A COMPARISON OF DATA COMPETENCIES AMONG PRACTITIONERS IN THE MALAYSIAN CONSTRUCTION INDUSTRY

LIM AI LING

A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Science (Honours) Quantity Surveying

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DECLARATION

I hereby declare that this project report is based on my original work except for 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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APPROVAL FOR SUBMISSION

I certify that this project report entitled **"A COMPARISON OF DATA COPETENCIES AMONG PRACTITIONERS IN THE MALAYSIAN CONSTRUCTION INDUSTRY"** was prepared by **LIM AI LING** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Science (Honours) Quantity Surveying at Universiti Tunku Abdul Rahman.

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ABSTRACT

The fourth industrial revolution is the trend towards automation and data exchange in technologies and processes. Consequently, data competencies become one of the important competences in demand. The literature search shows there is lack of study of data competences of construction industry practitioners. This research intends to bridge the gap by conducting an empirical study on the current data competencies among the construction practitioners. The objectives of this research include: exploring the data competence requirements in construction industry; evaluating the overall data competencies of the construction industry practitioners and analysing data competencies among different construction practitioners. Six data competencies, namely data fundamental, data generating, data filtering, data analysing, data modelling and data security and ethics have been synthesised from the literature reviewed. Questionnaire surveys were distributed to evaluate the data competencies level among the Malaysian construction industrial practitioners on the six data competencies was conducted. The results of 116 participants revealed that Data Security and Ethics, Data Fundamental and Data Filtering are the top three competence acquired and mostly applied by practitioners in construction industry. Developers are more competent in Data Fundamental compared to those providing consultation services. Architects are competent in Data Security and Ethics and Data Fundamental, Engineers are least competent in Data Fundamental, whereas Quantity Surveyors are least competent in Data Security and Ethics. Data Filtering and Data Analysing are frequently used by those working experience less than 3 years. Practitioners under 25 years are more frequently used Data Security and Ethics in industry. This conclusion was beneficial for academic institution to focus on the course curriculum design and the industry to plan for the training and retraining of their workforce. It also provided an indication to the regulatory agencies to direct their policies to support the data competences development of human resources in the construction industry.

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LIST OF SYMBOLS / ABBREVIATIONS

APC	Assessment of Professional Competency
AR	Augmented Reality
BIM	Building Information Modelling
CDBB	Centre for Digital Built Britain
CIDB	Construction Industry Development Board Malaysia
CLT	Central Limit Theorem
ICT	Information and Communication Technology
IoT	Internet of Things
MDEC	Malaysian Digital Economy Corporation
MQA	Malaysian Qualifications Agency
MQF	Malaysia Qualification Framework
RICS	Royal Institution of Chartered Surveyors
UK	United Kingdom

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CHAPTER 1

INTRODUCTION

1.1 Background

Construction industry is an important activity that evidently plays a very essential role in the process of economic growth. The construction contributed 6% to the economy of Malaysia (Department of Statistics Malaysia, 2021). Malaysia Productivity Corporation (2021) reported that the Malaysia annual productivity growth rate had dropped by 5.5% in the year 2020 when compared to the growth rate in year 2019. On the sectoral performance, the Construction sector dropped 15.7% which is much more serious than Manufacturing and Services sectors who recorded -2.6% and -6% respectively. Digital transformation is a way to improve the productivity, safety and accuracy of the industry (Sawhney, 2020; Wheelis, 2020). McKinsey Global Institute research showed that construction is one of the least digitised industries in United Kingdom (UK) (Agarwal, Chandrasekaran and Sridhar, 2016).

In Nigeria, Amusan, et al., (2018) found that adoption of digital technologies is very slow in construction industry due to a lack of staff with appropriate skills and knowledge of the technologies. Similar researches and results are happened in the construction industry of Malaysia (Oesterreich and Teuteberg, 2016; Ibrahim, et al., 2019; Klinc and Turk, 2019; Othman, et al., 2021).

Ministry of Education Malaysia has included data competencies in the Malaysia Qualification Framework (MQF). The Digital Skills Training Directory by Malaysian Digital Economy Corporation (MDEC) has covered digital skills and competencies programmes for the workplace such as MyDigitalWorkforce in Tech MyWiT (Yeo, 2022), but it was reported not carried out as planned due to limited expertise and widely acceptance (Ibrahim, et al., 2019). In 2020, the Ministry of Works through Construction Industry Development Board Malaysia (CIDB) published a Construction Strategy Plan 4.0 for five years from 2021 to 2025. The Strategy Plan provided a pathway to allow the government, industry and academia in the construction sector to cope with the rapid changes of the Fourth Industrial Revolution. The strategy plan envisioned that digital transformation in construction industry requires the future labour force to be equipped and prepared with new skills and competencies so that they can adapt to the changing built environment; the existing employees to be trained and upskilled for technology adoption (Hamid, Ibrahim, and Jusoh, 2020).

1.2 Problem Statement

There are several studies related to data competencies for digital transformation published. van Laar, et al. (2019) studied the 21st-century data competencies instrument aimed at working professionals, but the research is limited to creative industries. Fleaca and Stanciu (2019) studied technical knowledge and data competencies required by current economy, but the study is focused on Romanian students. Saikkonen and Kaarakainen (2021) studied the analysis of digital information competencies among the teachers but not the construction professionals. Ibrahim, et al. (2019) focused on building the Building Information Modelling (BIM) skilled talents in Malaysia. Other than that, Lee (2020) mainly studied the readiness of digital transformation in Malaysian construction industry. There is no further discussion on data competencies in construction industry in his research. Another research by Tan (2020) examined the current status of data competencies in Malaysian construction industry, but the research is focused on software usage. Furthermore, Sim (2021) focused on the digital skills and course curriculum of the quantity surveying undergraduate programme in Malaysia. Previous studies have not fully covered data competence requirements in the Malaysian construction industry, as well as overall data competencies among different construction practitioners. This study will bridge the gap by researching the different categories of data competencies possessed and used by the different construction industrial practitioners.

1.3 Research Aim

Hence, this research aims to compare the data competencies among practitioners in the Malaysian construction industry.

1.4 Research Objective

The following research objectives are formulated to achieve the above-mentioned research aim:

(i) To explore the data competence requirements in construction industry.

(ii) To evaluate the overall data competencies of the construction industry practitioners.

(iii) To analyse the data competencies among different construction practitioners.

1.5 Research Method

An explanatory research method was applied in this research to compare data competencies among construction practitioners in Malaysia. A questionnaire was created to collect data, while literature reviews were used to gather related information from existing published studies to support this research. Data was analysed through several methods, including Cronbach Alpha Reliability Test, Measure of Central Tendency, Spearmen Correlation and Pairwise Comparison.

1.6 Research Scope and Limitation

This research focused on practitioners who are currently working in the supply chain (namely, property development, consultation services, construction businesses and building materials merchants, manufacturers) of construction industry in Malaysia. The target respondents shall be part of the professional community within the construction industry such as Architecture, Engineering, Quantity Surveying, Project and Construction Management.

1.7 Report Structure

Chapter 1 described the importance of data competencies. It covered the research problems, research aim, objectives, methods, as well as scope and limitations of research. It also briefly outlined the contents of this research.

Chapter 2 presented the literature review on the existing research completed by other researchers regarding industrial revolution, digital transformation, and data competencies and skills. A conceptual framework was generated to summarise the information collected in this chapter.

Chapter 3 depicted research methods adopted in this research. The research design was discussed and research instrument was created in this chapter. Sample design covered the sampling frame, sampling method, sampling size, as well as target respondents. Besides that, data analysis approaches such as Cronbach Alpha Reliability test, Measure of Central Tendency, Spearman Rank Correlation and pairwise comparison were also explained in this chapter.

Chapter 4 showed and discussed the research results and findings. Background of respondents was summarised in descriptive statistics. Reliability test was conducted to test the reliability of the questionnaire construct. Spearmen Correlation was conducted to test the relationships between the data competence self-assessment and in use. Moreover, pairwise comparison was adopted to compare the median of data competence self-assessment and frequency of use among the respondents' attributes in pairs.

Chapter 5 concluded that Malaysian construction practitioners are more competent in Data Security and Ethics and more frequent application is in Data Security and Ethics. The research objectives were achieved and the research implications were covered in three aspects, namely academic and research, industrial application, and regulatory policy developments. Lastly, limitations and recommendations were illustrated for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

The fourth industrial revolution brought along benefits to industries. Brief account of the fourth industrial revolution is described in the following section. The needs of data transformation and the data competencies of key stakeholders such as Malaysian Qualifications Agency (MQA), Centre for Digital Built Britain (CDBB) and Royal Institution of Chartered Surveyors (RICS) are reviewed in the subsequent sections. The chapter is ended with a conceptual framework of data competencies from literature review.

2.2 The Fourth Industrial Revolution

The fourth industrial revolution involves the digital transformation of the industries and consumer markets, from the emergence of smart manufacturing to the digitisation of the entire value delivery channel. People are aimed at promoting the development of an industry to launch products faster and increase flexibility and resource efficiency through digitisation (Popkova, et al., 2018; Li, Hou and Wu, 2017). In the creation of smart factories by the fourth industrial revolution, a modular structured, cyber-physical system monitors physical processes, creates a virtual copy of the physical world, and makes decentralised decisions. Other than that, people use Internet of Things (IoT) and cloud computing in their daily life (Stăncioiu, 2017; Bloem, et al., 2014). Some people believe that digital transformation and industry restructuring will affect the labour market severely, while others believe that these are creating numberless employment opportunities established in various fields, such as machine learning, control system design, automation and software engineering (Kar, Kar and Gupta, 2021; Ghobakhloo, 2019; Ibrahim, et al., 2019; Klinc and Turk, 2019).

2.3 Digital Transformation

The fourth industrial revolution impacts all industries, including the construction industry (Vial 2019; Reis, et al., 2018). Construction 4.0 is being used to describe the revolution of construction industry transformed from automated production to high-level digitalisation, such as Building Information Modelling (BIM), Augmented Reality (AR), Big Data, and IoT. Information is connected between these technologies to monitor the progress of construction and improve the level of productivity (Ibrahim, et al., 2019; Klinc and Turk, 2019). Algorithms, big data and computation power are interrelated with each other to drive the Construction 4.0 (Adadi, 2021; Aly, 2020).

BIM tools are shifting the way of project is being constructed, designed, managed, and analysed within the whole life cycle of project (Klinc and Turk, 2019). During the ongoing construction phase, AR is applied to monitor and control the progress of construction and all the information obtained will be transferred into BIM tool (Ibrahim, et al., 2019).

Digital technologies are eventually changing the industry dealing with the built environment. However, the new technology implementations in construction sector are slow (Klinc and Turk, 2019) due to lack of knowledge and data competencies of workforce in using new technologies (Hecker and Loprest, 2019; Ibrahim, et al., 2019; Oesterreich and Teuteberg, 2016).

2.4 Data Competence and Data Skill

Data competence covers a set of data skills, which also refers to the ability to use data knowledge and skills for different contexts, including learning or working (Iordache, Mariën, and Baelden, 2017). On the other hand, data skill defines the more technical aspects of competencies and knowledge (Brolpito, 2018). Therefore, the term data competence is used in the following sections.

2.5 Data Competence

Data competencies are the range of skills to access and manage data by using digital devices, share data content with communication and collaboration applications, as well as solve the problem through networks. The second edition of Malaysian Qualification Framework (MQF) by Malaysian Qualification Agency (MQA) included digital skills as part of the functional work skills among the five clusters of learning outcomes. The digital skills include: using digital technologies, collecting and storing information, as well as processing the data. It also covers the ability to use the application for communication and problem solving, and the ethics while applying digital skills.

In UK, skills and competency published by Centre for Digital Built Britain (CDBB) mentioned that the digital skills required for digital construction transformation including data fundamentals, lifecycle assurance and quality management, data modelling, analytics and intelligence, experience and application, as well as security and ethics.

On the other hand, the pathway guide for Quantity Surveyors and Construction sectors by Royal Institution of Chartered Surveyors (RICS) specified Data management as a level 1 Mandatory competency in the Assessment of Professional Competency (APC). The document further defines Data competency encompasses the collection, storage and retrieval of data related to specific projects and a surveyor’s job in general, understanding of the various storage systems and data resources and how they work, and being familiar with generating and managing data, as well as increasing usage of computerised central project databases. This reflects that data competency is one of the important competencies to become a qualified professional in construction sector.

Table 2.1: A Comparison of Data Competencies Standards

MQA	CDBB	RICS
• Ability to use information/digital technologies to support work and studies	• Data fundamentals	• Data collection, storage and retrieval
• Sourcing and storing information	• Lifecycle assurance and quality management	• Understanding storage systems and data resources, and how they work
• Processing data	• Data modelling	• Generating data
• Using application for problem solving and communication	• Analytics and intelligence	• Managing data

Table 2.1 (Continued)

MQA	CDBB	RICS
• Ethics in applying digital skills	• Experience and application • Security and ethics	• Increasing usage of computerised central project databased

Table 2.1 summarises the data competencies included in the standards of MQA, CDBB and RICS. The standards of data competencies published by CDBB contains all the competencies required by MQA and RICS and it is more comprehensive. Therefore, the following sections were structured according to the CDBB standard data competencies requirements.

2.5.1 Data Fundamental

Data fundamental refers to the capability of generating and communicating data in context and expressing the comprehension of data definitions and methods (Plummer, et al, 2021). For example, people create and transfer digital context to others by using social media, email or Google Drive (Fleaca and Stanciu, 2019; van Laar, et al., 2019; Siddiq, Scherer and Tondeur, 2016). They can use various media and online formats to communicate information and ideas effectively with others (van Laar, et al., 2019). According to requirements or targets, they can create or pick different information to share (Fleaca and Stanciu, 2019). Besides that, data fundamental also included the ability to identify good quality data and express the purpose and value of using them. In order to support own or others' decision-making, high-quality data should be used and the required type of data should be identified (Plummer, et al, 2021). However, a person must have the skills to use information and communication technology (ICT) to effectively deal with media to achieve specific goals (Yu, Lin and Liao, 2017). For example, being able to perform a search query before evaluating the results of it, or able to create and register a user account before asking questions in an online forum.

2.5.2 Data Generating

In order to fill the gap between users, data, and technology, it is important to make technology more applicable and accessible by indicating the sympathy of facilitation, user interface design, and people. Therefore, people create an instinctive and attractive user experience through user testing and research (Plummer, et al, 2021). Other than analysing data for the user research and testing results, it is required to use digital technologies for exploring and generating new ideas or developing a new way of doing things, and transforming the ideas into a new product, service or process (van Laar, et al., 2019). Moreover, it covered the skill of generating a better application that is suitable for the particular content type and representing them in visuals, such as diagrams or infographics (Fleaca and Stanciu, 2019). Therefore, new data can be generated for new situations from existing data.

2.5.3 Data Filtering

A large number of data are created for capturing the decisions and results of lifecycle management activities. This is because there are many groups of players and stakeholders involved in creating and sharing data during the planning, design, construction and maintenance phases (Adeoye and Adeoye, 2017). Therefore, this required competencies in using applications to select the lifecycle input and output data, and identifying the quality of data for decision making. For example, consultant team needs to use historical data for cost estimating. Hence, they have to select the related and valid historical data for ensuring accuracy of cost estimating (Pang, et al., 2021). Furthermore, this is also related to the skills of selecting worthy data to exchange with others based on requirements of information and procedures. By selecting data, it establishes an improvement of transparency in data related processes and outcomes such as value of data (Plummer, et al, 2021).

2.5.4 Data Analysing

People gain knowledge about the new problem situation and apply new information from the most relevant sources to create new or most suitable solutions for the problem (van Laar, et al., 2019). Therefore, people are required to specify the requirements of data quality needed which being generated and analysed (Plummer, et al, 2021). A problem solver flexibly uses various online tools to create and connect information related to the problem, and generate the solution based on the quality of information found (van Laar, et al., 2019). In order to solve the problem, building valuable knowledge with the available digital resources is required (Clifford, et al., 2020; Fleaca and Stanciu, 2019). Data will have their value after being analysed, and the value obtained is the key to decision-making or problem-solving. Thus, digital analysing is important to inform data knowledge, which using analytics software such as Google Analytics, Looker and Pendo to structure and analyse data. Moreover, people require the skill to form the data sets in a graph, table or figure that is easy for others to read and understand the trends for selecting the best decision (Plummer, et al, 2021).

2.5.5 Data Modelling

Data modelling is a system thinking that demonstrates a clear understanding of engineering semantics including ontology, related classification and reference data. Other than that, it distinguishes the importance of these ideas in terms of data exchange and interoperability (Plummer, et al, 2021). In construction, works are completed by different teams of people who are having complementary knowledge and roles. Therefore, sharing and exchanging data with others online is also important for modelling the data sets (Fleaca and Stanciu, 2019; van Laar, et al., 2019).

2.5.6 Data Security and Ethics

Data security embodies a safe design method in terms of network security and business continuity, acting as a management and obedience agency to advise how data is used. While ensuring legal obligations and data privacy, data decisions are considered in the situation of business integrity and ethics (Plummer, et al, 2021). Protecting devices is one of the steps for digital safety, which has to protect devices and digital content. For example, setting passwords for personal laptops and smartphones. Besides that, people should be aware of the environmental impact of digital technologies and their use to protect the digital environment. Therefore, knowing the risks and threats in digital environment and digital safety is important to protect oneself from the danger's digital environment, such as cyberbullying (Kispeter, 2018).

2.6 Conceptual Framework

The literature review is summarised into a conceptual framework as shown in Figure 2.1. The 14 data competencies identified from Malaysian and UK regulators are synthesised into six data competencies.

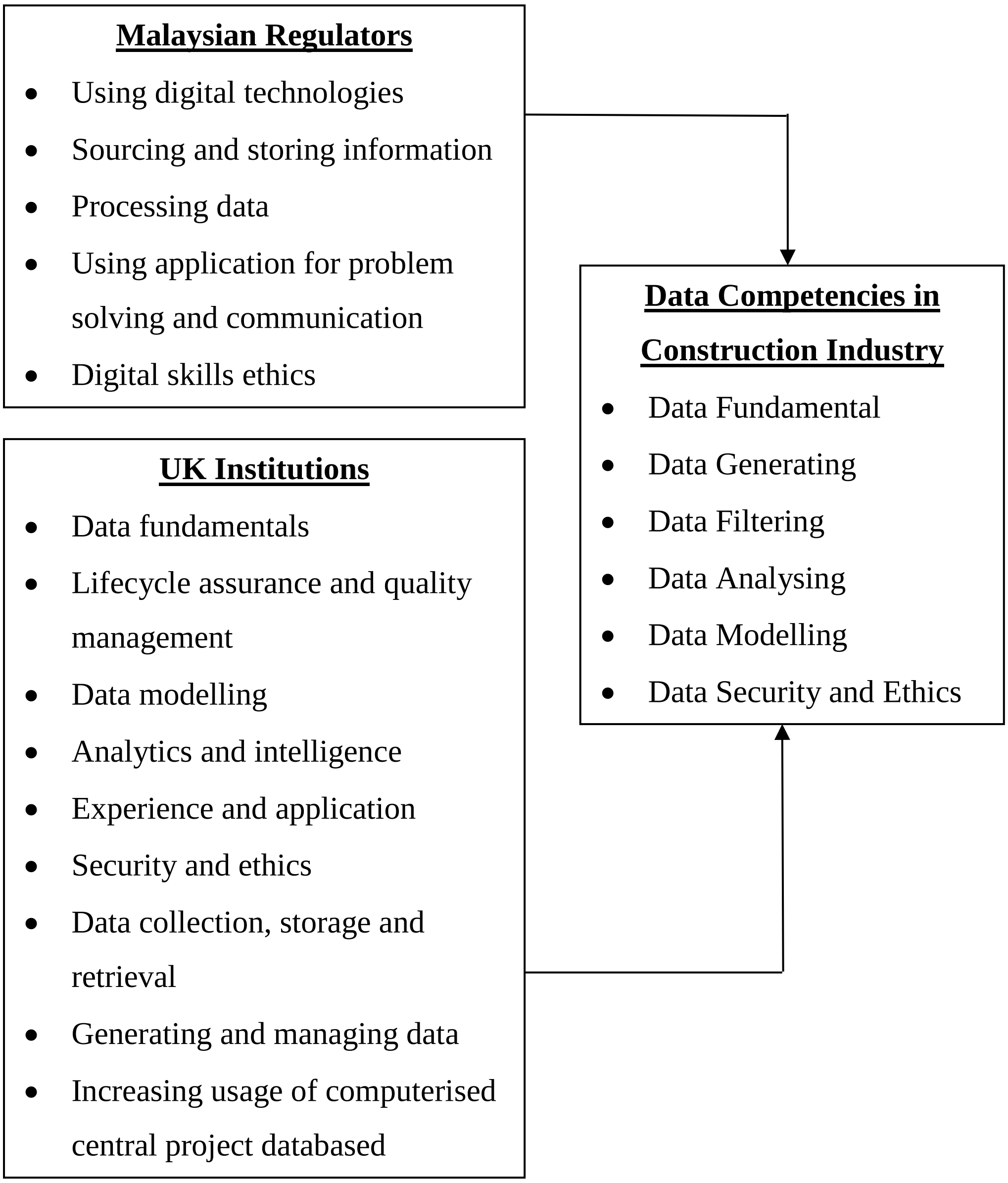

Figure 2.1: Comparison of Data Competencies between UK and Malaysia Regulators and the Synthesised Data Competencies in the Construction Industry

CHAPTER 3

METHODOLOGY AND WORK PLAN

3.1 Introduction

This chapter covered the research methodology applied to investigate the aim and objectives of this research. Research design and research instruments are discussed in the following sections. Sample design included sampling frame, sampling method, sampling size and target respondents are elaborated in the subsequent sections. Data analysis methods conducted such as Cronbach's Alpha Reliability Test, Measure of Central Tendency, Spearman Correlation, and Pairwise Comparisons are presented in the last section of this chapter.

3.2 Research Design

Explanatory research design explains the patterns of relationships between or among variables being studied (Sue and Ritter, 2012). In this research, explanatory research design was applied to explain different categories of data competencies possessed and used by the different construction industrial practitioners. Data competencies standards provided by Centre for Digital Built Britain (CDBB) were chosen for reviewing due to the standards are further details and covered data competencies mentioned in Malaysian Qualification Agency (MQA) and Royal Institution of Chartered Surveyors (RICS).

3.3 Research Instrument

The six data competencies identified from the conceptual framework shown in Figure 2.1 were used to design the questionnaire. The questionnaire consists of three main sections, namely Section A, Section B and Section C. Table 3.1 shows the detail of questionnaire design.

Table 3.1: Questionnaire Design

Section	Investigation Questions	Purposes
A	Please rate yourself in the following competencies.	To evaluate the data competencies of construction industry practitioners.
B	How frequent do you apply the following competencies in your working life?	To compile information on data competencies in practice.
C	Demographic Information	To collect the attributes of respondents

Same sets of statements were used in Sections A and B mentioned in Table 3.1. The reason to use similar statements for two different questions is to compare any mismatch between the competencies possessed and practiced by the industrial practitioners.

Closed-ended questions in scale ranking format were applied in the questionnaire. In Section A, 10 scale ranking was applied, which numerical value 1 to 2 indicating the fundamental awareness, value 3 to 4 representing the novice, value 5 to 6 showing the intermediate, value 7 to 8 classifying to advanced, and value 9 to 10 grouping to expert. Furthermore, 7 scale ranking was applied in Section B. Numerical value 1 is never true to me, value 2 is rarely true of me, value 3 is sometimes true of me, value 4 is true of me about half the time, value 5 is frequently true of me, value 6 is almost always true of me, and value 7 is always true of me.

A set of respondents' demographic backgrounds was collected in Section C of the questionnaire, including business activities, respondents' professions, working experiences and age range. These data were used to make in-depth comparisons according to the attributes of respondents.

The details statements adopted in the questionnaire to evaluate the respondent data competencies of the six data competence categories and the sources of references are shown in Table 3.2 to Table 3.7.

Table 3.2: Data Fundamental

Statements	Sources
a. Showing an understanding of different data terms, types and sources.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Fleaca and Stanciu (2019); RICS (2018); van Laar, et al. (2018); Siddiq, Scherer and Tondeur (2016)
b. Using established methods to collect, store and share data e.g. having a single source of truth for a digital file.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Fleaca and Stanciu (2019); Kispeter (2018); RICS (2018); van Laar, et al. (2018); Siddiq, Scherer and Tondeur (2016);
c. Showing awareness of what good quality data looks like and how it informs decision-making.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Fleaca and Stanciu (2019); Kispeter (2018); Siddiq, Scherer and Tondeur (2016);
d. Demonstrating a strong understanding of the value of data.	Plummer, et al. (2021)
e. Demonstrating the ability to manage different types of data according to its qualities.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Kispeter (2018); RICS (2018); van Laar, et al. (2018); Siddiq, Scherer and Tondeur (2016);
f. Using knowledge of data to help others in the team to collect and store it efficiently.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Fleaca and Stanciu (2019); Kispeter (2018)
g. Generating good quality data to support their decision making.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Kispeter (2018); Siddiq, Scherer and Tondeur (2016)
h. Articulating the value of data to others in a way that is easy to comprehend e.g. not using technical jargon.	Plummer, et al. (2021)
i. Guiding others in understanding of data terms, types and sources.	Plummer, et al. (2021)

Table 3.2 (Continued)

	Statements	Sources
j.	Recognising the benefits of data to inform how to collect and manage it using both established and novel methods.	Plummer, et al. (2021); van Laar, et al. (2018)
k.	Overseeing the use of good quality data to support their own and other's decisions, including the types and quality of data needed and questions being addressed.	Plummer, et al. (2021)
l.	Encouraging others to see the value in data by promoting data sharing and an open data culture	Plummer, et al. (2021)
m.	Challenging existing definitions of data terms, types and sources and write new definitions where applicable.	Plummer, et al. (2021); RICS (2018)
n.	Demonstrating knowledge of methods and tools with the ability to present new data collection and storage methods coherently.	Plummer, et al. (2021); RICS (2018)
o.	Making critical decisions by understanding and synthesising high volume, high velocity or complex heterogenous data and is able to spot data quality issues and recommend improvements.	Plummer, et al. (2021); RICS (2018)
p.	Enabling and coach others to make data-driven decisions.	Plummer, et al. (2021)
q.	Consistently defining new uses and value from data and is able to articulate the steps others need to take to generate increased value from data.	Plummer, et al. (2021); RICS (2018)

Table 3.3: Data Generating

	Statements	Sources
a.	Understanding the basic principles of user research and experience in relation to the psychological interaction between humans and data and technology	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Fleaca and Stanciu (2019); RICS (2018); Siddiq, Scherer and Tondeur (2016)
b.	Showing an awareness of how testing and reporting on user experience can add data value.	Plummer, et al. (2021); Fleaca and Stanciu (2019); Siddiq, Scherer and Tondeur (2016)
c.	Understanding the importance of user-led design data to support technology adoption.	Plummer, et al. (2021); Fleaca and Stanciu (2019); Siddiq, Scherer and Tondeur (2016)
d.	Using different user research techniques to collect data and elicit needs and build requirements	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021)
e.	Undertaking testing and acquires user feedback as data to report on current experiences with design, technology and information	Plummer, et al. (2021)
f.	Creating functional design and structure elements from the research data to make interfaces intuitive and engaging.	Plummer, et al. (2021)
g.	Using different user research techniques to collect data and elicit needs and build requirements through user flows and wireframes.	Plummer, et al. (2021); Fleaca and Stanciu (2019); RICS (2018)
h.	Performing Alpha/Beta testing and analyses user testing data results.	Plummer, et al. (2021); RICS (2018)
i.	Reporting on user experience as data in relation to technology adoption and is able to see trends and pinpoint why some choices are better/worse than others.	Plummer, et al. (2021); Fleaca and Stanciu (2019); RICS (2018)

Table 3.3 (Continued)

	Statements	Sources
j.	Taking a leading role as a designer, overseeing the usability and functionality of technology interfaces from research data, focusing on structure, contrast and accessibility.	Plummer, et al. (2021); RICS (2018)
k.	Showing a leading authority on user research data and design thinking with the ability to deep dive into user challenges and constraints when adopting technology.	Plummer, et al. (2021)
l.	Performing user testing data and analysis at scale and can articulate recommendations to improve and support technology development and adoption across different organisations.	Plummer, et al. (2021)
m.	Fully understanding the benefits of good user interface design and develops new and innovative techniques to improve the functionality and increase intuitive and engaging interaction with users.	Plummer, et al. (2021)

Table 3.4: Data Filtering

	Statements	Sources
a.	Showing awareness of what good quality data looks like in relation to its ability to be analysed and inform decision-making.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Siddiq, Scherer and Tondeur (2016)
b.	Showing knowledge of mathematical and statistical techniques for analysing data.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Fleaca and Stanciu (2019); Siddiq, Scherer and Tondeur (2016)

Table 3.4 (Continued)

	Statements	Sources
c.	Showing awareness of how to use scientific methods to manipulate data when running analyses, including extrapolation and regression.	Plummer, et al. (2021)
d.	Having knowledge of different mediums used to convey information and data (e.g. reports, visualisations, dashboards).	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); van Fleaca and Stanciu (2019); Laar, et al. (2018); Siddiq, Scherer and Tondeur (2016)
e.	Demonstrating the ability to define requirements of good quality data to support their analysis.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021)
f.	Demonstrating experience using statistical, practical and ethical methods to analyse data across different data sets.	Plummer, et al. (2021); Fleaca and Stanciu (2019); Adeoye and Adeoye (2017)
g.	Demonstrating the ability to follow data modelling principles when transforming and analysing data and can do so with different data sets.	Plummer, et al. (2021)
h.	Demonstrating the ability to draw insight from data in the form of visual communication that users are receptive to.	Plummer, et al. (2021)
i.	Actively engaging others to build an understanding on the quality requirements of data being produced and analysed and how this can enable better decision-making.	Plummer, et al. (2021)

Table 3.4 (Continued)

	Statements	Sources
j.	Using statistical, practical and ethical methods to design and enhance algorithms and has knowledge of how algorithms can be made scalable across various data sets.	Plummer, et al. (2021); Fleaca and Stanciu (2019); Adeoye and Adeoye (2017)
k.	Recognising the types of data needed to generate insights and support decision-making, and decides on the best principles to design/follow when transforming and analysing large and varied data sets.	Plummer, et al. (2021)
l.	Actively using a range of different data visualisation and sense-making techniques to present trends and inform decision making.	Plummer, et al. (2021)
m.	Championing the impact good quality data has on analytics and intelligence and helps process owners and modellers understand the standards for data within their part of the organisation.	Plummer, et al. (2021)
n.	Overseeing the design of algorithms, evaluating and championing ethics and advising on how they can be resiliently scaled across large data sets.	Plummer, et al. (2021)
o.	Using domain knowledge and industry experience to inform and influence the types of data and analysis methods that should be used to address business and industry needs.	Plummer, et al. (2021)
p.	Advising on best practice data visualisation methods to present new evidence as well as being able to evaluate the data quality and value of that evidence.	Plummer, et al. (2021)

Table 3.5: Data Analysing

Statements	Sources
a. Defining the purpose of data lifecycle management and explain how it may positively impact the quality of data.	Plummer, et al. (2021)
b. Defining the principles of process data modelling including the ‘as-is’ and ‘to-be’ states and how this is presented using workflow design.	Plummer, et al. (2021)
c. Knowing what good data looks like from understanding data quality dimensions (completeness, uniqueness, consistency, accuracy, timely, validity).	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Kispeter (2018); van Laar, et al. (2018)
d. Defining what questions need to be asked to understand data requirements.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Fleaca and Stanciu (2019); van Laar, et al. (2018); Siddiq, Scherer and Tondeur (2016)
e. Using knowledge of data lifecycle management to view processes in a holistic way, seeing the correlation between data inputs and outputs that occur as a result.	Plummer, et al. (2021)
f. Applying the principles of process data modelling and workflow design to create business process artefacts that show events, action and connection points of a process.	Plummer, et al. (2021)
g. Using knowledge of the data quality dimensions in their everyday practice to validate data.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Fleaca and Stanciu (2019); Kispeter (2018); van Laar, et al. (2018); Siddiq, Scherer and Tondeur (2016)

Table 3.5 (Continued)

	Statements	Sources
h.	Researching what data is needed to enable certain decisions to be made and can map these requirements to processes.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Siddiq, Scherer and Tondeur (2016)
i.	Demonstrating the ability to analyse the detail of data lifecycle inputs and outputs and can pinpoint process and data quality issues that affect outputs and suggest improvements.	Plummer, et al. (2021); Clifford, et al. (2020)
j.	Demonstrating the ability to model descriptive and perspective cross-functional processes, emphasising quality control for data inputs and outputs and the rationale for process design.	Plummer, et al. (2021)
k.	Evaluating the quality of data in relation to fit for purpose (business need).	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Clifford, et al. (2020); Siddiq, Scherer and Tondeur (2016);
l.	Suggesting improvements to data governance and process to improve quality.	Plummer, et al. (2021)
m.	Demonstrating the ability to influence process data modelling based on information requirements, governance and compliance procedures that must be in place	Plummer, et al. (2021)
n.	Advising on best practices for data lifecycle management to improve process and the quality of data outputs.	Plummer, et al. (2021)
o.	Predicting potential data quality risks and issues with lifecycles and suggest mitigation.	Plummer, et al. (2021)

Table 3.5 (Continued)

	Statements	Sources
p.	Modelling data lifecycle processes that consider internal and external events, actions and connection points.	Plummer, et al. (2021)
q.	Making critical decisions on process improvements to reduce waste and improve data quality and integration.	Plummer, et al. (2021)
r.	Demonstrating the impact fit for purpose data has on decision making and value.	Plummer, et al. (2021)
s.	Working with others to set standards, governance and targets for data quality in relation to the purpose it serves.	Plummer, et al. (2021)
t.	Inspiring teams to develop process and information requirements with the end in mind, focusing on what decisions need answering and working backwards to map data flows.	Plummer, et al. (2021)

Table 3.6: Data Modelling

	Statements	Sources
a.	Defining the purpose of data ontologies at a high level in relation to their organisation and industry.	Plummer, et al. (2021)
b.	Recognising the semantics and related taxonomies of the industry and can classify data	Plummer, et al. (2021)
c.	Showing awareness of different reference data models that exist within the organisation and how they relate to business processes.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021): RICS (2018);
d.	Showing insight into the flow of data, including how data travels between systems and how systems are able to share data with one another.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); RICS (2018)

Table 3.6 (Continued)

e.	Using knowledge of standard ontologies in relation to their organisation and industry to influence how they distinguish data concepts and their relationships.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Fleaca and Stanciu (2019); Kispeter (2018); RICS (2018)
f.	Using knowledge of taxonomies to create data models that classify and organise data into hierarchal meaning.	Plummer, et al. (2021); Saikkonen and Kaarakainen (2021); Fleaca and Stanciu (2019); RICS (2018); Siddiq, Scherer and Tondeur (2016)
g.	Using knowledge of reference data models to make organisable data models relevant to real world application.	Plummer, et al. (2021)
h.	Building data products that can be exposed and integrated with other external systems, such as through Application Programmable Interfaces (APIs).	Plummer, et al. (2021)
i.	Demonstrating the ability to write and maintain ontologies using logic and can represent how data concepts relate to each other.	Plummer, et al. (2021); Fleaca and Stanciu (2019); RICS (2018)
j.	Demonstrating the ability to relate external reference data models to internal data models so that data can be categorised and shared across an organisation and externally with a shared understanding.	Plummer, et al. (2021)
k.	Advising on design and data modelling to facilitate better data sharing and interoperability between systems.	Plummer, et al. (2021)
l.	Advising on industry wide data ontological development using logic, philosophy, collaboration and industry knowledge.	Plummer, et al. (2021); RICS (2018)

Table 3.6 (Continued)

	Statements	Sources
m.	Advising on the principles of logic and philosophy that apply to taxonomies and uses automation to classify and organise data at scale.	Plummer, et al. (2021); RICS (2018)
n.	Advising on industry wide reference data models based on industry knowledge of semantics to make data interoperability automated and coherent.	Plummer, et al. (2021); RICS (2018)
o.	Challenging behaviours that go against data sharing and interoperability and advocates for an open data approach through architecture model design.	Plummer, et al. (2021); RICS (2018)

Table 3.7: Data Security and Ethics

	Statements	Sources
a.	Adhering to ethical and legal standards and protocols when using data.	Plummer, et al. (2021); Fleaca and Stanciu (2019); Kispeter (2018); RICS (2018); van Laar, et al. (2018)
b.	Demonstrating an awareness of security, systems and legacy management when performing activities that involve data and technology.	Plummer, et al. (2021); Kispeter (2018); RICS (2018)
c.	Understanding the purpose of business impact data analysis, crisis management, continuity and recovery plans in relation to IT policy and regulatory requirements.	Plummer, et al. (2021); Fleaca and Stanciu (2019); RICS (2018)
d.	Understanding the regulatory and ethical importance of data privacy.	Plummer, et al. (2021); Fleaca and Stanciu (2019); RICS (2018); van Laar, et al. (2018);
e.	Understanding the reasoning behind different ethical and legal standards and protocols that surround data, including its quality and use (including sharing).	Plummer, et al. (2021); Kispeter (2018); RICS (2018)

Table 3.7 (Continued)

	Statements	Sources
f.	Practicing secure methods when collecting and analysing data whilst showing working knowledge of the different security and legacy requirements of different systems.	Plummer, et al. (2021); Kispeter (2018); RICS (2018)
g.	Performing business impact data analysis and technology risk assessments in relation to IT policy and regulatory requirements.	Plummer, et al. (2021); Kispeter (2018); RICS (2018)
h.	Practicing good understanding of data privacy by gaining consent to use personal data and/or anonymising data when individuals could be identified.	Plummer, et al. (2021); RICS (2018)
i.	Authoring internal organisational data ethical and governance standards and protocols.	Plummer, et al. (2021); RICS (2018)
j.	Acting as the first point of escalation for non-compliance.	Plummer, et al. (2021); RICS (2018)
k.	Articulating data security and ethical design requirements and recommend measures to ensure systems stay secure.	Plummer, et al. (2021); RICS (2018)
l.	Analysing data on risk and perform steps to manage crisis issues and develop and implement continuity and recovery plans.	Plummer, et al. (2021); RICS (2018)
m.	Justifying the use of personal or sensitive data when challenges on business, ethical and legal grounds.	Plummer, et al. (2021); RICS (2018)
n.	Defining best practice for data standards and protocols and sets tasks and targets in relation to legal compliance, governance procedures and business integrity.	Plummer, et al. (2021); RICS (2018)
o.	Acting as the final point of escalation for non-compliance.	Plummer, et al. (2021); RICS (2018)

Table 3.7 (Continued)

	Statements	Sources
p.	Actively driving a data secure by design approach to choosing, using and designing technology.	Plummer, et al. (2021); Fleaca and Stanciu (2019); RICS (2018)
q.	Raising awareness for data and cyber security risks and the role and methods systems can play to prevent them being realised.	Plummer, et al. (2021); Kispeter (2018); RICS (2018)
r.	Promoting continuous assessment of cyber security risk and resilience by ensuring penetration testing is performed to ensure business continuity and legal obligations are met.	Plummer, et al. (2021); RICS (2018)
s.	Staying up to date with hacking methods to recommend technology and processes to prevent attacks.	Plummer, et al. (2021); RICS (2018)
t.	Advocating for individual awareness of data privacy measures and promotes ethical considerations that puts control back in the hand of the individual for the public good.	Plummer, et al. (2021); RICS (2018)

3.4 Sample Design

The rationale for sampling frame, sampling method, sampling size and target respondent are detailed in the following sections.

3.4.1 Sampling Frame

There are several professions in construction industry, such as Quantity Surveyor, Architect, Contractor and more. However, this study covered those professional community in Malaysian construction industry.

3.4.2 Sampling Method

Based on the purpose of this study, simple random sampling method which is one of the probability sampling methods was applied. Simple random sampling provides samples that are highly representative of the population. This is because each member of population has an equal chance of being involved in the sample (Dudovskiy, 2018).

3.4.3 Sampling Size

The Central Limit Theorem (CLT) is applied to measure the sample size required. CLT stated that the sampling distribution of mean close to a normal distribution as the sample size expands. CLT holds valid only if the sample size is equal to or larger than 30 (Mcleod, 2019; Saunders, Lewis and Thornhill, 2019). Therefore, CLT was applied to this research for comparison of sub-grouping, such as the data competencies level among the practitioners. An estimate of 150 samples is required with consideration of five categories of respondents' attributes.

3.4.4 Target Respondents

In this research, the target respondents included all the Malaysian professional community who currently working in Malaysian construction industry. Those practitioners who are working overseas and/or not working in Malaysian construction industry currently are excluded from this research. This is because the research is limited to Malaysia area and the latest situation in Malaysian construction industry.

3.5 Data Analysis

Collected data were analysed with Cronbach's Alpha Reliability Test, Measure of Central Tendency, Spearman Correlation and pairwise comparison test.

3.5.1 Cronbach's Alpha Reliability Test

The validity of internal consistency of the questionnaire was evaluated by calculating the Cronbach's Alpha value. If the value of Alpha is equal to or greater than 0.7, the survey results are acceptable. (Glen, 2020; Tavakol and Dennick, 2011). Therefore, this test was conducted for testing the reliability of all statements in the questionnaire.

3.5.2 Measure of Central Tendency

Measure of central tendency is one of the descriptive statistics techniques, which is used to define the midpoint or average value of a dataset (Bhandari, 2020). In this study, measurement of central tendency was used to calculate the mean value to define the average data competencies level and frequency of use among practitioners in construction industry.

3.5.3 Spearman Correlation

Spearman correlation is a non-parametric test that is applied to measure the monotonic relationship between two variables (Mohr, Wilson, and Freund, 2022; Mahapatra, 2021). In this research, Spearman correlation was applied to test the relationship between respondents' self-assessed data competence level and data competencies in use, and positive correlation coefficient with p-value minor than 0.05 will be focused. Table 3.8 shows the interpretations of positive correlation coefficient (Akoglu, 2018).

Table 3.8: Interpretations of Positive Correlation Coefficient

Correlation Coefficient	Relationship Between the Variables
1	Perfect
≥0.7	Strong
≥0.4	Moderate
≥0.1	Weak
0	None

3.5.4 Pairwise Comparison

In this study, pairwise comparison was applied to determine the significant differences in the data competencies level and frequency of use with the respondent’s attributes in pairs of sample groups. In this test, 0.05 is used for the major p-value. There are two hypotheses are generated for this test as follow:

(i) Null hypothesis (H_0): There are the same between the pair of sample groups in data competencies self-assessment and data competence in use in construction industry. If $p > 0.05$, H_0 is failed to reject.

(ii) Alternative hypothesis (H_1): There are differences between the pair of sample groups in data competencies self-assessment and data competence in use in construction industry. If $p \leq 0.05$, H_1 is failed to reject.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

The collected primary data was analysed and presented in this chapter, including attributions of respondents who participate in the questionnaire survey, the result of statistic tests conducted such as Cronbach's Alpha Reliability Test and Spearman Correlation. The statically significant results are highlighted and the findings are discussed in the following section.

4.2 Respondent's Background

There was a total of 116 sets of questionnaires were received and collected. Table 4.1 summarised the attributions of respondents. More than half (64.6%) of the respondents are working in development (33.6%) and consultation business (31.0%). The highest professional group is quantity surveyor (29.3%), followed by architect and engineer with 26.7% respectively. 30.2% of respondents have the working experience of more than 1 year but less than 3 years, which is the highest group among the different working experience. The age group below 25 years (37.1%) is the highest among the others.

Table 4.1: Respondent's Attributions (N=116)

General Information	**Categories**	**Frequency (n)**	**Percentage (%)**
Business Activities	Consultation	36	31.0
	Development	39	33.6
	Construction Business	35	30.2
	Construction Manufacturers/ Distributors	6	5.2

Table 4.1 (Continued)

General Information	**Categories**	**Frequency (n)**	**Percentage (%)**
Profession	Architect	31	26.7
	Engineer	31	26.7
	Quantity Surveyor	34	29.3
	Construction/Project Manager	19	16.4
	Others	1	0.9
Working Experience	Less than 1 year	33	28.4
	More than 1 year but less than 3 years	35	30.2
	More than 3 years but less than 5 years	13	11.2
	More than 5 years but less than 10 years	33	28.4
	More than 10 years	2	1.7
Age Range	Below 25 years	43	37.1
	26 – 30 years	34	29.3
	31 – 40 years	31	26.7
	41 – 50 years	8	6.9
	Above 51 years	0	0

4.3 Reliability Analysis

The results of calculated Cronbach's Alpha value for data competencies level (Section A) and frequency of use (Section B) are depicted in Table 4.2 and Table 4.3. Overall, the Cronbach's Alpha values for both Section A and Section B are greater than 0.95, as well as all the sub-categorises under both sections. This result shows that the related statements used in the following analysis are internally consistent.

Table 4.2: Cronbach's Alpha Value of Reliability Test in Section A

Questions	Number of Items	Cronbach's Alpha Value
Section A: Data Competencies Level	101	0.994
A1. Data Fundamental	17	0.980
A2. Data Generating	13	0.977
A3. Data Filtering	16	0.982
A4. Data Analysis	20	0.984
A5. Data Modelling	15	0.983
A6. Data Security & Ethics	20	0.982

Table 4.3: Cronbach's Alpha Value of Reliability Test in Section B

Questions	Number of Items	Cronbach's Alpha Value
Section B: Frequency of Use	101	0.992
B1. Data Fundamental	17	0.964
B2. Data Generating	13	0.960
B3. Data Filtering	16	0.969
B4. Data Analysis	20	0.980
B5. Data Modelling	15	0.975
B6. Data Security & Ethics	20	0.974

4.4 Overall Self-Assessed Competencies Level and Data Competence in Use

Table 4.4 shows the overall self-assessed data competencies level and data competence in use. The personnel in Malaysian construction industry self-assessed Data Security and Ethics as the highest competence (mean = 7.16) among the six competence categories. However, Data Modelling is rated as the lowest (mean = 6.34) among the six different competence categories. Data Security and Ethics is the most frequent competence (mean = 5.15) in used whereas Data Modelling remains as most rarely applied (mean = 4.55) in the construction industry.

Table 4.4: Overall Self-Assessed Data Competencies Level and Data Competence in Use (N= 116)

Data Competencies	**Competencies Level**	**Frequency of Use**
	Mean	**Mean**
Data Fundamental	6.91	5.04
Data Generating	6.52	4.76
Data Filtering	6.73	4.75
Data Analysing	6.61	4.76
Data Modelling	6.34	4.55
Data Security and Ethics	7.16	5.15

4.5 Correlation of Self-Assessed Data Competencies Level and Data Competence in Use

Correlation test was conducted to find out the relationships between the respondents' self-rated data competencies level and the data competencies actually in use. Table 4.5 reveals that all the self-assessment of data competencies and data competencies in practice are in good relationship as correlation coefficients are greater than 0.6 when compared to the same data competence categories, except for self-assessment of Data Fundamental and Data Fundamental in practice as the correlation coefficient is minor than 0.5.

When comparing different data competence categories, self-assessment of Data Filtering and Data Generating in used are having high correlation as the correlation coefficient is 0.685. Besides that, self-assessed Data Modelling has a high correlation with Data Filtering and Data Analysing in practice which the correlation coefficients are 0.675 and 0.659 respectively. Hence, Data Modelling and Data Filtering emerged as two important data competencies because they are highly correlated with more than one competence.

Table 4.5: Correlation Coefficient Between Self-Assessed Data Competence Level and Data Competence in Use

Competencies Level	**Frequency of Use**					
	B1	**B2**	**B3**	**B4**	**B5**	**B6**
Data Fundamental	**0.402**	0.470	0.411	0.366	0.386	0.454
Data Generating	0.480	**0.629**	0.563	0.458	0.492	0.400
Data Filtering	0.541	0.685	**0.635**	0.601	0.566	0.501
Data Analysing	0.472	0.610	0.572	**0.646**	0.540	0.441
Data Modelling	0.479	0.610	0.675	0.659	**0.651**	0.420
Data Security and Ethics	0.520	0.578	0.502	0.518	0.421	**0.604**

Remark: B1 = Data Fundamental; B2 = Data Generating; B3 = Data Filtering; B4 = Data Analysing; B5 = Data Modelling; B6 = Data Security and Ethics
Correlation is significant at the 0.01 level (2-tailed)

4.6 Comparison of Self-Assessed Data Competence Level and Competence in Use Between Different Business Activities

There are three business activities are having adequate number of samplers for analysis, which are Consultation, Development and Construction Business. The following sections presented the comparison of self-assessed data competence level and data competence in use among business activities.

4.6.1 Comparison of Self-Assessed Data Competence Level Among Business Activities

Table 4.6 reveals that Data Security and Ethics is ranked first in all business activities, followed by Data Fundamental. Besides that, Data Analysing is ranked third in Consultation (mean = 6.73), while Data Filtering is ranked third in Development (mean = 6.96) and Construction (mean = 6.72).

Table 4.6: Average of Self-Assessed Data Competence Level Among Business Activities

Business Activities	Mean of Data Competence Level					
	A1	**A2**	**A3**	**A4**	**A5**	**A6**
Consultation	6.84	6.39	6.61	6.73	6.48	7.20
Development	6.96	6.70	6.96	6.85	6.36	7.26
Construction Business	6.98	6.54	6.72	6.37	6.28	7.17

Remark: A1 = Data Fundamental; A2 = Data Generating; A3 = Data Filtering; A4 = Data Analysing; A5 = Data Modelling; A6 = Data Security and Ethics

Pairwise comparison was conducted for comparing self-assessed data competence level of business activities in pairs. Table 4.7 reveals that there was a significant difference between the group Consultation and Development, which developers are more competent in Data Fundamental compared to those providing consultation services, especially in A1j "*Recognising the benefits of data to inform how to collect and manage it using both established and novel methods*".

Table 4.7: Comparison Between Consultation and Development in Self-Assessed Data Competence Level

Rejected Null Hypothesis	Median		Sig.
	Consultation	**Development**	
A1j	7	8	0.010

4.6.2 Comparison of Data Competence in Use Among Business Activities

Table 4.8 indicates that Data Security and Ethics is the most frequently used by development and construction business. However, Data Generating is the most frequently used by consultation business. For all three different businesses, Data Fundamental is the second frequent used in industry. Data Security and Ethics is the third frequent used by consultation business while Data Filtering is the third frequent used by developer. For construction business, Data Generating is the third frequent used in industry.

Table 4.8: Average of Data Competence in Use Among Business Activities

Business Activities	Mean of Frequency of Use					
	B1	**B2**	**B3**	**B4**	**B5**	**B6**
Consultation	5.17	5.76	4.72	4.76	4.61	5.13
Development	5.06	4.81	4.86	4.92	4.54	5.31
Construction Business	4.93	4.69	4.63	4.55	4.49	5.04

Remark: B1 = Data Fundamental; B2 = Data Generating; B3 = Data Filtering; B4 = Data Analysing; B5 = Data Modelling; B6 = Data Security and Ethics

4.7 Comparison of Self-Assessed Data Competence Level and Competence in Use Between Different Professions

There are three professions are having adequate number of samplers for analysis, which including Architect, Engineer and Quantity Surveyor. Comparison of self-assessed data competence level and competence in use among different groups of professions are conducted in the following sections.

4.7.1 Comparison of Self-Assessed Data Competence Level Among Professions

Table 4.9 shows that among three of the professions, Data Security and Ethics is the most competent among the six data competencies. Data Fundamental is ranked second for Architect and Quantity Surveyor, while Data Filtering is ranked second for Engineer. The third important data competence ranked by Architect and Engineer is Data Analysing, whereas for Quantity Surveyor, Data Filtering is the third important data competence.

Table 4.9: Average of Self-Assessed Data Competencies Level Among Professions

Profession	Mean of Data Competence Level					
	A1	**A2**	**A3**	**A4**	**A5**	**A6**
Architect	7.20	6.75	6.96	7.02	6.75	7.30
Engineer	6.55	6.47	6.83	6.60	6.39	7.41
Quantity Surveyor	6.91	6.28	6.56	6.51	6.24	7.03

Remark: A1 = Data Fundamental; A2 = Data Generating; A3 = Data Filtering; A4 = Data Analysing; A5 = Data Modelling; A6 = Data Security and Ethics

Pairwise comparison was conducted for comparing self-assessed data competence level among professions in pairs. Table 4.10 reveals that Architects are more competent in Data Fundamental compared to Engineers, especially in A1h "*Articulating the value of data to others in a way that is easy to comprehend e.g. not using technical jargon*".

Table 4.10: Comparison of Self-Assessed Data Competence Level Between Architects and Engineers

Rejected Null Hypothesis	**Median**		**Sig.**
	Architect	**Engineer**	
A1h	8	7	0.004

Table 4.11 reveals Quantity Surveyors are more competent in Data Fundamental such as A1a "*Showing an understanding of different data terms, types and sources*" and A1h "*Articulating the value of data to others in a way that is easy to comprehend e.g. not using technical* jargon". However, Engineers are more competent in Data Security and Ethics compared to Quantity Surveyors, especially in A6r "*Promoting continuous assessment of cyber security risk and resilience by ensuring penetration testing is performed to ensure business continuity and legal obligations are met*" and A6t "*Advocating for individual awareness of data privacy measures and promotes ethical considerations that puts control back in the hand of the individual for the public good*".

Table 4.11: Comparison of Self-Assessed Data Competence Level Between Quantity Surveyor and Engineers

Rejected Null Hypothesis	**Median**		**Sig.**
	Quantity Surveyor	**Engineer**	
A1a	8	7	<0.001
A1h	8	7	0.012
A6r	7	8	0.010
A6t	6	8	0.004

Table 4.12 reveals that Architects are more competent in Data Security and Ethics compared to Quantity Surveyors, especially in A6r "*Promoting continuous assessment of cyber security risk and resilience by ensuring*

penetration testing is performed to ensure business continuity and legal obligations are met" and A6t "*Advocating for individual awareness of data privacy measures and promotes ethical considerations that puts control back in the hand of the individual for the public good*".

Table 4.12: Comparison of Self-Assessed Data Competence Level Between Quantity Surveyor and Architect

Rejected Null Hypothesis	**Median**		**Sig.**
	Quantity Surveyor	**Architect**	
A6r	7	8	0.019
A6t	6	7	0.034

4.7.2 Comparison of Data Competence in Use Among Professions

Table 4.13 reveals Data Security and Ethics is most frequently used for all professions, followed by Data Fundamental. Data Generating is the third frequent used by Architects, Data Filtering is the third frequent used by Engineers, whereas Data Analysing is the third frequent used by Quantity Surveyors in industry.

Table 4.13: Average of Data Competence in Use Among Professions

Profession	**Mean of Frequency of Use**					
	B1	**B2**	**B3**	**B4**	**B5**	**B6**
Architect	5.19	5.13	5.09	5.04	5.04	5.34
Engineer	5.18	4.66	4.77	4.74	4.42	5.23
Quantity Surveyor	4.87	4.53	4.49	4.67	4.46	5.10

Remark: B1 = Data Fundamental; B2 = Data Generating; B3 = Data Filtering; B4 = Data Analysing; B5 = Data Modelling; B6 = Data Security and Ethics

Pairwise comparison was conducted for comparing data competencies in use among professions in pairs. Table 4.14 reveals Data Analysing is more frequently used by Architects compared to Engineers, especially in B4k "*Evaluating the quality of data in relation to fit for purpose (business need)*" and B4p "*Modelling data lifecycle processes that consider internal and external events, actions and connection points*".

Table 4.14: Comparison of Data Competence in Use Between Architect and Engineer

Rejected Null Hypothesis	Median		Sig.
	Architect	**Engineer**	
B4k	6	5	0.037
B4p	6	5	0.018

Table 4.15 indicates that, compared to Quantity Surveyors, Architects are more frequently used Data Analysing in industry, such as B4k "*Evaluating the quality of data in relation to fit for purpose (business need)*" and B4p "*Modelling data lifecycle processes that consider internal and external events, actions and connection points*".

Table 4.15: Comparison of Data Competence in Use Between Architect and Engineer

Rejected Null Hypothesis	Median		Sig.
	Quantity Surveyor	**Architect**	
B4k	4	6	0.009
B4p	4	6	0.037

4.8 Comparison of Self-Assessed Data Competence Level and Data Competence in Use Among Different Working Experiences

There are three working experience groups are having adequate number of samplers for analysis, which including less than 1 year, more than 1 year but less than 3 years, and more than 5 years but less than 10 years. Comparison of self-assessed data competence level and data competence in use between different groups of working experiences are discussed subsequently.

4.8.1 Comparison of Self-Assessed Data Competence Level Among Working Experiences

Table 4.16 shows that Data Security and Ethics is the most important data competence for all working experience groups, followed by Data Fundamental. Data Filtering is the third important data competence among the different working experience groups, except for those with less than 1 year of experience, for whom the third important data competence is Data Modelling.

Table 4.16: Average of Self-Assessed Data Competencies Level Among Working Experiences

Working Experiences	Mean of Data Competence Level					
	A1	**A2**	**A3**	**A4**	**A5**	**A6**
Less than 1 year	6.43	6.09	6.28	6.21	5.92	6.81
More than 1 year but less than 3 years	7.06	6.73	6.95	6.81	6.56	7.26
More than 5 years but less than 10 years	7.17	6.69	6.84	6.66	6.27	7.34

Remark: A1 = Data Fundamental; A2 = Data Generating; A3 = Data Filtering; A4 = Data Analysing; A5 = Data Modelling; A6 = Data Security and Ethics

Pairwise comparison was conducted for comparing self-assessed data competence level among working experiences in pairs. Table 4.17 reveals those more than 1 year but less than 3 years of working experience are more competent in Data Modelling especially in A5b "*Recognising the semantics and related taxonomies of the industry and can classify data*" and A5c "*Showing awareness of different reference data models that exist within the organisation and how they relate to business processes*" compared to those less than 1 year of working experience.

Table 4.17: Comparison of Self-Assessed Data Competence Level Between Working Experiences Less Than 1 Year and More Than 1 Year but Less Than 3 Years

Rejected Null Hypothesis	Median		Sig.
	Less Than 1 Year	**More Than 1 Year but Less Than 3 Years**	
A5b	6	7	0.006
A5c	6	7	0.008

Table 4.18 indicates that those working experience more than 1 year but less than 3 years more competent in Data Security and Ethics compared to those working experience more than 5 years but less than 10 years, especially in A6d "*Understanding the regulatory and ethical importance of data privacy*".

Table 4.18: Comparison of Self-Assessed Data Competence Level Between Working Experiences Less Than 1 Year and More Than 1 Year but Less Than 3 Years

Rejected Null Hypothesis	Median		Sig.
	More Than 1 Year but Less Than 3 Years	**More Than 5 Years but Less Than 10 Years**	
A6d	8	7	0.006

4.8.2 Comparison of Data Competence in Used Among Working Experiences

Table 4.19 indicates Data Security and Ethics is the most frequently used by all the different working experience groups, followed by Data Fundamental. For those working experience less than 1 year, Data Filtering is the third frequent used in industry. Data Analysing is the third frequent used by those working experience more than 1 year but less than 3 years, while Data Generating is the third frequent used by those working experience more than 5 year but less than 10 years.

Table 4.19: Average of Data Competence in Used Among Working Experiences

Organisation Activities	Mean of Frequency of Use					
	B1	**B2**	**B3**	**B4**	**B5**	**B6**
Less than 1 year	4.84	4.54	4.67	4.59	4.28	5.03
More than 1 year but less than 3 years	5.15	4.87	4.87	5.06	4.84	5.35
More than 5 years but less than 10 years	5.15	4.82	4.67	4.54	4.38	5.07

Remark: B1 = Data Fundamental; B2 = Data Generating; B3 = Data Filtering; B4 = Data Analysing; B5 = Data Modelling; B6 = Data Security and Ethics

Pairwise comparison was conducted for comparing data competence in use among working experience. Table 4.20 and Table 4.21 indicates that those with less than 1 year of work experience are more frequently used Data Filtering such as "*Recognising the types of data needed to generate insights and support* *decision-making, and decides on the best principles to design/follow when transforming and analysing large and varied data sets*" (B3k) compared to those with more than 5 years but less than 10 years of work experience.

Data Analysing is more frequently used by those with less than 1 year of work experience compared to those with more than 5 years but less than 10 years of work experience including "*Suggesting improvements to data governance and process to improve quality*" (B4l) and "Predicting potential data quality risks and issues with lifecycles and suggest mitigation" (B4o).

Table 4.20: Comparison of Data Competence in Use Between Working Experiences Less Than 1 Year and More Than 5 Years but Less Than 10 Years

Rejected Null Hypothesis	**Median**		**Sig.**
	Less Than 1 Year	**More Than 5 Years but Less Than 10 Years**	
B3k	5	4	0.003
B4l	5	4	0.008
B4o	5	4	0.002

Table 4.21: Comparison of Data Competence in Use Between Working Experiences More Than 1 Year but Less Than 3 Years and More Than 5 Years but Less Than 10 Years

Rejected Null Hypothesis	**Median**		**Sig.**
	More Than 1 Year but Less Than 3 Years	**More Than 5 Years but Less Than 10 Years**	
B3k	5	4	<0.001
B4l	6	4	<0.001
B4o	5	4	<0.001

4.9 Comparison of Self-Assessed Data Competence Level and Data Competence in Used Among Different Age Range

There are three groups of age range are having adequate number of samples for analysis, which including below 25 years, 26 to 30 years, and 31 to 40 years. The following sections discussed the comparison of self-assessed data competence level and data competence in use among different groups of age range.

4.9.1 Comparison of Self-Assessed Data Competence Level Among Age Range

Table 4.22 reveals that for all groups of age range, Data Security and Ethics is the most competent among the six data competencies, followed by Data Fundamental and Data Filtering.

Table 4.22: Average of Self-Assessed Data Competencies Level Among Age Range

Age Range	**Mean of Data Competence Level**					
	A1	**A2**	**A3**	**A4**	**A5**	**A6**
Below 25 years	6.64	6.33	6.64	6.52	6.26	7.14
26 – 30 years	6.92	6.61	6.70	6.59	6.36	7.00
31 – 40 years	7.12	6.76	7.01	6.89	6.65	7.42

Remark: A1 = Data Fundamental; A2 = Data Generating; A3 = Data Filtering; A4 = Data Analysing; A5 = Data Modelling; A6 = Data Security and Ethics

4.9.2 Comparison of Data Competence in Used Among Age Range

Table 4.23 indicates Data Security and Ethics is the most frequently used by practitioners who below 25 years and 26 to 30 years, but Data Fundamental is the most frequently used by those are 31 to 40 years. For those under 25 years and 26 to 30 years, Data Fundamental is the second frequent used, whereas for those 31 to 40 years, Data Security and Ethics is the second frequent used. The third frequent used by those under 25 years is Data Filtering. For those 26 to 30 years the third frequent use is Data Analysing. Data Generating is the third frequent used by those 31 to 40 years in industry.

Table 4.23: Average of Data Competence in Use Among Age Range

Age Range	**Mean of Frequency of Use**					
	B1	**B2**	**B3**	**B4**	**B5**	**B6**
Below 25 years	5.04	4.75	4.88	4.78	4.55	5.28
26 – 30 years	4.94	4.71	4.60	4.84	4.60	5.05
31 – 40 years	5.17	4.83	4.81	4.71	4.52	5.08

Remark: B1 = Data Fundamental; B2 = Data Generating; B3 = Data Filtering; B4 = Data Analysing; B5 = Data Modelling; B6 = Data Security and Ethics

Pairwise comparison was conducted for comparing data competence in use among age range. Table 4.24 indicates Data Security and Ethics is more frequently used by practitioners who below 25 years compared to those 26 to 30 years, especially in B6l "*Analysing data on risk and perform steps to manage crisis issues and develop and implement continuity and recovery plans*".

Table 4.24: Comparison of Data Competence in Use Between Age Range Below 25 Years and 26 to 30 Years

Rejected Null Hypothesis	**Median**		**Sig.**
	Below 25 Years	**26 – 30 Years**	
B6l	6	5	0.021

Table 4.25 reveals those under 25 years are more frequently used Data Security and Ethics in industry compared to those 31 to 40 years, such as B6l "*Analysing data on risk and perform steps to manage crisis issues and develop and implement continuity and recovery plans*" and B6n "*Defining best practice for data standards and protocols and sets tasks and targets in relation to legal compliance, governance procedures and business integrity*".

Table 4.25: Comparison of Data Competence in Use Between Age Range Below 25 Years and 31 to 40 Years

Rejected Null Hypothesis	**Median**		**Sig.**
	Below 25 Years	**31 – 40 Years**	
B6l	6	5	0.010
B6n	6	5	0.003

4.10 Discussion

The results revealed that Data Security and Ethics, Data Fundamental and Data Filtering are the most important data competence in construction industry, and these are discussed in the following section. Data competence among different business activities, professions, working experiences and age range are illustrated in the subsequent sections.

4.10.1 Overall Data Competence Level and Frequency of Use

The results indicate that Data Security and Ethics is the most important data competencies and is the most frequently used by practitioners. Self-assessment of Data Security and Ethics is highly correlated to Data Security and Ethics in practice. This is because most of the documents and information in construction companies are private and confidential, such as contract agreements, tender bidding prices and personal data (Berawi, 2018). Moreover, the study conducted by Plummer, et al. (2021) found that Data Security and Ethics are well established but looking for further development by 34% of respondents.

Data Fundamental is the second important in self-assessed data competence level and data competence in use to the practitioners. This is because practitioners must have the ability to use information and communication technology (ICT) for generating and sharing data with others to ensure the work done smoothly (Fleaca and Stanciu, 2019; van Laar, et al., 2019). There is similar research in Netherlands which 80% of respondents have successfully access to Internet and can easily get online information (van Laar, et al., 2019).

Data Filtering is ranked third in self-assessment of data competence level and data competence in use among the six data competencies. Furthermore, Data Filtering is highly correlated with more than one data competence. Therefore, Data Filtering is important for construction practitioners to identify and recognise the quality of data for decision making or estimating. According to Plummer, et al. (2021), half of the respondents are looking to make some improvement in Data Filtering.

4.10.2 Data Competence Among Different Business Activities

For all business activities, Data Security and Ethics is the most important data competence, followed by Data Fundamental. By conducting pairwise comparisons, A1j "*Recognising the benefits of data to inform how to collect and manage it using both established and novel methods*" is the only statement in Data Fundamental which developers are significantly more competent than those providing consultation services. On the other hand, Data Generating is the most frequently used by those providing consultation services, while Data

Security and Ethics is the most frequently used by developers and those in construction business.

4.10.3 Data Competence Among Professions

The results revealed that Data Security and Ethics is the most important data competence for all the professions, followed by Data Fundamental. However, Quantity Surveyor is the least competent in Data Security and Ethics compared to Engineers and Architects, especially in A6r "*Promoting continuous assessment of cyber security risk and resilience by ensuring penetration testing is performed to ensure business continuity and legal obligations are met*" and A6t "*Advocating for individual awareness of data privacy measures and promotes ethical considerations that puts control back in the hand of the individual for the public good*". Engineer is the least competent in Data Fundamental compared to Quantity Surveyor and Architects, especially in A1h "*Articulating the value of data to others in a way that is easy to comprehend e.g. not using technical jargon*". Furthermore, Data Analysing is the third frequent used by Quantity Surveyors in industry. However, Architects are more frequently used Data Analysing compared to Quantity Surveyors and Engineers in B4k "*Evaluating the quality of data in relation to fit for purpose (business need)*" and B4p "*Modelling data lifecycle processes that consider internal and external events, actions and connection points*".

Hence, Architects are competent in Data Security and Ethics and Data Fundamental, Engineers are least competent in Data Fundamental, while Quantity Surveyors are least competent in Data Security and Ethics. Moreover, Architects are more frequently used Data Analysing in industry compared to Quantity Surveyors and Engineers.

4.10.4 Data Competence Among Working Experience

Data Filtering is the third important data competence among the groups, except those with less than 1 year of experience rated Data Modelling as the third important. By comparing in Data Modelling (A5) and Data Security and Ethics (A6), those more than 1 year but less than 3 years of working experience are more competent in A5b "*Recognising the semantics and related taxonomies of the industry and can classify data*", A5c "*Showing awareness of different* *reference data models that exist within the organisation and how they relate to business processes*”, and A6d “*Understanding the regulatory and ethical importance of data privacy*”.

For those working experience less than 1 year, Data Filtering is the third frequent used in industry. Data Analysing is the third frequent used by those working experience more than 1 year but less than 3 years, while Data Generating is the third frequent used by those working experience more than 5 years but less than 10 years. As the comparison results in Data Filtering (B3) and Data Analysing (B4) statement B3k “*Recognising the types of data needed to generate insights and support decision-making, and decides on the best principles to design/follow when transforming and analysing large and varied data sets*”, B4l “*Suggesting improvements to data governance and process to improve quality*” and B4o “*Predicting potential data quality risks and issues with lifecycles and suggest mitigation*”, those working experience less than 3 years are more frequently used in industry compared to those working experience more than 5 years but less than 10 years.

In short, practitioners whose working experience more than 1 year but less than 3 years are more competent than those working experience less than 1 year in Data Modelling and more competent than those working experience more than 5 years but less than 10 years in Data Security and Ethics. Moreover, Data Filtering and Data Analysing are frequently used by those working experience of less than 3 years.

4.10.5 Data Competence Among Age Range

Table 4.24 indicates Data Security and Ethics is the most frequently used by practitioners who are below 25 years and 26 to 30 years, but Data Fundamental is the most frequently used by those are 31 to 40 years. By comparing the age range in Data Security and Ethics statement B6l “*Analysing data on risk and perform steps to manage crisis issues and develop and implement continuity and recovery plans*”, practitioners under 25 years are more frequently used Data Security and Ethics in industry compared to those 26 to 40 years.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

Research objectives achievements and research implications are discussed in the following sections. Furthermore, research limitations and recommendations are elaborated in the subsequent sections.

5.2 Accomplishment on Research Objectives

This research aims to explore the data competencies and determine any mismatch between the competencies possessed by and expected from the construction industrial practitioners. The aim is achieved through the accomplishments of the three research objectives as justified in the following sections

5.2.1 Objective 1: To Explore the Data Competence Requirements in Construction Industry

A total of 14 data competencies were found during the literature reviewed. The key references are data competencies included in the Malaysia Qualification Framework (MQF) published by Malaysia Qualification Agency (MQA), skills and competency published by Centre for Digital Built Britain (CDBB), and data management included in the mandatory competence of Assessment of Professional Competency (APC) of Royal Institution of Chartered Surveyors (RICS). These 14 competencies were used to synthesis six data competencies, namely Data Fundamental, Data Generating, Data Filtering, Data Analysing, Data Modelling, as well as Data Security and Ethics in this study. Data Security and Ethics, Data Fundamental and Data Filtering are the top three competence acquired and mostly applied by practitioners in construction industry.

5.2.2 Objective 2: To Evaluate the Overall Data Competencies of the Construction Industry Practitioners

A questionnaire survey consisting of 101 statements formulated from the six data competencies was used to collect the empirical information on the data competencies of the construction practitioners. The results of 116 respondents revealed that Data Security and Ethics is ranked first in both data competence self-assessment and frequency of use while Data Modelling is ranked last in both data competence self-assessment and frequency of use. Moreover, Data Modelling and Data Filtering emerged as two important data competencies because they are highly correlated with more than one competence.

5.2.3 Objective 3: To Analyse the Data Competencies Among Different Construction Practitioners

This study also revealed that those involved in development activities are more competent in Data Fundamental compared to those providing consultation services. Architects are competent in Data Security and Ethics and Data Fundamental, Engineers are least competent in Data Fundamental, while Quantity Surveyors are least competent in Data Security and Ethics. Moreover, Architects are more frequently used Data Analysing in industry compared to Quantity Surveyors and Engineers. Practitioners whose working experience more than 1 year but less than 3 years are more competent in Data Modelling and Data Security and Ethics. Data Filtering and Data Analysing are frequently used by those working experience less than 3 years. Practitioners under 25 years are more frequently used Data Security and Ethics in industry.

5.2.4 Conclusion

In short, this research revealed that Malaysian construction practitioners are more competent in Data Security and Ethics and more frequent application is in Data Security and Ethics.

5.3 Research Implications

There are few implications of this study. The following illustrates these implications in three aspects, namely academic and research, industrial application, as well as regulatory policy developments.

The results revealed that Data Security and Ethics are most frequent applied data competencies in the industry. Therefore, the academic institution should have emphasised this in the course curriculum. Moreover, Data Modelling are being rated as the least competent. Thus, higher education providers should look at ways to enhance the data competencies in this aspect.

As a result, Architects are competent in Data Security and Ethics and Data Fundamental, Engineers are least competent in Data Fundamental, whereas Quantity Surveyors are least competent in Data Security and Ethics. Thus, the training and retraining of the professional institution and the company concerned should target these aspects of knowledge respectively.

Since Data Security and Ethics has been identified as the most frequently practiced by the industrial practice, the regulatory body should always update and develop up-to-date policy, rule and regulation for the proper governance of data management.

5.4 Research Limitations

Although all the results reported in this research are meeting the statistic requirements for their significant study, some of the groups are below 30 respondents such as construction manufacturers/distributors, construction/project managers, working experience more than 3 years but less than 5 years and more than 10 years, as well as age range 41 to 50 years and above 51 years are inadequate to represent their respective group for pairwise comparisons. These may discount the validity of the conclusions. Besides that, there are some specific terms applied in the questionnaire. Therefore, respondents may misunderstand the meaning of specific terms and affecting the accuracy of the results.

5.5 Research Recommendations

This research is worth to continue by collecting the samples for the groups highlighted in the previous section. In addition, a qualitative inquiry into the underlying factors influenced the outcome of this research will provide more insights into data competencies among the construction industry practitioners.

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APPENDICES

Appendix A: Questionnaire

A COMPARISON OF DATA COMPETENCIES AMONG PRACTITIONERS IN THE MALAYSIAN CONSTRUCTION INDUSTRY

Dear Sir/Madam,

I am a final year undergraduate student currently pursuing Bachelor of Science (Honours) Quantity Surveying in Universiti Tunku Abdul Rahman (UTAR), Lee Kong Chian Faculty of Engineering and Science (LKC FES). You are invited to take part in a survey regarding "A Comparison of Data Competence Among Practitioners in the Malaysia Construction Industry". It would be appreciated if you could spare around 10 minutes to answer this questionnaire survey. Participation is voluntary and you may refuse to participate at any time. All the data collected will be kept private and confidential and will be strictly used for academic purposes only. If you have any questions or further enquiries, please do not hesitate to contact me at ailing227@1utar.my.

Thank you for your participation.

Yours faithfully,
Lim Ai Ling
Bachelor of Science (Honours) Quantity Surveying
Universiti Tunku Abdul Rahman

Section A) Self-Assessment – Data Competencies

Please rate yourself in the following competencies.

(1=Fundamental Awareness; 10=Expert)

1. **Data Fundamental**	1	2	3	4	5	6	7	8	9	10
a. Showing an understanding of different data terms, types and sources.										
b. Using established methods to collect, store and share data e.g. having a single source of truth for a digital file.										
c. Showing awareness of what good quality data looks like and how it informs decision-making.										
d. Demonstrating a strong understanding of the value of data.										
e. Demonstrating the ability to manage different types of data according to its qualities.										
f. Using knowledge of data to help others in the team to collect and store it efficiently.										
g. Generating good quality data to support their decision making.										
h. Articulating the value of data to others in a way that is easy to comprehend e.g. not using technical jargon.										
i. Guiding others in understanding of data terms, types and sources.										

j. Recognising the benefits of data to inform how to collect and manage it using both established and novel methods.										
k. Overseeing the use of good quality data to support their own and other's decisions, including the types and quality of data needed and questions being addressed.										
l. Encouraging others to see the value in data by promoting data sharing and an open data culture										
m. Challenging existing definitions of data terms, types and sources and write new definitions where applicable.										
n. Demonstrating knowledge of methods and tools with the ability to present new data collection and storage methods coherently.										
o. Making critical decisions by understanding and synthesising high volume, high velocity or complex heterogenous data and is able to spot data quality issues and recommend improvements.										
p. Enabling and coach others to make data-driven decisions.										
q. Consistently defining new uses and value from data and is able to articulate the steps others need to take to generate increased value from data.										
2. Data Generating	1	2	3	4	5	6	7	8	9	10

a. Understanding the basic principles of user research and experience in relation to the psychological interaction between humans and data and technology										
b. Showing an awareness of how testing and reporting on user experience can add data value.										
c. Understanding the importance of user-led design data to support technology adoption.										
d. Using different user research techniques to collect data and elicit needs and build requirements										
e. Undertaking testing and acquires user feedback as data to report on current experiences with design, technology and information										
f. Creating functional design and structure elements from the research data to make interfaces intuitive and engaging.										
g. Using different user research techniques to collect data and elicit needs and build requirements through user flows and wireframes.										
h. Performing Alpha/Beta testing and analyses user testing data results.										
i. Reporting on user experience as data in relation to technology adoption and is able to see trends and pinpoint why some choices are better/worse than others.										

j. Taking a leading role as a designer, overseeing the usability and functionality of technology interfaces from research data, focusing on structure, contrast and accessibility.										
k. Showing a leading authority on user research data and design thinking with the ability to deep dive into user challenges and constraints when adopting technology.										
l. Performing user testing data and analysis at scale and can articulate recommendations to improve and support technology development and adoption across different organisations.										
m. Fully understanding the benefits of good user interface design and develops new and innovative techniques to improve the functionality and increase intuitive and engaging interaction with users.										
3. Data Filtering	1	2	3	4	5	6	7	8	9	10
a. Showing awareness of what good quality data looks like in relation to its ability to be analysed and inform decision-making.										
b. Showing knowledge of mathematical and statistical techniques for analysing data.										
c. Showing awareness of how to use scientific methods to manipulate data when running analyses, including extrapolation and regression.										

d. Having knowledge of different mediums used to convey information and data (e.g. reports, visualisations, dashboards).										
e. Demonstrating the ability to define requirements of good quality data to support their analysis.										
f. Demonstrating experience using statistical, practical and ethical methods to analyse data across different data sets.										
g. Demonstrating the ability to follow data modelling principles when transforming and analysing data and can do so with different data sets.										
h. Demonstrating the ability to draw insight from data in the form of visual communication that users are receptive to.										
i. Actively engaging others to build an understanding on the quality requirements of data being produced and analysed and how this can enable better decision-making.										
j. Using statistical, practical and ethical methods to design and enhance algorithms and has knowledge of how algorithms can be made scalable across various data sets.										
k. Recognising the types of data needed to generate insights and support decision-making, and decides on the best principles to design/follow when transforming and analysing large and varied data sets.										

l. Actively using a range of different data visualisation and sense-making techniques to present trends and inform decision making.										
m. Championing the impact good quality data has on analytics and intelligence and helps process owners and modellers understand the standards for data within their part of the organisation.										
n. Overseeing the design of algorithms, evaluating and championing ethics and advising on how they can be resiliently scaled across large data sets.										
o. Using domain knowledge and industry experience to inform and influence the types of data and analysis methods that should be used to address business and industry needs.										
p. Advising on best practice data visualisation methods to present new evidence as well as being able to evaluate the data quality and value of that evidence.										
4. Data Analysing	1	2	3	4	5	6	7	8	9	10
a. Defining the purpose of data lifecycle management and explain how it may positively impact the quality of data.										
b. Defining the principles of process data modelling including the 'as-is' and 'to-be' states and how this is presented using workflow design.										

c. Knowing what good data looks like from understanding data quality dimensions (completeness, uniqueness, consistency, accuracy, timely, validity).										
d. Defining what questions need to be asked to understand data requirements.										
e. Using knowledge of data lifecycle management to view processes in a holistic way, seeing the correlation between data inputs and outputs that occur as a result.										
f. Applying the principles of process data modelling and workflow design to create business process artefacts that show events, action and connection points of a process.										
g. Using knowledge of the data quality dimensions in their everyday practice to validate data.										
h. Researching what data is needed to enable certain decisions to be made and can map these requirements to processes.										
i. Demonstrating the ability to analyse the detail of data lifecycle inputs and outputs and can pinpoint process and data quality issues that affect outputs and suggest improvements.										
j. Demonstrating the ability to model descriptive and perspective cross-functional processes, emphasising quality control for data inputs and outputs and the rationale for process design.										

k. Evaluating the quality of data in relation to fit for purpose (business need).										
l. Suggesting improvements to data governance and process to improve quality.										
m. Demonstrating the ability to influence process data modelling based on information requirements, governance and compliance procedures that must be in place										
n. Advising on best practices for data lifecycle management to improve process and the quality of data outputs.										
o. Predicting potential data quality risks and issues with lifecycles and suggest mitigation.										
p. Modelling data lifecycle processes that consider internal and external events, actions and connection points.										
q. Making critical decisions on process improvements to reduce waste and improve data quality and integration.										
r. Demonstrating the impact fit for purpose data has on decision making and value.										
s. Working with others to set standards, governance and targets for data quality in relation to the purpose it serves.										
t. Inspiring teams to develop process and information requirements with the end in mind, focusing on what decisions need answering and working backwards to map data flows.										

5. **Data Modelling**	1	2	3	4	5	6	7	8	9	10
a. Defining the purpose of data ontologies at a high level in relation to their organisation and industry.										
b. Recognising the semantics and related taxonomies of the industry and can classify data										
c. Showing awareness of different reference data models that exist within the organisation and how they relate to business processes.										
d. Showing insight into the flow of data, including how data travels between systems and how systems are able to share data with one another.										
e. Using knowledge of standard ontologies in relation to their organisation and industry to influence how they distinguish data concepts and their relationships.										
f. Using knowledge of taxonomies to create data models that classify and organise data into hierarchal meaning.										
g. Using knowledge of reference data models to make organisable data models relevant to real world application.										
h. Building data products that can be exposed and integrated with other external systems, such as through Application Programmable Interfaces (APIs).										

i. Demonstrating the ability to write and maintain ontologies using logic and can represent how data concepts relate to each other.										
j. Demonstrating the ability to relate external reference data models to internal data models so that data can be categorised and shared across an organisation and externally with a shared understanding.										
k. Advising on design and data modelling to facilitate better data sharing and interoperability between systems.										
l. Advising on industry wide data ontological development using logic, philosophy, collaboration and industry knowledge.										
m. Advising on the principles of logic and philosophy that apply to taxonomies and uses automation to classify and organise data at scale.										
n. Advising on industry wide reference data models based on industry knowledge of semantics to make data interoperability automated and coherent.										
o. Challenging behaviours that go against data sharing and interoperability and advocates for an open data approach through architecture model design.										
6. Data Security and Ethics	1	2	3	4	5	6	7	8	9	10
a. Adhering to ethical and legal standards and protocols when using data.										

b. Demonstrating an awareness of security, systems and legacy management when performing activities that involve data and technology.										
c. Understanding the purpose of business impact data analysis, crisis management, continuity and recovery plans in relation to IT policy and regulatory requirements.										
d. Understanding the regulatory and ethical importance of data privacy.										
e. Understanding the reasoning behind different ethical and legal standards and protocols that surround data, including its quality and use (including sharing).										
f. Practicing secure methods when collecting and analysing data whilst showing working knowledge of the different security and legacy requirements of different systems.										
g. Performing business impact data analysis and technology risk assessments in relation to IT policy and regulatory requirements.										
h. Practicing good understanding of data privacy by gaining consent to use personal data and/or anonymising data when individuals could be identified.										
i. Authoring internal organisational data ethical and governance standards and protocols.										
j. Acting as the first point of escalation for non-compliance.										

k. Articulating data security and ethical design requirements and recommend measures to ensure systems stay secure.										
l. Analysing data on risk and perform steps to manage crisis issues and develop and implement continuity and recovery plans.										
m. Justifying the use of personal or sensitive data when challenges on business, ethical and legal grounds.										
n. Defining best practice for data standards and protocols and sets tasks and targets in relation to legal compliance, governance procedures and business integrity.										
o. Acting as the final point of escalation for non-compliance.										
p. Actively driving a data secure by design approach to choosing, using and designing technology.										
q. Raising awareness for data and cyber security risks and the role and methods systems can play to prevent them being realised.										
r. Promoting continuous assessment of cyber security risk and resilience by ensuring penetration testing is performed to ensure business continuity and legal obligations are met.										
s. Staying up to date with hacking methods to recommend technology and processes to prevent attacks.										

t. Advocating for individual awareness of data privacy measures and promotes ethical considerations that puts control back in the hand of the individual for the public good.										

Section B) Behaviour - Data Competencies

How frequent do you apply the following competencies in your working life?

1=Never true of me; 2=Rarely true of me; 3=Sometimes true of me; 4=True of me about half the time; 5=Frequently true of me; 6=Almost always true of me; 7=Always true of me

1. **Data Fundamental**	1	2	3	4	5	6	7
a. Showing an understanding of different data terms, types and sources.							
b. Using established methods to collect, store and share data e.g. having a single source of truth for a digital file.							
c. Showing awareness of what good quality data looks like and how it informs decision-making.							
d. Demonstrating a strong understanding of the value of data.							
e. Demonstrating the ability to manage different types of data according to its qualities.							
f. Using knowledge of data to help others in the team to collect and store it efficiently.							
g. Generating good quality data to support their decision making.							
h. Articulating the value of data to others in a way that is easy to comprehend e.g. not using technical jargon.							
i. Guiding others in understanding of data terms, types and sources.							
j. Recognising the benefits of data to inform how to collect and manage it using both established and novel methods.							
k. Overseeing the use of good quality data to support their own and other's decisions, including the types and quality of data needed and questions being addressed.							

l. Encouraging others to see the value in data by promoting data sharing and an open data culture							
m. Challenging existing definitions of data terms, types and sources and write new definitions where applicable.							
n. Demonstrating knowledge of methods and tools with the ability to present new data collection and storage methods coherently.							
o. Making critical decisions by understanding and synthesising high volume, high velocity or complex heterogenous data and is able to spot data quality issues and recommend improvements.							
p. Enabling and coach others to make data-driven decisions.							
q. Consistently defining new uses and value from data and is able to articulate the steps others need to take to generate increased value from data.							
2. Data Generating	1	2	3	4	5	6	7
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d. Using different user research techniques to collect data and elicit needs and build requirements							
e. Undertaking testing and acquires user feedback as data to report on current experiences with design, technology and information							

f. Creating functional design and structure elements from the research data to make interfaces intuitive and engaging.							
g. Using different user research techniques to collect data and elicit needs and build requirements through user flows and wireframes.							
h. Performing Alpha/Beta testing and analyses user testing data results.							
i. Reporting on user experience as data in relation to technology adoption and is able to see trends and pinpoint why some choices are better/worse than others.							
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k. Showing a leading authority on user research data and design thinking with the ability to deep dive into user challenges and constraints when adopting technology.							
l. Performing user testing data and analysis at scale and can articulate recommendations to improve and support technology development and adoption across different organisations.							
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c. Showing awareness of how to use scientific methods to manipulate data when running analyses, including extrapolation and regression.							
d. Having knowledge of different mediums used to convey information and data (e.g. reports, visualisations, dashboards).							
e. Demonstrating the ability to define requirements of good quality data to support their analysis.							
f. Demonstrating experience using statistical, practical and ethical methods to analyse data across different data sets.							
g. Demonstrating the ability to follow data modelling principles when transforming and analysing data and can do so with different data sets.							
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t. Inspiring teams to develop process and information requirements with the end in mind, focusing on what decisions need answering and working backwards to map data flows.							
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f. Using knowledge of taxonomies to create data models that classify and organise data into hierarchal meaning.							
g. Using knowledge of reference data models to make organisable data models relevant to real world application.							

h. Building data products that can be exposed and integrated with other external systems, such as through Application Programmable Interfaces (APIs).							
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e. Understanding the reasoning behind different ethical and legal standards and protocols that surround data, including its quality and use (including sharing).							
f. Practicing secure methods when collecting and analysing data whilst showing working knowledge of the different security and legacy requirements of different systems.							
g. Performing business impact data analysis and technology risk assessments in relation to IT policy and regulatory requirements.							
h. Practicing good understanding of data privacy by gaining consent to use personal data and/or anonymising data when individuals could be identified.							
i. Authoring internal organisational data ethical and governance standards and protocols.							
j. Acting as the first point of escalation for non-compliance.							
k. Articulating data security and ethical design requirements and recommend measures to ensure systems stay secure.							

l. Analysing data on risk and perform steps to manage crisis issues and develop and implement continuity and recovery plans.							
m. Justifying the use of personal or sensitive data when challenges on business, ethical and legal grounds.							
n. Defining best practice for data standards and protocols and sets tasks and targets in relation to legal compliance, governance procedures and business integrity.							
o. Acting as the final point of escalation for non-compliance.							
p. Actively driving a data secure by design approach to choosing, using and designing technology.							
q. Raising awareness for data and cyber security risks and the role and methods systems can play to prevent them being realised.							
r. Promoting continuous assessment of cyber security risk and resilience by ensuring penetration testing is performed to ensure business continuity and legal obligations are met.							
s. Staying up to date with hacking methods to recommend technology and processes to prevent attacks.							
t. Advocating for individual awareness of data privacy measures and promotes ethical considerations that puts control back in the hand of the individual for the public good.							

Section C) Demographic Information

C1 Which of the following best describe the main activity of your organisation?

	Consultation
	Development
	Construction Business
	Construction Manufacturers/Distributors
	Others

C2 Which of the following best describes your profession in construction industry?

	Architect
	Engineer
	Quantity Surveyor
	Construction/Project Manager
	Others

C3 How long have you been in the construction industry?

	Less than 1 year
	More than 1 year but lesser than 3 years
	More than 3 year but lesser than 5 years
	More than 5 year but lesser than 10 years
	More than 10 years

C4 What is your age range?

	Below 25 years
	26 - 30 years
	31 - 40 years
	41 - 50 years
	Above 51 years