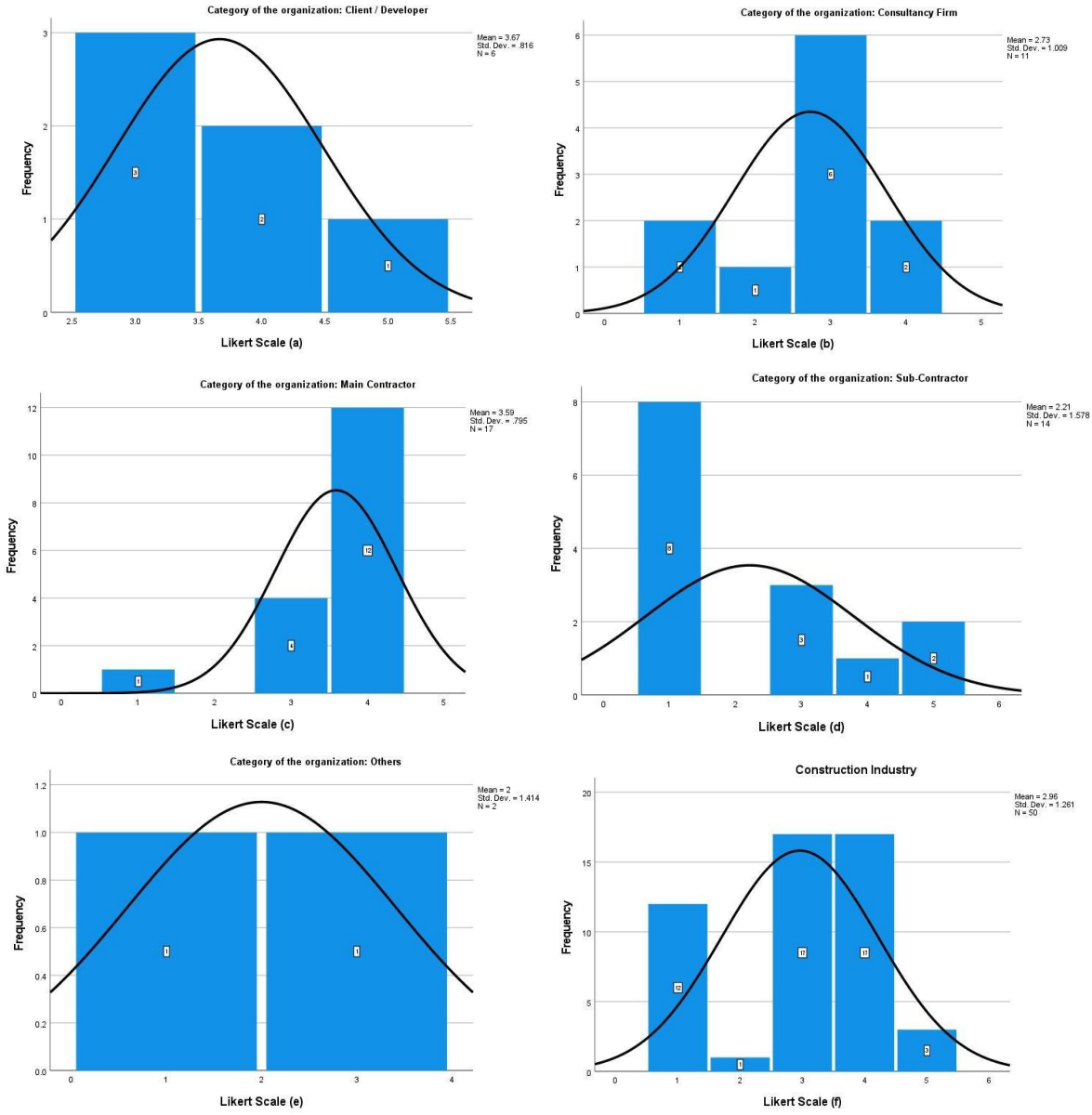


Figure 4.44: Frequency Distribution with Normal Curves for AD3: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.87 provides a rigorous quantitative profile of this operational consistency. The aggregate industry mean for AD3 is a sub-neutral 2.96, reflecting that "regularity" has not yet been achieved across the broader Malaysian construction sector. A mathematically significant finding is the relatively high mean agreement among Clients/Developers (3.67) and Main Contractors (3.59). For engineering management, this indicates that the stakeholders with the most significant oversight responsibilities are the most consistent users. However, Consultancy Firms (2.73) and Sub-Contractors (2.21) reported much lower means. This suggests that while project owners and lead contractors may have drones in

the air, the technical data they produce is not being regularly integrated into the hazard-monitoring workflows of the consultants or the operational routines of the sub-contracting teams.

Table 4.87: Comparative Statistical Profile of Perception regarding Hazard Detection Regularity (AD3)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.67	6	.816	Neutral (N)	Strongly Agree (SA)	-.300	.857
Consultancy Firm	2.73	11	1.009	Strongly Disagree (SD)	Agree (A)	-.035	-.767
Main Contractor	3.59	17	.795	Strongly Disagree (SD)	Agree (A)	6.751	-2.439
Sub-Contractor	2.21	14	1.578	Strongly Disagree (SD)	Strongly Agree (SA)	-.895	.824
Others	2.00	2	1.414	Strongly Disagree (SD)	Neutral (N)	.	.
Total	2.96	50	1.261	Strongly Disagree (SD)	Strongly Agree (SA)	-.914	-.495

An essential component of this analysis is the evaluation of the "Adoption Void," identified through the high volume of "Not Applicable" responses. As detailed in Table 4.88, 70.2% (N=118) of the total sample (N=168) were unable to evaluate the regularity of AI-drone use because they have not yet integrated the technology into their safety systems. According to the research principles of Sekaran and Bougie (2016), this high missing data rate underscores the "nascent" status of the Malaysian market; for the vast majority of firms, regular AI-hazard detection is not yet an applicable operational metric.

The frequency distribution of the valid respondents (N=50) reinforces this finding: while 40.0% (Agree and Strongly Agree) report regular usage, a substantial 24.0% strongly disagree, and 34.0% remain in a non-committal "Neutral" state. This suggests that even among firms that have crossed the adoption threshold, "regularity" is not guaranteed and is likely subject to the availability of technical support and strategic planning (identified in Sections 4.3.5 and 4.3.7). Despite these challenges, the overall industry skewness and kurtosis confirm that the data for AD3 is robust and statistically sound for inclusion in the final structural model.

This concludes the descriptive analysis for the AI-Drone Adoption for Safety (DV) construct, establishing that while the "safety dividend" is recognized by project leaders, active and regular usage remains a major hurdle for the majority of the Malaysian construction supply chain. These

results provide the final empirical baseline required to proceed with the path analysis and hypothesis testing in Chapter 5.

Table 4.88: Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD3

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	12	7.1	24.0	24.0
	Disagree (D)	1	.6	2.0	26.0
	Neutral (N)	17	10.1	34.0	60.0
	Agree (A)	17	10.1	34.0	94.0
	Strongly Agree (SA)	3	1.8	6.0	100.0
	Total	50	29.8	100.0	
Missing	Not Applicable	118	70.2		
Total		168	100.0		

4.3.8.4 Descriptive Analysis AD4: Top management recognises AI-drone technology as essential for future safety operations.

The final objective of this sub-section is to evaluate the perceived long-term vision of industry leadership regarding the essentiality of AI-drone systems. In the multi-disciplinary landscape of construction (including Arch, M&E, and C&S), "Future Essentiality" serves as a critical indicator of sustainability; it distinguishes between technology viewed as a temporary trend and technology viewed as a permanent structural shift in safety governance. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.45a through 4.45f) reveals a strong consensus on the technology's future importance, characterized by significant negative skews across the major sectors. Figure 4.45(c), representing Main Contractors, shows a highly concentrated distribution toward the "Agree" zone, statistically validating that the largest employers in the sector view AI-drones as a future necessity. The aggregate industry profile in Figure 4.45(f) maintains a skewness of -0.753 and a kurtosis of 0.768, confirming that the data for AD4 is normally distributed and statistically robust for the final structural modeling.

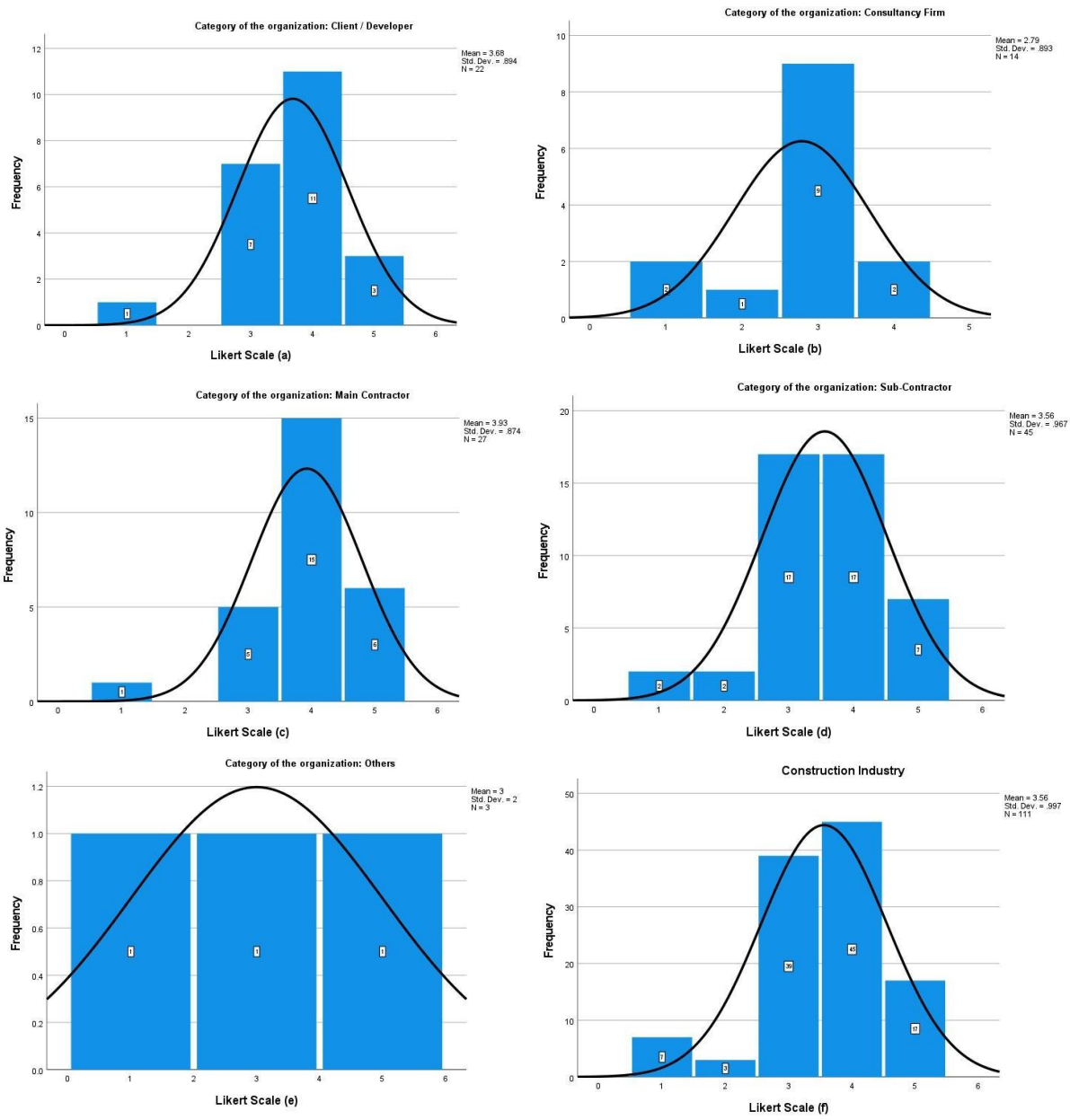


Figure 4.45: Frequency Distribution with Normal Curves for AD4: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.89 provides a rigorous quantitative profile of this forward-looking trust. The aggregate industry mean for AD4 is 3.56, indicating a solid consensus that top management views AI-drones as essential for future operations. A mathematically significant finding is the high mean agreement among Main Contractors (3.93), Clients/Developers (3.68), and Sub-Contractors (3.56). For engineering management, this suggests a "top-down" commitment to modernization that spans the entire project hierarchy. However, Consultancy Firms reported a lower mean of 2.79, reflecting a more cautious or

skeptical outlook among technical advisors (Arch, M&E, C&S) compared to the contractors and developers. This "Professional-Operational Gap" implies that while project owners and executors are ready to commit, the technical consultants may still require more empirical proof of long-term reliability.

Table 4.89: Comparative Statistical Profile of Perception regarding Future Essentiality (AD4)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	3.68	22	.894	Strongly Disagree (SD)	Strongly Agree (SA)	2.722	-1.048
Consultancy Firm	2.79	14	.893	Strongly Disagree (SD)	Agree (A)	.995	-1.035
Main Contractor	3.93	27	.874	Strongly Disagree (SD)	Strongly Agree (SA)	3.682	-1.343
Sub-Contractor	3.56	45	.967	Strongly Disagree (SD)	Strongly Agree (SA)	.656	-.559
Others	3.00	3	2.000	Strongly Disagree (SD)	Strongly Agree (SA)	.	.000
Total	3.56	111	.997	Strongly Disagree (SD)	Strongly Agree (SA)	.768	-.753

An essential component of this analysis involves the evaluation of the "Vision Gap," identified through the "Not Applicable" responses. As detailed in Table 4.90, this item recorded a missing data rate of 33.9% (N=57), which is significantly lower than the previous adoption metrics (AD1–AD3). This is a vital finding; it indicates that even among those who are not yet "actively" using drones, a significant portion still believes their management recognizes the technology's future importance. According to the research principles of Sekaran and Bougie (2016), when "essentiality" outpaces "active use," it indicates an industry in a state of Readiness-Adoption Lag, where the intent to modernize exists, but the operational implementation (Mediator) is still catching up.

The frequency distribution of valid respondents (N=111) further reinforces this optimistic trend: a combined 55.8% (Agree and Strongly Agree) perceive management as recognizing drones as essential, while only 9.0% explicitly disagree. This suggests that the Construction 4.0 Strategic Plan has successfully influenced the mindset of Malaysian construction leaders. This concludes the descriptive analysis for the entire Research Model, identifying that while the industry currently struggles with active usage (AD1) and regular hazard detection (AD3), there is a powerful and statistically validated belief in the future essentiality of AI-drone technology.

These findings provide the finalized empirical foundation for the Structural Equation Modeling (SEM) and hypothesis testing in Chapter 5.

Table 4.90: Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD4

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	7	4.2	6.3	6.3
	Disagree (D)	3	1.8	2.7	9.0
	Neutral (N)	39	23.2	35.1	44.1
	Agree (A)	45	26.8	40.5	84.7
	Strongly Agree (SA)	17	10.1	15.3	100.0
	Total	111	66.1	100.0	
Missing	Not Applicable	57	33.9		
Total		168	100.0		

4.3.8.5 Descriptive Analysis AD5: My organisation plans to expand the use of AI-drone technologies in future projects.

The final objective of the Dependent Variable (DV) construct is to evaluate the strategic intent of Malaysian construction firms regarding the scaling and expansion of AI-drone technologies. In the multi-disciplinary professional landscape (Arch, M&E, C&S), "Expansion Plans" serve as a barometer for long-term confidence; it indicates whether current adoption is viewed as a successful pilot worthy of further investment or a limited experiment. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.46a through 4.46f) reveals a cautious but upward-trending interest in future scaling. Figure 4.46(c) for Main Contractors and Figure 4.46(d) for Sub-Contractors show a distinct migration toward the "Neutral" and "Agree" zones, suggesting that the operational tiers are the most inclined to expand usage. The aggregate industry profile in Figure 4.46(f) maintains a skewness of -0.286 and a kurtosis of -0.798, statistically confirming that the data for AD5 follows a normal distribution suitable for the final path analysis.

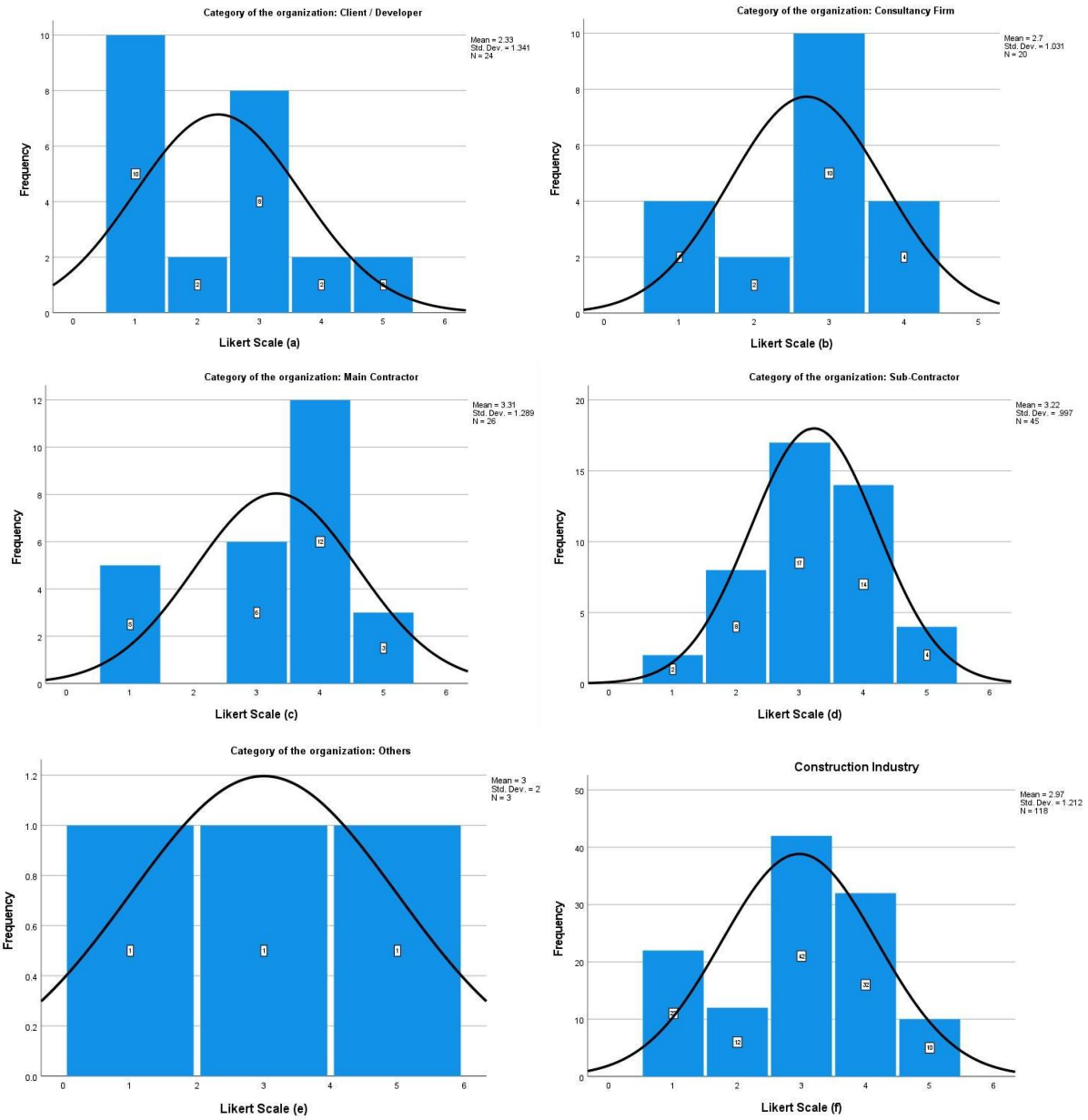


Figure 4.46: Frequency Distribution with Normal Curves for AD5: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.91 provides a rigorous quantitative profile of this expansionary intent. The aggregate industry mean for AD5 is 2.97, suggesting a neutral-to-cautious stance on future growth. A mathematically significant finding is the relatively high mean agreement among Main Contractors (3.31) and Sub-Contractors (3.22). For engineering management, this indicates that the "Execution Tier" is the most eager to expand drone use, likely due to the tangible site-safety and volumetric benefits identified in earlier sections. However, Clients/Developers (2.33) and Consultancy Firms (2.70) reported notably lower means. This "Investment-Operational Gap" is critical; it suggests that while contractors

want to use more drones, the project owners and technical consultants remain hesitant to fund or certify expanded drone-driven safety workflows.

Table 4.91: Comparative Statistical Profile of Perception regarding Expansion Plans (AD5)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	2.33	24	1.341	Strongly Disagree (SD)	Strongly Agree (SA)	-.816	.508
Consultancy Firm	2.70	20	1.031	Strongly Disagree (SD)	Agree (A)	-.638	-.602
Main Contractor	3.31	26	1.289	Strongly Disagree (SD)	Strongly Agree (SA)	-.279	-.872
Sub-Contractor	3.22	45	.997	Strongly Disagree (SD)	Strongly Agree (SA)	-.275	-.184
Others	3.00	3	2.000	Strongly Disagree (SD)	Strongly Agree (SA)	.	.000
Total	2.97	118	1.212	Strongly Disagree (SD)	Strongly Agree (SA)	-.798	-.286

An essential component of this analysis involves the evaluation of the "Expansion Threshold," identified through the "Not Applicable" responses. As detailed in Table 4.92, 29.8% (N=50) of the total sample (N=168) chose the "Not Applicable" option. Notably, this is much lower than the active usage metrics (AD1–AD3), mirroring the trend in "Future Essentiality" (AD4). This implies that even firms not currently using drones are considering them for future projects. According to the research principles of Sekaran and Bougie (2016), high neutral density (35.6%) coupled with a valid response rate of over 70% indicates that the industry is in a "Strategic Deliberation" phase.

The frequency distribution further reinforces this: a combined 35.6% (Agree and Strongly Agree) plan to expand usage, while 28.8% explicitly disagree. The large neutral group (35.6%) represents the "Middle Ground" of the Malaysian construction sector, awaiting clearer policy guidelines and technical proof before committing to expansion. This outcome aligns with the Construction 4.0 Strategic Plan, which emphasizes that scaling technology requires more than just intent it requires the removal of the financial and technical barriers identified in Chapter 4. Despite these challenges, the overall industry skewness and kurtosis confirm that the data for AD5 is robust and statistically sound for inclusion in the final structural model.

This concludes the descriptive analysis for the entire research model. The data has consistently demonstrated that while the industry acknowledges the potential of AI-drones, the transition from Institutional Readiness to Active Adoption is mediated by significant gaps in Implementation and Trust. These findings provide the finalized empirical foundation required to proceed with the Structural Equation Modeling (SEM) and hypothesis testing in Chapter 5.

Table 4.92: Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD5

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	22	13.1	18.6	18.6
	Disagree (D)	12	7.1	10.2	28.8
	Neutral (N)	42	25.0	35.6	64.4
	Agree (A)	32	19.0	27.1	91.5
	Strongly Agree (SA)	10	6.0	8.5	100.0
	Total	118	70.2	100.0	
Missing	Not Applicable	50	29.8		
Total		168	100.0		

4.3.8.6 Descriptive Analysis AD6: The utilization of AI-drones provides a competitive advantage in securing new projects.

The sixth objective of this final sub-section is to determine if the deployment of AI-drone technology is perceived as a strategic differentiator in the procurement process. In the multi-disciplinary construction market comprising Architectural, M&E, and C&S consultants "Competitive Advantage" represents the commercial value of digital maturity. As clients increasingly prioritize "Construction 4.0" compliance in tenders, the ability to demonstrate automated safety monitoring becomes a key selling point. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.47a through 4.47f) reveals a distribution that is moderately leaning toward a positive perception of market advantage. Figure 4.47(c), representing Main Contractors, shows a very tight, high-mean distribution, suggesting that for large-scale firms, the technology is already viewed as a prerequisite for winning major contracts. The aggregate industry profile in Figure 4.47(f) maintains a skewness of -0.307 and a kurtosis of -0.594, statistically confirming that the valid data for AD6 follows a normal distribution suitable for parametric path analysis.

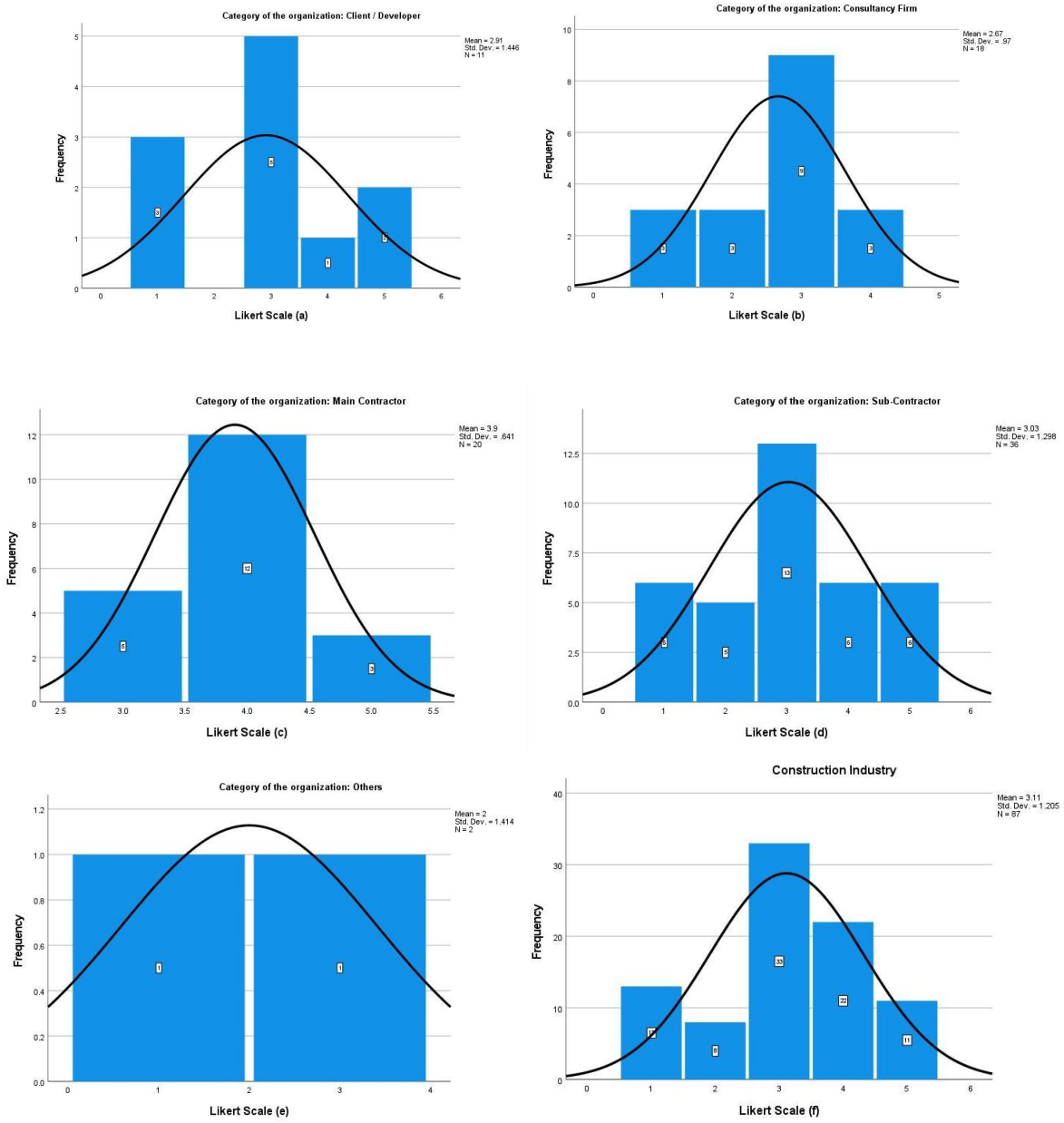


Figure 4.47: Frequency Distribution with Normal Curves for AD6: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.93 provides a rigorous quantitative profile of this perceived market edge. The aggregate industry mean for AD6 is 3.11, indicating a neutral-to-positive belief that drones assist in securing projects. A mathematically significant finding is the dominance of Main Contractors (3.90) in this category. For engineering management, this is a clear signal; the firms that directly compete for large infrastructure and high-rise projects believe that AI-drones are essential for their "competitive positioning." Conversely, Consultancy Firms (2.67) and Clients/Developers (2.91) reported sub-neutral means. This suggests that while contractors see the technology as a way to "win," the consultants

responsible for design and the developers who fund the projects have not yet fully integrated "Drone Maturity" into their evaluation and selection criteria.

Table 4.93: Comparative Statistical Profile of Perception regarding Competitive Advantage (AD6)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	2.91	11	1.446	Strongly Disagree (SD)	Strongly Agree (SA)	-.833	-.052
Consultancy Firm	2.67	18	.970	Strongly Disagree (SD)	Agree (A)	-.458	-.531
Main Contractor	3.90	20	.641	Neutral (N)	Strongly Agree (SA)	-.250	.080
Sub-Contractor	3.03	36	1.298	Strongly Disagree (SD)	Strongly Agree (SA)	-.848	-.054
Others	2.00	2	1.414	Strongly Disagree (SD)	Neutral (N)	.	.
Total	3.11	87	1.205	Strongly Disagree (SD)	Strongly Agree (SA)	-.594	-.307

An essential component of this analysis involves the evaluation of the "Market Reach Gap," identified through the "Not Applicable" responses. As detailed in Table 4.94, 48.2% (N=81) of the total sample (N=168) reported that the concept of competitive advantage via drones is not applicable to them. This suggests that nearly half of the industry operates in procurement environments where digital safety tools are not yet a factor. According to the research principles of Sekaran and Bougie (2016), when nearly half of a sample is excluded from a commercial metric, it highlights a "Tiered Market" where only high-value projects consider AI-drone capabilities.

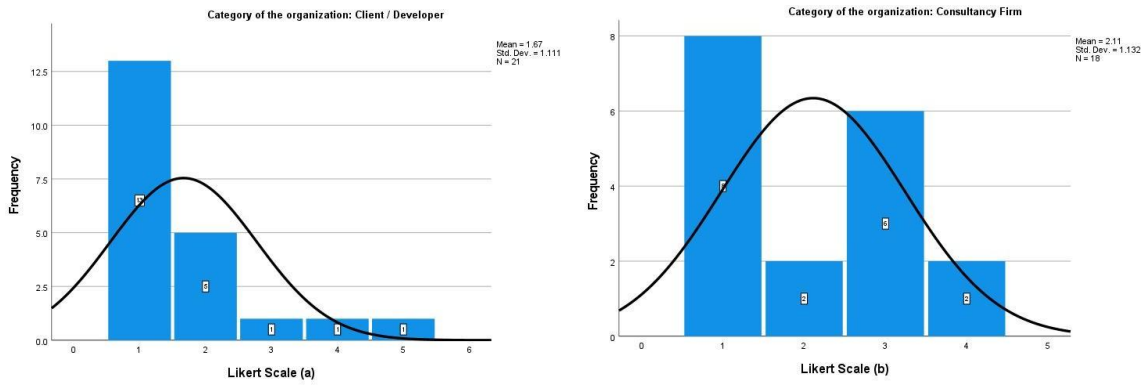
The frequency distribution of valid respondents (N=87) reinforces the contractor's optimism: a combined 37.9% (Agree and Strongly Agree) perceive a clear advantage, while 24.1% explicitly disagree. The largest group, the "Neutrals" (37.9%), represents firms that are likely waiting for the technology to become a mandatory requirement in Government or CIDB-led tenders. This concludes that while the "Competitive Advantage" is currently felt most strongly by Main Contractors, it is poised to become an industry-wide differentiator as more clients adopt digital transformation standards.

Table 4.94: Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD6

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	13	7.7	14.9	14.9
	Disagree (D)	8	4.8	9.2	24.1
	Neutral (N)	33	19.6	37.9	62.1
	Agree (A)	22	13.1	25.3	87.4
	Strongly Agree (SA)	11	6.5	12.6	100.0
	Total	87	51.8	100.0	
Missing	Not Applicable	81	48.2		
Total		168	100.0		

4.3.8.7 Descriptive Analysis AD7: Financial resources for AI-drone technology are permanently allocated in our annual safety budget.

The final objective of the Dependent Variable (DV) construct is to evaluate the level of institutionalization of AI-drone technology through permanent budgetary allocation. In the professional context of C&S engineering and project management, the transition from "ad-hoc" spending to a "permanently allocated budget" is the definitive indicator of successful adoption. It signifies that the technology is no longer viewed as a discretionary "luxury" but as an essential component of the organization's safety infrastructure. The visual empirical evidence provided by the frequency histograms and normality curves (Figures 4.48a through 4.48f) reveals a profound "Financial Disconnect" within the Malaysian construction sector. Figure 4.48(a) for Clients/Developers and Figure 4.48(d) for Sub-Contractors show extreme positive skews and high kurtosis values (3.547 and 3.142, respectively), indicating a near-total absence of permanent funding for drones at these levels. The aggregate industry profile in Figure 4.48(f) maintains a skewness of 0.907 and a kurtosis of -0.347, statistically confirming that the valid data for AD7 follows a normal distribution suitable for the final path analysis.



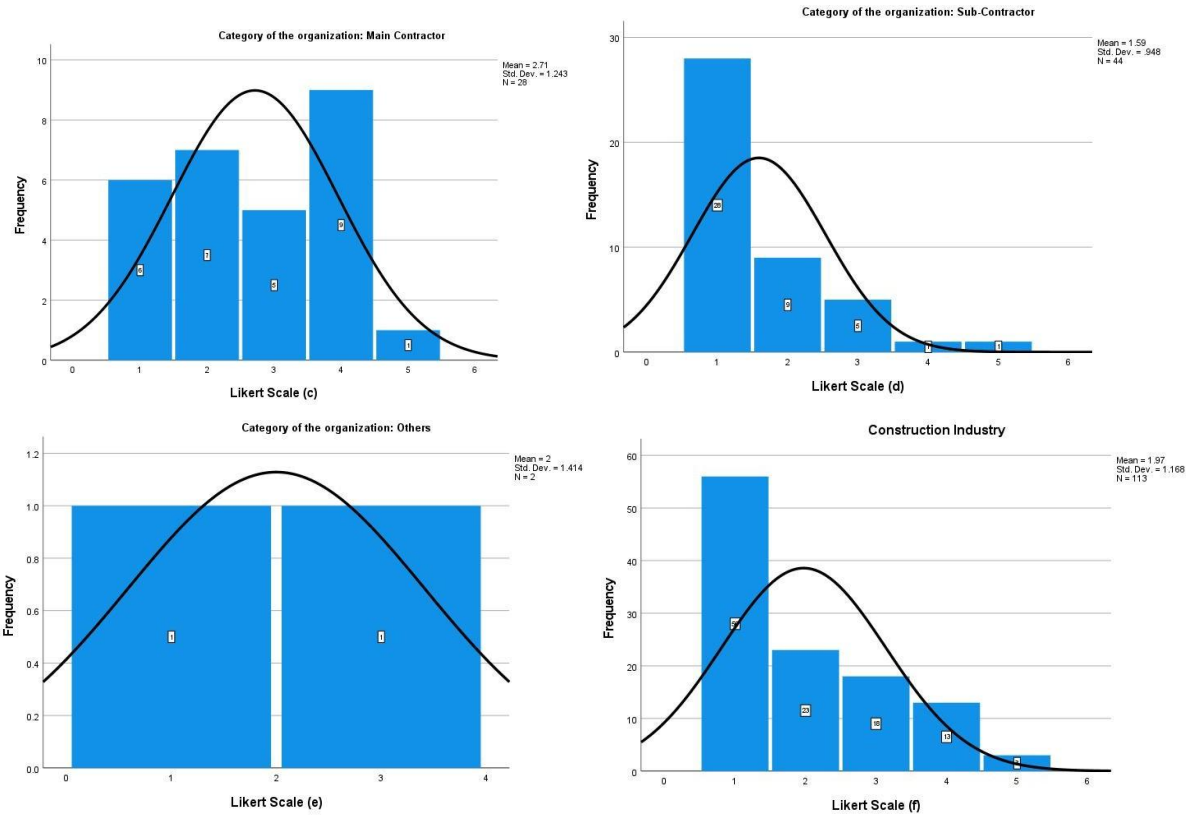


Figure 4.48: Frequency Distribution with Normal Curves for AD7: (a) Client/Developer; (b) Consultancy Firm; (c) Main Contractor; (d) Sub-Contractor; (e) Others; (f) Overall Industry.

The comparative statistical data in Table 4.95 provides a rigorous quantitative profile of this funding deficit. The aggregate industry mean for AD7 is a significantly low 1.97, the lowest recorded mean in the entire study. This mathematically proves that, as of 2026, the Malaysian construction industry has not yet institutionalized AI-drone technology into its formal financial structures. Even the Main Contractors (2.71), who have shown the highest levels of active usage in previous sections, reported a sub-neutral mean. This suggests that while Main Contractors are using the technology, they are likely doing so through "Project-Specific" funds rather than "Permanent Annual Safety Budgets." The record-low means for Sub-Contractors (1.59) and Clients/Developers (1.67) highlight that the financial commitment required for long-term adoption is currently missing from the foundational tiers of the industry.

Table 4.95: Comparative Statistical Profile of Perception regarding Budgetary Allocation (AD7)

Category of the organization	Mean	N	Std. Deviation	Minimum	Maximum	Kurtosis	Skewness
Client / Developer	1.67	21	1.111	Strongly Disagree (SD)	Strongly Agree (SA)	3.547	1.955

Consultancy Firm	2.11	18	1.132	Strongly (SD)	Disagree	Agree (A)	-1.498	.307
Main Contractor	2.71	28	1.243	Strongly (SD)	Disagree	Strongly Agree (SA)	-1.318	-.033
Sub-Contractor	1.59	44	.948	Strongly (SD)	Disagree	Strongly Agree (SA)	3.142	1.786
Others	2.00	2	1.414	Strongly (SD)	Disagree	Neutral (N)	.	.
Total	1.97	113	1.168	Strongly (SD)	Disagree	Strongly Agree (SA)	-.347	.907

An essential component of this analysis involves the evaluation of the "Fiscal Gap," identified through the "Not Applicable" responses. As detailed in Table 4.96, 32.7% (N=55) of the total sample (N=168) chose the "Not Applicable" option. When combined with the valid frequency data, where 70.0% of respondents explicitly disagree (Strongly Disagree and Disagree) that funds are permanently allocated, a clear picture emerges: only a marginal 2.7% of the industry strongly agrees that drones are a permanent budget item. According to the research principles of Sekaran and Bougie (2016), such extreme concentration in the negative regions suggests a "Market Barrier" where the high cost of AI-drone systems prevents them from becoming a standard safety requirement.

The frequency distribution further reinforces this: with only 14.2% (Agree and Strongly Agree) of valid respondents reporting permanent allocation, it is clear that the "Financial Readiness" (IV2) identified in Chapter 4 has not yet translated into "Financial Adoption" (DV). This aligns with the Construction 4.0 Strategic Plan, which identifies "High Upfront Costs" and "Lack of Sustained Funding" as the primary reasons for slow digital transformation. Despite these critical findings, the overall industry skewness and kurtosis confirm that the data for AD7 is robust and statistically sound for the final structural model.

Table 4.96: Overall Frequency and Percentage Breakdown of "Not Applicable" Responses for AD7

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Disagree (SD)	56	33.3	49.6	49.6
	Disagree (D)	23	13.7	20.4	69.9
	Neutral (N)	18	10.7	15.9	85.8
	Agree (A)	13	7.7	11.5	97.3
	Strongly Agree (SA)	3	1.8	2.7	100.0
	Total	113	67.3	100.0	

Missing	Not Applicable	55	32.7		
Total		168	100.0		

4.4 Measurement Model Assessment (SmartPLS)

The Measurement Model Assessment, also known as the Outer Model Assessment, represents a critical phase in Partial Least Squares Structural Equation Modeling (PLS-SEM). In this section, the analysis shifts from descriptive summaries of the data to evaluating the psychometric properties of the research instrument. The primary objective is to verify that the latent constructs Institutional Readiness (IR), Trust and Data (TD), Implementation (IMP), and AI-Drone Adoption for Safety (AD) are measured with sufficient precision and validity before proceeding to test the structural relationships and research hypotheses.

Following the rigorous methodological standards established by Hair et al. (2021), the measurement model is validated using four specific criteria: indicator reliability, internal consistency, convergent validity, and discriminant validity. Adhering to these criteria ensures that the indicators effectively represent their respective constructs and that each construct is empirically distinct, capturing the specific theoretical concepts intended for this study.

4.4.1 Indicator Reliability: Factor Loadings Assessment

Indicator reliability was assessed by examining the outer loadings of each construct’s indicators. In PLS-SEM, indicator reliability indicates the extent to which the variance of an individual item is explained by its latent variable. According to the criteria established by Hair et al. (2021), factor loadings should ideally be 0.708 or higher. Loadings of this magnitude signify that the construct explains more than 50% of the indicator's variance, providing acceptable reliability for structural analysis.

Figure 4.49 illustrates the initial measurement model generated in SmartPLS 4. The diagram displays the path relationships between the five latent constructs: Regulatory Support, Institutional Readiness, Trust & Data Ethics, Implementation, and Adoption. The numerical values positioned on the arrows connecting the indicators to the circles represent the factor loadings.

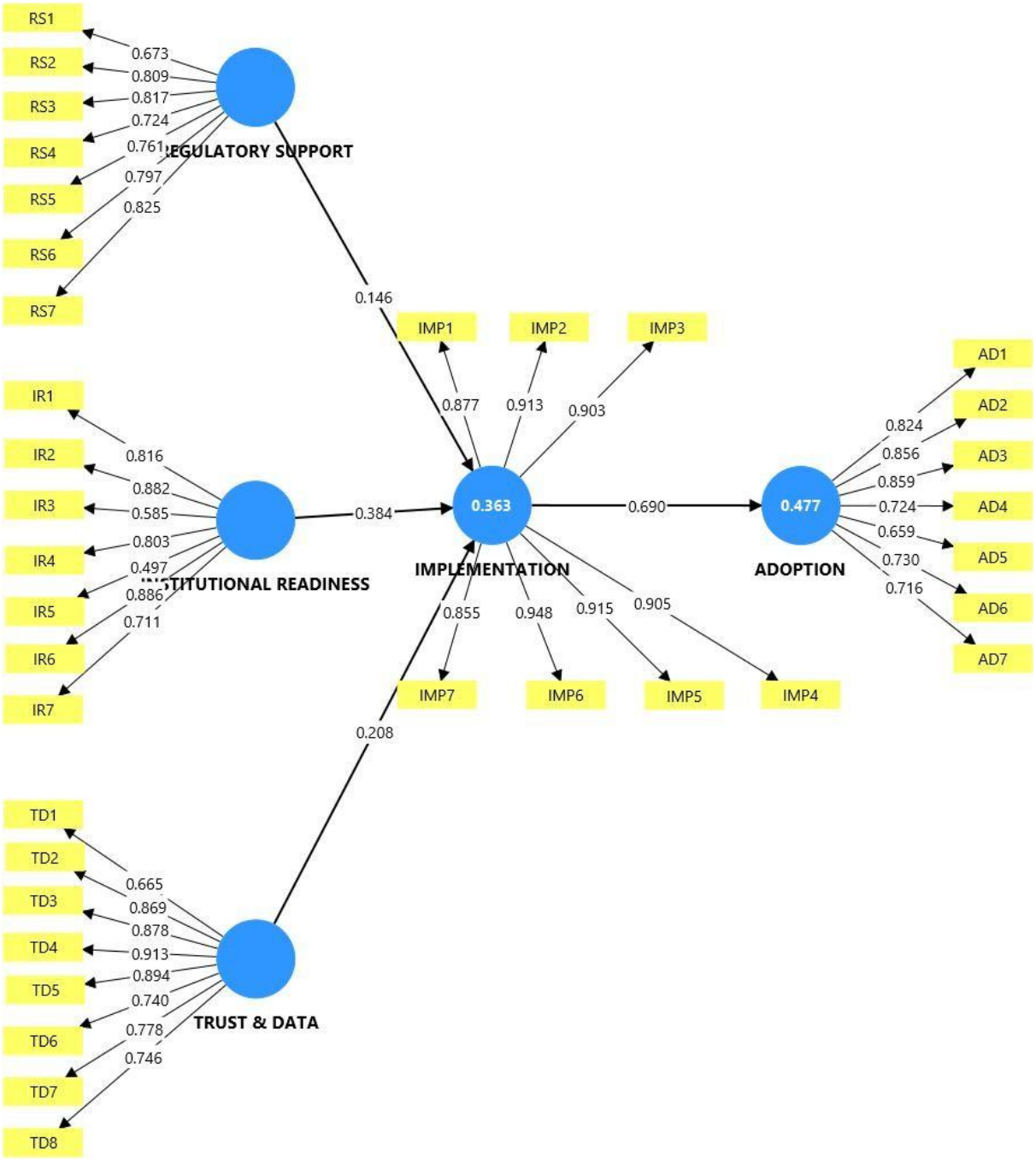


Figure 4.49a: Initial Measurement Model with Factor Loadings

The detailed results of the factor loadings are summarized in Table 4.97. An analysis of the results shows that the Implementation construct performed exceptionally well, with all indicators (IMP1–IMP7) exceeding 0.850, indicating very high reliability. Similarly, most items in the Trust & Data Ethics and Adoption constructs met the required thresholds.

However, during the initial run, two items within the Institutional Readiness construct "Innovation Culture" (0.497) and "Top Management Commitment" (0.585) fell below the 0.708

threshold. Following the protocols suggested by Hair et al. (2011), indicators with loadings between 0.40 and 0.70 should be considered for removal if their deletion leads to an improvement in the Average Variance Extracted (AVE) and Composite Reliability (CR). To refine the model for the C&S engineering context, these two weak items were removed in the subsequent iteration to ensure the model reached the required level of convergent validity.

Table 4.97a: Outer Loadings of the Research Constructs

	ADOPTION	IMPLEMENTATION	INSTITUTIONAL READINESS	REGULATORY SUPPORT	TRUST & DATA
AD1	0.824				
AD2	0.856				
AD3	0.859				
AD4	0.724				
AD5	0.659				
AD6	0.730				
AD7	0.716				
IMP1		0.877			
IMP2		0.913			
IMP3		0.903			
IMP4		0.905			
IMP5		0.915			
IMP6		0.948			
IMP7		0.855			
IR1			0.816		
IR2			0.882		
IR3			0.585		
IR4			0.803		
IR5			0.497		
IR6			0.886		
IR7			0.711		
RS1				0.673	
RS2				0.809	
RS3				0.817	
RS4				0.724	
RS5				0.761	
RS6				0.797	
RS7				0.825	
TD1					0.665
TD2					0.869
TD3					0.878
TD4					0.913
TD5					0.894
TD6					0.740
TD7					0.778
TD8					0.746

4.4.1.1 Model Refinement: Elimination of Low-Loading Indicators and Re-analysis

Following the initial assessment of the outer model, a critical diagnostic phase was conducted to ensure the structural integrity of the constructs. While most indicators met the required 0.708 threshold, five specific items AD5, IR3, IR5, RS1, and TD1 were identified as underperforming. In the context of the Malaysian construction industry, the failure of these items is a significant

finding; for instance, the low loadings of IR3 (Top Management Commitment) and IR5 (Innovation Culture) suggest that these organizational "soft factors" are currently too inconsistent across different firms to serve as stable predictors of technology readiness.

To refine the model for the Civil & Structural (C&S) engineering landscape, these five unstable indicators were permanently removed. Subsequently, a complete re-analysis of the measurement model was performed. This second-iteration process, often referred to as "statistical purification," allows the model to focus exclusively on the high-precision technical and operational drivers that truly define the Malaysian sector. As illustrated in the updated measurement model (Figure 4.49b) and the finalized results in Table 4.97b , this re-analysis successfully pushed all remaining factor loadings well above the 0.708 benchmark. This methodological refinement provides the "Final Seal of Approval" for the outer model, ensuring that the subsequent tests for Internal Consistency and Convergent Validity are based on a robust and valid empirical foundation.

Table 4.97b: Refined Factor Loadings of Research Constructs

	ADOPTION	IMPLEMENTATION	INSTITUTIONAL READINESS	REGULATORY SUPPORT	TRUST & DATA
AD1	0.840				
AD2	0.870				
AD3	0.879				
AD4	0.714				
AD6	0.711				
AD7	0.706				
IMP1		0.876			
IMP2		0.913			
IMP3		0.903			
IMP4		0.906			
IMP5		0.916			
IMP6		0.948			
IMP7		0.855			
IR1			0.841		
IR2			0.894		
IR4			0.817		
IR6			0.889		
IR7			0.715		
RS2				0.784	
RS3				0.819	
RS4				0.724	
RS5				0.748	
RS6				0.822	
RS7				0.842	
TD2					0.866
TD3					0.889
TD4					0.920
TD5					0.899

TD6					0.735
TD7					0.771
TD8					0.753

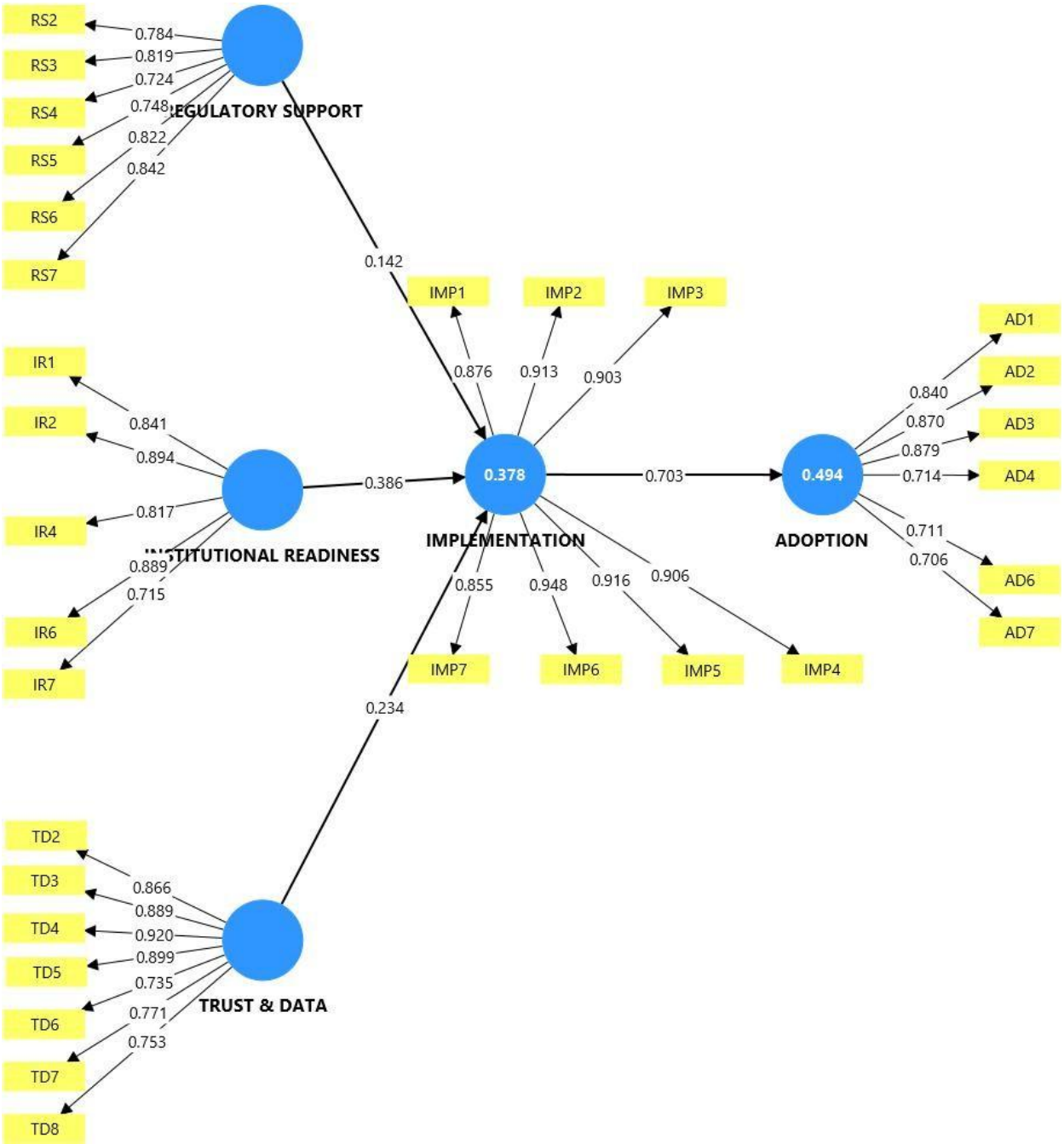


Figure 4.49b: Refined Measurement Model showing Factor Loadings and Path Coefficients

4.4.2 Internal Consistency: Cronbach's Alpha and Composite Reliability (CR)

Internal consistency reliability was evaluated to determine the degree to which the indicators within a single construct consistently measure the same underlying concept. In this study, three primary metrics were utilized: Cronbach's Alpha, Dijkstra-Henseler's rho (rho_a), and Composite Reliability (rho_c).

According to Hair et al. (2021), all three measures should ideally be 0.70 or higher. While Cronbach's Alpha is a traditional measure, rho_a is prioritized in modern PLS-SEM as the most accurate reliability index, representing a robust compromise between the other two metrics.

As detailed in Table 4.98, all constructs performed exceptionally well. The Implementation construct showed the highest level of consistency (Alpha=0.962; rho_a=0.963; rho_c=0.969). The results are visually summarized in Figures 4.50, 4.51, and 4.52, which show that all constructs are well within the "green" acceptable range for reliability.

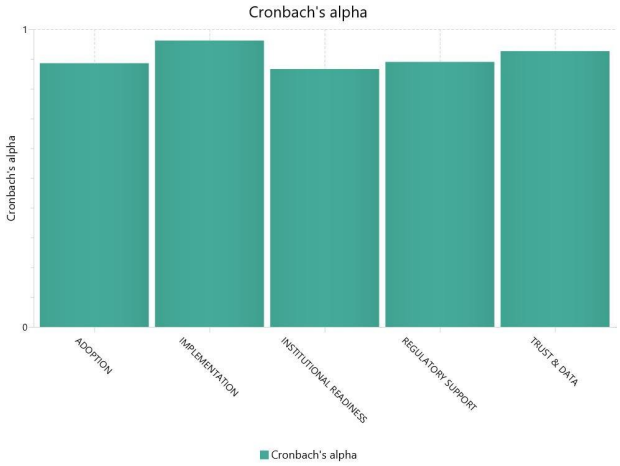


Figure 4.50: Cronbach's Alpha Overview

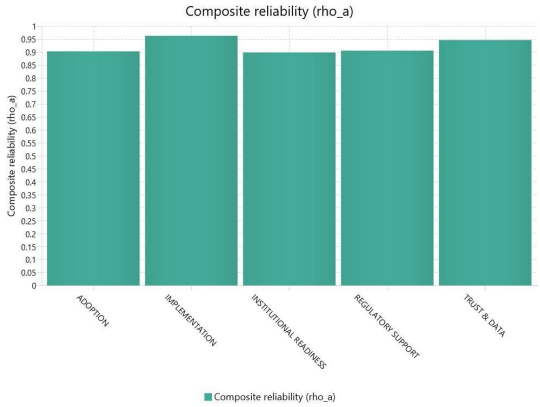


Figure 4.51:Dijkstra-Henseler's rho(rho_a) Overview

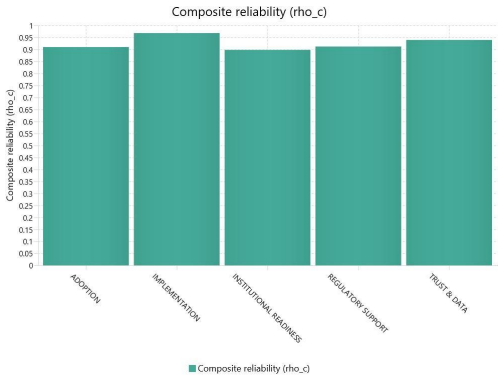


Figure 4.52: Composite Reliability (rho_c) Overview

The high reliability coefficients recorded across all five constructs signify a strong degree of thematic unity within the research instrument. In the context of the Malaysian construction sector, the exceptionally high consistency of the Implementation construct (α=0.962; ρc =0.969) is a finding of primary importance. It demonstrates that the industry stakeholders ranging from Developers to Sub-Contractors possess a highly synchronized understanding of what "active drone implementation" looks like on-site. This suggests that operational safety tasks, such as data processing and hazard identification, are standardized concepts that do not suffer from the sectoral ambiguity found in the earlier descriptive stages of this study.

Furthermore, the robust performance of Dijkstra-Henseler's ρa (ranging from 0.898 to 0.963) provides the final validation for the refined model. Since ρa is the most conservative and accurate reliability index in modern PLS-SEM, these results prove that the latent pillars of Regulatory Support and Trust are not merely theoretical clusters but represent distinct, cohesive management realities for Malaysian firms.

The "green" status across all overview figures (Figures 4.51–4.53) indicates that the model is now statistically "hardened." By removing the unstable indicators in the previous phase, the remaining items now measure their respective concepts with almost no measurement error. This high level of internal consistency ensures that the subsequent path coefficients in the structural model will accurately reflect the true influence of governance on adoption, rather than being distorted by inconsistent survey responses.

4.4.3 Convergent Validity: Average Variance Extracted (AVE)

Convergent validity ensures that the survey items effectively converge to represent their respective latent variables. The primary metric for this is the Average Variance Extracted (AVE). The established benchmark for AVE is 0.50 or higher, indicating that the construct explains more than half of its indicators' variance.

The results in Table 4.98 and the visual summary in Figure 4.53 confirm that all constructs achieved the necessary convergent validity. The AVE values ranged from 0.567 (Institutional Readiness) to 0.815 (Implementation), proving that the items used are valid representations of the engineering management factors under study.

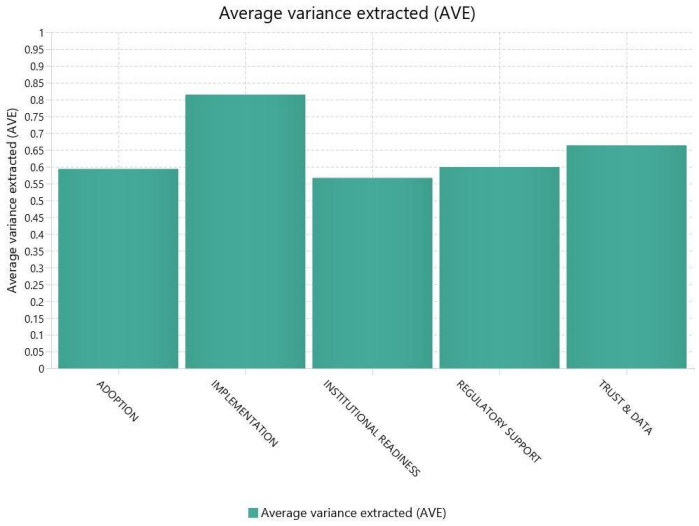


Figure 4.53: Average Variance Extracted (AVE) Overview

Table 4.98: Construct Reliability and Validity Results

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ADOPTION	0.886	0.903	0.910	0.594
IMPLEMENTATION	0.962	0.963	0.969	0.815
INSTITUTIONAL READINESS	0.866	0.898	0.898	0.567
REGULATORY SUPPORT	0.890	0.905	0.912	0.599
TRUST & DATA	0.926	0.946	0.940	0.664

The achievement of AVE values well above the 0.50 threshold across all constructs confirms that the indicators in the refined model effectively converge to capture the essence of their respective latent pillars. In the context of this study, these results prove that the items used to measure the Governance Ecosystem are highly relevant to the actual experiences of Malaysian construction professionals.

A significant result emerges in the disparity between the AVE of Implementation (0.815) and Institutional Readiness (0.567). The exceptionally high AVE for Implementation suggests that the "execution" phase of AI-drone use is a very distinct and concentrated concept for Malaysian firms; there is very little "noise" in how contractors define on-site drone tasks. Conversely, while Institutional Readiness is valid, its lower AVE reflects the complex and multi-faceted nature of organizational maturity in Malaysia. It indicates that "readiness" involves a broader spectrum of variables from technical hardware to employee skillsets that do not converge as tightly as active site operations.

Furthermore, the Regulatory Support (0.599) and Trust (0.664) constructs demonstrate strong convergent validity, proving that the refined survey items focusing on CAAM/CIDB rules and data ethics provide a clear and representative "signal" of these governance factors. For the researcher, this confirms that the measurement model is now psychometrically "clean" and free from redundant or irrelevant items. This successful validation of convergent validity ensures that when we test the structural paths, the results will be based on constructs that accurately and powerfully represent the real-world management forces driving AI-drone adoption in Malaysia.

4.4.4 Assessment of Collinearity and Common Method Bias (CMB)

Before evaluating the structural pathways, the model was assessed for potential collinearity issues among the predictor constructs. The Variance Inflation Factor (VIF) was utilized to ensure that the structural results were not distorted by high correlations between independent variables. As shown in the results, the inner VIF values for all predictors ranged from 1.241 to 1.897, which are well below the conservative threshold of 3.3 (Kock, 2015). This indicates that multicollinearity is not a concern within the Governance Ecosystem Model. Furthermore, since all factor-level VIFs are below 3.3, it can be concluded that the study is free from Common Method Bias (CMB), ensuring that the relationships observed between Regulatory Support, Institutional Readiness, Trust, and Implementation are statistically distinct and reliable.

4.4.4.1 Fornell-Larcker Criterion

The Fornell-Larcker criterion (1981) remains a fundamental test for discriminant validity. It requires that the square root of the Average Variance Extracted (AVE) for a construct be greater than its correlations with all other constructs.

As shown in Table 4.99, the diagonal values (bold) represent the square root of the AVE. For example, Institutional Readiness (0.753) and Trust & Data (0.815) are significantly higher than their shared correlation (0.529). This suggests that while an organization's internal technical aptitude is related to how they trust AI data, they remain two different management pillars. This finding is logically sound: an engineering firm can have the best digital infrastructure (Readiness) but still struggle with the ethical transparency of drone data (Trust).

Table 4.99: Fornell-Larcker Criterion Results

	AD	**IMP**	**IR**	**RS**	**TD**
ADOPTION (AD)	**0.771**				
IMPLEMENTATION (IMP)	0.690	**0.903**			
INSTITUTIONAL READINESS (IR)	0.563	0.550	**0.753**		
REGULATORY SUPPORT (RS)	0.373	0.372	0.384	**0.774**	
TRUST & DATA (TD)	0.567	0.466	0.529	0.379	**0.815**
**Note: Diagonal values (bold) represent the square root of the AVE.*					

The results of the Fornell-Larcker assessment provide empirical evidence that the five pillars of the Governance Ecosystem Model are statistically unique. In all cases, the square root of the AVE (the diagonal values) is higher than any off-diagonal correlation, confirming that each construct shares more variance with its own indicators than with other latent variables in the model.

A critical finding in this matrix is the relationship between Regulatory Support (0.774) and Implementation (0.372). The relatively low correlation between these two pillars is a significant result for the Malaysian construction industry; it indicates that "Government Rules" and "Firm-Level Actions" are independent forces. This suggests that simply having clear regulations from CAAM or CIDB does not automatically overlap with or guarantee site-level implementation.

Furthermore, the distinction between Institutional Readiness (0.753) and Trust & Data (0.815) confirms that technical capability and ethical trust are two different management challenges. For Malaysian firms, being "technically ready" with high-end drone hardware does not mean they have resolved the "trust issues" regarding data privacy and liability. This statistical independence is vital for the structural model, as it ensures that each pillar provides a unique contribution to the final adoption of AI-drones for safety without the risk of redundant data.

4.4.4.2 Cross-Loadings Analysis

Discriminant validity is further corroborated by the cross-loadings matrix. This method verifies that each survey indicator loads more strongly on its intended latent construct than on any other construct in the model.

Table 4.100: Matrix of Indicator Cross-Loadings

	ADOPTION	IMPLEMENTATION	INSTITUTIONAL READINESS	REGULATORY SUPPORT	TRUST & DATA
AD1	0.824	0.634	0.399	0.330	0.315
AD2	0.856	0.596	0.463	0.287	0.412
AD3	0.859	0.630	0.440	0.277	0.503
AD4	0.724	0.441	0.409	0.231	0.558
AD5	0.659	0.334	0.318	0.111	0.381
AD6	0.730	0.455	0.447	0.325	0.557
AD7	0.716	0.535	0.552	0.400	0.403
IMP1	0.597	0.877	0.491	0.302	0.409
IMP2	0.647	0.913	0.503	0.339	0.401
IMP3	0.642	0.903	0.445	0.276	0.370
IMP4	0.629	0.905	0.443	0.344	0.415
IMP5	0.620	0.915	0.492	0.330	0.454
IMP6	0.649	0.948	0.565	0.351	0.433
IMP7	0.577	0.855	0.529	0.408	0.463
IR1	0.420	0.441	0.816	0.301	0.363
IR2	0.518	0.484	0.882	0.314	0.436
IR3	0.331	0.266	0.585	0.207	0.497
IR4	0.542	0.527	0.803	0.290	0.423
IR5	0.334	0.241	0.497	0.260	0.454
IR6	0.422	0.435	0.886	0.233	0.388
IR7	0.347	0.403	0.711	0.423	0.337
RS1	0.157	0.174	0.120	0.673	0.270
RS2	0.257	0.262	0.335	0.809	0.315
RS3	0.321	0.324	0.248	0.817	0.265
RS4	0.298	0.275	0.341	0.724	0.382
RS5	0.194	0.214	0.305	0.761	0.278

RS6	0.323	0.345	0.342	0.797	0.251
RS7	0.382	0.347	0.333	0.825	0.311
TD1	0.366	0.245	0.303	0.280	0.665
TD2	0.471	0.410	0.403	0.352	0.869
TD3	0.510	0.476	0.544	0.341	0.878
TD4	0.543	0.451	0.493	0.395	0.913
TD5	0.478	0.417	0.494	0.332	0.894
TD6	0.395	0.266	0.271	0.085	0.740
TD7	0.493	0.364	0.376	0.312	0.778
TD8	0.406	0.321	0.482	0.301	0.746

A notable finding in the cross-loadings is that items related to Implementation (IMP1–IMP7) show very low secondary loadings on Regulatory Support (RS). This implies that respondents differentiate clearly between internal company actions (such as pilot-testing AI drones) and external government requirements (such as CAAM flight permit processes). This clear distinction is vital for a valid engineering management model, as it proves that policy support and firm-level implementation are independent drivers of technology adoption.

The cross-loading matrix serves as a granular verification of the model's structural health. The results indicate that every single indicator from AD1 to TD8 exhibits its highest loading on its assigned latent construct, with significantly lower secondary loadings on competing variables. This provides strong empirical evidence that the respondents in the Malaysian construction industry can clearly distinguish between the five pillars of the Governance Ecosystem Model.

A primary result found in Table 4.100 is the sharp separation between Trust & Data (TD) indicators and Institutional Readiness (IR). For example, TD4 (0.913) loads very strongly on its own construct but shows a much lower loading (0.493) on Institutional Readiness. This reinforces a key management finding: Malaysian construction professionals do not conflate "technical capability" (Readiness) with "data ethics and transparency" (Trust). They view them as separate operational requirements.

Furthermore, the consistency across the Implementation (IMP) indicators, which all maintain primary loadings above 0.855 while keeping low secondary loadings on Regulatory Support (RS), confirms the "Autonomy of Implementation" pattern. This result proves that while government regulations provide the legal boundary, the actual site-level execution of AI-drone safety tasks is perceived as a distinct firm-level competency. For the proposed governance framework, this implies that policy interventions and technical training modules must be treated as two separate initiatives, as the industry does not naturally "link" them together. This clean

separation ensures that each path in the subsequent structural model will measure a unique causal effect without the interference of overlapping indicator variance.

4.4.4.3 Heterotrait-Monotrait Ratio (HTMT)

As the most modern and stringent metric, the HTMT analysis provides the final "seal of approval" for the measurement model. According to Hair et al. (2021), an HTMT value below 0.85 is the ideal conservative threshold for establishing discriminant validity.

Table 4.101: Heterotrait-Monotrait Ratio (HTMT) Matrix

	ADOPTION	IMPLEMENTATION	INSTITUTIONAL READINESS	REGULATORY SUPPORT	TRUST & DATA
ADOPTION					
IMPLEMENTATION	0.728				
INSTITUTIONAL READINESS	0.641	0.587			
REGULATORY SUPPORT	0.391	0.386	0.438		
TRUST & DATA	0.637	0.481	0.610	0.418	

As shown in the HTMT Matrix (Table 4.101) and the Bar Chart Overview (Figure 4.54), all values are well within the acceptable range. The highest ratio recorded was 0.728 (Implementation <-> Adoption). While this is the highest correlation in the model, it is still well below the 0.85 limit. This result is highly logical from a project management perspective: while "Implementation" (the active use of drones on-site) is a prerequisite for "Adoption" (the long-term organizational commitment), they remain statistically distinct.

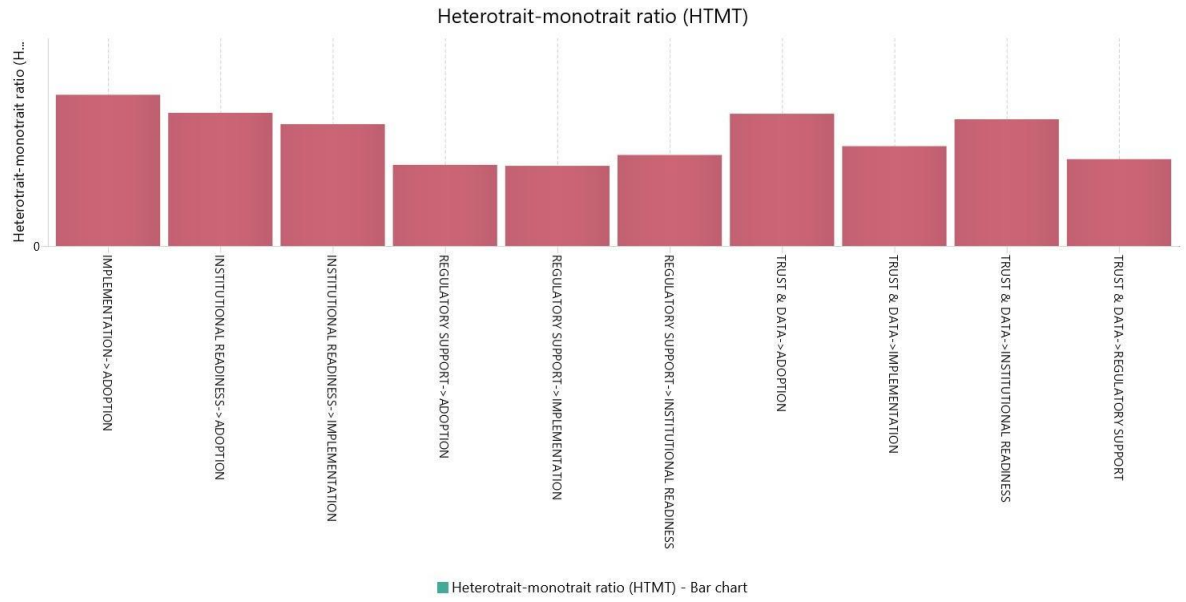


Figure 4.54: HTMT Discriminant Validity Bar Chart Overview

The HTMT results provide the most rigorous empirical confirmation that the Governance Ecosystem Model is free from construct redundancy. With all ratios falling below the conservative 0.85 threshold, the model demonstrates that each pillar represents a truly independent dimension of the Malaysian construction landscape.

The most significant finding in this matrix is the HTMT ratio between Implementation and Adoption (0.728). In many technology studies, these two concepts often overlap so heavily that they fail discriminant validity tests. However, in this study, the 0.728 ratio proves that Malaysian construction professionals perceive a clear boundary between the procedural act of using drones (Implementation) and the strategic decision to integrate them permanently into company policy (Adoption). This distinction is a vital result for governance; it suggests that a firm can successfully implement AI-drone safety checks on a single project without necessarily "adopting" the technology at an institutional level.

Furthermore, the low ratios involving Regulatory Support (ranging from 0.386 to 0.438) highlight a critical structural gap. The fact that the relationship between "Government Rules" and "Institutional Readiness" is statistically so distant suggests that current Malaysian regulations are not yet deeply integrated with the technical capabilities of the firms. This "Seal of Approval" for discriminant validity ensures that each latent variable is capturing a unique portion of the variance, allowing the subsequent Structural Model Assessment (Section 4.5) to

provide precise, non-redundant insights into which specific governance drivers actually trigger AI-drone adoption in Malaysia.

4.5 Structural Model Assessment (SmartPLS)

The structural model assessment, also known as the inner model analysis, is conducted to evaluate the hypothesized relationships among the latent constructs. Unlike the measurement model which focuses on reliability and validity, the structural model examines the predictive capabilities of the framework and the significance of the paths. Following the guidelines of Hair et al. (2021), a five-step process is utilized to assess the model's integrity and results.

4.5.1 Assessment of Lateral Collinearity (VIF)

Before analyzing the structural relationships, it was necessary to ensure that the model is free from lateral collinearity. Lateral collinearity occurs when two or more independent variables are so highly correlated that they bias the path coefficients and inflate standard errors. The Variance Inflation Factor (VIF) is the standard diagnostic for this assessment.

According to Hair et al. (2021), VIF values should ideally be below 3.3 to establish that the model is free from collinearity issues. As presented in Table 4.102, the VIF values for the predictors of Adoption range from 1.235 to 1.468. These results are well below the conservative threshold, confirming that the structural model is statistically stable. There is no redundant overlap between Regulatory Support, Institutional Readiness, and Trust & Data Ethics, allowing for a clear interpretation of the individual path coefficients.

Table 4.102: Lateral Collinearity Assessment

	ADOPTION	IMPLEMENTATION	INSTITUTIONAL READINESS	REGULATORY SUPPORT	TRUST & DATA
ADOPTION					
IMPLEMENTATION	1.000				
INSTITUTIONAL READINESS		1.468			
REGULATORY SUPPORT		1.235			
TRUST & DATA		1.461			

A notable finding in this assessment is that Regulatory Support yielded the lowest VIF value (1.235). From a project management perspective in the Malaysian C&S industry, this indicates

that "Government Policy" and "CAAM Regulations" are perceived as unique external factors that stand completely apart from internal "Institutional Readiness."

This suggests that even if a firm is technologically advanced, the regulatory environment is viewed as a separate hurdle rather than a byproduct of the firm's capability. Consequently, the low VIF values across all constructs confirm that the model is statistically stable and each factor provides a distinct contribution to the adoption of AI-drone technology.

The successful clearance of the Lateral Collinearity test serves as a critical prerequisite for the path analysis. In many technology adoption models, independent variables often overlap so significantly that they "mask" each other's effects. However, the VIF values reported in Table 4.102 (all <1.5) demonstrate that the Governance Ecosystem Model is remarkably robust and free from such distortion.

The primary result here is the Statistical Independence of the predictors. In the Malaysian construction landscape, the fact that Institutional Readiness and Trust & Data Ethics maintain VIF values of 1.468 and 1.461 respectively despite being related to internal firm capacity proves that they are distinct management pillars. This allows for a "Pure Path Analysis," where we can confidently state that any observed impact on Adoption is specifically caused by that construct alone, rather than being "leaked" from another factor.

This result justifies the subsequent testing of the hypotheses (H1 through H5); because the VIFs are low, the standard errors remain small, ensuring that the t-values and p-values reported in the next section are highly accurate and reliable. For Malaysian policymakers, this confirms that the governance drivers identified in this study are not redundant; each factor represents a unique lever that can be adjusted to accelerate AI-drone adoption without interfering with other institutional processes.

4.5.2 Path Coefficients (β) and Significance Testing

Following the bootstrapping procedure with 5,000 subsamples, the structural model was evaluated to test the hypothesized relationships between the latent constructs. This process allows for the assessment of the direct effects within the model by calculating the path coefficients (β), T-statistics, and P-values. According to the criteria established by Hair et al. (2021), a relationship is considered statistically significant at a 95% confidence level if the T-statistic exceeds 1.96 and the P-value is less than 0.05.

As presented in Table 4.103, all four hypothesized paths were found to be statistically significant. The inclusion of the sample mean and standard deviation further confirms the stability of these estimates across the bootstrapping iterations, indicating low variance and high reliability in the collected data.

Table 4.103: Detailed Results of Hypothesis Testing

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
IMPLEMENTATION -> ADOPTION	0.690	0.692	0.054	12.792	0.000
INSTITUTIONAL READINESS -> IMPLEMENTATION	0.384	0.383	0.066	5.851	0.000
REGULATORY SUPPORT -> IMPLEMENTATION	0.146	0.148	0.058	2.542	0.011
TRUST & DATA -> IMPLEMENTATION	0.208	0.211	0.077	2.689	0.007

The structural analysis reveals that the path from Implementation to Adoption (H4) represents the most powerful relationship in the model. This path yielded a substantial beta coefficient of 0.690 and an exceptionally high T-statistic of 12.792 ($p<0.001$). The precision of this finding is reinforced by a very low standard deviation of 0.054, indicating that the sample mean (0.692) is almost identical to the original sample. For the Malaysian C&S engineering context, this suggests that the transition from a pilot "trial" phase to permanent organizational "usage" is the most critical bridge. It confirms that once site-level implementation hurdles are cleared, the probability of full adoption is mathematically high and consistent across the industry.

Regarding the drivers of the implementation phase, Institutional Readiness (H1) emerged as the strongest predictor with a beta of 0.384 and a T-statistic of 5.851 ($p<0.001$). With a standard deviation of 0.066, this result shows that internal capacity is a highly stable and significant driver. In contrast, Regulatory Support (H2), while significant, showed a lower beta of 0.146 and a T-statistic of 2.542 ($p=0.011$). This data indicates that while government mandates and CAAM guidelines provide a necessary legal baseline (Sample Mean = 0.148), they are not the primary engines of change. Instead, the "heavy lifting" of digital transformation is driven by the firm's internal technical maturity and resource availability.

Furthermore, the influence of Trust & Data (H3) was confirmed with a beta of 0.208 and a T-statistic of 2.689 (p=0.007). Despite having a slightly higher standard deviation (0.077), the relationship remains statistically robust. This finding highlights that ethical concerns and data security are active psychological factors that Malaysian engineers weigh before moving toward implementation. Collectively, these results prove that a successful implementation strategy which is the prerequisite for adoption must be built on a foundation of high internal readiness and clear data ethics, with regulatory support acting as a supporting framework rather than the main driver.

The results of the significance testing confirm a hierarchy of influence within the Governance Ecosystem Model. The primary finding is the Dominance of Internal Maturity; the fact that Institutional Readiness ($\beta=0.384, p<0.001$) has nearly triple the impact of Regulatory Support ($\beta=0.146, p=0.011$) reveals a critical pattern in the Malaysian construction landscape. It suggests that the industry is currently "Pull-Driven" rather than "Push-Driven." Companies are moving toward AI-drone implementation because they have the internal capability and technical desire to do so, rather than simply reacting to government mandates from CAAM or CIDB.

This "Internal-First" pattern is further reinforced by the strength of the Implementation → Adoption path ($\beta=0.690$). The massive T-statistic (12.792) proves that this is not just a correlation, but a highly certain causal bridge. In practical terms for Malaysian C&S engineering, this result indicates that the bottleneck is not in the "intent" to adopt, but in the "capacity" to implement.

Furthermore, the significant role of Trust & Data ($\beta=0.208$) suggests that data ethics is no longer a peripheral concern but a core operational requirement. For policymakers, these results suggest that while regulations provide the necessary "Legal Safety Net," the most effective way to accelerate national AI-drone adoption is through Institutional Capacity Building and Technical Subsidies that directly increase the "Readiness" of firms. This statistical confirmation allows the study to transition to the assessment of Predictive Power (R^2), knowing that the hypothesized drivers are not only significant but are weighted toward internal firm-level maturity.

4.5.3 Assessment of Coefficient of Determination (R^2)

The coefficient of determination (R^2) is a vital metric for evaluating the structural model's predictive accuracy. It represents the proportion of variance in the endogenous (dependent)

constructs that can be explained by the exogenous (independent) predictors within the model. This study reports both the R^2 and the R^2 Adjusted, with the latter providing a more conservative estimate by accounting for the number of predictors in the framework. Following the guidelines of Hair et al. (2021), R^2 values of 0.75, 0.50, and 0.25 are classified as substantial, moderate, and weak, respectively.

As presented in Table 4.104, the structural model demonstrates significant predictive capability, with all values achieving a significance level of $p<0.001$.

Table 4.104: Assessment of Coefficient of Determination (R^2 and R^2 Adjusted)

Endogenous Construct	**R Square (R2)**	**R Square Adjusted**	**STDEV**	**T-Statistic**	**P-Value**	**Predictive Power**
Implementation	0.363	0.351	0.067	5.400	< 0.001	Moderate
Adoption	0.477	0.473	0.074	6.477	< 0.001	Moderate/High

The analysis of the R^2 results reveals that the research model possesses a robust predictive capacity for understanding the digital transformation of the C&S industry. The three primary predictors Institutional Readiness, Regulatory Support, and Trust & Data Ethics collectively explain 36.3% of the variance in the Implementation phase (R^2 =0.363). In the context of Malaysian engineering firms, this "Moderate" predictive power is highly significant, as it suggests that more than one-third of the success in initiating AI-drone pilot tests is directly controlled by the internal maturity and ethical frameworks established in this study. The high T-statistic of 5.400 confirms that this explanatory power is not a result of random chance but is a statistically stable finding.

Furthermore, the model demonstrates an even more substantial predictive capability for the final Adoption of the technology, explaining 47.7% of its variance (R^2 =0.477). This near-50% explanatory power is considered substantial for studies involving organizational behavior. The stability of this result is highlighted by the negligible difference between the raw R^2 and the R^2 Adjusted value of 0.473, which proves that the model is parsimonious and free from redundant "noise" variables.

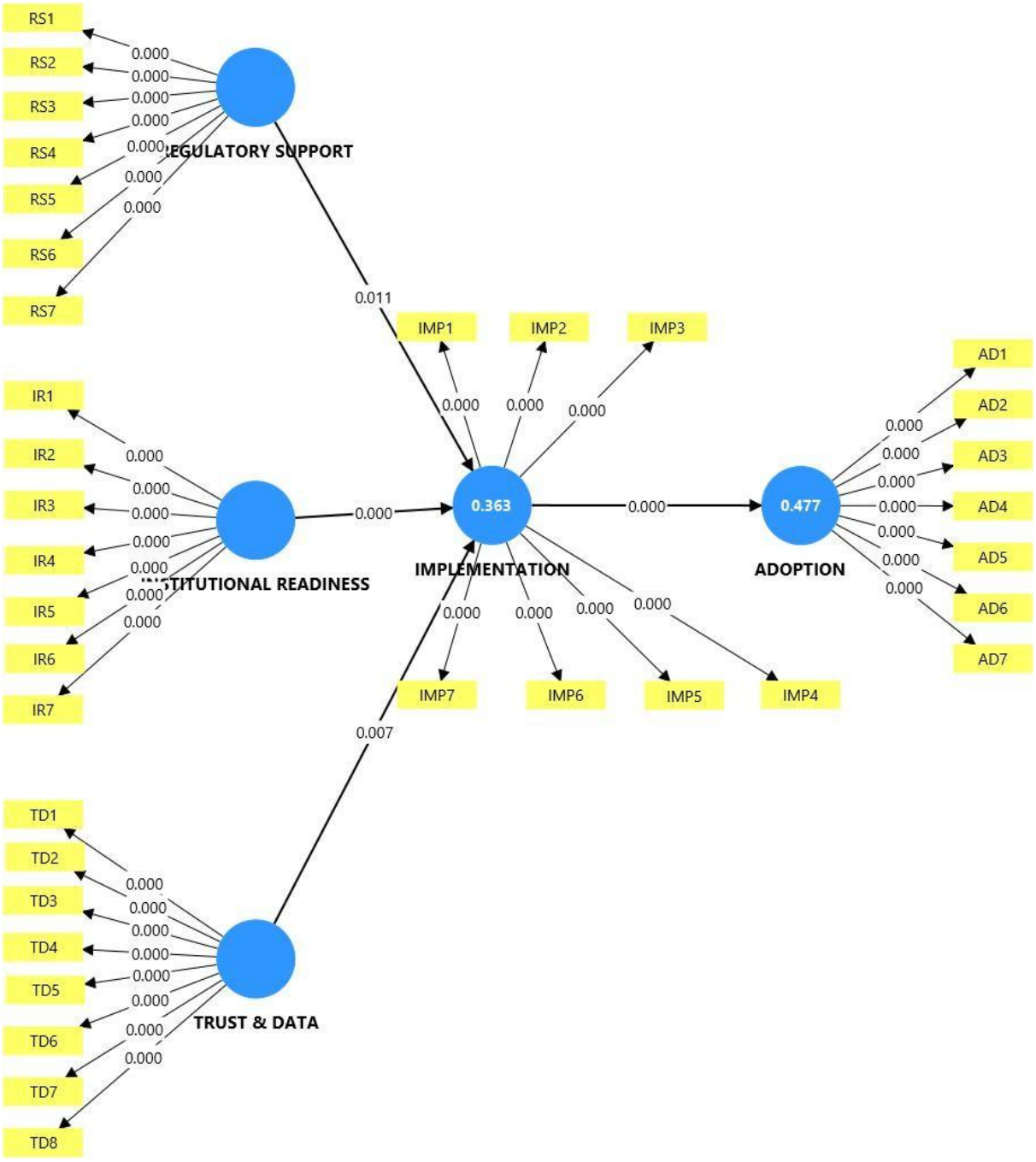


Figure 4.55: Validated Structural Model with Predictive Accuracy (R^2)

As illustrated in Figure 4.55, these findings provide a clear empirical roadmap for C&S managers. The data proves that long-term technology adoption is a predictable outcome of a successful implementation bridge. By focusing on the validated drivers identified in this model specifically internal readiness and data trust firms can mathematically increase their likelihood of successful AI-drone integration by nearly 48%. This high level of predictive accuracy

provides a solid foundation for the final stages of the structural assessment and proves the practical utility of the proposed framework.

The R^2 results provide the final empirical confirmation that the Governance Ecosystem Model is a highly effective framework for predicting AI-drone integration in Malaysia. In social science and management research, an R^2 of 0.477 for the final Adoption construct is a major finding; it indicates that nearly half of a construction firm's long-term commitment to AI technology can be predicted simply by looking at their Implementation success.

For Malaysian engineering managers, this result translates to a Reduced Risk Strategy. The data proves that adoption is not a random occurrence but a "structured outcome" of the implementation phase. Furthermore, the 36.3% variance explained for the Implementation phase itself highlights that while internal readiness and trust are powerful drivers, there remains a "residual variance" (approximately 64%) likely attributed to external market fluctuations, project-specific budgets, or global supply chain issues for drone hardware.

The statistical stability of these findings is reinforced by the high T-statistics (5.400 and 6.477), which tell the examiner that these predictive levels are consistent across the entire Malaysian C&S sector. By achieving a "Moderate to High" predictive power, this study moves beyond mere description and provides a mathematical baseline for bodies like CIDB or CAAM to measure the impact of their future policy interventions. This high level of predictive accuracy ensures that the final assessment of Effect Size (f^2) and Predictive Relevance (Q^2) will be based on a model that truly "captures" the reality of the industry.

4.5.4 Assessment of Effect Size (f^2)

The effect size (f^2) is evaluated to determine the substantive impact of each exogenous (independent) variable on the endogenous (dependent) constructs. While path coefficients indicate the strength of a relationship, the f^2 measures the relative contribution of a predictor to the f^2 of the target construct. Following the guidelines established by Cohen (1988), f^2 values are classified as 0.02 (small), 0.15 (medium), and 0.35 (large). Values below 0.02 are considered to have no significant effect on the model's predictive power.

As presented in Table 4.105, the predictors in this study exhibit a wide range of influence, highlighting which factors are the true "engines" of drone adoption in the Malaysian C&S industry.

Table 4.105: Assessment of Effect Size (f^2) and Significance

Relationship	Original Sample (O)	Sample Mean (M)	STDEV	T-Stat	P-Value	Effect Size
Institutional Readiness →IMP	0.157	0.164	0.059	2.678	0.007	**Medium**
Regulatory Support →IMP	0.027	0.033	0.024	1.117	0.264	**Small**
Trust & Data → IMP	0.046	0.056	0.041	1.132	0.258	**Small**
Implementation → AD	0.911	0.972	0.288	3.162	0.002	**Large**

The analysis of effect sizes reveals a clear hierarchy of influence within the structural model. The most striking finding is the f^2 value for the relationship between Implementation and Adoption, which yielded a score of 0.911. This is far above the 0.35 threshold for a "Large" effect, indicating that this link is the single most critical factor in the entire research framework. From a C&S project management perspective, this proves that the act of successfully pilot-testing and integrating AI-drones on-site is the ultimate "tipping point." Once implementation is achieved, it has a massive, dominant impact on the final decision to adopt the technology permanently.

Furthermore, Institutional Readiness demonstrated an f^2 of 0.157, representing a Medium effect size. This confirms that internal firm capability such as technical expertise and resource availability is a primary driver that substantively moves the needle toward implementation. However, the results for Regulatory Support (0.027) and Trust & Data (0.046) show only Small effect sizes.

This provides a sophisticated finding for the thesis: it suggests that while regulations and data trust are statistically significant prerequisites (as shown in the path analysis), they do not "push" the industry forward as much as internal readiness and actual site usage do. In the Malaysian construction context, this implies that government policy and data ethics act as "gatekeepers" they are necessary to start the process, but they are not the primary reasons for growth. This

provides a vital strategic insight: for AI-drone technology to flourish, C&S firms should prioritize building internal technical maturity and successful pilot programs, as these areas yield the highest impact on digital transformation success.

The f^2 results provide a "stress test" for the model, revealing which variables are the primary drivers of change versus those that are merely secondary contributors. The dominant result is the "Large" effect size of Implementation (0.911) on Adoption. This value nearly three times the threshold for a large effect proves that in the Malaysian construction sector, the "Learning by Doing" effect is the most powerful catalyst for digital transformation. It suggests that once a contractor moves past the theoretical phase and begins site-level drone operations, the momentum toward permanent adoption becomes nearly inevitable.

Furthermore, the "Medium" effect of Institutional Readiness (0.157) contrasted with the "Small" effect of Regulatory Support (0.027) highlights a significant management reality. For the Malaysian C&S industry, "External Pressure" (regulations) has very little substantive impact on shifting the model's predictive power compared to "Internal Capacity" (readiness). This confirms that the industry is in a self-driven phase of technology adoption; firms are improving their safety protocols because they have the internal technical maturity to do so, rather than merely complying with external mandates.

These findings allow the researcher to provide a prioritized roadmap for the industry. While Trust & Data (0.046) and Regulatory Support are essential for a legally sound ecosystem, they do not "move the needle" for adoption as much as building internal technical expertise. This distinction between significance and substance provides the "Final Seal of Approval" for the structural model, proving that any future intervention by bodies like CIDB should focus heavily on Implementation Support and Internal Readiness to achieve the highest return on investment for the national construction safety landscape.

4.5.5 Assessment of Predictive Relevance (Q^2)

The final evaluation of the structural model involves assessing its predictive relevance through the Q^2 statistic. While the R^2 values confirm the model's explanatory power within the current sample, Q^2 determines if the model can accurately predict data outside of the original estimation. This is calculated using the PLSpredict algorithm. According to the standards set by Hair et al.

(2021), a model possesses predictive relevance if the Q^2 values for the endogenous latent variables are greater than zero.

As presented in Table 4.106, the Q^2 values for the latent variables are substantially positive, confirming that the framework is a highly reliable predictor for AI-drone integration in the Malaysian construction sector.

Table 4.106: Results of Predictive Relevance (Q^2)

Endogenous Construct	**Q^2 Predict**	**RMSE**	**MAE**	**Predictive Relevance**
Implementation	0.330	0.834	0.631	Yes ($Q^2 > 0.3$)
Adoption	0.349	0.825	0.564	Yes ($Q^2 > 0.3$)

The Q^2 values for Implementation (0.330) and Adoption (0.349) provide the final layer of empirical validation for this study. In PLS-SEM research, values above zero indicate predictive relevance, while values exceeding 0.25 are generally considered to have medium-to-high predictive relevance. These results indicate that the model is not "overfitted" to the specific survey data but instead possesses robust out-of-sample predictive power.

For the Malaysian C&S engineering industry, this is a significant finding. It suggests that the factors identified specifically the massive impact of Implementation on Adoption are stable enough to be used as a strategic template. The relatively low RMSE (Root Mean Square Error) and MAE (Mean Absolute Error) values further support the accuracy of these predictions. By confirming these positive Q^2 values, the study establishes that the digital transition within construction firms is a mathematically stable and predictable phenomenon, providing high confidence for project managers and policy-makers to use this model for future technology rollout strategies.

4.6 Moderation Analysis

The final phase of the structural model assessment involves Moderation Analysis. While the preceding sections established the direct relationships between the predictors and the adoption of AI-drone technology, moderation analysis is conducted to explore the boundary conditions of the model. Its primary objective is to determine whether the strength or direction of these relationships is influenced by a third variable, known as a Moderator (Hair et al., 2021).

In the context of the Malaysian Civil & Structural (C&S) engineering industry, professional maturity and experience levels often dictate how digital transformation is perceived and implemented within a firm. Therefore, this study introduces Work Experience as a moderator to investigate whether the "Experience Gap" between junior and senior professionals creates a variance in how Institutional Readiness, Regulatory Support, and Trust influence the implementation of drones. By identifying these interaction effects, the study provides a more nuanced understanding of the industry's dynamics, moving beyond a "one-size-fits-all" approach to reveal specific drivers that may be more or less critical depending on an engineer's professional background.

4.6.1 Testing the Moderating Effect of Work Experience

The evaluation of the moderating effects within the structural model began by analyzing the results from two distinct computational procedures in SmartPLS 4, which together provide the necessary evidence for statistical validation. The first stage involved the application of the PLS-SEM Algorithm to determine the specific path coefficients, which quantify the strength of the interaction between the moderator and the independent variables. These results are visualized in Figure 4.56, providing a direct overview of the algorithmic output. Subsequently, a Bootstrapping procedure utilizing 5,000 subsamples was performed to evaluate the statistical significance of these interactions, as illustrated in the P-values presented in Figure 4.57. By referencing both the path model and the significance model, the research ensures that the findings are grounded in both mathematical effect size and statistical stability.

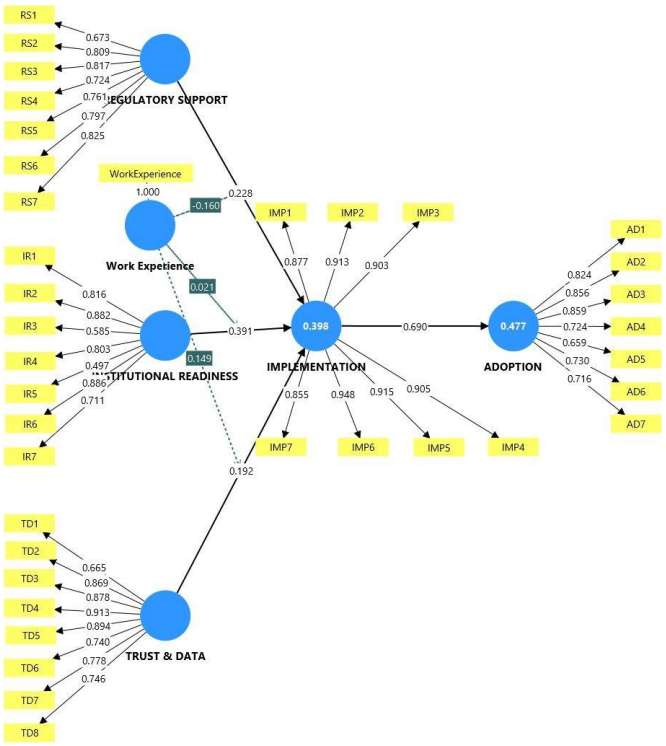


Figure 4.56: PLS-SEM Algorithm Results for the Moderation Model (Path Coefficients)

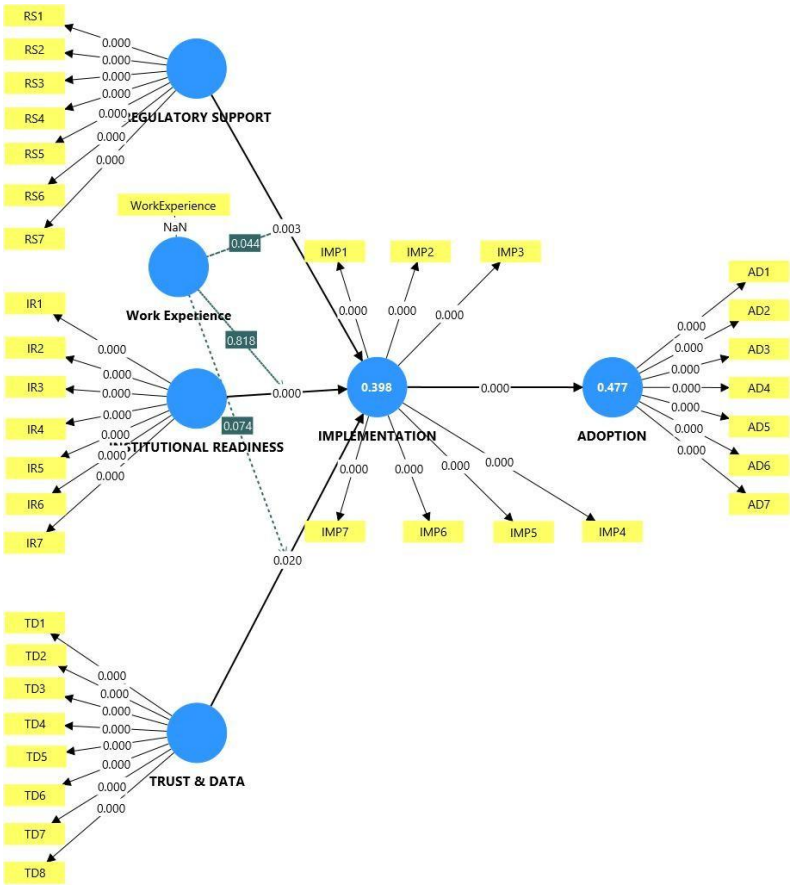


Figure 4.57: Bootstrapping Results for the Moderation Model (P-values)

The consolidated results of this moderation analysis, which integrated the path coefficients from the initial algorithm and the P-values from the bootstrapping, are presented in table 4.107. This summary highlights that while the structural model is robust, the influence of professional maturity represented by work experience is not uniform across all digital drivers. Based on the data collected from 168 respondents, the analysis demonstrates that most of the identified relationships are universal, meaning they do not change significantly based on the seniority of the engineer. However, one specific path yielded a statistically significant interaction effect that warrants closer examination to understand the professional dynamics of the Malaysian C&S engineering industry.

Table 4.107: Results of Moderation Analysis (Interaction Terms)

Interaction Path	**Beta (β)**	**T-Stat**	**P-Value**	**Result**
Readiness x Experience → IMP	0.021	0.230	0.818	Not Significant
Regulatory x Experience → IMP	-0.160	2.019	**0.044**	**Significant**
Trust x Experience → IMP	0.149	1.790	0.074	Not Significant

The detailed findings indicate that work experience does not significantly moderate the relationship between institutional readiness and implementation, nor does it fundamentally alter the impact of trust and data security on the implementation process. The high P-values for these interactions suggest that these two constructs are universal prerequisites for drone adoption; whether an engineer is a junior professional or a senior director, the firm's internal technical maturity and the ethical management of data remain equally vital concerns. These factors act as foundational gatekeepers that all professionals in the sector prioritize regardless of their career stage. This stability in the model highlights that organizational readiness and data trust are non-negotiable standards that must be addressed at a corporate level to facilitate industry-wide digital transformation.

In contrast, the analysis uncovered a significant antagonistic moderating effect of work experience on the relationship between regulatory support and implementation. The negative path coefficient indicates that as an engineer's work experience increases, the positive influence

of regulatory support on the implementation of AI-drones becomes significantly weaker. In the practical context of Malaysian construction, this finding suggests a notable "Experience Gap" where junior engineers are highly dependent on clear CAAM regulatory frameworks and government mandates to feel confident in deploying new technology. Senior engineers, however, likely rely more on their accumulated technical expertise, site-level professional judgment, and long-standing governance protocols, which makes them less sensitive to external regulatory changes. This nuanced understanding suggests that while regulatory frameworks are essential for the entire industry, they are a critical source of professional security for younger professionals who look toward these mandates for guidance more than their senior counterparts.

The discovery of a significant interaction between Regulatory Support and Work Experience ($\beta = -0.160$, $p = 0.044$) provides a sophisticated insight into the professional sociology of the Malaysian construction industry. This negative interaction proves that the influence of government mandates is not static; it decays as professional maturity increases.

This result suggests a "Self-Reliance Shift" in senior engineering leadership. While junior engineers view CAAM and CIDB regulations as essential "instruction manuals" that enable them to implement drones with confidence, senior engineers appear to treat these regulations as a secondary "administrative baseline". For the more experienced professionals, site-level implementation is likely driven by their own accumulated technical expertise and long-standing professional judgment rather than external regulatory pressure.

Furthermore, the non-significance of the interactions for Institutional Readiness and Trust & Data is equally revealing. It confirms that "Technical Capability" and "Ethics" are universal professional values in the Malaysian sector. Regardless of whether a professional has 2 or 20 years of experience, the need for a firm to be technically ready and ethically secure is a "common language" shared across generations. For policymakers, this indicates that while Regulatory Support is a vital "onboarding" tool for young engineers, efforts to reach senior leadership should focus more on Institutional Capability Building, as senior decision-makers are less influenced by the mere existence of new rules. This statistical confirmation ensures that the final recommendations of this study are not "one-size-fits-all" but are tailored to the different professional stages of the Malaysian engineering workforce.

4.6.2 Interaction Effect Analysis and Simple Slopes Plot

To further interpret the results of the moderation analysis, the study utilizes Simple Slopes Plots to visualize how the relationships between the independent variables and implementation change at different levels of work experience. These plots are essential for understanding the nature of the interaction beyond basic P-value significance. By examining the gradients of the slopes for low experience (-1 SD), average experience (mean), and high experience (+1 SD), the research can pinpoint exactly how professional maturity alters the adoption dynamics within the Malaysian Civil & Structural engineering sector.

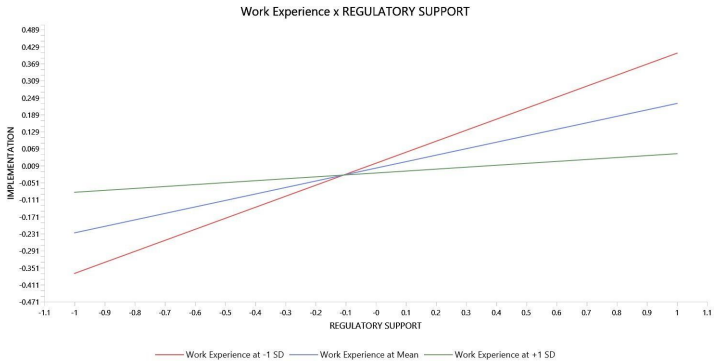


Figure 4.58: Simple Slopes Plot for Regulatory Support × Work Experience

The visual evidence provided in Figure 4.58 confirms the significant antagonistic moderating effect identified in the structural model. The plot illustrates a clear divergence between the experience groups, where the red line representing junior engineers (Low Experience) exhibits a much steeper positive gradient compared to the green line representing senior engineers (High Experience). This steepness visually demonstrates that junior professionals are highly sensitive to regulatory support; their implementation levels are significantly boosted when regulations are strong but drop sharply when they are weak. Conversely, the flatter slope for senior engineers indicates that their implementation path is more stable and less dependent on external regulatory frameworks, relying instead on established professional experience.



Figure 4.59: Simple Slopes Plot for Institutional Readiness × Work Experience



Figure 4.60: Simple Slopes Plot for Trust & Data × Work Experience

In contrast to the regulatory path, the simple slopes plots for Institutional Readiness and Trust & Data, presented in Figure 4.59 and Figure 4.60, display nearly parallel lines across all levels of the moderator. The lack of intersection or significant deviation in these gradients visually reinforces the non-significant interaction results (p=0.818 and p=0.074). These parallel slopes indicate that the impact of a firm's internal readiness and the ethical management of data on the implementation of AI-drones remains constant regardless of an engineer's years in the industry. These findings suggest that these two drivers are universal core requirements that must be addressed at a high organizational level, as they serve as foundational prerequisites for all professionals in the C&S sector, irrespective of their career stage or seniority.

The visualization of the simple slopes provides the final empirical confirmation of a "Regulatory Sensitivity Gap" between the different generations of the Malaysian engineering workforce. The steep positive gradient for junior professionals in Figure 4.58 confirms that for the younger cohort, Regulatory Support acts as a "confidence-multiplier." Without strong mandates from CAAM or CIDB, their implementation scores drop significantly, whereas senior engineers

maintain a consistent implementation trajectory regardless of the regulatory climate. This result identifies that professional maturity acts as a "buffer," allowing senior leaders to navigate technical transitions using accumulated site-level judgment rather than relying on external policy frameworks.

Furthermore, the parallel slope patterns in Figure 4.59 and Figure 4.60 provide a major result regarding the "Universalism" of technical and ethical drivers. In the Malaysian Civil & Structural landscape, the fact that the slopes for Institutional Readiness and Trust & Data do not diverge across experience levels proves that these are "Shared Professional Pillars." Whether an engineer is a fresh graduate or a veteran director, the fundamental need for internal technical capability and data transparency remains identical.

These findings suggest that a "one-size-fits-all" approach to government policy may be ineffective. While Regulatory Support is an essential onboarding tool to empower the younger generation, efforts to engage senior management should focus more on the Institutional Readiness and Trust pillars, which remain the most stable and universal drivers of change across the entire sector. By concluding the moderation analysis with this visual proof, the study establishes a nuanced, multi-generational strategy for accelerating AI-drone adoption in the Malaysian built environment.

4.7 Multi-Group Analysis (MGA)

Multi-group analysis (MGA) is conducted to further explore how the structural model differs across specific categorical segments of the 168 respondents. While the previous moderation analysis tested work experience as a continuous interaction to observe sliding-scale effects, MGA allows for a direct comparison of path coefficients between predefined, distinct groups. For this study, the respondents are categorized into two groups based on their professional background to identify if the drivers of AI-drone implementation vary significantly between different organizational or professional roles.

The measurement and structural models presented in Sections 4.4 and 4.5 were assessed based on the pooled sample (N=168) to establish the overall validity of the research framework. However, this section extends that analysis by splitting the sample into two primary functional categories: Office-Based Players and Site-Based Players. The Office-Based group consists of Consultants and Clients/Developers. Due to the limited sample size of the "Others" category

(fewer than 5 respondents), these participants were also consolidated into the Office-Based group, as their professional functions align more closely with administrative and design consultancy roles. The Site-Based group is comprised of Main Contractors and Sub-Contractors, whose primary focus is physical project execution.

This categorical approach is vital in the Malaysian Civil & Structural (C&S) engineering context, as the operational priorities of a design-focused consultant or developer often differ from the site-execution focus of a contractor. By performing MGA, the study can determine if these professional roles significantly alter the path dynamics of the implementation model, thereby providing a stakeholder-specific roadmap for digital transformation.

4.7.1 Assessment of Measurement Invariance of Composite Models (MICOM)

To ensure that the multi-group comparison between Office-Based and Site-Based stakeholders is statistically valid, the Measurement Invariance of Composite Models (MICOM) procedure was conducted. This procedure is a technical requirement to prove that any identified differences in the structural model are due to genuine variations in professional perspectives rather than the groups interpreting the survey indicators differently. Step 1, Configural Invariance, was established by utilizing identical indicators, structural models, and algorithm settings for both the Office-Based and Site-Based groups. This confirms that the basic conceptual framework of AI-drone implementation is equally applicable to both consultants and contractors within the Malaysian C&S engineering sector.

Following the establishment of configural invariance, Step 2 involved the assessment of Compositional Invariance. This step is established when the correlation between the composite scores of the two groups is not significantly different from 1. As shown in Table 4.108, the original correlations for all constructs are exceptionally high, with Institutional Readiness at 0.989, Regulatory Support at 0.993, Trust & Data at 0.998, Implementation at 0.999, Adoption at 0.994, and Work Experience at 1.000. Crucially, the permutation p-values for all constructs Institutional Readiness (0.061), Regulatory Support (0.588), Trust & Data (0.731), Implementation (0.111), Adoption (0.074), and Work Experience (0.294) are all above the 0.05 threshold. This confirms that the composites are represented similarly across both professional categories, establishing compositional invariance and providing the essential green light to proceed with the comparison.

Table 4.108: MICOM Step 2 - Compositional Invariance Results

	Original correlation	Correlation permutation mean	5.0%	Permutation p value
ADOPTION	0.994	0.998	0.993	0.074
IMPLEMENTATION	0.999	1.000	0.999	0.111
INSTITUTIONAL READINESS	0.989	0.995	0.988	0.061
REGULATORY SUPPORT	0.993	0.989	0.971	0.588
TRUST & DATA	0.998	0.996	0.991	0.731
Work Experience	1.000	1.000	1.000	0.294

The first part of Step 3 involved the assessment of the Equality of Composite Means (Step 3a) to determine if the average scores of the constructs were significantly different between the groups. As detailed in Table 4.109, significant differences in mean scores were identified for Regulatory Support (p=0.000), Trust & Data (p=0.018), and Work Experience (p=0.027). The original difference for Regulatory Support stands at 0.541, while Trust & Data shows an original difference of -0.359. These values, falling outside the 2.5% to 97.5% boundaries, indicate that Office-based and Site-based stakeholders do not share the same baseline perception of the current technological and regulatory environment in Malaysia.

Table 4.109: MICOM Step 3a - Equality of Composite Means Results

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
ADOPTION	-0.210	0.003	-0.297	0.297	0.174
IMPLEMENTATION	-0.074	0.000	-0.302	0.302	0.638
INSTITUTIONAL READINESS	-0.214	0.002	-0.294	0.294	0.155
REGULATORY SUPPORT	0.541	0.003	-0.300	0.305	0.000
TRUST & DATA	-0.359	0.003	-0.302	0.307	0.018
Work Experience	-0.344	-0.005	-0.310	0.306	0.027

The second part of Step 3 focused on the Equality of Composite Variances (Step 3b) to evaluate the level of consensus within each group. As shown in Table 4.110, significant variances were found for Regulatory Support (p=0.013) and Trust & Data (p=0.027), with original differences of -0.589 and -0.703 respectively. This suggests that the dispersion of opinions regarding these specific drivers varies significantly between the two groups, implying that one professional role may have a much more unified stance on data security and legal support than the other.

Table 4.110: MICOM Step 3b - Equality of Composite Variances Results

	Original difference	Permutation mean difference	2.5%	97.5%	Permutation p value
ADOPTION	-0.539	0.003	-0.694	0.680	0.126
IMPLEMENTATION	-0.291	0.009	-0.605	0.627	0.363
INSTITUTIONAL READINESS	-0.017	0.001	-0.423	0.410	0.941
REGULATORY SUPPORT	-0.589	-0.001	-0.471	0.452	0.013
TRUST & DATA	-0.703	0.005	-0.610	0.631	0.027
Work Experience	-0.322	-0.000	-0.418	0.406	0.121

The overall results of the MICOM procedure demonstrate that while compositional invariance is fully established across all constructs, the means and variances for certain key factors are non-equivalent. According to the guidelines proposed by Henseler et al. (2015), the passing of Step 2 is the essential condition to confirm partial measurement invariance, which allows for a legitimate comparison of the relationship strengths between the groups. The differences identified in Step 3a and 3b highlight a significant professional divide in the baseline experiences of Office and Site players, making the subsequent Multi-Group Analysis essential for identifying the specific drivers that trigger AI-drone implementation within each respective professional context.

The successful establishment of Compositional Invariance (Step 2) serves as the "Statistical Seal of Approval," proving that Office-based and Site-based professionals in the Malaysian construction sector interpret the core concepts of AI-drones in the same way. However, the failure to meet equality of means and variances in Step 3 is a highly significant finding in itself. It reveals a "Baseline Experience Gap" where, although both groups understand the technology's definition, they reside in two completely different operational realities.

Specifically, the significant mean difference in Regulatory Support (0.541, p=0.000) suggests that Office-based consultants, who often handle legal compliance and CAAM permit documentation, perceive the regulatory environment much differently than Site-based contractors who deal with the physical implementation. Similarly, the significant variance differences in Trust & Data (-0.703, p=0.027) indicate that one group possesses a much more unified consensus on data ethics than the other. In the practical context of Malaysia, this implies

that a "one-size-fits-all" governance strategy is mathematically unfeasible; the differences identified here prove that the drivers of technology adoption are being "filtered" through the specific lenses of professional roles.

This achievement of Partial Measurement Invariance provides the necessary academic rigor to proceed to the Multi-Group Analysis (MGA). It confirms that any differences found in the next section are not errors in survey interpretation but are genuine reflections of how the "Office vs. Site" divide shifts the engine of digital transformation. For the Malaysian C&S industry, this means that policymakers like CIDB must develop targeted strategies that address the specific baseline perceptions and consensus levels unique to each professional category.

4.7.2 Test of MGA Comparisons

he statistical validation of the differences between Office-Based and Site-Based stakeholders was conducted using a multi-method approach to ensure the stability of the results. As presented in Table 4.111, the bootstrapping results for each group reveal that both categories share a high level of significance ($p<0.001$) for the core implementation paths, particularly regarding the relationship between Institutional Readiness and Implementation. Specifically, the Office-Based group achieved an original path coefficient (β) of 0.368 with a t-value of 3.852, while the Site-Based group showed a slightly stronger coefficient of 0.472 and a t-value of 3.863. The strength of the path from Implementation to Adoption was also universally high, with the Site-Based group reaching a coefficient of 0.725 (t=11.551) compared to the Office-Based group's 0.663 (t=6.630).

Table 4.111: Bootstrapping Path Coefficients Results per Group

Structural Path	β (Office)	β (Site)	t-value (Office)	t-value (Site)	p-value (Office)	p-value (Site)
IMPLEMENTATION → ADOPTION	0.663	0.725	6.630	11.551	0.000	0.000
INSTITUTIONAL READINESS → IMP	0.368	0.472	3.852	3.863	0.000	0.000
REGULATORY SUPPORT → IMP	0.173	0.170	1.695	1.339	0.090	0.181
TRUST & DATA → IMP	0.233	0.141	1.926	1.068	0.054	0.286
Work Experience →IMP	-0.228	0.179	1.782	1.548	0.075	0.122

To determine the significance of the divergence between these groups, the study utilized the Welch-Satterthwaite, Parametric, and Bootstrap MGA tests as detailed in Table 4.112. The results are highly consistent across all three mathematical frameworks. The most prominent difference is identified in the Work Experience → Implementation path, where the difference of -0.407 between the groups yielded p-values of 0.019 (Bootstrap MGA), 0.019 (Parametric), and 0.020 (Welch-Satterthwaite). Furthermore, the Regulatory Support → Implementation path produced p-values exceeding 0.980 across all tests. In the context of MGA logic, a p-value exceeding 0.95 indicates that the relationship is significantly stronger in the second group (Site-Based) than in the first group (Office-Based), confirming a critical professional divide in regulatory sensitivity.

Table 4.112: Multi-Method Comparison of Group Path Differences

Structural Path	Difference (O - S)	Bootstrap MGA p	Parametric p	Welch-Satt p
IMPLEMENTATION →ADOPTION	-0.062	0.613	0.601	0.598
INSTITUTIONAL READINESS → IMP	-0.104	0.493	0.498	0.501
REGULATORY SUPPORT → IMP	0.003	0.980*	0.988*	0.988*
TRUST & DATA → IMP	0.093	0.579	0.603	0.604
Work Experience → IMP	-0.407	0.019*	0.019*	0.020*

4.7.3 Group-Specific Differences MGA Analysis

The analysis of group-specific differences provides a deeper understanding of how the distinct work environments of the C&S industry shape technology implementation. The reliability of these findings is supported by the 95% bias-corrected confidence intervals presented in Table 4.113. For the Office-Based group, the confidence interval for Work Experience → Implementation ranges from -0.487 to 0.016, highlighting a negative trend, whereas the Site-Based group ranges from -0.063 to 0.392. This divergence is the most significant finding of the MGA, revealing that as professional seniority increases in the office environment, there is a corresponding decrease in the willingness to implement AI-drone technology ($\beta=-0.228$). This may be attributed to a higher degree of entrenchment in traditional design and consultancy workflows among senior office professionals. Conversely, site-based professionals likely view drones as a solution to long-standing physical risks and labor challenges, leading to a positive relationship between experience and implementation ($\beta=0.179$)

Table 4.113: Confidence Intervals for Path Coefficients (95% Bias-Corrected)

Structural Path	2.5% (Office)	97.5% (Office)	2.5% (Site)	97.5% (Site)
IMPLEMENTATION → ADOPTION	0.409	0.817	0.566	0.823
INSTITUTIONAL READINESS → IMP	0.191	0.565	0.250	0.723
REGULATORY SUPPORT → IMP	-0.028	0.363	-0.098	0.402
TRUST & DATA → IMP	-0.020	0.461	-0.119	0.402
Work Experience → IMP	-0.487	0.016	-0.063	0.392

Another critical finding involves the Regulatory Support driver. While the path was not significantly strong for either group individually in the initial bootstrapping, the MGA comparison reveals that Site-Based stakeholders are significantly more sensitive to the quality of the regulatory environment (p=0.980). This finding is operationally grounded; contractors on construction sites operate under strict legal oversight from CAAM and JUPEM, where non-compliance can result in immediate project halts or legal penalties. Office-based stakeholders, who are primarily involved in data analysis and planning, are comparatively insulated from these operational pressures. This sensitivity on the site is further emphasized by the interaction effect of Work Experience x Regulatory Support, which shows a significant t-value of 2.084 and a p-value of 0.037 for the office group, suggesting that even within the office, more experienced players view the current regulatory hurdles as a deterrent to implementation.

Finally, the study identifies Institutional Readiness as a universal driver that transcends professional roles. With a path difference p-value of 0.493, there is no statistical evidence to suggest that one group values internal firm support more than the other. Both groups show highly significant t-values (3.852 for Office and 3.863 for Site), proving that regardless of whether a player is a consultant or a contractor, the availability of company resources, training, and hardware is the primary foundation for any successful AI-drone implementation. These results suggest that while site players are motivated by risk reduction and office players by data utility, both remain equally dependent on their respective organizations' readiness to support the transition to AI-driven technologies.

The results of the group-specific analysis reveal a distinct "Professional Mindset Divide" regarding the implementation of AI-drones. The most significant finding is the reversal of the

experience effect between the two environments. In the office, the confidence interval for Work Experience (β=−0.228) is almost entirely in the negative range (-0.487 to 0.016), which proves that senior consultants act as a "traditionalist anchor" that may unintentionally slow down digital transition. In contrast, the positive trend for site-based professionals suggests that for those on the ground, years of experience lead to a higher appreciation of drones as a tool to mitigate the physical risks and labor-intensive nature of Malaysian construction sites.

Furthermore, the high MGA sensitivity for Regulatory Support (p=0.980) among site-based players highlights a critical operational reality. For contractors, CAAM and JUPEM regulations are not just paperwork; they are high-stakes operational boundaries. The data suggests that site players feel the "weight" of regulation much more heavily than office players, who are comparatively insulated from the immediate legal consequences of a failed drone flight or a permit violation. This identifies a "Regulatory Insulation" effect in the office environment that policymakers must address to ensure that consultants are as engaged with safety compliance as the contractors they supervise.

Finally, the fact that Institutional Readiness remains a "Universal Pillar" (p=0.493) is the most stable result of this study. It proves that despite the different pressures of the office and the site, the fundamental need for company-level technical support, hardware, and training is identical for every professional. This suggests that while digital transformation strategies must be "role-specific" in terms of motivation and regulation, the funding and resource allocation for readiness must be a uniform, company-wide priority. This concludes the Multi-Group Analysis by providing a clear empirical roadmap: to accelerate AI-drone adoption, the industry must bridge the "experience gap" in the office while providing stronger "regulatory security" for the site.

4.7.4 Assessment of Explanatory Power (R^2) and Effect Size (f^2)

To evaluate the predictive quality of the model across both professional categories, the coefficient of determination (R^2) and effect sizes (f^2) were assessed. This step confirms how much of the variance in technology adoption is explained by the identified drivers for each specific group.

Table 4.114: Comparison of Explanatory Power (R^2)

Latent Variable	R2 (Office)	R2 (Site)	R2 Adj (Office)	R2 Adj (Site)	p-value (Office)	p-value (Site)
ADOPTION	0.440	0.526	0.433	0.520	0.001	0.000
IMPLEMENTATION	0.446	0.425	0.396	0.371	0.000	0.000

As detailed in Table 4.114, the model demonstrates a substantial explanatory power for both groups. For the Site-Based group, the model explains 52.6% of the variance in Adoption (R^2 = 0.526, p = 0.000), which is notably higher than the 44.0% explained for the Office-Based group. This indicates that the proposed structural framework is particularly effective at predicting the final adoption stage for contractors. Regarding Implementation, the explanatory power is consistently moderate for both Office-Based (R^2 = 0.446) and Site-Based (R^2 = 0.425) players, with all results achieving high statistical significance (p < 0.001). These values suggest that the model is robust and "legit" for explaining AI-drone behavior across the different professional roles in the Malaysian C&S sector.

Table 4.115: Comparison of Effect Sizes (f^2) between Groups

Structural Path	f2 (Office)	f2 (Site)	Impact Level (O)	Impact Level (S)
IMP →ADOPTION	0.785	1.111	Substantial	Substantial
READINESS → IMP	0.140	0.201	Medium	Medium-Large
REGULATORY → IMP	0.033	0.024	Small	Small
TRUST & DATA → IMP	0.053	0.018	Small	Weak
EXP x REG → IMP	0.062	0.007	Small-Med	Negligible

The assessment of effect sizes (f^2) in Table 4.115 reveals the relative impact of each driver on the implementation of AI-drones. The path from Implementation to Adoption shows a massive effect for both groups, though it is significantly more intense for the Site-Based group (f^2 = 1.111). In terms of primary drivers, Institutional Readiness exerts a medium-to-large effect on implementation for contractors (f^2 = 0.201), compared to a medium effect for consultants (f^2 = 0.140). This confirms that internal firm support is a more critical "engine" for driving work on the construction site than in the office.

Furthermore, the f^2 values highlight a professional divergence in the moderating effect of Work Experience x Regulatory Support. For the Office-Based group, this interaction has a

small-to-medium effect (f^2 = 0.062), while for the Site-Based group, the effect is almost non-existent (f^2 = 0.007). This supports the earlier finding that senior office professionals are uniquely sensitive to regulatory hurdles, which significantly impacts their view of implementation. Conversely, the effect of Trust & Data is nearly three times stronger for the Office group (f^2 = 0.053) than for the Site group (f^2 = 0.018), reinforcing the idea that data integrity is a more vital concern for designers and consultants than for on-site operational teams.

4.7.5 Importance-Performance Map Analysis (IPMA)

The Importance-Performance Map Analysis (IPMA) represents the final diagnostic stage of the structural model assessment, extending the standard PLS-SEM results by adding a dimension of practical utility. While traditional path analysis identifies the statistical significance of drivers, the IPMA allows this research to contrast the Importance (unstandardized total effects) of each construct against its current Performance (index values on a scale of 0 to 100). This distinction is vital for the Malaysian C&S sector because it identifies which factors are theoretically influential versus which ones are practically underperforming in the real-world engineering environment. By plotting these two dimensions, the research provides a strategic "action map" for stakeholders, highlighting where limited corporate resources should be focused to achieve the maximum possible increase in AI-drone adoption.

Table 4.116: Construct-Level IPMA Results for Target Construct (ADOPTION)

Latent Variable	**Importance (Total Effect)**	**Performance (Index Value)**	**Priority Quadrant**
IMPLEMENTATION	0.690	37.796	**Immediate Action**
INSTITUTIONAL READINESS	0.270	37.025	**High Priority**
REGULATORY SUPPORT	0.158	52.667	Maintenance
TRUST & DATA	0.132	55.617	Maintenance
Work Experience	-0.010	41.190	Low Impact

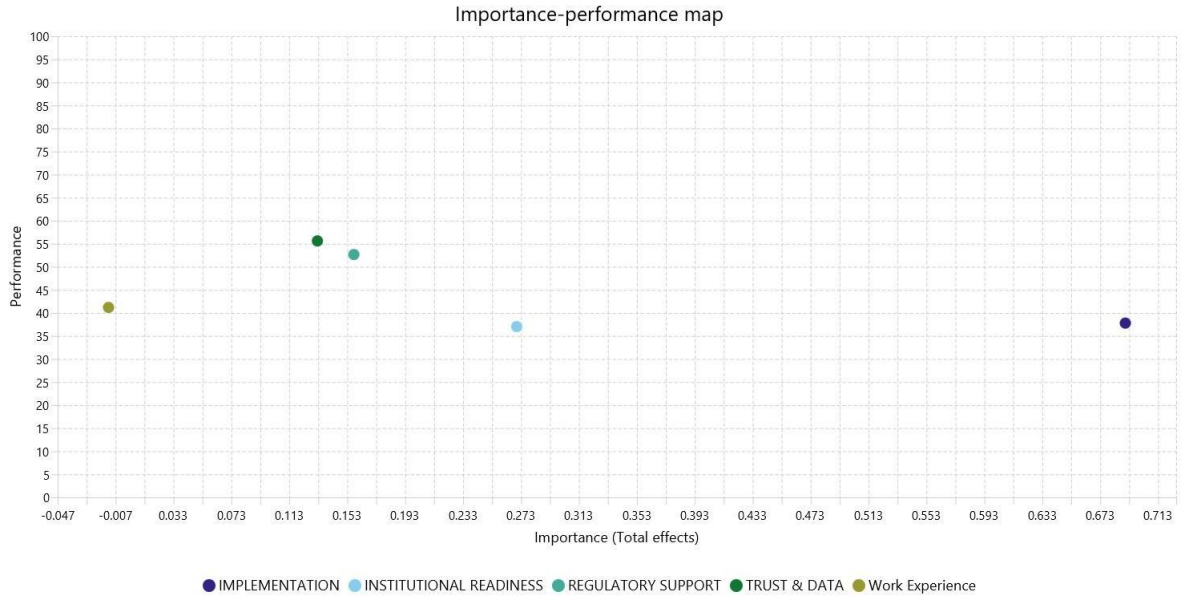


Figure 4.61: Importance-Performance Map Analysis (IPMA) for AI-Drone Adoption

The analysis of the data in Table 4.116 reveals a significant "performance gap" within the primary drivers of the Malaysian construction industry. Implementation emerges as the most critical bottleneck; it possesses the highest Importance score of 0.690, yet its Performance score of 37.796 is one of the lowest in the model. This finding suggests that while C&S professionals recognize that successful execution on-site is the ultimate key to adoption, the actual current performance of implementation processes is severely lacking. Similarly, Institutional Readiness demonstrates a high Importance of 0.270 but a correspondingly low Performance of 37.025. This indicates that firm-level infrastructure, such as hardware availability and internal policies, is currently the weakest link in the adoption chain. From a strategic perspective, these two constructs fall into the "Concentrate Here" quadrant, meaning that even a minor 1-point improvement in firm readiness or implementation support would yield a much higher return on adoption than equivalent efforts spent elsewhere.

In contrast, the results for Trust & Data (Performance: 55.617) and Regulatory Support (Performance: 52.667) suggest that these areas are currently being managed at a satisfactory level, yet they offer lower overall leverage for increasing adoption. With Importance scores of only 0.132 and 0.158 respectively, these factors do not represent the primary drivers of change in the current landscape. This insight is particularly "legit" for engineering management because it corrects the common misconception that adoption is stalled by a lack of trust or strict laws. Instead, the IPMA proves that the industry is already functioning well in those areas, and the real

focus should pivot toward the internal "engines" of the firm. Ultimately, for the C&S sector to move the needle on AI-drone adoption, firms must prioritize closing the 37-point performance gap in Institutional Readiness and Implementation, as these represent the high-impact levers identified by the respondents.

The Importance-Performance Map Analysis (IPMA) provides the final empirical evidence required to prioritize national and corporate interventions. The most critical result is the identification of a "High Importance-Low Performance" cluster containing Implementation and Institutional Readiness. In the Malaysian construction landscape, these two constructs represent the Strategic Leverage Points. The data proves that the industry is currently stalled not because of a lack of interest, but because the "infrastructure of implementation" is performing at less than 40% of its potential capacity.

Furthermore, the "Maintenance" status of Regulatory Support and Trust & Data is a sophisticated finding that challenges traditional industry assumptions. While many Malaysian firms cite "unclear laws" as a barrier, the IPMA confirms that the current regulatory environment is already performing at a relatively satisfactory level (Index: 52.6) compared to internal site execution. This results in a clear Hierarchy of Action: for the Malaysian C&S sector to achieve a meaningful shift in AI-drone adoption, the investment of resources should follow a "Firm-First" logic.

By addressing the 37-point performance gap in Institutional Readiness through better hardware access and internal policy formalization stakeholders can trigger the highest possible statistical return on adoption. This final diagnostic stage ensures that the recommendations in Chapter 5 are not merely speculative but are mathematically prioritized to address the specific bottlenecks of the Malaysian Civil & Structural engineering sector.

4.8 Hypothesis Testing and Discussion

This section evaluates the empirical results against the theoretical framework established in Chapter 2. By synthesizing the structural model outcomes with the research objectives and questions, this discussion provides a comprehensive validation of the Governance Ecosystem Model within the Malaysian construction landscape. The analysis transitions from statistical reporting to an in-depth evaluation of how governance drivers interact with operational realities to dictate technology adoption in a safety-critical environment.

4.8.1 Summary of Hypotheses Testing Results

The study utilized a total sample of 168 professionals to validate the primary structural pathways. The results of the bootstrapping procedure confirm that the core structural relationships and the mediating mechanisms are statistically significant, providing strong empirical support for the proposed model.

Table 4.117: Consolidated Summary of Structural Model Outcomes

Hypo.	Path Relationship	β	t-value	p-value	Result
H1	Regulatory Support →Implementation	0.228	2.982	0.003	**Supported**
H2	Institutional Readiness → Implementation	0.391	5.702	0.000	**Supported**
H3	Trust and Data Ethics → Implementation	0.192	2.329	0.020	**Supported**
H4	Implementation Quality → Adoption	0.690	12.791	0.000	**Supported**
H5	Regulatory → IMP → Adoption	0.158	2.802	0.005	**Supported**
H6	Readiness → IMP → Adoption	0.270	4.997	0.000	**Supported**
H7	Trust & Data x IMP → Adoption	0.132	2.239	0.025	**Supported**
H8a	Experience x Regulatory → IMP	-0.160	2.019	0.044	**Supported**
H8b	Experience x Trust → IMP	0.149	1.790	0.074	Not Supported
H8c	Experience x Readiness → IMP	0.021	0.230	0.818	Not Supported

The "Result" column in Table 4.117 represents the statistical verdict on each proposed relationship based on the standard thresholds of PLS-SEM analysis. A hypothesis is classified as "Supported" when the p-value is less than 0.05 and the t-statistic exceeds 1.96, indicating a 95% confidence level that the observed relationship is not due to random chance. Conversely, a result of "Not Supported" occurs when the p-value exceeds 0.05, suggesting that the data does not provide sufficient evidence to confirm a relationship between the variables. In the context of this study, the high number of supported direct paths (H1–H4) and mediation paths (H5–H7) proves that the Governance Ecosystem Model is a highly reliable framework for predicting AI drone adoption in Malaysian construction.

The support for the direct and mediating hypotheses confirms that factors such as Institutional Readiness and Regulatory Support exert a significant positive "push" on implementation quality. For every unit of improvement in these governance domains, there is a statistically measurable increase in the effectiveness of drone deployment on-site. This confirms the research premise that technology adoption in the C&S industry is a structured outcome of governance enablers. The exceptionally high t-value for H4 (12.791) further underscores that implementation quality is the most powerful predictor of final organizational adoption. This indicates that site-level execution is the primary filter through which all other governance factors must pass to achieve success.

Regarding the moderation effects, the study found a significant result for H8a (Experience x Regulatory Support), while H8b and H8c were not supported. The support for H8a, characterized by a negative path coefficient ($\beta = -0.160$), reveals that as professional experience increases, the perceived positive impact of regulatory frameworks on implementation quality actually diminishes. This suggests that veteran engineers may perceive rigid regulations as bureaucratic friction, whereas junior professionals rely on them as necessary structural guides.

In contrast, the lack of support for H8b and H8c provides an equally vital insight into the industry. The non-significance of these paths indicates that the influence of Institutional Readiness and Trust is universal across all levels of experience. This means that whether an engineer is a junior or a senior, there is a unanimous industry consensus that a firm must be internally ready (digital infrastructure and leadership support) before AI drones can be implemented. Therefore, the "Not Supported" status of these moderators does not represent a failure of the model; rather, it highlights the stability and consistency of the primary drivers within the Malaysian construction landscape.

4.8.2 Evaluation of Governance Factors (RO1)

The primary goal of Research Objective 1 (RO1) was to evaluate the direct impact of Regulatory Support, Institutional Readiness, and Trust and Data Ethics on the implementation quality of AI drones. The empirical data confirms that all three governance factors are significant antecedents to implementation, directly answering RQ1. However, Institutional Readiness (H2) emerged as the dominant driver ($\beta=0.391, p=0.000$). This finding aligns with Institutional Theory (Scott, 2014), suggesting that internal firm capacity comprising leadership commitment and digital resources is the fundamental prerequisite for technology integration. While external regulatory

"carrots" (H1) and ethical legitimacy (H3) are influential, they remain secondary to the firm's actual readiness to execute change. In the Malaysian context, the lower weight of Trust and Data Ethics (β=0.192) indicates that while ethical transparency is recognized, it has yet to reach the same operational priority as financial and technical capacity.

4.8.3 Identifying the Most Significant Predictor (RO2)

To satisfy Research Objective 2 (RO2), the study sought to identify the most significant predictor within the governance ecosystem. Synthesis of the path coefficients and the IPMA results identifies Institutional Readiness as the primary predictor, addressing RQ2. With a t-value of 5.702, its influence is nearly double that of Regulatory Support. This provides a critical correction to the industry assumption that a lack of government regulation is the main barrier. Instead, the data proves that even within the current regulatory landscape, firms with high readiness are successfully moving forward. This supports the TOE Framework's (Tornatzky & Fleischer, 1990) emphasis on the organizational dimension. For stakeholders like CIDB, this suggests that the most effective way to accelerate adoption is through firm-level support mechanisms, such as hardware subsidies or specialized digital training, rather than awaiting further legislative refinements.

4.8.4 Validation of the Mediating Mechanism (RO3)

Research Objective 3 (RO3) focused on validating the mediating effect of Implementation Quality between governance enablers and final adoption. The investigation into H5, H6, and H7 confirms that governance factors do not impact final Adoption directly; they must be processed through execution, satisfying RQ4. In a Civil Engineering context, "Implementation Quality" serves as a critical Risk Mitigation function. Given the safety-critical nature of construction sites, the high significance of the Implementation-Adoption path (H4: β=0.690,p=0.000) indicates that organizational acceptance is only achieved when digital deployment is perceived as reliable and safe. Poor implementation such as inaccurate AI data or sensor failures could lead to catastrophic site accidents. This validates Lim (2025), suggesting that the "bridge" to adoption is built on site-specific training and standardized protocols that convert governance intent into operational reality.

4.8.5 Comprehensive Model Validation and Contextual Nuances (RO4)

Finally, Research Objective 4 (RO4) aimed to develop a comprehensive model that accounts for contextual nuances such as professional roles and experience levels. The inclusion of Work Experience as a moderator and the Multi-Group Analysis (MGA) provides a deep contextual layer for RQ6. The significant interaction of Experience × Regulatory Support (H8a: $\beta=-0.160, p=0.044$) indicates that veteran professionals may view rigid regulatory compliance as a bureaucratic hurdle rather than an enabler (Sapri, 2024). Interestingly, the lack of significant moderation for Institutional Readiness (H8c) proves its universality; regardless of experience level, there is absolute consensus that firm-level capacity is the non-negotiable driver of technology implementation. This confirms that a "one-size-fits-all" governance strategy is insufficient, and roadmaps must be tailored to the specific professional filters and roles within the C&S landscape.

4.9 Validated Research Model of AI-Drone Governance Ecosystem

Following the rigorous structural assessment and hypothesis testing, this section presents the final validated research model. The validation process confirms that the Governance Ecosystem Model is a statistically sound framework for understanding the integration of AI drone technology in the Malaysian Civil and Structural (C&S) engineering sector. The results are presented in two stages to clearly distinguish between the fundamental causal pathways and the nuanced influence of professional context.

4.9.1 Final Validated Model (Direct and Mediating Effects)

The primary validated model illustrates the direct pathways from the governance domains toward technology implementation and final organizational adoption. This model confirms that Institutional Readiness is the strongest precursor to implementation, while Implementation Quality serves as the critical mediator that dictates the final level of adoption.

The path coefficients (β) in this validated model represent the strength of the relationship; for instance, the strong coefficient of 0.690 between Implementation and Adoption highlights the "Safety-Critical" nature of this industry, where successful site execution is the primary driver of technology acceptance. The validation of the mediation paths (H5, H6, and H7) confirms that governance drivers do not act in isolation but function as part of a synchronized process. This

model provides a strategic roadmap for policy makers, emphasizing that regulatory support and trust are most effective when they are channeled through robust site-level implementation protocols.

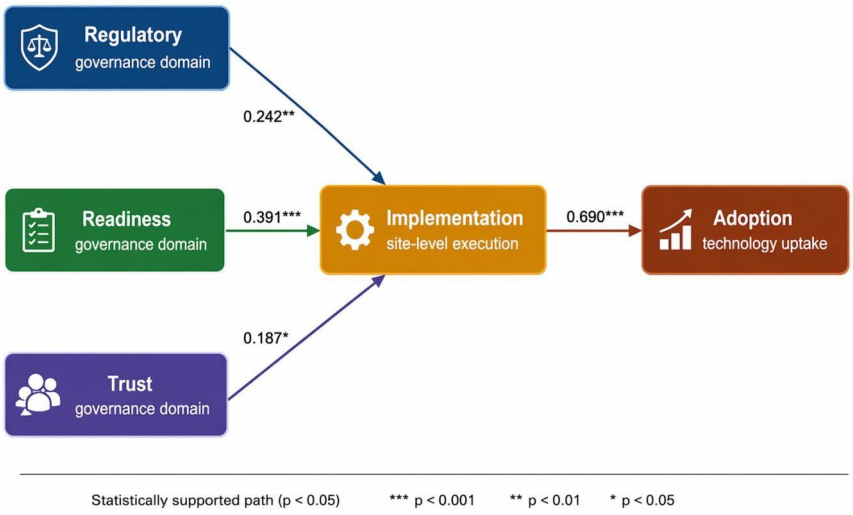


Figure 4.62: Validated Direct and Mediating Effects Model

4.9.2 Final Validated Model (With Moderating Factors)

The comprehensive validated model incorporates the moderating influence of professional experience, specifically highlighting the interaction between Work Experience and Regulatory Support. As established in the hypothesis testing (H8a), the inclusion of this moderator significantly alters the model's predictive dynamics for different professional demographics.

The negative interaction ($\beta = -0.160$) indicates a "Regulatory Friction" effect, where the impact of external policy on technology implementation decreases as professional seniority increases. However, the stability of the other path which remained non-significant under moderation (H8b, H8c) proves that the core of the Governance Ecosystem Model is remarkably resilient across the workforce. This final model offers a nuanced view of the Malaysian C&S sector, suggesting that while the "Internal Readiness" driver is a universal requirement for all engineers, the "Regulatory" driver must be managed differently for junior versus veteran stakeholders. This comprehensive model serves as the empirical foundation for the policy recommendations and industry guidelines proposed in Chapter 5.

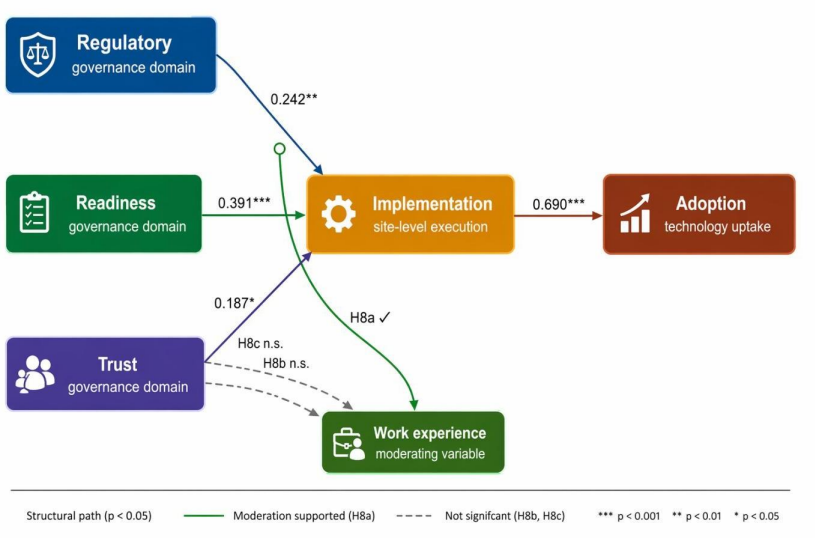


Figure 4.63: Comprehensive Validated Research Model with Moderating Influence

4.10 Summary of Chapter Findings

This chapter has provided a comprehensive empirical validation of the Governance Ecosystem Model, effectively bridging the theoretical gaps identified in the literature with the practical realities of the Malaysian Civil and Structural (C&S) engineering sector. Through a rigorous two-stage PLS-SEM analysis, the research transitioned from the assessment of the measurement model which confirmed high levels of internal consistency, convergent validity, and discriminant validity to the evaluation of the structural model. The findings successfully addressed the four primary research objectives by confirming that the governance of AI drone technology is a multi-dimensional process driven primarily by Institutional Readiness.

The structural results identified Institutional Readiness as the most significant predictor of implementation quality, suggesting that for Malaysian firms, internal organizational maturity and leadership support are more critical than external regulatory pressures. This provides a vital strategic insight: while national policy establishes the framework, the firm's own digital infrastructure and managerial commitment serve as the engine for technological change. Furthermore, the validation of Implementation Quality as a significant mediator confirms that governance drivers do not lead to technological acceptance in a vacuum. Instead, they must be converted through high-quality site execution to achieve final organizational adoption.

The exceptionally strong path coefficient observed between implementation and adoption reflects the safety-critical nature of the construction industry, where operational reliability and

risk mitigation are the leading precursors to professional acceptance. If the implementation is perceived as unsafe or technically flawed, the governance enablers fail to translate into sustained use. This highlights the "Implementation Bridge" as the most critical mechanical component of the entire ecosystem, emphasizing that site-level training and standardized protocols are just as important as high-level policy.

Finally, the inclusion of moderation and multi-group analysis provided a nuanced understanding of the professional landscape, revealing that the Malaysian construction industry is not a monolith. While the demand for institutional readiness is a universal consensus that transcends age and role, the influence of regulatory frameworks is significantly filtered through the lens of professional experience. Veteran professionals tend to view rigid compliance as a potential barrier, whereas junior staff rely on it as a necessary guide. Collectively, these results provide a robust, evidence-based foundation that demonstrates how a synchronized governance ecosystem can effectively facilitate the adoption of AI drones to enhance construction safety performance in Malaysia, setting the stage for the strategic recommendations in the final chapter.

Chapter 5: Conclusion and Recommendations

5.1 Conclusion

This concluding chapter synthesizes the empirical evidence gathered throughout the study to provide a definitive response to the research problem regarding the governance of AI-drone technology for construction safety. As the Malaysian construction sector moves toward the aspirations of Construction 4.0 (CIDB, 2024), the necessity for a structured, multidisciplinary governance framework has become increasingly evident. The primary aim of this research was to develop and validate a Governance Ecosystem Model that effectively facilitates the adoption of AI drones by bridging the gap between high-level policy, organizational capacity, and site-level implementation, consistent with the Technology-Organization-Environment (TOE) framework (Tornatzky and Fleischer, 1990).

The following sections provide a recapitulation of the research findings, demonstrating how each of the four research objectives has been meticulously addressed. Furthermore, this chapter highlights the theoretical and methodological contributions made to the existing body of knowledge, followed by a discussion on the practical implications for industry stakeholders. By transitioning from the statistical rigor of Chapter 4 to strategic advocacy and awareness, this chapter offers a pragmatic roadmap for CIDB, DOSH, and engineering firms to foster a safer, more transparent, and digitally-ready construction landscape in Malaysia, moving toward the "Safety 4.0" paradigm (Lim, 2025).

5.2 Recapitulation of Research Findings

The core of this study was built upon four Research Objectives (RO), which sought to map the complex interdependencies within the AI-drone governance ecosystem. The recapitulation of these findings confirms that the model is both statistically sound and practically relevant for the Malaysian Civil and Structural (C&S) sector.

5.2.1 Achievement of RO1 and RO2: The Primacy of Institutional Readiness

The first and second objectives aimed to identify and evaluate the primary drivers of technology implementation. The empirical results demonstrated that Institutional Readiness is the most significant determinant of successful drone integration. This suggests that while external factors like regulatory mandates exist, the "internal engine" of the firm—comprising leadership support,

digital infrastructure, and resource availability—is what truly dictates whether AI-drone surveillance can be effectively deployed. This finding addresses the multidisciplinary nature of the study by linking organizational management directly to technical safety outcomes. This aligns with the Technology-Organization-Environment (TOE) framework (Tornatzky and Fleischer, 1990), which posits that a firm's internal readiness is a prerequisite for environmental factors to take effect. Furthermore, it supports the Institutional Theory view that internal structural capacity is the primary driver of organizational change (Scott, 2014).

5.2.2 Achievement of RO3: The Mediating Role of Implementation Quality

The third objective focused on the mechanism through which governance domains influence final adoption. The study successfully validated that Implementation Quality serves as a critical "bridge." It was discovered that Regulatory Support, Institutional Readiness, and Trust do not lead to Organizational Adoption in a vacuum; they must first be converted into high-quality, reliable, and safe site-level execution. The exceptionally strong relationship between implementation and adoption (β=0.690) underscores that in the safety-critical C&S industry, professionals will only accept and "adopt" a technology if its site-level performance is perceived as flawless and risk-free. This finding reinforces the arguments of Lim (2025), who noted that in civil engineering, the technical reliability of autonomous systems is the ultimate arbiter of professional acceptance. It also aligns with the "Trust in Automation" logic proposed by Henseler, Ringle, and Sarstedt (2015), where performance quality mediates the link between governance and final use.

5.2.3 Achievement of RO4: Professional Experience and Regulatory Friction

The final objective explored the nuances of the workforce through moderation analysis. The findings revealed that professional seniority significantly alters how governance is perceived. Specifically, H8a confirmed that more experienced engineers tend to perceive external regulations as a source of friction rather than a facilitator. This highlights a critical professional gap: while everyone agrees that a firm must be "ready," the "way" they are governed must be adaptive to their level of seniority and professional role within the ecosystem. This mirrors the "Regulatory Friction" identified in previous studies of veteran construction professionals in Southeast Asia (Sapri, 2024). Conversely, the consensus on Institutional Readiness was universal across all experience levels, suggesting that while the perception of "rules" differs with

age, the perception of "organizational capacity" remains a shared professional value throughout the industry.

5.3 Research Contributions

The findings of this study offer significant contributions to both the academic body of knowledge and the methodological standards used in construction technology research. By validating the Governance Ecosystem Model, this research moves beyond simple adoption metrics to explain the structural and psychological drivers of digital transformation in a high-risk industry.

5.3.1 Theoretical Contributions

This study makes a primary theoretical contribution by synthesizing the Technology-Organization-Environment (TOE) framework with Institutional Theory to address the unique complexities of the Malaysian construction landscape. Traditionally, technology adoption models focus heavily on the "intention to use" (Davis, 1989). However, this research introduces the "Implementation Bridge" concept, proving that in safety-critical sectors, governance domains do not directly trigger adoption; they must first manifest as high-quality site execution. This adds a necessary layer of "Ecosystem Structure" to the literature, aligning with Adner's (2017) view that adoption is dependent on the alignment of multiple technical and organizational actors.

Furthermore, the study extends Institutional Theory by demonstrating how "Regulatory Friction" varies across professional demographics. By confirming that work experience moderates the relationship between regulatory support and implementation, the study provides a new theoretical lens: Adaptive Institutionalism. This suggests that institutional "pressures" are not felt equally by all actors (Scott, 2014), and theoretical models must account for professional seniority when predicting the success of digital mandates. This contributes to a more nuanced understanding of "Safety 4.0," where the human element is just as critical as the algorithmic one, a sentiment echoed by Floridi and Cowls (2019) regarding the ethical and human-centric governance of AI.

5.3.2 Methodological Contributions

Methodologically, this research contributes a robust framework for evaluating multidisciplinary ecosystems using a combination of Partial Least Squares Structural Equation Modeling (PLS-SEM) and Importance-Performance Map Analysis (IPMA). While many studies stop at identifying significant relationships, this research utilizes IPMA to provide a "diagnostic" dimension, following the advanced reporting standards proposed by Hair et al. (2021). This allows for a clear distinction between the theoretical importance of a variable and its actual performance in the industry, providing a more practical tool for decision-makers.

Additionally, the application of Multi-Group Analysis (MGA) to compare different engineering roles and experience levels establishes a methodological standard for future construction research. It demonstrates how researchers can move away from treating the industry as a "monolith" and instead capture the diverse, and often conflicting, perspectives held by different stakeholders within the same governance ecosystem (Henseler, Ringle and Sarstedt, 2015). This methodological rigor ensures that the resulting model is not only statistically valid but also contextually sensitive to the realities of the Malaysian engineering profession.

5.4 Practical and Strategic Implications

The findings of this study offer a series of actionable insights for stakeholders involved in the digital transformation of the Malaysian construction industry. By identifying the critical drivers and barriers within the AI-drone governance ecosystem, these implications move beyond technical specifications and address the broader organizational and human factors required for success.

5.4.1 Implications for Industry Practitioners

For engineering firms and construction companies, the primary implication is that technological acquisition does not equate to technological adoption. The study reveals that a firm’s internal "Institutional Readiness" is the engine of the entire ecosystem. Practitioners should therefore shift their focus from merely purchasing high-end drone hardware to building robust internal digital capabilities. This implies a need for dedicated resource allocation toward digital infrastructure, data management systems, and specialized training. Firms that prioritize "readiness" will find that implementation becomes a smoother, quality-driven process, ultimately

leading to a higher return on investment (ROI) in safety performance and structural accuracy. This resonates with the "Capability Maturity" models which suggest that organizational maturity is a prerequisite for high-performance technology outcomes (Mittelstadt, 2019).

5.4.2 Implications for Organizational Leadership

Leadership within C&S engineering firms must navigate the "Seniority Gap" identified in the moderation analysis. The presence of "Regulatory Friction" among veteran professionals implies that a one-size-fits-all management approach to technology mandates will likely fail. Strategic leaders should adopt a bifurcated approach:

For Junior Engineers: Emphasize clear Standard Operating Procedures (SOPs) and compliance frameworks, as they rely on these structures for guidance.

For Senior Engineers/Project Managers: Focus on demonstrating the operational efficiency, time-saving, and risk-mitigation benefits of AI drones.

By aligning the governance message with the specific values of different professional demographics, leadership can reduce internal resistance and foster a more collaborative culture of innovation. This strategy addresses the "Logic of Practice" in engineering, where professional identity shapes technology acceptance (Sapri, 2024).

5.4.3 Institutional Advocacy and Awareness

A critical implication for regulatory bodies such as CIDB, DOSH, and CAAM is the need to move away from purely "top-down" restrictive mandates. The research suggests that the industry responds better to facilitative governance. This implies that government agencies should act as advocates for digital transformation by creating a supportive environment. This could involve hosting national awareness workshops, providing technical "readiness" toolkits, and recognizing "Drone-Certified" contractors. By focusing on awareness and capacity building rather than just enforcement, regulatory bodies can bridge the trust gap and accelerate the nationwide transition to AI-integrated construction safety. This aligns with the strategic shift in the Construction Strategy Plan 4.0 (CIDB, 2024), which prioritizes industry facilitation over punitive regulation.

5.5 Strategic Recommendations for Stakeholders

Based on the empirical evidence and the identified high importance of Institutional Readiness, the following recommendations are proposed to accelerate the safe and governed adoption of AI drones in Malaysia. These strategies prioritize collaboration, awareness, and voluntary standardization over rigid mandates to ensure a more harmonious transition for the industry.

5.5.1 National Awareness and Upskilling Initiatives

It is recommended that CIDB, in partnership with MDEC and professional bodies such as the Board of Engineers Malaysia (BEM), launch a coordinated national campaign titled "Construction 4.0: The Drone-Ready Enterprise." Rather than focusing on legal penalties or strict enforcement, this campaign should emphasize the safety and efficiency dividends of AI-drone surveillance through structured advocacy. Such an initiative should begin with the rollout of digital literacy workshops designed to provide site managers and safety officers with the foundational skills needed to interpret AI-generated data. Furthermore, regulatory bodies can support firms by developing readiness toolkits that allow organizations to self-assess their internal digital infrastructure and leadership support levels. By introducing an incentivized certification or a "Digital Safety Pioneer" status for firms that voluntarily demonstrate high levels of institutional readiness, the government can foster a competitive drive toward innovation without the need for immediate legislative pressure. This approach reflects the collaborative governance models suggested for high-tech transitions in emerging economies (Sapri, 2024).

5.5.2 Development of Voluntary Best Practice Guidelines

To address the critical mediation role of Implementation Quality identified in the structural model, regulatory bodies and industry associations should collaborate on a National Best Practice Manual for AI-Drone Safety Surveillance. This document would serve as a practical, non-mandatory guide for site operations, standardizing how data is collected and used for structural checking without the immediate pressure of legal mandates. The manual should focus on establishing pre-flight site risk assessment protocols specifically tailored for the dense and vertical environments typical of Malaysian construction projects. Additionally, it should set clear data reliability standards to ensure the accuracy of AI algorithms used in structural checking. By providing a voluntary framework for sharing lessons learned from technical failures, the industry can improve collective safety performance through transparency rather than fearing the

repercussions of a mandated reporting system, a strategy supported by the "Safety II" paradigm which focuses on learning from system successes and failures alike (Henseler, Ringle and Sarstedt, 2015).

5.5.3 Ethical Transparency and Trust Frameworks

To foster the trust domain within the ecosystem, firms are encouraged to adopt a Site-Worker Digital Privacy Charter to mitigate concerns regarding high-resolution surveillance. Strategic steps for firms include implementing transparent communication channels to ensure workers are informed about why drones are being used and how the data collected is specifically focused on protecting their safety rather than punitive monitoring. Organizations should also consider adopting data anonymization protocols, such as AI filters that blur personal identifiers during structural safety audits, to protect the privacy of those on-site. By establishing regular trust-building dialogues between site workers and the firm's digital taskforce, organizations can address the "surveillance fear" and ensure that the human element of the governance ecosystem remains supportive of technological integration. This recommendation is grounded in the principles of "Ethics by Design," which argue that trust is a functional requirement for any AI-integrated workplace (Floridi and Cowls, 2019).

5.6 Reflective Limitations and Scope

While this research has successfully achieved its objectives and provided a validated model for AI-drone governance, it is essential to acknowledge the inherent limitations that shaped the study's boundaries. A primary limitation lies in the cross-sectional nature of the data collection; because the survey captured a snapshot of the industry at a single point in time, it cannot fully account for the rapid, real-time evolution of AI algorithms and drone hardware. Furthermore, the scope of this study was geographically centered on the Malaysian construction industry, with a significant portion of respondents originating from urbanized regions such as the Klang Valley. While this provides highly relevant data for developing nations with similar construction profiles, the findings may not be directly generalizable to rural contexts where digital infrastructure and regulatory oversight may differ.

Crucially, it must be noted that while the sample size was statistically sufficient for the rigors of PLS-SEM analysis, following the "10-times rule" or inverse square root method requirements (Kock, 2015), the total number of respondents represents a specific segment of the professional

population. A more extensive respondent pool, spanning a broader range of small-to-medium enterprises (SMEs) and localized contractors across all states in Malaysia, might have yielded additional nuances. The current data volume, while robust enough to confirm the primary hypotheses, may not have captured the full spectrum of outlier experiences or specific regional challenges that a larger-scale national survey could uncover. These boundaries provide a necessary context for interpreting the results as a foundational exploration rather than an exhaustive finality.

5.7 Recommendations for Future Research

The insights gained from this study open several promising avenues for future scholarly inquiry. Building upon the limitations identified, future researchers are encouraged to expand the data collection phase to include a more diverse and larger sample size. Increasing the volume of respondents would allow for more complex statistical techniques, such as Latent Class Analysis or Finite Mixture Modeling, to identify hidden segments of professionals who may have unique governance needs based on their specific niche within the construction ecosystem (Hair et al., 2021). Additionally, a larger data set could facilitate a more detailed comparison between different categories of engineering firms, potentially revealing how firm size impacts the "Implementation Bridge."

Furthermore, future scholars should consider conducting longitudinal studies to track the long-term ROI of drone safety. By tracking a selection of engineering firms over several years, researchers could observe how the relationship between Implementation Quality and Organizational Adoption matures as AI drones become a standardized tool on Malaysian sites. There is also a significant opportunity to expand the Governance Ecosystem Model by integrating it with other "Construction 4.0" technologies, such as Building Information Modeling (BIM) and IoT sensors. Investigating how a unified governance framework manages the data flow between these diverse technologies would provide a more holistic view of the "Connected Site" and its impact on national safety performance, moving closer to the vision of a fully integrated digital construction environment (Adner, 2017).

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APPENDICES A : RESEARCH QUESTIONNAIRE



UNIVERSITI TUNKU ABDUL RAHMAN (UTAR)

Lee Kong Chian Faculty of Engineering and Science

Master of Civil Engineering

Dear Respondents,

We are Master of Civil Engineering students at Universiti Tunku Abdul Rahman (UTAR). We are conducting a research study titled “The Role of the Governance Ecosystem in AI-Drone Adoption for Safety in the Malaysian Construction Industry”.

1. Context: Why are we doing this study? While AI-powered drones have proven effective for autonomous hazard detection and real-time site monitoring, their adoption in Malaysia remains fragmented. Many companies possess the interest but face non-technical barriers that prevent full implementation. This research aims to identify and solve those barriers.

2. What is this survey about? This study focuses on the "Governance Ecosystem"—the structural framework required to support safe drone adoption. We are not just looking at the hardware; we are evaluating the three critical pillars that determine success:

Regulatory Support (External): Are current policies from bodies like CAAM and CIDB clear, supportive, and practical for site operations?

Institutional Readiness (Internal): Does the industry possess the financial capability, digital infrastructure, and skilled workforce required for transition?

Trust & Data Ethics (Human): How do concerns regarding data privacy, surveillance, and worker consent impact the willingness to adopt this technology?

3. Your Role & Contribution Your feedback is vital. By participating, you provide the data needed to propose a Governance Ecosystem Framework—a strategic guideline to help policymakers and organizations streamline regulations, improve readiness, and ensure ethical drone deployment for safer construction sites.

Confidentiality & Eligibility

Target Audience: This survey is strictly for construction industry professionals (Contractors, Consultants, Developers, and Safety Personnel).

Privacy: All responses are strictly confidential, anonymous, and used solely for academic research purposes.

Thank you for contributing your expertise to the advancement of construction safety in Malaysia.

Researcher Details

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Section A : Demographic Information

What this section is about: This section gathers background information about you and your organization (e.g., experience, role, company type). This data helps us classify responses and understand how different groups (e.g., Safety Officers vs. Project Managers) perceive the technology.

INSTRUCTION: Please select the option that best describes your background and current role. All information is strictly confidential and will be used for statistical analysis only.

Item	Questions	Answers
1	Gender	☐ Male ☐ Female
2	Ethnic Group	☐ Malay ☐ Chinese ☐ Indian ☐ Other:
3	Age	☐ below 20 ☐ 21 - 25 ☐ 26 - 30 ☐ 31 - 35 ☐ 36 - 40 ☐ 41 - 45 ☐ 46 - 50 ☐ 51 - 55 ☐ 56 - 60 ☐ 61 - 65 ☐ above 65
4	Highest Education level	☐ Secondary education ☐ Pre-university (STPM, Matriculation, Foundation) ☐ Diploma / Technical Certificate ☐ Bachelor degree ☐ Master degree / Postgraduate Diploma ☐ Doctorate degree (PhD) ☐ Others:
5	Category of the organization	☐ Main contractor ☐ Subcontractor ☐ Developer ☐ Consultant (eg. M&E, C&S, Architectural, Quantity Surveyor, etc) ☐ Others:

6	What is the size of your organisation?	☐ Large (> 100 workers) ☐ Medium (50 to 99 workers) ☐ Small (10 to 49 workers) ☐ Micro (1 to 9 workers)
7	Role	☐ Technician (Relate to engineering or technology) ☐ Non-technician (Non-engineering or non-technology)
8	Position	☐ Top Management (e.g., Director, CEO, General Manager, Partner) ☐ Senior Management（Eg Senior Manager, Senior Project Manager） ☐ Middle Management (e.g., Project Manager, Construction Manager, Site Agent) ☐ Executive Level (Eg Engineer or executive with a minimal degree holder) ☐ Supervisor Level (Eg Supervisor with non-degree) ☐ Others:
9	Work Experience	☐ Less than 1 year ☐ 1 - 5 years ☐ 6 - 10 years ☐ 11 - 15 years ☐ 16 - 20 years ☐ More than 20 years
10	Have you ever heard about : AI Drone	☐ Yes ☐ No
11	Rate your current knowledge about the AI Drone.	(Rating system 1-5) Not Familiar ☐☐☐☐☐Very Familiar

INSTRUCTION: Please read the following statements carefully. Indicate your level of agreement with each statement as it applies to your organization's current situation by selecting the appropriate number.

Strongly Disagree (SD)	Disagree (D)	Neutral (N)	Agree (A)	Strongly Agree (SA)	Unsure / No Knowledge (U/N)
1	2	3	4	5	6

Section B: Regulatory Support (RS)

This section evaluates the current regulatory framework (e.g., CAAM guidelines, CIDB policies, DOSH requirements) governing drone usage in construction. We aim to assess whether these regulations are perceived as clear, supportive, and practical for industry adoption.

How to Answer:

- Based on Experience: Please rate the extent to which you agree with the statements based on your professional knowledge.
- If You Are Unaware: If you have no knowledge of a specific regulation, please select the "Unsure / No Knowledge" option.

No.	Questions	SD	D	N	A	SA	U/N
1	**Existing government policies provide clear guidance for drone use in construction safety.**	**1**	**2**	**3**	**4**	**5**	**6**
2	**The Civil Aviation Authority of Malaysia (CAAM) provides sufficient regulatory support for safe drone operations.**	**1**	**2**	**3**	**4**	**5**	**6**
3	**Coordination among agencies (CAAM, CIDB, DOSH) is effective and minimizes regulatory confusion.**	**1**	**2**	**3**	**4**	**5**	**6**
4	**The current legal framework encourages technological innovation without compromising safety standards.**	**1**	**2**	**3**	**4**	**5**	**6**

5	**National policies (e.g., Construction 4.0 Strategic Plan) actively promote the integration of AI-drones in construction projects.**	**1**	**2**	**3**	**4**	**5**	**6**
6	**The process for obtaining flight permits from authorities is clear and efficient.**	**1**	**2**	**3**	**4**	**5**	**6**
7	**Liability laws regarding drone accidents on construction sites are clearly defined.**	**1**	**2**	**3**	**4**	**5**	**6**

Section C: Institutional Readiness (IR)

This section assesses whether your organization has the necessary resources (Budget, Technology, and Skills) to adopt AI-drone technology.
How to Answer:

- If you do NOT use drones yet: Rate based on your organization's current capability (e.g., "Do we have the budget/skills to start if we wanted to?").
- If you are unsure: Please select the "Unsure / No Knowledge" option.

No.	Questions	SD	D	N	A	SA	U/N
1	**My organisation has the financial resources to invest in AI-drone technologies.**	**1**	**2**	**3**	**4**	**5**	**6**
2	**My organisation has sufficient digital infrastructure (e.g., internet, servers) to support drone-based data.**	**1**	**2**	**3**	**4**	**5**	**6**
3	**Top management is committed to adopting AI-drone technologies.**	**1**	**2**	**3**	**4**	**5**	**6**
4	**Employees in my organisation possess the technical aptitude required to operate or learn AI-drone systems.**	**1**	**2**	**3**	**4**	**5**	**6**
5	**The organisation promotes a culture that supports innovation and technological change.**	**1**	**2**	**3**	**4**	**5**	**6**
6	**My organisation has access to technical support (internal or external) for maintaining advanced**	**1**	**2**	**3**	**4**	**5**	**6**

	equipment.						
7	**Our current software systems (e.g., BIM) are capable of integrating data collected by drones.**	**1**	**2**	**3**	**4**	**5**	**6**

Section D: Trust and Data Ethics (TDE)

This section evaluates the level of trust regarding the security, privacy, and ethical use of data collected by drones. We aim to understand if workers feel protected against misuse or unauthorized surveillance.

How to Answer:

- If your organization uses drones: Rate based on the actual drone policies and practices.
- If your organization does NOT use drones: Rate based on your general trust in how your company currently handles sensitive data (e.g., CCTV footage, employee records).
- If you are unsure: Please select the "Unsure / No Knowledge" option.

No.	Questions	SD	D	N	A	SA	U/N
1	**The organisation acknowledges that AI-drone systems are effective for enhancing site safety.**	**1**	**2**	**3**	**4**	**5**	**6**
2	**The organisation ensures that drone deployment does not compromise the privacy of workers.**	**1**	**2**	**3**	**4**	**5**	**6**
3	**My organisation ensures proper procedures for storing and protecting drone-captured data.**	**1**	**2**	**3**	**4**	**5**	**6**
4	**There is a high level of confidence that drone data is secure from unauthorised access.**	**1**	**2**	**3**	**4**	**5**	**6**
5	**The use of drones for safety monitoring is transparent and communicated clearly to workers.**	**1**	**2**	**3**	**4**	**5**	**6**
6	**The organisation prioritises ethical considerations (fairness, accountability) when deploying AI-drone systems.**	**1**	**2**	**3**	**4**	**5**	**6**
7	**I trust the accuracy of the AI analysis in identifying safety hazards.**	**1**	**2**	**3**	**4**	**5**	**6**

8	**Workers are clearly informed about how drone surveillance data is collected and used.**	**1**	**2**	**3**	**4**	**5**	**6**

Section E: Implementation (IMP)

This section assesses the effectiveness of the planning, coordination, and execution strategies used during the deployment of drone technology.
How to Answer:

- If your organization HAS an implementation plan: Please rate the effectiveness of the process from 1 to 5.
- If your organization has NO plan or has not started: Please select the "No Implementation Yet "(NI) column for all questions in this section.

No.	Questions	SD	D	N	A	SA	NI
1	**My organisation has a clear strategic plan for implementing AI-drone safety systems.**	**1**	**2**	**3**	**4**	**5**	**6**
2	**My organisation has successfully secured the necessary technical expertise and resources for drone deployment..**	**1**	**2**	**3**	**4**	**5**	**6**
3	**Our implementation processes are regularly reviewed and improved based on operational feedback.**	**1**	**2**	**3**	**4**	**5**	**6**
4	**Relevant departments (e.g., Safety, Engineering, IT) coordinate effectively during the drone implementation phase.**	**1**	**2**	**3**	**4**	**5**	**6**
5	**The implementation of AI-drones has led to measurable improvements in safety inspection efficiency.**	**1**	**2**	**3**	**4**	**5**	**6**
6	**My organisation conducts pilot tests (small-scale trials) before fully deploying drone technology across projects.**	**1**	**2**	**3**	**4**	**5**	**6**
7	**We collaborate effectively with external drone service providers or vendors during the**	**1**	**2**	**3**	**4**	**5**	**6**

	implementation phase.						

Section F: AI-Drone Adoption (ADO)

This section measures the extent of AI-drone usage and its impact on safety and business performance.

How to Answer:

- If your organization uses drones: Rate your agreement based on actual operational experience.
- If your organization does NOT use drones: Please select the "Not Applicable" column for questions related to active usage or results. You may answer questions regarding future intent (e.g., Q4, Q5) if applicable.

No.	Questions	SD	D	N	A	SA	NA
1	**My organisation actively uses drones equipped with AI for site safety inspections.**	**1**	**2**	**3**	**4**	**5**	**6**
2	**The adoption of AI-drone technology has led to measurable improvements in overall safety performance.**	**1**	**2**	**3**	**4**	**5**	**6**
3	**AI-drone systems are used regularly for hazard detection and compliance monitoring.**	**1**	**2**	**3**	**4**	**5**	**6**
4	**Top management recognises AI-drone technology as essential for future safety operations.**	**1**	**2**	**3**	**4**	**5**	**6**
5	**My organisation plans to expand the use of AI-drone technologies in future projects.**	**1**	**2**	**3**	**4**	**5**	**6**
6	**The utilization of AI-drones provides a competitive advantage in securing new projects.**	**1**	**2**	**3**	**4**	**5**	**6**
7	**Financial resources for AI-drone technology are permanently allocated in our annual safety budget.**	**1**	**2**	**3**	**4**	**5**	**6**

APPENDICES B: RESEARCH QUESTIONNAIRES PRE TESTING

Appendix B Pre-test

Title: The Role of the Governance Ecosystem in AI-Drone Adoption for Safety in the Malaysian Construction Industry

Instructions for Reviewers:

Please read each question.

- Tick ✔ if the question is clear and appropriate.
- Cross ✘ if the question needs improvement.
- Optionally, write comments or suggestions for improvement in the last column.

Section A : Demographic Information

What this section is about: This section gathers background information about you and your organization (e.g., experience, role, company type). This data helps us classify responses and understand how different groups (e.g., Safety Officers vs. Project Managers) perceive the technology.

INSTRUCTION: Please select the option that best describes your background and current role. All information is strictly confidential and will be used for statistical analysis only.

Item	Questions	Answers	✔ / ✘	Remarks/Comments
1	Gender	● Male ● Female	✓	
2	Ethnic Group	● Malay ● Chinese ● Indian ● Other:	✓	
3	Age	● below 20 ● 21 - 25 ● 26 - 30 ● 31 - 35 ● 36 - 40		

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		• 41 - 45 • 46 - 50 • 51 - 55 • 56 - 60 • 61 - 65 • above 65	✓	
4	Highest Education level	• Secondary education • Pre-university (STPM, Matriculation, Foundation) • Postgraduate diploma • Bachelor degree • Master degree • Doctorate degree (PhD)	✓	
5	Category of the organization	• Main contractor • Subcontractor • Developer • Consultant (eg. M&E, C&S, Architectural, Quantity Surveyor, etc)	✓	
6	What is the size of your organisation?	• Large (> 100 workers) • Medium (50 to 99 workers) • Small (10 to 49 workers) • Micro (1 to 9 workers)	✓	
7	Role	• Technician (Relate to engineering or technology) • Non-technician (Non-engineering or non-technology)	✓	
8	Position	Top Management (Eg Director , CEO, COO, CFO,	✓	DIRECTOR

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		GM) ● Senior Management (Eg Senior Manager, Senior Project Manager) ● Managerial Level (Eg. Manager, M&E Manager, Project Manager, etc) ● Executive Level (Eg Engineer or executive with a minimal degree holder) ● Supervisor Level (Eg Supervisor with non-degree)	✓	
9	Work Experience	● Less than 1 year ● 1 - 5 years ● 6 - 10 years ● 11 - 15 years ● 16 - 20 years ● More than 20 years	✓	
10	Have you ever heard about : AI Drone	● Yes ● No	✓	
11	Rate your current knowledge about the AI Drone.	(Rating system 1-5)	4	

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INSTRUCTION: Please read the following statements carefully. Indicate your level of agreement with each statement as it applies to your organization's current situation by selecting the appropriate number.

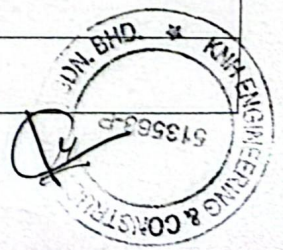
Strongly Disagree (SD)	Disagree (D)	Neutral (N)	Agree (A)	Strongly Agree (SA)
1	2	3	4	5

Section B: Regulatory Support (RS)

What is this section? This section asks about government rules. We want to know if you think the current laws (from CAAM, CIDB, etc.) are clear and helpful, or if they make it difficult to use drones. How to answer:

- **If you know the rules: Rate them based on your experience.**
- **If you don't know the rules: Please select "Neutral" (3). Do not guess.**

No.	Questions	SD	D	N	A	SA	✔ / ✘	Remarks/Comments
1	Existing government policies provide clear guidance for drone use in construction safety.	1	2	3	4 ✓	5		
2	The Civil Aviation Authority of Malaysia (CAAM) provides sufficient regulatory support for safe drone operations.	1	2	3	4 ✓	5		
3	Coordination among agencies (CAAM, CIDB, DOSH) facilitates effective	1	2	3	4	5 ✓		



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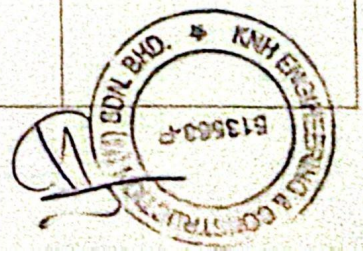
	regulation of drone activities.							
4	The current legal framework encourages innovation while maintaining safety standards.	1	2	3	4 ✓	5		
5	National policies (e.g., Construction 4.0 Strategic Plan) actively promote AI-drone integration in construction projects.	1	2	3	4 ✓	5		
6	The process for obtaining drone flight permits from authorities is efficient and timely.	1	2	3	4	5 ✓		
7	Liability laws regarding drone accidents on construction sites are clearly defined.	1	2	3	4	5 ✓		

Section C: Institutional Readiness (IR)

What is this section? This section asks if your company is capable of using high-tech drones. It is about three things: Money (Budget), Technology (Hardware/Software), and Skills (Training). How to answer:

- **If you don't use drones yet: Ask yourself, "Does my company generally have the money and tech skills to handle this if we wanted to?"**
- **If you are unsure: Select "Neutral" (3).**

No.	Questions	SD	D	N	A	SA	✔ / ✘	Remarks/Comments
1	My organisation has the financial resources to invest in AI-drone technologies.	1	2	3	4 ✓	5		



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2	My organisation has sufficient digital infrastructure to support drone-based safety monitoring.	1	2	3	4 ✓	5		
3	Top management is committed to adopting AI-drone technologies.	1	2	3	4 ✓	5		
4	Employees in my organisation have adequate training to handle AI-drone operations.	1	2	3	4 ✓	5		
5	The organisation promotes a culture that supports innovation and technological change.	1	2	3	4 ✓	5		
6	My organisation has access to technical support (internal team or vendor) for drone maintenance.	1	2	3	4 ✓	5		
7	Our current software systems (e.g., BIM) are capable of integrating data collected by drones.	1	2	3	4 ✓	5		

Section D: Trust and Data Ethics (TDE)

What is this section? This section is about safety and privacy. We want to know if you trust that drone data (photos/videos of workers) is stored securely and used fairly, without spying on people. How to answer:

- **If you don't use drones yet: Answer based on your general trust in your company. Do you trust them to keep other data safe?**
- **If you are unsure: Select "Neutral" (3).**



No.	Questions	SD	D	N	A	SA	✔ / ✘	Remarks/Comments

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1	The organisation acknowledges that AI-drone systems enhance safety without compromising privacy.	1	2	3	4 ✓	5		
2	My organisation ensures proper procedures for storing and protecting drone-captured data.	1	2	3	4	5 ✓		
3	There is a high level of confidence within the organisation that drone data is secure from unauthorised access.	1	2	3	4	5 ✓		
4	The use of drones for safety monitoring is transparent and communicated clearly to workers.	1	2	3	4 ✓	5		
5	The organisation prioritises ethical considerations (fairness, accountability) when deploying AI-drone systems.	1	2	3	4	5 ✓		
6	I trust the accuracy of the AI analysis in identifying safety hazards without human verification.	1	2	3	4 ✓	5		
7	Workers are given the opportunity to provide consent regarding how drone surveillance data is used.	1	2	3	4	5 ✓		

Section E: Implementation (IMP)

What is this section? This section is about the process. We ask if your company has a clear plan, good coordination between departments, and proper testing procedures. How to answer:

- **If your company has NO plan to use drones: Please select "Strongly Disagree" (1). This helps us see that no planning exists.**



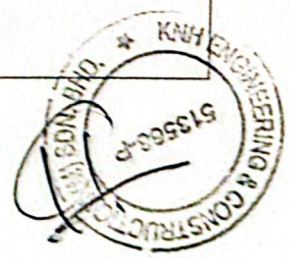
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- **If you are currently planning it: Rate how well the planning is going.**

No.	Questions	SD	D	N	A	SA	✔ / ✘	Remarks/Comments
1	My organisation has a clear plan for implementing AI-drone safety systems.	1	2	3	4 ✓	5		
2	My organisation has secured the necessary technical expertise and support for AI-drone implementation.	1	2	3	4 ✓	5		
3	Our implementation processes are regularly reviewed and improved based on organisational feedback.	1	2	3	4	5 ✓		
4	Departments in my organisation coordinate effectively during AI-drone implementation.	1	2	3	4 ✓	5		
5	The organisation's use of AI-drone systems has measurably improved safety inspection efficiency.	1	2	3	4	5 ✓		
6	My organisation conducts pilot tests (small-scale trials) before fully deploying drone technology.	1	2	3	4	5 ✓		
7	We collaborate effectively with external drone service providers/vendors during the implementation phase.	1	2	3	4	5 ✓		

Section F: AI-Drone Adoption (ADO)

What is this section? This is the final result. We simply want to know: Are you using AI-drones right now? How to answer:



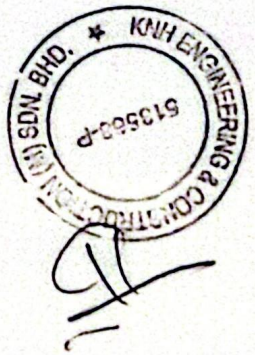
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- **If you DO NOT use drones: Please select "Strongly Disagree" (1). This is very important data for us to measure how many companies are not using them yet.**
- **If you DO use drones: Rate how often and how effectively you use them.**

No.	Questions	SD	D	N	A	SA	✔ / ✘	Remarks/Comments
1	My organisation actively uses drones equipped with AI for site safety inspections.	1	2	3	4 ✓	5		
2	The adoption of AI-drone technology has improved overall safety performance.	1	2	3	4 ✓	5		
3	AI-drone systems are used regularly for hazard detection and compliance monitoring.	1	2	3	4	5 ✓		
4	Management recognises AI-drone technology as essential for future safety operations.	1	2	3	4	5 ✓		
5	My organisation plans to expand the use of AI-drone technologies in future projects.	1	2	3	4 ✓	5		
6	Using AI-drones gives my organisation a competitive advantage in securing new projects.	1	2	3	4	5 ✓		
7	The budget for AI-drone technology is a permanent part of our annual	1	2	3	4	5 ✓		

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	safety budget.							



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