EXPLICATING THE INFLUENCE OF ARTIFICIAL INTELLIGENCE (AI) LITERACY ON EMPLOYEE PERFORMANCE

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BY

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DECLARATION

I hereby declare that:

(1) This undergraduate FYP is the end result of my own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Sole contribution has been made by me in completing the FYP.

(4) The word count of this research report is 10976.

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DEDICATION

This research project is lovingly dedicated to:

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whose patient guidance, valuable knowledge, and unwavering support have been instrumental in the successful completion of this research. Her dedication, expertise, and encouragement from the beginning to the end of this journey have made an indelible impact on my academic growth.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AVE	Average Variance Extracted
CR	Composite Reliability
EP	Employee Performance
f^2	Effect Size
H1	Hypothesis 1
H2	Hypothesis 2
H3	Hypothesis 3
H4	Hypothesis 4
HTMT	Heterotrait-Monotrait
ICT	Information and Communication Technologies
M	Sample Mean
MST	Media Synchronicity Theory
p	P-value
PLS-SEM	Partial Least Squares Structural Equation Model
R^2	R-squared
rho_c	Composite Reliability
STDEV	Standard Deviation
TAM	Technology Acceptance Model
TTFT	Task Technology Fit Theory

VIF	Variance Inflation Factor
β	Beta
|O/STDEV|	T Statistics

PREFACE

Artificial intelligence (AI) has rapidly transformed workplace dynamics across industries, reshaping roles, processes, and employee expectations. With organisations increasingly adopting AI technologies, understanding their influence on employee performance has become paramount. While numerous studies explore AI's technological potential, limited research examines how employees' AI literacy, including awareness, usage, evaluation, and ethics, impacts their performance in diverse organisational settings.

This study addresses this gap by exploring the relationship between AI literacy and employee performance. The research aims to provide meaningful insights for organisations striving to enhance productivity and adaptability in the AI-driven era. The findings are expected to benefit both academics and practitioners, contributing to the discourse on AI integration and workforce development.

ABSTRACT

Artificial Intelligence (AI) technology's swift incorporation into the workplace has made AI literacy a crucial skill for workers in several sectors. This study examines how employee performance is affected by AI literacy, with a particular emphasis on four important areas: awareness, usage, evaluation, and ethics. The association between AI literacy and performance results is not well-established, even though AI is often considered in terms of its potential. By investigating the various ways in which AI literacy enhances employee performance, the study closes that knowledge gap and offers insightful information to both academics and businesses. The study utilised a quantitative causal research methodology and collected data from 219 employees across various sectors in Malaysia through the administration of an online survey. The survey evaluated the respondents' perceived influence on employee performance and their level of AI literacy. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used for data analysis to assess the constructs' validity and reliability as well as to validate the suggested relationships. AI literacy is positively influencing employee performance. Employees who actively used and were more aware of AI technologies performed better, which emphasises the need to improve these aspects of AI literacy through focused training programs. In addition, the study emphasises the significance of ethical considerations and careful assessment of AI literacy to optimise their benefits in the workplace. This study adds to the body of knowledge in academia and in real-world applications by providing a thorough framework for comprehending the relationship between AI literacy and employee performance. The knowledge acquired may assist companies in creating AI strategies and employee development plans that are more successful, and it can also advise schools on how to better prepare students for work settings that are driven by AI.

Keywords: Artificial Intelligence (AI), awareness, usage, evaluation, ethics, employee performance

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

Research background, research problem, research questions, research aims, and research relevance are all covered in Chapter 1.

1.1 Research Background

Artificial intelligence (AI) has transformed from a futuristic notion to an essential tool that businesses worldwide are incorporating into their everyday operations in today's quickly changing digital ecosystem. According to Dwivedi et al. (2021) and Peres et al. (2020), the widespread application of AI technology is revolutionising whole sectors by automating repetitive tasks and enabling data-driven decision-making. AI may boost the global economy by up to $15.7 trillion by 2030 and is crucial to a nation's economic growth (PwC, 2018, as cited in Kar et al., 2022). With forecasts that AI may accelerate growth in emerging economies, AI's revolutionary potential is particularly attractive for nations aiming for economic development (Travaly & Muvunyi, 2020, as cited in Mdladla et al., 2024). According to Naidu and Maddala (2024), AI is having a significant influence on many industries, including healthcare, banking, retail, and education. Innovation and economic expansion are made possible by it.

In Malaysia, the government has acknowledged the significance of AI and digital transformation as vital elements of the country's economic growth. AI integration across sectors is being attempted through programs such as the Malaysia Digital Economy Blueprint (MyDIGITAL) (Ng, 2022). That being said, as AI technologies continue to gain traction, workers will need to acquire the skills necessary to use them efficiently. Enhancing employee performance and optimising the advantages of AI in the workplace require AI literacy, which involves understanding AI technologies, evaluating their relevance, applying them in routine activities, and taking ethical considerations into account.

Even while the promise of AI is highly exciting, most conversations tend to ignore the human factor in favour of concentrating just on the technology's capabilities. Even while AI is becoming more and more integrated into daily life and the workplace, much focus is being placed on its capabilities rather than the human-centered design that is necessary for fruitful engagement. The transition from traditional human-computer interfaces to interactions with autonomous, behavior-driven AI systems necessitates addressing human difficulties as technology advances (Rahwan et al., 2019; Kaber, 2018; Xu, 2021, as cited in Xu et al., 2021). Employees are crucial to the successful integration of AI, and an organisation's ability to deploy AI technology effectively has a significant impact on its performance. The purpose of this study is to examine how employee performance and AI literacy connect, particularly in terms of awareness, utilisation, assessment, and ethics. By understanding this connection and how AI literacy enhances performance, creativity, and productivity, organisations can fully utilise AI.

1.1.1 AI Literacy

AI literacy is a collection of skills that allow people to successfully interact and cooperate with AI, critically assess AI technology, and utilise AI as a tool in the office, at home, and online. Other skill sets, such as digital literacy, which is essential for comprehending AI, and data literacy, which intersects with AI, especially in machine learning, are intimately linked to this literacy. Those who engage with AI daily without knowing how to code might benefit from AI literacy since, unlike computational literacy, it does not necessitate programming knowledge (Long & Magerko, 2020). This study views AI literacy as including awareness, usage, evaluation, and ethical considerations which are critical for using AI in the workplace responsibly and efficiently.

1.1.2 Employee Performance

Employee performance is the efficacy and efficiency with which a worker accomplishes duties and advances the objectives of the company. According to TR Mitchell (Sedarmayanti, 2001, as cited in Sudiardhita et al., 2018), it is multifaceted and includes elements like communication, initiative, promptness, quality of work, and capacity. Armstrong emphasises that performance is not just the outcome but also the consequence of both mental and physical exertion made during task execution. Performance is defined as both behaviour and results. The following are important measures of employee performance: (1) Quality of Work, which is demonstrated by the production of high-quality results; (2) Quantity of Work, or the amount of work finished; (3) Punctuality, or the effective use of time; (4) Effectiveness, or the best use of resources to maximise results; and (5) Cooperation, which includes the maintenance of positive working relationships and constructive communication. Combining these perspectives, employee performance is defined as the quantifiable output of work completed following duties assigned, impacted by drive, aptitude, abilities, and career progression prospects (Sudiardhita et al., 2018).

1.2 Research Problem

The discourse surrounding artificial intelligence (AI) technologies increasingly focuses on their technical prowess and possible influence on business results. However, what is less spoken about is how AI literacy affects how well employees use AI to enhance their performance. There is presently little empirical evidence connecting worker performance to AI literacy, even though AI has the potential to radically revolutionise the workplace. By examining the connection between employee performance and several facets of AI literacy, including awareness, usage, evaluation, and ethics, this study seeks to bridge this gap.

Although AI's benefits are often mentioned, specific evidence about the effects of comprehending and using AI technology on individual performance is still lacking. Does increased awareness of AI's potential lead to an increase in productivity? Do improved results in the workplace result from the capacity to assess and employ AI tools? Furthermore, ethical issues might guarantee the effective and responsible use of AI. This study aims to provide answers to these significant questions.

This research aims to provide useful information for businesses, educators, and legislators by demonstrating the relationship between AI literacy and employee performance via empirical evidence. This study aims to clarify the factors that contribute to enhanced performance and provide a clear path for maximising AI use in the workplace by analysing AI awareness, usage, evaluation, and ethics. In the end, this study will assist businesses in using AI to boost productivity and assist educators in preparing future workers for a world powered by AI.

1.3 Research Questions

The impact of artificial intelligence (AI) literacy on worker performance is investigated in this study. The research background informs the formulation of the following research questions:

(1) Does AI literacy awareness affect employee performance?
(2) Does AI literacy usage affect employee performance?

(3) Does AI literacy evaluation affect employee performance?
(4) Does AI literacy ethics affect employee performance?

1.4 Research Objectives

The following are the research goals after the formulation of the study question:

(1) To study the relationship between the awareness of AI and employee performance.
(2) To study the relationship between the usage of AI and employee performance.
(3) To study the relationship between the evaluation of AI and employee performance.
(4) To study the relationship between the ethics of AI and employee performance.

1.5 Scope of Study

In particular, the study looks at how the awareness, usage, assessment, and ethical elements of AI literacy affect job outcomes to explain how AI literacy affects employee performance. Data was gathered using a Google Form-administered online survey to evaluate employees' degrees of AI literacy and how they believed it affected their performance.

The study's focus is restricted to workers in different industries who often use AI technology at work. Convenience sampling was used to establish the sample size, which includes 219 Malaysian respondents. The period of data gathering was around three months. All of the study's results and conclusions are exclusive to this particular respondent group.

1.6 Research Significance

This study is important because it might influence scholars and professionals by providing useful data and significantly advancing our knowledge of AI literacy and how it affects worker performance.

1.6.1 For Practitioners

By examining the empirical relationship between AI literacy and employee outcomes, this research closes a significant knowledge gap for practitioners. AI has gained popularity in businesses, yet no evidence that AI literacy affects employee performance. Moreover, the data presented in this study helps managers and decision-makers comprehend which aspects of AI literacy have the most impact on raising employee performance and productivity. A basis for strategic decision-making about AI adoption is provided by the research's findings, which also help organisations evaluate the applicability of AI in their work settings. Finally, the study provides insights into the possible benefits of raising employee AI literacy, assisting organisations in identifying domains where increased AI expertise may result in enhanced performance and more successful AI integration.

1.6.2 For Academics

Three important contributions are provided by this study to academics. The influence of AI literacy on employee performance has not received enough empirical investigation, and this study fills that gap. This paper advances the theoretical understanding of how AI literacy affects workplace outcomes by looking at the four elements of AI literacy which are awareness, usage, evaluation, and ethics. The lack of research on the human aspects of integrating AI in businesses is filled in part by this contribution. Secondly, this study provides a strong foundation for further investigation, enabling academics to expand on these results in many situations, such as different sectors, occupations, or cultural contexts. Future research aiming to comprehend the relationship between AI literacy and other performance-related factors like job happiness, creativity, or teamwork might be guided by the framework. Thirdly, educators may better prepare their students for AI-driven workplaces by incorporating the research findings into their curricula. The findings of this study may be used by academics to create AI literacy programs that provide students the know-how to successfully traverse AI technology in their future employment and prepare them for the constantly changing needs of the modern workplace.

1.7 Summary

An overview of the state of AI literacy in the workplace is given in this chapter. The purpose of this study is to investigate how AI literacy affects worker performance and provide insightful information.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

A comprehensive literature review of variables is presented in this chapter. The formulation of hypotheses and the proposed conceptual framework for this study are presented after a relevant underlying theory is provided as a guide for this research.

2.1 Underlying Theory

2.1.1 Task Technology Fit Theory (TTFT)

Task-Technology Fit Theory (TTFT) by Goodhue and Thompson (1995) has become a key concept in the study of the relationship between the requirements of a given task, the functionalities of technology selected to accomplish the task, and the individual characteristics of the employee performing the task. Functional capacity, particularly as it is made possible by the technology chosen, is referred to as technical functionality. Individual characteristics include an employee's motivation, attitude, and socioeconomic status. The theory clarifies how and to what degree technology aids a person in completing a task. The theory includes how the task, technology, and individual interact throughout the performance (Goodhue et al., 2000).

Davis and Venkatesh (2000), Dennis et al. (2008), Lin (2012), and Mathieson (1991) (as cited in Howard & Rose, 2019) argue that according to TTFT, tasks and technologies may combine to create effects that are more powerful than the sum of their components. Many other theories and models about technological applications, like the technology acceptance model (TAM) and media synchronicity theory (MST), refer to aspects of technologies like processing, transmission, and media capabilities that have a direct impact on performance or utilisation. Contrarily, according to Howard and Rose (2019), TTFT is unrelated to specific traits or immediate consequences. Rather than suggesting any particular activity or technology, TTF theory highlights how technologies often depend on the environment in which they are used.

The TTFT posits that when a new technology aligns its capabilities with the tasks that the user needs to do, there is a greater chance of positive individual performance outcomes and adoption (Goodhue & Thompson, 1995). According to Goodhue and Thompson (1995), the TTF measure consists of the following eight components: (1) data compatibility; (2) authorization to access data; (3) locatability of data; (4) data quality; (5) training and ease of use; (6) production timeliness; (7) systems reliability; and (8) interface with users. Numerous information systems, such as electronic health systems, electronic commerce, and electronic learning, have seen the application of the task-technology fit (Bere, 2018; Khoa, 2021).

In the TTFT, the fit between the technology and the task is the first dimension (Liang & Wei, 2004). Based on the theory, performance will improve with a good task-technology fit. The concept of "task-technology fit" describes an information provider's capacity to assist in matching task requirements with technological capabilities (Gyires et al., 2003). Hence, TTFT is used to investigate the influence of AI literacy on employee performance in organisations.

2.2 Independent Variables

2.2.1 Awareness

Awareness is recognizing and understanding artificial intelligence (AI) technology when utilising AI-related applications (Rau et al., 2023). It is a fundamental degree of AI literacy and necessary to work with AI technology efficiently. Martin (2006), Hallaq (2016), and Antunes and Ferreira (2011) all claim that awareness is a cognitive process that occurs before the usage of a particular technology. Hallaq (2016) goes on to say that one of the five essential elements of media literacy is awareness. In a similar vein, Cartelli (2010) contends that one of the three crucial elements of digital competency is the cognitive dimension, which involves awareness. According to Martin and Grudziecki (2006), the DigEuLit framework also highlights the importance of awareness as the first step towards developing digital competence. Likewise, Katz (2007) highlighted that the iSkills framework underscores the importance of awareness in understanding and articulating information challenges. Research indicates that there is a high correlation between awareness and attitude (Kim, 2013; Weisberg, 2011, as cited in Wang et al., 2023). According to Donat et al. (2009, as cited in Wang et al., 2023), the cultivation of positive attitudes via awareness can enhance the readiness to use digital technology. This implies that raising employees' AI awareness may benefit their use of AI tools and increase their level of engagement.

2.2.2 Usage

According to Wang et al. (2023), usage describes the capacity to use and make use of AI methods to proficiently do tasks. The operational parts of this idea are centered around the ease of access to AI applications and tools, the ability to operate them proficiently, and the capacity to combine various types of AI tools efficiently to enhance job performance.

Usage is central to digital literacy frameworks, with the ECDL highlighting key computer skills like word processing (Leahy & Dolan, 2010), the iSkills framework emphasizing information integration (Katz, 2007), and the KSAVE framework focusing on operational skills (Wilson, Scalise, & Gochyyev, 2015). These frameworks underline the importance of digital competence across literacies. In AI literacy, usage refers to the basic operation of AI tools and their integration into routine processes to boost productivity (Božić & Poola, 2023; Malik, 2023; Tzirides, 2024). Research shows that being adept with digital technologies is often associated with having a positive attitude towards technology (Donat et al., 2009; Porter & Donthu, 2006, as cited in Wang et al., 2023). This demonstrates that workers who are adept at using AI applications are more likely to see AI technology favourably, which can increase their level of engagement and output. Regular usage of AI technologies can also enhance work performance because of reduced mistake rates and increased familiarity (Tong et al., 2021).

2.2.3 Evaluation

Evaluation describes the capacity to choose, assess, and critically analyse AI applications and their results (Wang et al., 2023). Due to its complexity and black-box nature, artificial intelligence results need to be thoroughly examined and assessed (Mueller et al., 2019). Assessment is therefore one of the core competencies of AI literacy. For AI literacy and other related literacies, the idea of evaluation is essential (Hallaq, 2016; Katz, 2007 Martin & Grudziecki, 2006, as referenced in Wang et al., 2023). Digital literacy frameworks that emphasise analysis, evaluation, and interpretation as critical skills for evaluating data and outcomes across professions, such as DigEuLit (Martin & Grudziecki, 2006), iSkills (Katz, 2007), and the digital media literacy model (Hallaq, 2016), place a strong emphasis on critical evaluation. Evaluation in the context of AI literacy extends beyond conventional literacy. Users should not only evaluate information but also accurately develop views on AI goods and applications (Wang et al., 2023). This entails being aware of the ethical implications, constraints, and potential biases of AI technology (Osasona et al., 2024). Moreover, those who are proficient at evaluating AI tools frequently have a great deal of expertise with these tools, indicating that evaluation is a talent in and of itself (Wang et al., 2023).

2.2.4 Ethics

According to Wang et al. (2023), ethics is the capacity to understand the obligations and dangers associated with adopting AI technology. This entails being aware of the ethical implications of artificial intelligence, such as privacy issues, algorithmic bias, liability, and possible effects on employment and society (Li, 2024; Reddy et al., 2024). The public has long been concerned about the ethical implications of AI, particularly as AI technology advances and becomes more pervasive in daily life. Although AI offers convenience and empowerment, it also has ethical considerations that must be carefully considered. Gunkel (2012, as cited in Wang et al., 2023) states that the emergence of AI has compelled society to consider the ethics and intelligence of AI technology. Therefore, a human with AI literacy must be able to effectively understand and assess these ethical concerns to ensure the responsible and appropriate application of AI technology (Wang et al., 2023).

Many scholars see ethics as a crucial element of the foundation for media and digital literacy. One of the three fundamental elements of the Digital Competency Assessment Framework, for example, is the ethical dimension (Calvani et al., 2010). Likewise, moral awareness is a crucial component of media literacy (Hallaq, 2016). Wilson et al. (2015) emphasise that attitudes, values, and ethics are important behavioural and affective factors that are linked to ICT literacy. These frameworks stress the role that ethics plays in responsibly directing technology usage. Studies indicate that people's views towards AI may be positively impacted by their ethical awareness as measured by their AI literacy (Wang et al., 2023).

2.3 Dependent Variable

2.3.1 Employee Performance

According to Onuoha (2023), the company's employees are its driving power. Therefore, it should come as no surprise that the daily performance of its employees greatly influences an organisation's success or failure. Employee performance describes how workers carry out their assigned duties, finish necessary projects, and behave at work. An employee's ability to carry out his assigned tasks effectively and promptly, as well as how quickly they fulfil deadlines and requirements, is measured as their employee performance. It is frequently evaluated using a range of indicators, including quality of work, quantity, timeliness, effectiveness, and independence (Pratiwi et al., 2019).

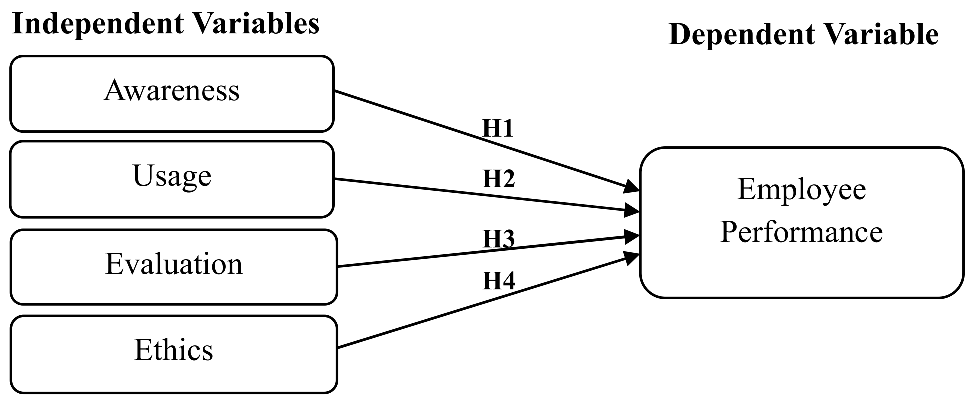
The Task Technology Fit Theory (TTFT) suggests that employee performance improves when there is a strong alignment between work requirements and the available technology, including AI technologies (Goodhue & Thompson, 1995, as cited in Sturm & Peters, 2020). Employee productivity and efficiency may be increased by utilising AI technologies more effectively in an AI environment (Ramachandran et al., 2022).

Technology is having a positive effect on employee performance because it may automate repetitive operations, freeing up employees to concentrate on more complicated, high-value tasks that boost output (Haleem et al., 2021). By giving employees rapid access to reliable data that supports improved decision-making, artificial intelligence (AI) solutions may foster innovation and improve problem-solving skills (Houser, 2019). The idea is that understanding, evaluating, and ethically using AI technologies is part of AI literacy, and it plays a critical role in how well employees work. Professional AI users may enhance task performance and trust in the workplace by selecting the appropriate tools, using them efficiently, and making moral judgments.

2.4 Conceptual Framework

The variables that are expected to affect employee performance through AI literacy in the workplace are visually represented by the conceptual framework shown in Figure 2.1.

Figure 2.1: Conceptual Framework



Source: Developed for the research.

2.5 Hypotheses Development

2.5.1 The Relationship between AI Awareness and Employee Performance

According to Chowdhury et al. (2023), a higher level of awareness of AI technology among employees enables them to recognise possibilities for the efficient use of AI tools, which improves productivity and job performance. Adoption of AI may specifically enhance decision-making, automate processes, and optimise company operations, all of which can boost productivity and operational effectiveness. This aligns with the notion that awareness and understanding of AI can result in greater AI tool utilisation, which can improve employee performance.

Hypothesis 1 (H1): AI awareness is positively affecting employee performance.

2.5.2 The Relationship between AI Usage and Employee Performance

According to Sandeep et al. (2022), employees may concentrate on more difficult, high-value jobs by using AI solutions to automate repetitive chores. This change has the potential to boost productivity and job performance overall, making usage an essential component of AI literacy that affects worker performance.

Hypothesis 2 (H2): AI usage is positively affecting employee performance.

2.5.3 The Relationship between AI Evaluation and Employee Performance

According to Amoako et al. (2021), The article explores how artificial intelligence (AI) systems, encompassing methods like cloud computing, machine learning, big data analytics, and data mining, might greatly improve the decision-making process in entrepreneurial settings. By enhancing their capacity to examine consumer preferences and industry benchmarks, these AI technologies can assist business owners in making more informed judgements. The efficacy of AI judgements has also been found to be influenced by human engagement in these processes, indicating that employee input is essential to optimising AI-driven workflows. It takes this skill set to fully realise AI's potential benefits in improving employee performance.

Hypothesis 3 (H3): AI evaluation is positively affecting employee performance.

2.5.4 The Relationship between AI Ethics and Employee Performance

According to Osasona et al. (2024), the maintenance of trust and equity in judgements made by AI heavily depends on ethical issues in AI deployment. Employees who are conscious of AI's ethical implications are more likely to use the technology ethically, create a positive work environment, and perform better all around.

Hypothesis 4 (H4): AI ethics is positively affecting employee performance.

2.6 Summary

In conclusion, this chapter examines how various aspects of AI literacy impact employee performance and offers a conceptual framework based on Task Technology Fit Theory (TTFT) to investigate the connections between performance and AI literacy (awareness, usage, assessment, and ethics).

CHAPTER 3: METHODOLOGY

3.0 Introduction

Sridhar (2008, as cited in Patel & Patel, 2019) defined research methodology as the science of researching research methodologies, offering a methodical approach to research issues. It helps in understanding both the results and the methods of scientific inquiry, evaluating techniques, resources, limitations, and implications. The research design, sampling strategies, data collection methods, and data analysis tools employed in the study are described in this chapter, with a focus on the significance of a well-defined methodology for guaranteeing the validity and dependability of results.

3.1 Research Design

Sidharth (2023) defines a research design as a strategy that guides judgements on technique, guaranteeing professionalism and reducing process challenges. It provides the structure for carrying out methodical scientific investigations and determining the quantity, kinds, and connections among the variables being studied. The conceptual and theoretical framework, the research question, and the identification and explanation of the research problem all contribute to a well-developed research design. To meet research goals, it summarises earlier studies, establishes hypotheses, describes data-gathering procedures, and details analytic strategies. As Library Guides (2022, as cited in Sidharth, 2023) illustrates, a research design acts as a steering wheel, guiding the entire research project toward addressing the research question logically and effectively.

3.1.1 Quantitative Research

The goal of quantitative research, according to Kandel (2020), is to quantify changes in a condition, issue, or phenomena using mathematical models, theories, and hypotheses. It is regulated, objective, and product-oriented. Central to this approach is measurement, linking empirical observations to mathematical representations of relationships. Quantitative techniques ensure precision and reliability in examining the interaction between independent and dependent variables, typically using instruments to collect numbered data for statistical analysis. As Disman et al. (2017) noted, quantitative research addresses research questions and tests hypotheses through statistical data. Consequently, a questionnaire survey is used in this study's quantitative methodology.

3.1.2 Causal Research

The causal technique is used in this research. According to Erickson (2017), a causal study's objective is to confirm a hypothesis. It is the only way to show causality or the evidence that a change will result in a certain consequence.

With a special focus on the effect of AI literacy on worker performance, causal research seeks to establish the causal link between variables. This involves exploring whether changes in independent variables, such as awareness, usage, evaluation, and ethics, lead to changes in the dependent variable, employee performance. By proving causality, the study seeks to identify the key elements of AI literacy that influence employees' productivity and efficiency at work. This study uses a causal research method called Partial Least Squares Structural Equation Modelling (PLS-SEM) to assess the strength and direction of these associations.

3.2 Sampling Design

Hossan et al. (2023) explained that sampling design is the process by which researchers choose a small but representative group of people to study out of a larger population. In particular, when the population is too big for an in-depth investigation, this technique enables researchers to examine samples and make generalisations about the full population.

3.2.1 Target Population

According to Hossan et al. (2023), a target population is a subset of the population in general that the researcher plans to examine, as indicated by particular attributes, which may or may not include potential participants. This group has to be precisely defined to be both sufficiently large to yield adequate data and sufficiently narrow to omit participants who are not involved in the study. Effective research and resource allocation may be ensured by specifying the target population.

The target population of this research includes people currently working in various industries. This includes employees at different organisational levels, roles, and departments who may be exposed to AI technologies in the workplace. The choice of this group makes sense as every employee may share insights on their degree of AI literacy (awareness, usage, evaluation, ethics) and how it relates to employee performance, independent of their particular job role or industry.

3.2.2 Sampling Frame

A sampling frame can be defined as the collection of source materials that are used to pick the sample (Turner, 2003). Also, Rahman et al. (2022) defined a sampling frame as a comprehensive collection of sample units drawn from a population. The sampling frame for this research is made up of people who are actively employed in any industry, regardless of their ethnicity or region. This encompasses workers from different sectors. Due to their varied work experiences and degrees of exposure to AI technology, this group of people is well-suited for research. These factors are important for evaluating AI literacy and its effect on worker performance. It will be necessary for employees to respond to an online survey using Google Forms.

3.2.3 Sampling Technique

Sampling is a technique that a researcher uses to methodically choose a smaller number of representative objects or people from a pre-defined population to use as subjects for experimentation or observation to meet the goals of the study (Sharma, 2017). This research will employ convenience sampling which is a nonprobability sampling technique. Convenience sampling is used because it is a practical way to contact people who are prepared to take part in the online survey and are conveniently available. Convenience remains a key advantage of online research, especially as participants can now use various mobile devices like tablets and smartphones to easily participate (Evans & Mathur, 2018). This method also works well for rapidly obtaining information from employees since it enables the researcher to get answers from a wide range of accessible participants.

3.2.4 Sampling Size

The sample size is crucial in empirical studies to ensure valid generalizations without bias or error (Taherdoost, 2017). This research aimed to analyze the relationship between AI literacy and employee performance, with a sample size determined using the G*Power software, which suggested a minimum of 129 respondents (see Appendix 3.1). Hair et al. (2010, as cited in Ainur et al., 2017) recommend at least 100 respondents for models with fewer than six constructs and high item communalities. Based on Roscoe's (1975) guideline, an optimal sample size ranges from 30 to 500 (Malhotra & Peterson, 2006). This study targeted 250 employees, receiving 219 valid responses, which is adequate for a statistically significant analysis of AI literacy's impact on employee performance.

3.3 Data Collection Method

According to Taherdoost (2021), when information regarding a particular study variable is gathered, it is referred to as data collection. This information is then used during the data analysis phase of the study to produce research findings, uncover research questions, or test hypotheses. Data collection is the main stage of research, and it may reduce project errors and enhance the calibre of research results. Therefore, in addition to a well-designed study, a significant amount of work should be put into data collecting to ensure appropriate outcomes, as inaccurate or insufficient data might jeopardise the validity of research findings. Both primary and secondary data will be gathered for this project.

3.3.1 Primary Data

According to Saman (2017), primary data collection is information that is obtained directly from study participants by the researcher or a qualified data collector using surveys, questionnaires, interviews, observations, or biophysiologic measures. According to Wilcox et al. (2012), researchers have long sought out and used electronic data systems to gather raw data because of the advantages they provide over paper-based methods. These advantages are most apparent in data storage and management.

An online survey was used to collect primary data for this study to answer the research questions and assess the hypotheses on how AI literacy affects worker performance. Appendix 3.2 shows the two sections of the questionnaire layout: Section A, focuses on employee performance and artificial intelligence (AI) literacy, and Section B, asks about respondents' demographic profile. Using a 7-point Likert scale, a comprehensive questionnaire assessing awareness, usage, appraisal, ethics, and the perceived impact of AI literacy on employee performance was created as part of the preparation work. Google Forms was used to distribute the survey to ensure respondents' comfort and convenience.

3.3.2 Secondary Data

Secondary data is information that has been collected by others and is available to researchers (Clark, 2013). Compared to primary marker research, secondary data almost always yields a solution more rapidly and at a lower cost (McQuarrie, 2015).

Secondary data from credible sources such as academic journals, business studies, official publications, and databases like UTAR library and Google Scholar provided context and support for this research. Reliability was ensured through peer-reviewed, highly cited sources, while appropriateness was evaluated based on alignment with research objectives. Comprehensive and timely data were essential for analyzing the relationship between AI literacy and employee performance.

3.4 Measurement Scales

Stevens' foundational study from 1946 states that there are four different measuring scales (Idika et al., 2023). These comprise the ratio, interval, nominal, and ordinal scales arranged in increasing order of complexity and sophistication. The survey questionnaire employed in this study collects data using both ordinal and nominal scales.

3.4.1 Nominal Scale

According to Idika et al. (2023), the nominal scale groups observations based on shared qualitative characteristics, using numbers arbitrarily rather than quantitatively. Section B of this study's questionnaire applied the nominal scale to categorize demographics such as gender, age group, education level, employment status, position, industry type, company size, and years of establishment. These categories, being mutually exclusive and non-hierarchical, enable data segmentation and the identification of trends or changes within groups. This breakdown enhances the understanding of variables influencing AI literacy and employee performance across different demographics.

Figure 3.1: Nominal Scale Example in Questionnaire

Gender

- Male
- Female

Source: Developed for the research.

3.4.2 Ordinal Scale

Likert scales and other ordinal scales use ordered categories (strongly agree to strongly disagree) to evaluate attitudes; they assume equal intervals and lack empirical evidence (Tastle & Wierman, 2006). To compare respondents' opinions and analyse the effect of AI literacy on employee performance, this study employed a 7-point Likert scale in Section A to gauge agreement with statements on the aspects of AI literacy (awareness, usage, evaluation, and ethics).

Figure 3.2: Ordinal Scale Example in Questionnaire

1. I can distinguish between smart devices and non-smart devices. *

	1	2	3	4	5	6	7	
Strongly disagree	○	○	○	○	○	○	○	Strongly agree

Source: Developed for the research.

Table 3.1: Summary of the Measurement Scales Derived from the Questionnaire Page

Section	**Title**	**Items**	**Measurement Scales**
A	Artificial Intelligence (AI) Literacy and Employee Performance	Awareness	Ordinal (Likert Scale)
		Usage	
		Evaluation	
		Ethics	
		Employee Performance	
B	Demographic	Gender	Nominal
		Age Group	
		Highest Educational Level	
		Employment Status	
		Current Position	
		Type of Industry	
		Size of Company	
		Year(s) of Establishment	

Source: Developed for the research.

3.4.3 Measurement Instruments

The measuring tools used in this investigation were borrowed from previous studies. Table 3.2 shows where the variables and matching measurement items were found in different study studies.

Table 3.2: Measurement Instruments

Variables	**Measurement Items**	**Sources**
Awareness	1. I can distinguish between smart devices and non-smart devices. 2. I know how AI technology can help me. 3. I can identify the AI technology employed in the applications and products I use.	Wang, B., Rau, P. L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. *Behaviour & information technology*, *42*(9), 1324-1337.
Usage	1. I can skilfully use AI applications or products to help me with my daily work. 2. It is usually easy for me to learn to use a new AI application or product. 3. I can use AI applications or products to improve my work efficiency.	Wang, B., Rau, P. L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. *Behaviour & information technology*, *42*(9), 1324-1337.
Evaluation	1. I can evaluate the capabilities and limitations of an AI application or	Wang, B., Rau, P. L. P., & Yuan, T. (2023). Measuring user competence in using

	product after using it for a while. 2. I can choose a proper solution from various solutions provided by a smart agent. 3. I can choose the most appropriate AI application or product from a variety for a particular task.	artificial intelligence: validity and reliability of artificial intelligence literacy scale. *Behaviour & information technology*, *42*(9), 1324-1337.
Ethics	1. I always comply with ethical principles when using AI applications or products. 2. I am often alert to privacy and information security issues when using AI applications or products. R 3. I am always alert to the abuse of AI technology.	Wang, B., Rau, P. L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. *Behaviour & information technology*, *42*(9), 1324-1337.
Employee Performance	1. I understand the need for my department team members to be AI-literate and adding value to the organisation. 2. I understand my organisation's AI strategy, my department's AI goals,	Abas, M. K. M., Yahaya, R. A., & Din, M. S. F. (2019). Digital Literacy and its Relationship with Employee Performance in the 4IR. *Journal of International*

	and my role in achieving these objectives. 3. I understand specifically what my manager expects of me in terms of AI literacy. 4. I understand how well I am performing in AI literacy compared to expectations. 5. I understand what I have to do to enhance my AI literacy for optimal job performance. 6. I have access to AI tools and resources necessary for my work, or I understand the reasons for any limitations in access. 7. I understand that the company benefited from my participation in AI initiatives. 8. I understand that changes in AI policies, procedures, and technology introduced by management often lead to better ways of doing things.	*Business, Economics and Entrepreneurship*, *4*(2), 29-29.

Source: Developed for the research.

3.5 Pilot Test

Ten percent of the planned sample size of 250 respondents, or 25 sets of questionnaires, were used in a pilot test. It is common practice to do a pilot test with 10% of the intended sample size to guarantee the research tool's viability and dependability without demanding excessive resources (Lackey & Wingate, 1998). According to Straub et al. (2004), a pilot study's dependability should also be at least 0.60 Cronbach's Alpha. The reliability and acceptability of the variables were confirmed by the pilot test's findings, which showed that all constructs' Cronbach's Alpha values were above this cutoff. Based on responder input, only small changes were made, such as grammatical and typographical repairs. The questionnaire was judged appropriate for delivery to the entire sample following these improvements.

3.6 Methods of Analysis

When it comes to finding patterns and trends in big data sets, statistics is a crucial component of data analysis. It can interpret and comprehend complicated data because it is a branch of mathematics. To examine the collected data and extract important insights for this study, descriptive and inferential statistics will be used. A partial least squares structural equation model (PLS-SEM) will be used in statistical analysis to manage the data gathered from the questionnaire.

3.6.1 Descriptive Statistics

According to Kaur et al. (2018), by highlighting the connections between the variables in a sample or population, descriptive statistics help to organise data into a concise summary. Before doing any inferential statistical comparisons, it is imperative to calculate descriptive statistics as a crucial preliminary step in research. Along with measurements of frequency, central tendency, dispersion/variation, and location, descriptive statistics also contain variables of the nominal, ordinal, interval, and ratio kinds. According to Mishra et al. (2019), a reliable and insightful technique to summarise data statistically is using descriptive statistics. Measurement quality and appropriateness are critical for both data and statistical procedures employed in hypothesis testing.

This method involves the selection of a particular interest group by the researchers, data collection from that group, and data analysis utilising graphical representations and summary statistics to characterise the group's characteristics. In this research, the demographic profile of the respondents was analysed using both tabular (frequency distribution tables) and graphical (pie charts) approaches. This is because frequency distribution tables allow researchers to immediately identify trends by providing a clear summary of the data that has been gathered. On the other hand, a pie chart clearly illustrates the proportional proportion of each part and provides information that is simpler to understand.

3.6.2 Inferential Statistics

According to Alem (2020), inferential statistics is extrapolating conclusions or forecasts about a broader population from a sample. It enables the testing of hypotheses and the estimation of population characteristics using sample data. The methods used in this procedure, which include determining confidence intervals and significance tests, are based on probability theory. While descriptive statistics provide an overview of data from a sample, inferential statistics try to deduce features of the population and evaluate how reliable these conclusions are.

Inferential statistics will be used in this study to make predictions and judgements about the general workforce's level of AI literacy and how it will affect performance. A more precise knowledge of all employees may be attained by extrapolating insights from the sample data, which will enable the formulation of significant conclusions regarding the study topics being examined.

3.7 Data Cleaning

Ensuring the quality and dependability of the replies gathered via the online survey required data cleansing. To eliminate missing values, all questions were set as mandatory in the survey form to ensure consistency and completeness across responses. Straightlining, where participants repeatedly select the same option without consideration, was also checked and removed from the dataset. By ensuring that only trustworthy and correct data were included, these steps improved the dataset's overall quality for further analysis.

3.8 Partial Least Squares Equation Modelling (PLS-SEM)

Sarstedt et al. (2021) state that Partial Least Squares Structural Equation Modelling (PLS-SEM) is a statistical technique that blends elements of principal component analysis with regression-based route analysis. Latent variables are constructs that allow researchers to estimate complex path models by reflecting unobserved concepts like customer satisfaction or loyalty. As the approach concentrates on maximising the explained variance in dependent items rather than fitting covariance matrices, PLS-SEM is especially helpful when prediction is the aim. Its loose assumptions on data distribution and measurement make it ideal for small samples and exploratory research as well.

This study used Smart PLS version 3.2.4, and the two-stage approach proposed by Anderson and Gerbing (1988). The first step is to analyse the measurement model, which includes internal consistency reliability, convergent validity, and discriminant validity for reflective measures and collinearity, convergent validity, and the significance and applicability of formative indicators for formative measures. If the measurement model yields acceptable results, stage two examines the structural model and places a strong emphasis on hypothesis testing and the significance of structural links (Hair et al., 2014, as quoted in Low et al., 2017).

Hair et al. (2019b) state that PLS-SEM creates composite variables that accurately reflect the constructs being discussed by linearly combining indicator estimates from the measurement model. Hair et al. (2021) emphasize that PLS-SEM facilitates the estimation of model parameters while allowing the use of reflectively specified measurement models. This approach ensures accurate operationalization and analysis of constructs in research.

This study uses PLS-SEM to analyze the causal relationships between AI literacy dimensions (awareness, usage, evaluation, ethics) and employee performance. Complex models with several constructs and indicators are best handled by PLS-SEM, which also accepts real-world data without making rigid normality assumptions. PLS-SEM successfully analyses complex models with a sample size of 219 respondents, offering insightful information on the causal relationships between AI literacy and employee performance that advances both theoretical knowledge and real-world applications.

3.9 Summary

In conclusion, this chapter described the research methodologies, such as causal and quantitative techniques. To verify hypotheses and evaluate internal dependability, primary data was gathered using a convenience sample approach, and secondary data confirmed the results. The techniques for descriptive and inferential analysis were also discussed in this chapter.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

The links between latent variables and observable indicators are examined in depth in Chapter 4 through the use of Partial Least Squares Structural Equation Modelling (PLS-SEM). The validity of the measurement model is evaluated, and then the suggested correlations are examined by analysing the structural model. The findings shed light on the relationship between employee performance and AI literacy variables.

4.1 Descriptive Analysis

By transforming raw data into an easily comprehensible format, descriptive analysis draws attention to the sample's salient features. The data from this study's examination of 219 replies is presented in tables and pie charts to help with understanding. Summarising the demographic information collected in Section B of the questionnaire (see Appendix 3.2) gives a clear picture of the sample population. This information includes the respondents' gender, age group, highest level of education, employment status, current position, industry type, company size, and year or years of establishment. These demographic characteristics are visualised using tabular forms (e.g., frequency distribution tables) and graphic representations (e.g., pie charts), providing context for the subsequent inferential analysis and providing insight into the respondents' backgrounds.

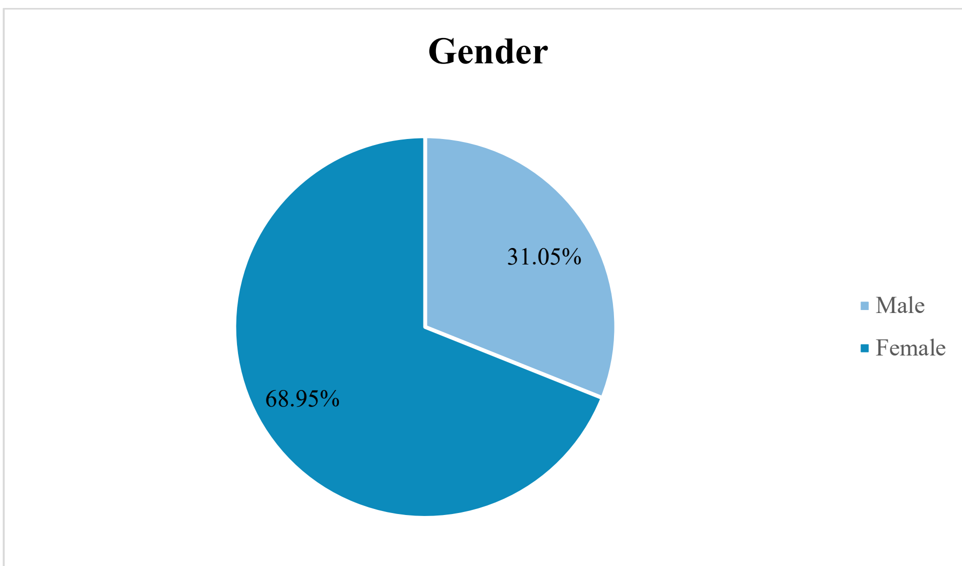
4.1.1 Gender

Table 4.1: Gender

	Frequency	**Percent (%)**	**Cumulative Percent (%)**
Male	68	31.05	31.05
Female	151	68.95	100.00
Total	**219**	**100.00**	

Source: Developed for the research.

Figure 4.1: Gender



Source: Developed for the research.

The respondents' gender distribution is shown in Table 4.1 and Figure 4.1. In all, 68 respondents (31.05% of the sample) were male, and 151 respondents (68.95% of the sample) were female.

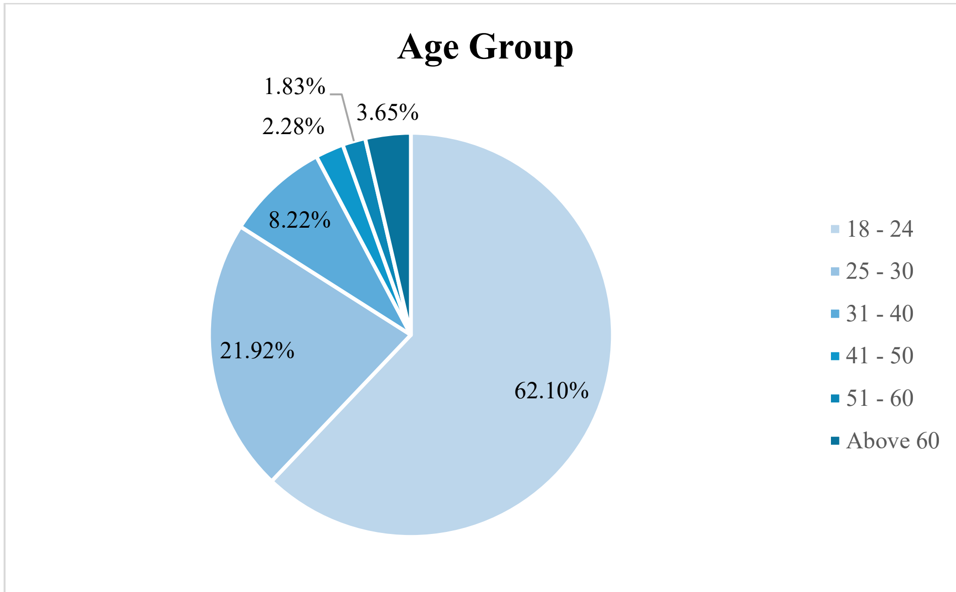
4.1.2 Age Group

Table 4.2: Age Group

	Frequency	**Percent (%)**	**Cumulative Percent (%)**
18 - 24 years old	136	62.10	62.10
25 - 30 years old	48	21.92	84.02
31 - 40 years old	18	8.22	92.24
41 - 50 years old	5	2.28	94.52
51 - 60 years old	4	1.83	96.35
Above 60 years old	8	3.65	100.00
Total	**219**	**100.00**	

Source: Developed for the research.

Figure 4.2: Age Group



Source: Developed for the research.

The respondents' age distribution is shown in Table 4.2 and Figure 4.2. 136 people between the ages of 18 and 24 made up the biggest group, accounting for 62.10% of the sample. Subsequently, 48 respondents (21.92%) were between the ages of 25 and 30, and 18 respondents (8.22%) were between the ages of 31 and 40.

4.1.3 Highest Education Level

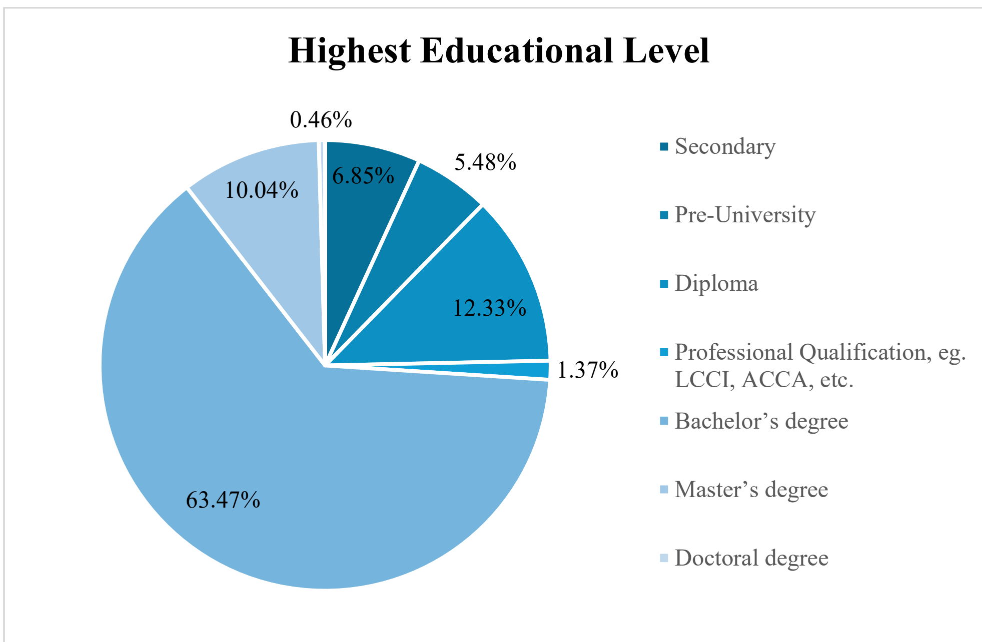
Table 4.3: Highest Education Level

	Frequency	Percent (%)	Cumulative Percent (%)
Secondary	15	6.85	6.85

Pre-University	12	5.48	12.33
Diploma	27	12.33	24.66
Professional Qualification, eg. LCCI, ACCA, etc.	3	1.37	26.03
Bachelor's degree	139	63.47	89.50
Master's degree	22	10.04	99.54
Doctoral degree	1	0.46	100.00
Total	**219**	**100.00**	

Source: Developed for the research.

Figure 4.3: Highest Education Level



Source: Developed for the research.

The 219 respondents' greatest educational degree is displayed in Table 4.3 and Figure 4.3. The majority of respondents (63.47% of the sample, or 139 people) possessed a bachelor's degree. Subsequently, there are 22 respondents with a master's degree (10.04%) and 27 respondents with a diploma (12.33%).

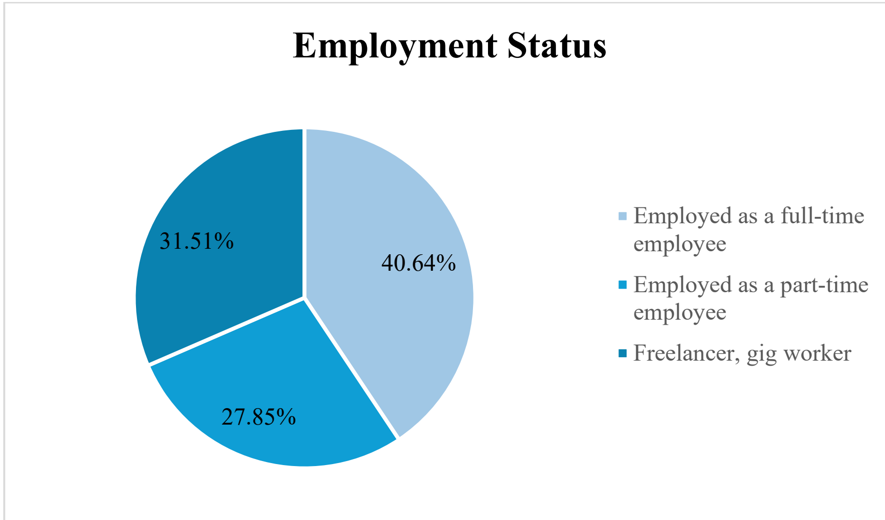
4.1.4 Employment Status

Table 4.4: Employment Status

	Frequency	**Percent (%)**	**Cumulative Percent (%)**
Employed as a full-time employee	89	40.64	40.64
Employed as a part-time employee	61	27.85	68.49
Freelancer, gig worker	69	31.51	100.00
Total	**219**	**100.00**	

Source: Developed for the research.

Figure 4.4: Highest Education Level



Source: Developed for the research.

According to Table 4.4 and Figure 4.4, the respondents' job status distribution is fairly balanced, with respondents identifying as full-time employees, part-time employees, and freelancers or gig workers.

4.1.5 Current Position

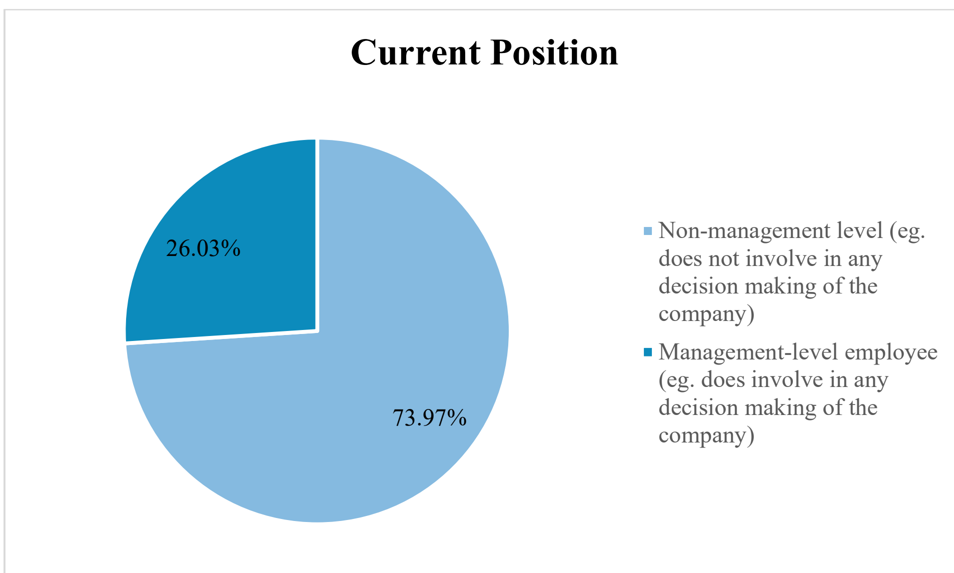
Table 4.5: Current Position

	Frequency	Percent (%)	Cumulative Percent (%)
Non-management level (eg. does not involve in any	162	73.97	73.97

decision-making of the company)			
Management-level employee (eg. does involved in any decision-making of the company)	57	26.03	100.00
Total	**219**	**100.00**	

Source: Developed for the research.

Figure 4.5: Current Position



Source: Developed for the research.

The respondents' present positions are shown in Table 4.5 and Figure 4.5 above. 162 respondents, or 73.97% of the sample, were non-managers who did not participate in business decision-making. In contrast, 57 respondents, or 26.03%, held management-level positions, which involve participation in decision-making within the company.

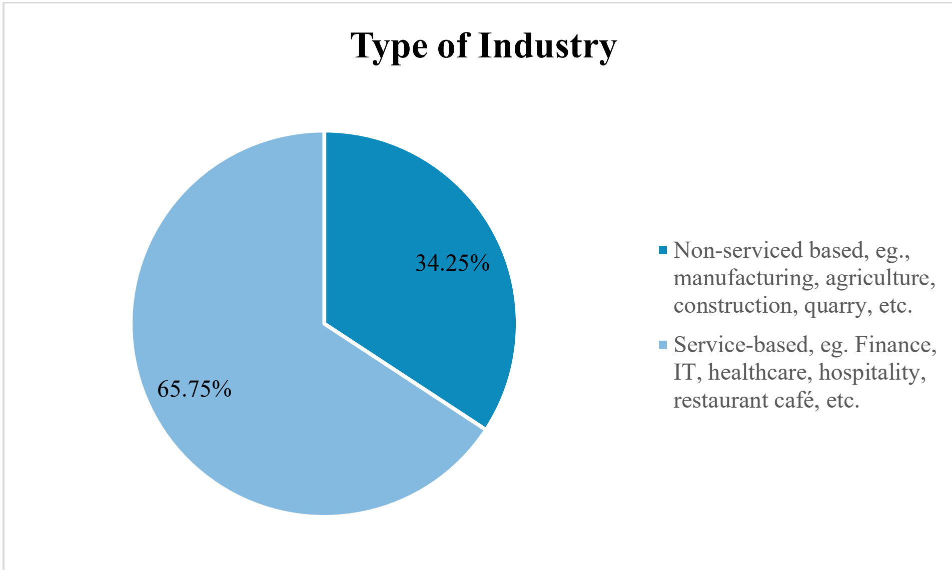
4.1.6 Type of Industry

Table 4.6: Type of Industry

	Frequency	Percent (%)	Cumulative Percent (%)
Non-serviced based, eg., manufacturing, agriculture, construction, quarry, etc.	75	34.25	34.25
Service-based, eg. Finance, IT, healthcare, hospitality, restaurant café, etc.	144	65.75	100.00
Total	**219**	**100.00**	

Source: Developed for the research.

Figure 4.6: Type of Industry



Source: Developed for the research.

Table 4.6 and Figure 4.6 above list the industries in which the respondents were employed. 65.75% of the sample, or 144 respondents, were employed in service-based industries including finance, information technology, healthcare, hospitality, and food services. In contrast, 75 respondents, or 34.25% of the sample, worked in non-service-based industries such as manufacturing, agriculture, construction, and quarrying.

4.1.7 Size of Company

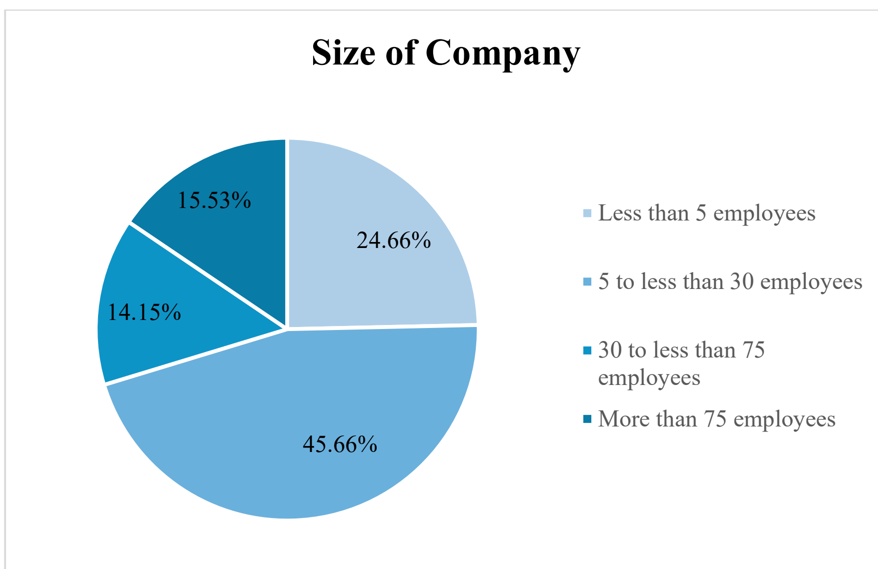
Table 4.7: Size of Company

	Frequency	Percent (%)	Cumulative Percent (%)

Less than 5 employees	54	24.66	24.66
5 to less than 30 employees	100	45.66	70.32
30 to less than 75 employees	31	14.15	84.47
More than 75 employees	34	15.53	100.00
Total	**219**	**100.00**	

Source: Developed for the research.

Figure 4.7: Size of Company



Source: Developed for the research.

100 respondents, or 45.66% of the sample, were employed by businesses with five to less than thirty employees, as indicated in Table 4.7 and Figure 4.7. This was followed by 54 respondents in companies with fewer than 5 employees,

making up 24.66%, and 34 respondents in companies with more than 75 employees, representing 15.53%.

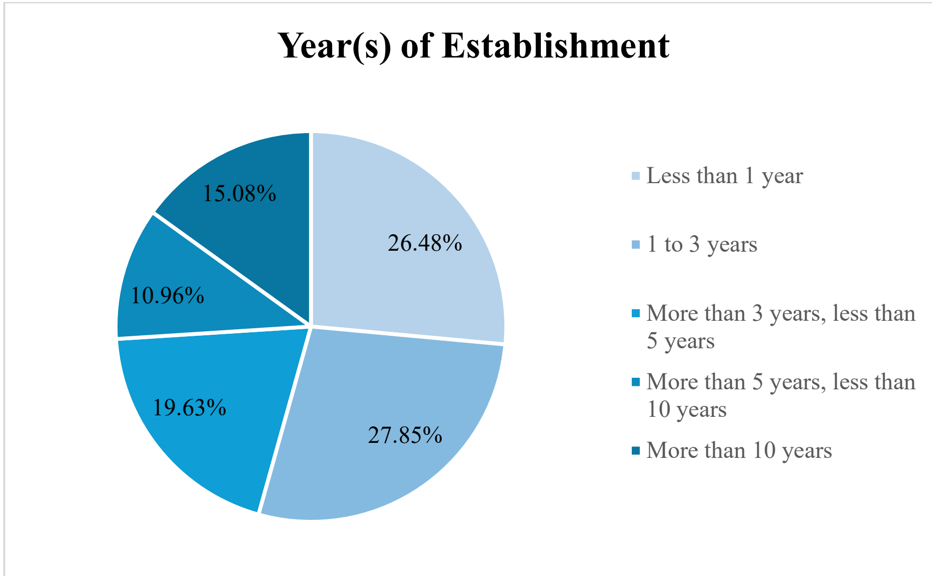
4.1.8 Year(s) of Establishment

Table 4.8: Year(s) of Establishment

	Frequency	**Percent (%)**	**Cumulative Percent (%)**
Less than 1 year	58	26.48	26.48
1 to 3 years	61	27.85	54.33
More than 3 years, less than 5 years	43	19.63	73.96
More than 5 years, less than 10 years	24	10.96	84.92
More than 10 years	33	15.08	100.0
Total	**219**	**100.0**	

Source: Developed for the research.

Figure 4.8: Year(s) of Establishment



Source: Developed for the research.

As shown in Table 4.8 and Figure 4.8, the largest proportion of respondents, 61 individuals or 27.85%, worked in companies established between 1 and 3 years ago. This was followed by 58 respondents or 26.48% in companies less than 1 year old, and 43 respondents, or 19.63% in companies established for more than 3 but less than 5 years.

4.2 Measurement Model Evaluation

PLS-SEM was used to assess the conceptual model for this investigation in two stages. In the first step, the measuring model was examined, and in the second, the structural model. Factor loadings of more than 0.708, Cronbach's alpha over 0.7, composite reliability (CR) greater than 0.7, and average variance extracted (AVE) greater than 0.5 are all recommended for reflective measurement models (Hair et al., 2019a). The results of the reflective measurement model are shown in Table 4.9 and Figure 4.9, respectively. Since the AVE values for each component were more than 0.5, the study accepted them. The criteria of having an AVE of more than 0.5 and a CR greater than 0.7 were met by all five constructions. Every concept met the criteria for convergent validity and reliability.

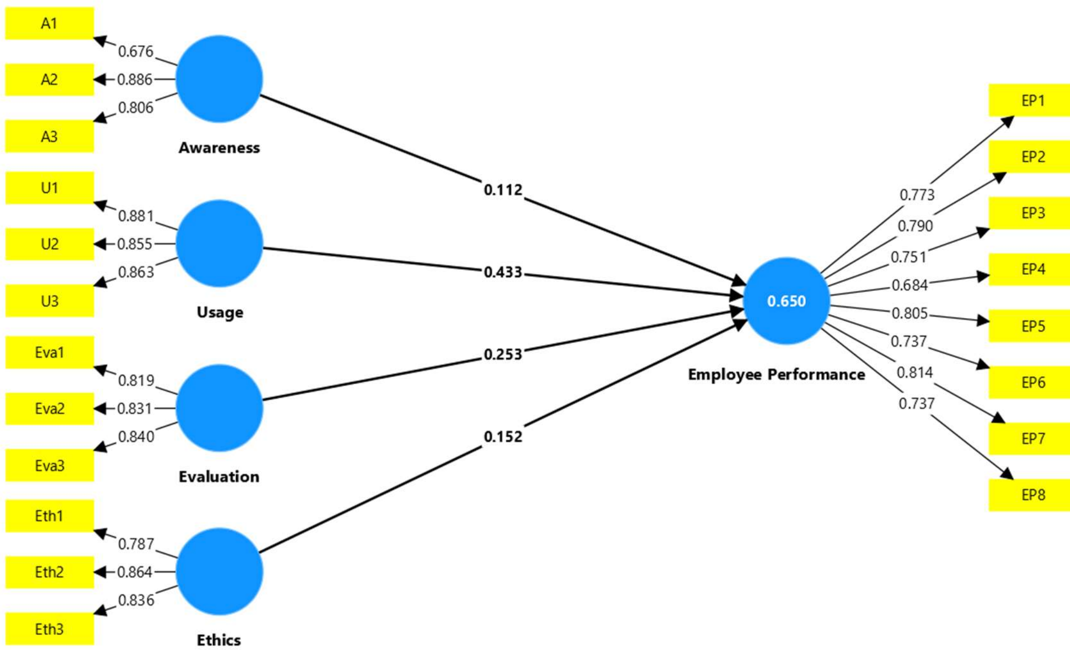
In particular, the AVE values of the Awareness and Employee Performance constructs stayed above 0.5, meeting the acceptance criterion for convergent validity even though their factor loadings were somewhat below 0.708. Consequently, nothing was taken out. Overall, all AVE values were greater than 0.5 and all CR values were greater than 0.7, indicating that each concept satisfied the standards for convergent validity and reliability.

Table 4.9: Reflective Measurement Model Evaluation

Construct	Items	Factor Loading	Cronbach's Alpha	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Awareness	A1	0.676	0.712	0.835	0.630
	A2	0.886			
	A3	0.806			
Employee Performance	EP1	0.773	0.897	0.917	0.581
	EP2	0.790			
	EP3	0.751			
	EP4	0.684			
	EP5	0.805			
	EP6	0.737			
	EP7	0.814			
	EP8	0.737			
Ethics	Eth1	0.787	0.773	0.868	0.688
	Eth2	0.864			
	Eth3	0.836			
Evaluation	Eva1	0.819	0.774	0.869	0.689
	Eva2	0.831			
	Eva3	0.840			
Usage	U1	0.881	0.835	0.901	0.751
	U2	0.855			
	U3	0.863			

Source: Developed for the research.

Figure 4.9: Measurement Model Evaluation



Source: Developed for the research.

According to Hair et al. (2014), discriminant validity explains how well each latent variable varies from other constructs in the model and highlights the extent to which indicators are exclusive to their respective constructs. Recently, Hair et al. (2019b) suggested that researchers investigate discriminant validity using the heterotrait-monotrait (HTMT) ratio of correlation criteria. When assessing discriminant validity, it is consistent with the HTMT ratio of correlation criteria (Rönkkö & Evermann, 2013; Henseler et al., 2015). HTMT scores at or below these limits indicate adequate discriminant validity, and researchers may utilise cutoff values of 0.85 or 0.90 to evaluate the results (Hair et al., 2020). Since none of the HTMT values are more than 0.90 and there is not a value of 1 in the confidence intervals, Table 4.10 demonstrates that discriminant validity has been effectively shown.

Table 4.10: HTMT Discriminant Validity Criteria

	Awareness	Employee Performance	Ethics	Evaluation	Usage
Awareness					
Employee Performance	0.737 [0.644; 0.825]				
Ethics	0.517 [0.379; 0.657]	0.662 [0.547; 0.776]			
Evaluation	0.776 [0.686; 0.864]	0.823 [0.747; 0.901]	0.765 [0.648; 0.876]		
Usage	0.837 [0.746; 0.920]	0.854 [0.784; 0.916]	0.602 [0.478; 0.724]	0.804 [0.709; 0.898]	

Source: Developed for the research.

4.3 Structural Model Evaluation

Hair et al. (2014) state that the model's prediction accuracy is represented by the coefficient of determination or R^2. From 0 to 1, where 1 represents perfect prediction accuracy, it shows the total of the exogenous factors' impacts on the endogenous variable or variables. Strong, moderate, and weak predictive accuracy are often represented by R2 values of 0.75, 0.50, and 0.25, respectively (Hair et al., 2011; Henseler et al., 2009). With the model accounting for 65.0% of the variation in employee performance, the study's R2 score of 0.650 indicates a moderate to strong explanatory power. This is regarded as good as it shows a moderate to significant amount of explanatory power and is above the 50% criterion.

To evaluate each structural path's magnitude, effect sizes (f^2) were also computed. According to Cohen's (1988) recommendations, tiny, moderate, and large effects are denoted by f^2 values of 0.02, 0.15, and 0.35, respectively. Evaluation (0.083), Ethics (0.042), and Awareness (0.018) had the smallest effects, whereas Usage had the biggest effect size (0.236), suggesting a substantial influence.

The variance inflation factor (VIF), which is the reciprocal of tolerance, is frequently used to evaluate collinearity (Hair & Alamer, 2022; Hair et al., 2019a). Critical collinearity issues between the indicators of formatively evaluated constructs are indicated by VIF values of 5 or above. However, collinearity issues may also occur at lower VIF values of 3 (Becker et al., 2015). Ideally, the VIF values should be close to or less than 3. There are no multicollinearity problems because the VIF values are below both criteria, as seen in Table 4.11.

Table 4.11: Structural Model Results

	R-square	Adjusted R-square	f^2	VIF
Employee Performance	0.650	0.644		
Awareness			0.018	1.974
Ethics			0.042	1.586
Evaluation			0.083	2.198
Usage			0.236	2.275

Source: Developed for the research.

4.4 Hypothesis Testing

Coefficient parameters were examined to test the hypothesis, and values derived from the 95% bias-corrected confidence interval for each exogenous variable were deemed significant. According to Hair et al. (2019a), for weights to be statistically significant, the p-value must be less than 0.050. Alternatively, if the 95% confidence interval, which is determined using the percentile approach or the bias-corrected and accelerated (BCa) bootstrap method for skewed distributions, excludes zero, significance can be demonstrated. The results of the hypothesis test for the 219 respondent sample are shown in Table 4.12.

As shown in Table 4.12, all four direct correlations were significant. With corresponding beta values of 0.112, 0.433, 0.253, and 0.152 and p-values less than 0.050, awareness, utilisation, evaluation, and ethics all showed strong positive correlations with worker performance. Furthermore, none of the hypotheses' 95% confidence intervals included zero, indicating that the correlations were statistically significant.

Table 4.12: Hypothesis Testing Results

Hypothesis Testing	**Beta (β)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**5.00%**	**95.00%**	**Decision**
H1: Awareness →EP	0.112	0.110	0.060	1.861	0.031	0.013	0.212	Supported
H2: Usage →EP	0.433	0.432	0.074	5.825	0.000	0.308	0.552	Supported
H3: Evaluation →EP	0.253	0.254	0.069	3.687	0.000	0.137	0.362	Supported
H4: Ethics →EP	0.152	0.156	0.059	2.559	0.005	0.060	0.256	Supported

EP Employee Performance

Source: Developed for the research.

4.5 Summary

This chapter provides a summary of the data analysis and interpretation of the study. In summary, the results showed that every hypothesis put out is being validated.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

The major conclusions and research limitations from the previous chapter are summarised in this chapter. It concludes with a thorough synopsis of the research findings and addresses ramifications as well as suggestions for more study.

5.1 Discussions of Major Findings

To ensure the reliability of the independent and dependent variables, several tests were conducted, building on the data collected and analysed in the previous chapter. The reliability tests confirmed that all variables were above the 0.7 criterion, indicating strong internal consistency. The results of hypothesis testing are displayed in Table 5.1, which provides crucial details on the relationships between worker performance and the awareness, application, assessment, and ethical components of AI literacy.

H1: AI awareness is positively affecting employee performance.

Result: $p=0.031$ ($p < 0.05$), Supported

Table 5.0 supports H1, which states that there is a favourable correlation between employee performance and AI awareness. Employees are more likely to perform well in their positions if they are more knowledgeable about AI ideas and capabilities. This result seems to be consistent with earlier studies that found a favourable correlation between employee performance and AI awareness (Chowdhury et al., 2023; Kazmi et al., 2024, Lestari et al., 2023). The results are consistent with previous studies (Ibrahim

Hassan et al., 2024), demonstrating that increasing knowledge of AI might encourage adaptability and participation, ultimately leading to better performance. Additionally, Liang et al. (2022) found that by addressing job demands, encouraging proactive behaviour, and boosting motivation, employee performance is improved by awareness of AI. Therefore, a high level of AI awareness might lead to better worker performance.

H2: AI usage is positively affecting employee performance.

Result: $p=0.000$ ($p < 0.05$), Supported

H2 shows that the study supports a beneficial association between employee performance and AI adoption (Table 5.0). Higher performance is more likely to be achieved by workers who successfully integrate their understanding of AI into their regular jobs. Previous studies have also demonstrated a favourable correlation between AI use and worker performance (Ahn, 2024; Indrasari & Pamuji, 2024). The results are consistent with earlier studies by Bashir and Nazim (2024), which found a substantial positive correlation between AI use and worker performance, as shown by a beta coefficient ($\beta = 0.492$, $p < 0.000$). This illustrates how greater use of AI results in observable improvements in worker performance. Furthermore, Chowdhury et al. (2023) asserted that the focus on understanding, interpreting, and ensuring the ethical use of AI technologies is compatible with the hypothesis and strongly supports the idea that efficient usage enhances performance.

Aside from that, the f^2 of AI usage for employee performance is the highest at 0.236 which means it has a large effect size. It makes sense and is logical since employees' performance will improve when they use AI extensively.

H3: AI evaluation is positively affecting employee performance.

Result: $p=0.000$ ($p < 0.05$), Supported

Table 5.0 illustrates H3, which states that the study supports a favourable association between staff performance and AI evaluation. Employees who critically evaluate and understand the applicability of AI systems demonstrate better work outcomes. According to Chen et al. (2024), the study found that evaluating AI's applicability in tasks significantly increases employees' competency and job performance, with those possessing skills to assess and adapt AI tools reporting higher efficiency and output. In addition, Chukwuka and Kashiari (2024) found that employees' ability to evaluate and adapt to AI applications enhances job engagement and performance. For instance, critical assessment of AI applications improves employees' alignment with organisational goals, ultimately boosting their productivity and performance.

H4: AI ethics is positively affecting employee performance.

Result: $p=0.005$ ($p < 0.05$), Supported

Table 5.0 provides evidence for H4, which states that there is a positive correlation between employee performance and AI ethics. Employees who are well-versed in the ethical issues surrounding the use of AI perform better, demonstrating sensible and well-informed decision support. Prior studies highlight that ethical considerations in AI deployment positively influence employee performance. For instance, Bankins and Formosa (2023) found that incorporating fairness, transparency, and accountability into AI systems enhances employee trust, adaptability, and productivity, ultimately leading to better performance. This implies that putting AI ethics first produces a positive workplace that encourages worker performance and engagement.

In summary, the hypothesis testing reveals that AI literacy significantly influences employee performance, with all associations demonstrating positive effects.

Table 5.1: Hypothesis Testing Results

Hypothesis	**P-value score**	**Decision**
H1: AI awareness is positively affecting employee performance.	0.031 ($p < 0.050$)	Supported
H2: AI usage is positively affecting employee performance.	0.000 ($p < 0.050$)	Supported
H3: AI evaluation is positively affecting employee performance.	0.000 ($p < 0.050$)	Supported

H4: AI ethics is positively affecting employee performance.	0.005 ($p < 0.050$)	Supported

Source: Developed for the research.

5.2 Implications of the Study

5.2.1 The Practical Implications for Policy Makers and/or Practitioners

This study demonstrates that AI literacy aspects, including awareness, evaluation, usage, and ethics, significantly impact employee performance. It emphasizes the importance of fostering an environment where employees can develop and apply AI skills. Managers can use these insights to identify areas for improvement, such as enhancing critical assessment of AI systems or better implementing AI principles. By offering resources, tailored training, and continuous feedback, organisations can enhance workplace outcomes and gain a competitive advantage.

5.2.1.1 For Practitioners

Organisations should give top priority to creating tailored training programs that improve employees' literacy of AI and its uses. The goals of these programs have to be to increase awareness, enhance evaluation abilities, foster ethical comprehension, and support the efficient use of AI in daily work. Employees are better able to adjust to technology developments when this knowledge gap is closed, which boosts productivity and encourages creativity. Employee skill development may also be facilitated by frequent performance reviews and feedback, which guarantees alignment with company objectives.

Organisations should incorporate AI literacy as a fundamental skill into their workforce development strategies in addition to training programs. For example, establishing AI literacy certificates or mentorship programs might aid in standardising skill sets throughout teams. Furthermore, fostering collaborative environments where employees can share AI-related insights and solutions encourages continuous learning and growth.

5.2.1.2 For Policy Makers

Establishing a framework that promotes AI literacy across industries is a critical task for policymakers. Workforce readiness for an AI-driven economy may be guaranteed by programs like national AI literacy campaigns, financing for AI training courses, and collaborations with academic institutions. Incentives for AI literacy initiatives might help politicians encourage widespread employee readiness and lessen resistance to technology adoption.

Additionally, policy makers should prioritize the development and implementation of ethical AI regulations that tackle important concerns like algorithmic transparency, privacy, and fairness. By working together with organisations, they may create frameworks that guarantee ethical AI use, reducing dangers such as technology biases and data exploitation. These steps will increase confidence in AI technologies by encouraging ethical awareness and responsibility in AI applications. This will enable staff members to utilise AI efficiently and confidently, which will improve their performance.

In conclusion, the real-world ramifications for practitioners and policymakers highlight the necessity of teamwork in advancing AI literacy in the workplace.

Businesses and governments may improve employee performance and facilitate a more seamless transition to the AI-driven future by funding specialised training, developing ethical AI frameworks, and encouraging critical assessment abilities.

5.2.2 The Theoretical Implications from Academic Perspective

As AI becomes more integrated into workplaces, AI literacy is increasingly recognized as crucial for enhancing employee performance and organisational success. By providing several important theoretical implications, this study adds to the body of knowledge.

Firstly, it extends the Task Technology Fit Theory (TTFT) by incorporating AI literacy dimensions (awareness, evaluation, usage, and ethics) and demonstrating how performance improves when employees' understanding of AI aligns with job needs. This enhances the theoretical framework by adding AI literacy as a key component.

Secondly, the study highlights the multifaceted nature of AI literacy, which includes ethical considerations, usage, evaluation, and awareness, and shows how these factors impact performance outcomes. This research fills gaps in existing literature, focusing on AI literacy rather than acceptance or resistance.

Thirdly, the study highlights the significance that ethical literacy plays in AI-driven workplaces and how crucial it is for enhancing employee performance. This result calls for further exploration of ethical awareness in organisational effectiveness.

In conclusion, this study broadens TTFT's scope and offers a valuable framework for understanding how AI literacy impacts employee behavior and performance in technologically advanced environments.

5.3 Limitations of the Study

First off, the results' potential to be applied broadly is restricted by the convenience sampling method, which may not accurately reflect Malaysia's workforce as a whole. A more randomized sampling approach would improve applicability across industries and regions.

Second, using self-reported information from an online survey might lead to response bias since participants might have given responses that were deemed acceptable by society. Furthermore, the survey does not go into great detail about how to verify that respondents are using AI technology at work. Future research should incorporate mechanisms to validate respondents' actual engagement with AI, such as using activity logs, observational data, or direct questions about specific AI tools used.

The study's geographic focus on Malaysia also limits its applicability to other countries or cultures. Expanding future research to include global perspectives would provide more diverse insights.

Lastly, the cross-sectional design makes it challenging to establish causal relationships. The long-term effects of AI literacy on performance might be better understood with a longitudinal study.

Notwithstanding these drawbacks, the study offers a strong starting point for more research into the connection between employee performance and AI literacy.

5.4 Recommendations for Future Research

For a more thorough understanding of AI literacy's influence on employee performance, future studies should examine additional facets of the concept, such as flexibility, creativity, or teamwork in AI-driven environments. To enhance the generalizability of findings, probability sampling methods, like random sampling, should be used to ensure a more representative sample across industries and regions, improving external validity.

Longitudinal studies could also track changes in AI literacy over time to establish causal relationships. Incorporating measures to confirm respondents' active engagement with AI would address a critical gap. For example, future studies could ask respondents to specify the frequency and types of AI tools they use, validate engagement through organisational records, or include indirect measures, such as testing respondents' familiarity with key AI functionalities.

Mixed-method approaches, integrating quantitative surveys with qualitative techniques, would provide deeper insights into employees' experiences with AI technology. Additionally, exploring cross-cultural perspectives would help understand how organisational and cultural factors influence the relationship between AI literacy and employee performance.

These approaches would strengthen the conceptual framework and deepen our understanding of AI literacy's role in workforce development.

5.5 Summary

The potential of AI to revolutionise workplace efficiency has been shown by this study's investigation of the impact of AI literacy factors, such as awareness, evaluation, usage, and ethics, on employee performance. While addressing important issues including transparency, ethical usage, and practical application, the findings emphasise the significance of creating a supportive atmosphere where staff members may advance their understanding of AI.

Despite the study's shortcomings, which included a cross-sectional design and the use of convenience sampling, these present chances for further research to improve and broaden the conclusions. By integrating the strengths of AI technology with a focus on ethical and skillful implementation, organisations can create an inclusive and innovative workforce that effectively leverages AI's potential to enhance performance.

This study lays the groundwork for comprehending how AI literacy affects employee outcomes and highlights the necessity of ongoing initiatives to provide employees with the abilities and information required to succeed in an AI-driven workplace.

REFERENCES

Ahn, H. Y. (2024). AI-Powered E-Learning for Lifelong Learners: Impact on Performance and Knowledge Application. *Sustainability*, *16*(20), 9066.

Ainur, A. K., Sayang, M. D., Jannoo, Z., & Yap, B. W. (2017). Sample size and non-normality effects on goodness of fit measures in structural equation models. *Pertanika Journal of Science & Technology*, *25*(2).

Alem, D. D. (2020). An overview of data analysis and interpretations in research. *International Journal of Academic Research in Education and Review*, *8*(1), 1-27.

Amoako, G., Omari, P., Kumi, D. K., Agbemabiase, G. C., & Asamoah, G. (2021). Conceptual framework—artificial intelligence and better entrepreneurial decision-making: the influence of customer preference, industry benchmark, and employee involvement in an emerging market. *Journal of Risk and Financial Management*, *14*(12), 604.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological bulletin*, *103*(3), 411.

Antunes, P., & Ferreira, A. (2011, January). Developing collaboration awareness support from a cognitive perspective. In *2011 44th Hawaii International Conference on System Sciences* (pp. 1-10). IEEE.

Bankins, S., & Formosa, P. (2023). The ethical implications of artificial intelligence (AI) for meaningful work. *Journal of Business Ethics*, *185*(4), 725-740.

Bashir, K., & Nazim, M. (2024). The Impact of Artificial Intelligence on Employee Performance and Satisfaction: A Study from Academic Sector. *Innovative Journal of Business and Economics Strategy (IJBES)*, *1*(1).

Becker, J. M., Ringle, C. M., Sarstedt, M., & Völckner, F. (2015). How collinearity affects mixture regression results. *Marketing letters*, *26*, 643-659.

Bere, A. (2018). Applying an extended task-technology fit for establishing determinants of mobile learning: an instant messaging initiative. *Journal of Information Systems Education*, *29*(4), 239-252.

Božić, V., & Poola, I. (2023). The role of artificial intelligence in increasing the digital literacy of healthcare workers and standardization of healthcare. *no. April*, 1-13.

Calvani, A., Fini, A., & Ranieri, M. (2010). Digital Competence in K-12: theoretical models, assessment tools and empirical research. *Anàlisi: quaderns de comunicació i cultura*, (40), 157-171.

Cartelli, A. (2010, January). Frameworks for digital competence assessment: Proposals, instruments, and evaluation. In *Proceedings of informing science & it education conference (InSITE)* (pp. 561-573).

Chen, N., Zhao, X., & Wang, L. (2024). The Effect of Job Skill Demands Under Artificial Intelligence Embeddedness on Employees' Job Performance: A Moderated Double-Edged Sword Model. *Behavioral Sciences*, *14*(10), 974.

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human resource management review*, *33*(1), 100899.

Chukwuka, E. J., & Dibie, K. E. (2024). Strategic role of artificial intelligence (AI) on human resource management (HR) employee performance evaluation function. *International Journal of Entrepreneurship and Business Innovation*, *7*(2), 269-282.

Clark, G. (2013). Secondary data. *Methods in Human Geography*, 57-73.

Cohen, J. (1992). A power primer. In A. E. Kazdin (Ed.), *Methodological issues and strategies in clinical research* (4th ed., pp. 279–284). American Psychological Association. https://doi.org/10.1037/14805-018

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences (2nd ed.). *Routledge.* https://doi.org/10.4324/9780203771587

Disman, D., Ali, M., & Barliana, M. S. (2017). The use of quantitative research method and statistical data analysis in dissertation: an evaluation study. *International Journal of Education*, *10*(1), 46-52.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International journal of information management*, *57*, 101994.

Erickson, G. S. (2017). *New methods of market research and analysis*. Edward Elgar Publishing.

Evans, J. R., & Mathur, A. (2018). The value of online surveys: A look back and a look ahead. *Internet research*, *28*(4), 854-887.

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. *MIS Quarterly*, *19*(2), 213–236. https://doi.org/10.2307/249689

Goodhue, D. L., Klein, B. D., & March, S. T. (2000). User evaluations of IS as surrogates for objective performance. *Information & management*, *38*(2), 87-101.

Gyires, T., Klaus, T., & Wen, H. J. (2003). The use of Web-based information systems for non-work activities: An empirical study. *Human Systems Management*, *22*(3), 105.

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3), 100027.

Hair Jr, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of business research*, *109*, 101-110.

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook* (p. 197). Springer Nature.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice*, *19*(2), 139-152.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019a). When to use and how to report the results of PLS-SEM. *European business review*, *31*(1), 2-24.

Hair, J., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. (2014). Partial Least Squares Structural Equation Modeling (PLS-SEM): An Emerging Tool for Business Research. *European Business Review*, *26*(2), 106–121

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019b). Rethinking some of the rethinking of partial least squares. *European journal of marketing*, *53*(4), 566-584.

Haleem, A., Javaid, M., Singh, R. P., Rab, S., & Suman, R. (2021). Hyperautomation for the enhancement of automation in industries. *Sensors International*, *2*, 100124.

Hallaq, T. G. (2016). *Evaluating online media literacy in higher education: Validity and reliability of the digital online media literacy assessment (DOMLA)*. Idaho State University.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, *43*, 115-135.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In *New challenges to international marketing* (pp. 277-319). Emerald Group Publishing Limited.

Hossan, D., Dato'Mansor, Z., & Jaharuddin, N. S. (2023). Research population and sampling in quantitative study. *International Journal of Business and Technopreneurship (IJBT)*, *13*(3), 209-222.

Houser, K. A. (2019). Can AI solve the diversity problem in the tech industry: Mitigating noise and bias in employment decision-making. *Stan. Tech. L. Rev.*, *22*, 290.

Howard, M. C., & Rose, J. C. (2019). Refining and extending task–technology fit theory: Creation of two task–technology fit scales and empirical clarification of the construct. *Information & Management*, *56*(6), 103134. https://doi-org.libezp2.utar.edu.my/10.1016/j.im.2018.12.002

Ibrahim Hassan, A. H., Baquero, A., Salama, W. M., & Ahmed Khairy, H. (2024). Engaging Hotel Employees in the Era of Artificial Intelligence: The Interplay of Artificial Intelligence Awareness, Job Insecurity, and Technical Self-Efficacy. *Journal of Logistics, Informatics and Service Science, 11*(5), 522-539. 10.33168/JLISS.2024.0530

Idika, D. O., Owan, V. J., & Agama, V. U. (2023). The application of the nominal scale of measurement in research data analysis.

Indrasari, M., & Pamuji, E. (2024). Enhancing Employee Performance through Strategic Initiatives (Working in the Middle of the Artificial Intelligence Era: Employee Performance Improvement Strategy). *Journal of Business Management and Economic Development, 2*(1), 383-396. https://doi.org/10.59653/jbmed.v2i01.548

Kandel, B. (2020). Qualitative versus quantitative research. *Journal of product Innovation management*, *32*(5), 658.

Kar, A. K., Choudhary, S. K., & Singh, V. K. (2022). How can artificial intelligence impact sustainability: A systematic literature review. *Journal of Cleaner Production*, *376*. https://doi-org.libezp2.utar.edu.my/10.1016/j.jclepro.2022.134120

Katz, I. R. (2007). Testing information literacy in digital environments: ETS's iSkills assessment. *Information technology and Libraries*, *26*(3), 3-12.

Kaur, P., Stoltzfus, J., & Yellapu, V. (2018). Descriptive statistics. *International Journal of Academic Medicine*, *4*(1), 60-63.

Kazmi, S. I. H., Afzal, M. F., Gondal, S., Ashraf, M. U., & Umair, M. (2024). Evaluating the Impact of Artificial Intelligence on Employee Engagement and Performance in Pakistan. *Journal of Excellence in Social Sciences*, *3*(1), 30-42.

Khoa, B. T., Kien, D. T., & Oanh, L. T. K. (2021, September). Students' Learning Management System Adoption Intention in COVID-19: An Integration of TPB and TTF Model. In *2021 7th International Conference on Education and Technology (ICET)* (pp. 187-193). IEEE.

Lackey, N.R., & Wingate, A.L. (1998). The pilot study: One key to research success. In P.J. Brink & M.J. Wood (Eds.), *Advanced design in nursing research* (2nd ed.). Thousand Oaks, CA: Sage.

Leahy, D., & Dolan, D. (2010, September). Digital literacy: A vital competence for 2010?. In *IFIP international conference on key competencies in the knowledge society* (pp. 210-221). Berlin, Heidelberg: Springer Berlin Heidelberg.

Lestari, N. S., Rosman, D., Veithzal, A. P., Zainal, V. R., & Triana, I. (2023). Analysing the Impact of Robot, Artificial Intelligence, and Service Automation Awareness, Technostress and Technology Anxiety on Employees's Job Performance in The Foodservice Industry. In *2023 5th International Conference on Cybernetics and Intelligent System (ICORIS)* (pp. 1-6). IEEE.

Li, Z. (2024). Ethical frontiers in artificial intelligence: navigating the complexities of bias, privacy, and accountability. *International Journal of Engineering and Management Research*, *14*(3), 109-116.

Liang, T. P., & Wei, C. P. (2004). Introduction to the special issue: Mobile commerce applications. *International journal of electronic commerce*, *8*(3), 7-17.

Liang, X., Guo, G., Shu, L., Gong, Q., & Luo, P. (2022). Investigating the double-edged sword effect of AI awareness on employee's service innovative behavior. *Tourism Management*, *92*, 104564.

Long, D., & Magerko, B. (2020, April). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI conference on human factors in computing systems* (pp. 1-16).

Low, M. P., Ong, S. F., & Tan, P. M. (2017). Would internal corporate social responsibility make a difference in professional service industry employees' turnover intention? A two-stage approach using PLS-SEM. *Global Business and Management Research*, *9*(1), 24.

Malhotra, N. K., & Peterson, M. (2006). *Basic marketing research: A decision making approach* (2nd ed.). Upper Saddle River, NJ: Prentice Hall.

Malik, S. A. (2023). Unlocking Organizational Potential: Harnessing AI literacy for Dynamic Capabilities through sensing, seizing and reconfiguring initiatives in IT firms.

Martin, A., & Grudziecki, J. (2006). DigEuLit: Concepts and tools for digital literacy development. *Innovation in teaching and learning in information and computer sciences*, *5*(4), 249-267.

McQuarrie, E. F. (2015). *The market research toolbox: a concise guide for beginners*. Sage Publications.

Mdladla, L. T. S., Wider, W., & Thanathanchuchot, T. (2024). Navigating the AI revolution: A review of the transformative strategies for economic development in Africa's emerging economies. *Journal of Infrastructure, Policy and Development*, *8*(9), 5436.

Mishra, P., Pandey, C. M., Singh, U., Gupta, A., Sahu, C., & Keshri, A. (2019). Descriptive statistics and normality tests for statistical data. *Annals of cardiac anaesthesia*, *22*(1), 67-72.

Mueller, S. T., Hoffman, R. R., Clancey, W., Emrey, A., & Klein, G. (2019). Explanation in human-AI systems: A literature meta-review, synopsis of key ideas and publications, and bibliography for explainable AI. *arXiv preprint arXiv:1902.01876*.

Naidu, K., & Maddala, S. (2024). AI in the Present Era: Overview and Insights. *Journal of Informatics Education and Research*, *4*(2).

Ng, C. (2022, November 29). Government support for digital transformation in Malaysia. *Employment Hero.* https://employmenthero.com/my/blog/digital-transformation-government-support/

Onuoha, E. O. (2023). Organizational Ethics: A Panacea for Employee Performance in Nigerian Institutions.

Osasona, F., Amoo, O. O., Atadoga, A., Abrahams, T. O., Farayola, O. A., & Ayinla, B. S. (2024). Reviewing the ethical implications of AI in decision making processes. *International Journal of Management & Entrepreneurship Research*, *6*(2), 322-335.

Patel, M., & Patel, N. (2019). Exploring research methodology. *International Journal of Research and Review*, *6*(3), 48-55.

Peres, R. S., Jia, X., Lee, J., Sun, K., Colombo, A. W., & Barata, J. (2020). Industrial artificial intelligence in industry 4.0-systematic review, challenges and outlook. *IEEE access*, *8*, 220121-220139.

Pratiwi, N. J., Jamaluddin, J., Niswaty, R., & Salam, R. (2019). The Influence of work facilities on employee performance at the regional financial management agency secretariat section of South Sulawesi Province. *Jurnal Ad'ministrare*, *6*(1), 35-44.

Rahman, M. M., Tabash, M. I., Salamzadeh, A., Abduli, S., & Rahaman, M. S. (2022). Sampling techniques (probability) for quantitative social science researchers: a conceptual guidelines with examples. *Seeu Review*, *17*(1), 42-51.

Ramachandran, K. K., Mary, A. A. S., Hawladar, S., Asokk, D., Bhaskar, B., & Pitroda, J. R. (2022). Machine learning and role of artificial intelligence in optimizing work performance and employee behavior. *Materials Today: Proceedings*, *51*, 2327-2331.

Rau, P.-L. P., Wang, B., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. *Behaviour & Information Technology*, *42*(9), 1324–1337. https://doi-org.libezp2.utar.edu.my/10.1080/0144929X.2022.2072768

Reddy, K. S., Kethan, M., Basha, S. M., Singh, A., Kumar, P., & Ashalatha, D. (2024, April). Ethical and Legal Implications of AI on Business and Employment: Privacy, Bias, and Accountability. In *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS)* (Vol. 1, pp. 1-6). IEEE.

Rönkkö, M., & Evermann, J. (2013). A critical examination of common beliefs about partial least squares path modeling. *Organizational Research Methods*, *16*(3), 425-448.

Sadan, V. (2017). Data collection methods in quantitative research. *Indian Journal of Continuing Nursing Education*, *18*(2), 58-63.

Sandeep, S. R., Ahamad, S., Saxena, D., Srivastava, K., Jaiswal, S., & Bora, A. (2022). To understand the relationship between Machine learning and Artificial intelligence in large and diversified business organisations. *Materials Today: Proceedings*, *56*, 2082-2086.

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2021). Partial least squares structural equation modeling. In *Handbook of market research* (pp. 587-632). Cham: Springer International Publishing.

Sharma, G. (2017). Pros and cons of different sampling techniques. *International journal of applied research*, *3*(7), 749-752.

Sidharth, G. (2023). Research Designs for Contemporary Social Science Research: An Overview. *International Research Journal of Management, Sociology & Humanities*, *14*(1), 381-392.

Straub, D., Boudreau, M. C., & Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of the Association for Information systems*, *13*(1), 24.

Sturm, T., & Peters, F. (2020). The impact of artificial intelligence on individual performance: Exploring the fit between task, data, and technology.

Sudiardhita, K. I., Mukhtar, S., Hartono, B., Sariwulan, T., & Nikensari, S. I. (2018). The effect of compensation, motivation of employee and work satisfaction to employee performance Pt. Bank Xyz (Persero) Tbk. *Academy of Strategic Management Journal*, *17*(4), 1-14.

Taherdoost, H. (2017). Determining sample size; how to calculate survey sample size. *International Journal of Economics and Management Systems*, *2*.

Taherdoost, H. (2021). Data collection methods and tools for research; a step-by-step guide to choose data collection technique for academic and business research projects. *International Journal of Academic Research in Management (IJARM)*, *10*(1), 10-38.

Tastle, W. J., & Wierman, M. J. (2006). An information theoretic measure for the evaluation of ordinal scale data. *Behavior Research Methods*, *38*, 487-494.

Tong, S., Jia, N., Luo, X., & Fang, Z. (2021). The Janus face of artificial intelligence feedback: Deployment versus disclosure effects on employee performance. *Strategic Management Journal*, *42*(9), 1600-1631.

Turner, A. G. (2003). Sampling frames and master samples. *United Nations secretariat statistics division*, 1-26.

Tzirides, A. O. O., Zapata, G., Kastania, N. P., Saini, A. K., Castro, V., Ismael, S. A., ... & Kalantzis, M. (2024). Combining human and artificial intelligence for enhanced AI literacy in higher education. *Computers and Education Open*, *6*, 100184.

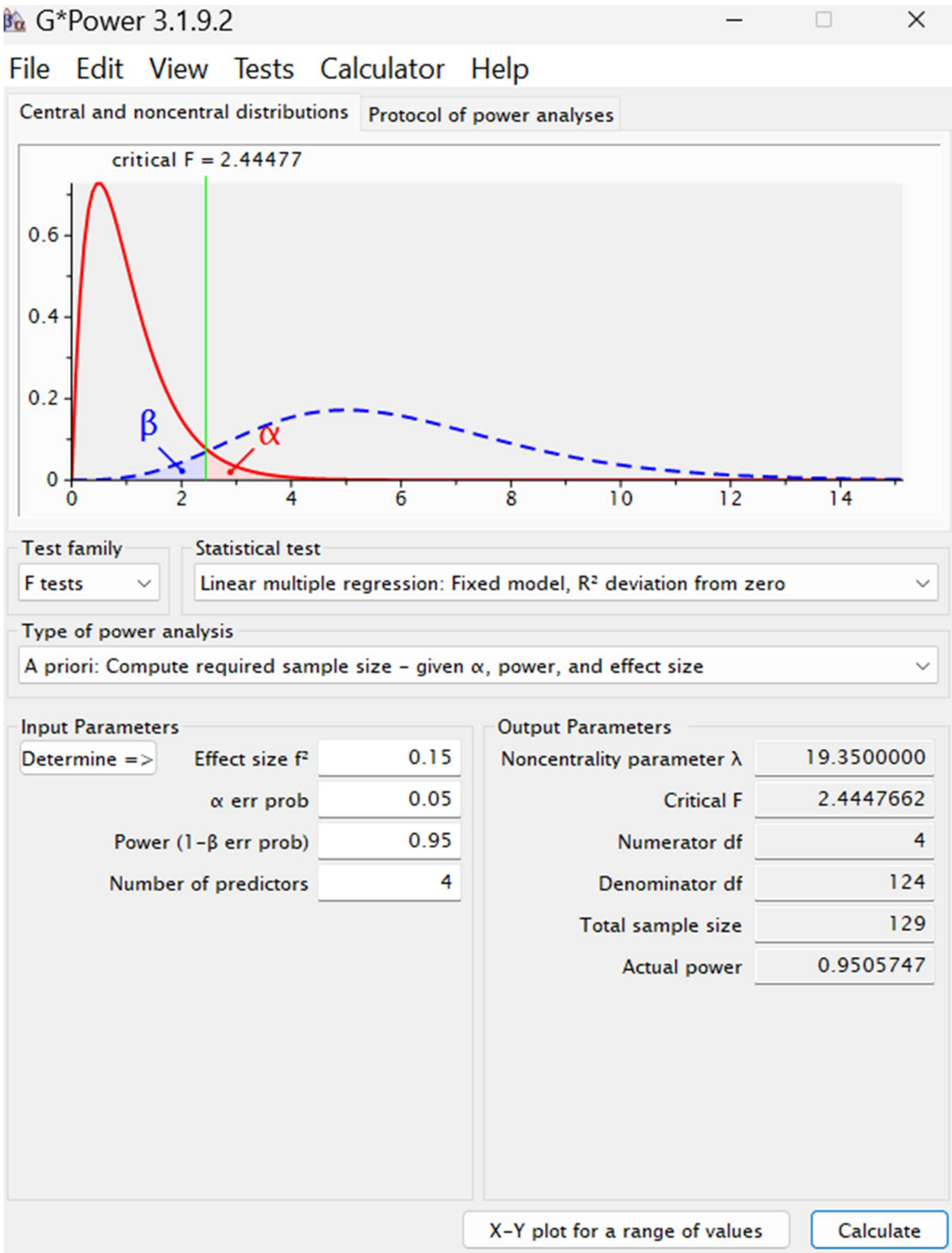
Wilcox, A. B., Gallagher, K. D., Boden-Albala, B., & Bakken, S. R. (2012). Research data collection methods: from paper to tablet computers. *Medical care*, *50*, S68-S73.

Wilson, M., Scalise, K., & Gochyyev, P. (2015). Rethinking ICT literacy: From computer skills to social network settings. *Thinking Skills and Creativity*, *18*, 65-80.

Xu, W., Dainoff, M. J., Ge, L., & Gao, Z. (2021). From human-computer interaction to human-AI Interaction: new challenges and opportunities for enabling human-centered AI. *arXiv preprint arXiv:2105.05424*, *5*.

APPENDICES

Appendix 3.1: G*Power Software, version 3.1.9.2



Appendix 3.2: Questionnaire

UNIVERSITI TUNKU ABDUL RAHMAN

FACULTY OF ACCOUNTANCY AND MANAGEMENT

BACHELOR OF INTERNATIONAL BUSINESS (HONS)

Title of Research:

AI: Just a Buzzword or the Real Deal? Explicating the Influence of Artificial Intelligence (AI) Literacy on Employee Performance

Dear Esteemed Respondents,

I am Loke Li Ying, a Y2S3 student of Bachelor of International Business (Hons) from Universiti Tunku Abdul Rahman (UTAR), Sungai Long. Currently, I am working on Final Year Project entitled "Explicating the Influence of Artificial Intelligence (AI) Literacy on Employee Performance".

The objective of this survey is to examine the interrelations between Artificial Intelligence (AI) literacy, encompassing awareness, usage, evaluation, and ethics, and employee performance.

I humbly request your voluntary participation in this study.

Guidelines for completing the questionnaire:

- It will take you approximately 10-15 minutes to complete this questionnaire.
- Please answer ALL questions.

All of the information obtained regarding this study will be kept strictly confidential and aggregated. Your response will be solely used for academic purposes and not be identified in any data or report.

If you have any questions about this study at any time, please feel free to contact the primary researcher, Ms. Loke Li Ying at liyingloke@1utar.my.

Thank you.

Regards,
Loke Li Ying
Bachelor of International Business (Hons)
Universiti Tunku Abdul Rahman Sungai Long

Personal Data Protection Statement

Please be informed that in accordance with Personal Data Protection Act 2010 ("PDPA") which came into force on 15 November 2013, Universiti Tunku Abdul Rahman ("UTAR") is hereby bound to make notice and require consent in relation to collection, recording, storage, usage and retention of personal information.

Notice:

1. The purposes for which your personal data may be used are inclusive but not limited to:-

- For assessment of any application to UTAR
- For processing any benefits and services
- For communication purposes
- For advertorial and news

- For general administration and record purposes
- For enhancing the value of education
- For educational and related purposes consequential to UTAR
- For the purpose of our corporate governance
- For consideration as a guarantor for UTAR staff/ student applying for his/her scholarship/ study loan

2. Your personal data may be transferred and/or disclosed to third party and/or UTAR collaborative partners including but not limited to the respective and appointed outsourcing agents for purpose of fulfilling our obligations to you in respect of the purposes and all such other purposes that are related to the purposes and also in providing integrated services, maintaining and storing records. Your data may be shared when required by laws and when disclosure is necessary to comply with applicable laws.

3. Any personal information retained by UTAR shall be destroyed and/or deleted in accordance with our retention policy applicable for us in the event such information is no longer required.

4. UTAR is committed in ensuring the confidentiality, protection, security and accuracy of your personal information made available to us and it has been our ongoing strict policy to ensure that your personal information is accurate and complete.

Consent

1. By submitting this form you hereby authorize and consent to us processing (including disclosing) your personal data and any updates of your information, for the purposes and/or for any other purposes related to the purpose.

2. If you do not consent or subsequently withdraw your consent to the processing and disclosure of your personal data, UTAR will not be able to fulfill our obligations or to contact you or to assist you in respect of the purposes and/or for any other purposes related to the purpose.

Acknowledgement of Notice

By participating in this study, your participation is voluntary. Your information will be kept confidential and will only be used in this study.

( ) I have been notified by you and that I hereby understood, consented and agreed per UTAR above notice.

Section A: Artificial Intelligence (AI) Literacy and Employee Performance

This section is seeking your opinion on how employee performance is impacted by employee awareness, usage, evaluation, and ethics regarding AI technologies. Please select the best answer based on a scale of 1 to 7.

1-	2-	3-	4-	5-	6-	7-
Strongly Disagree (SD)	Disagree (D)	Somewhat Disagree (SWD)	Neutral (N)	Somewhat Agree (SWA)	Agree (A)	Strongly Agree (SA)

i	Awareness	SD	D	SWD	N	SWA	A	SA
1.	I can distinguish between smart devices and non-smart devices.	1	2	3	4	5	6	7

2.	I know how AI technology can help me.	1	2	3	4	5	6	7
3.	I can identify the AI technology employed in the applications and products I use.	1	2	3	4	5	6	7
ii	**Usage**	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
1.	I can skillfully use AI applications or products to help me with my daily work.	1	2	3	4	5	6	7
2.	It is usually easy for me to learn to use a new AI application or product.	1	2	3	4	5	6	7
3.	I can use AI applications or products to improve my work efficiency.	1	2	3	4	5	6	7
iii	**Evaluation**	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
1.	I can evaluate the capabilities and limitations of an AI application or product after using it for a while.	1	2	3	4	5	6	7
2.	I can choose a proper solution from various solutions provided by a smart agent.	1	2	3	4	5	6	7
3.	I can choose the most appropriate AI application or product from a variety for a particular task.	1	2	3	4	5	6	7
iv	**Ethics**	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**
1.	I always comply with ethical principles when using AI applications or products.	1	2	3	4	5	6	7
2.	I am often alert to privacy and information security issues when using AI applications or products.	1	2	3	4	5	6	7
3.	I am always alert to the abuse of AI technology.	1	2	3	4	5	6	7
v	**Employee Performance**	**SD**	**D**	**SWD**	**N**	**SWA**	**A**	**SA**

1.	I understand the need for my department team members to be AI-literate and adding value to the organisation.	1	2	3	4	5	6	7
2.	I understand my organisation's AI strategy, my department's AI goals, and my role in achieving these objectives.	1	2	3	4	5	6	7
3.	I understand specifically what my manager expects of me in terms of AI literacy.	1	2	3	4	5	6	7
4.	I understand how well I am performing in AI literacy compared to expectations.	1	2	3	4	5	6	7
5.	I understand what I have to do to enhance my AI literacy for optimal job performance.	1	2	3	4	5	6	7
6.	I have access to AI tools and resources necessary for my work, or I understand the reasons for any limitations in access.	1	2	3	4	5	6	7
7.	I understand that the company benefited from my participation in AI initiatives.	1	2	3	4	5	6	7
8.	I understand that changes in AI policies, procedures, and technology introduced by management often lead to better ways of doing things.	1	2	3	4	5	6	7

<u>Section B: Demographic</u>

1. Gender
   - □ Male
   - □ Female

2. Age group □ 18 - 24 □ 25 - 30 □ 31 - 40 □ 41- 50 □ 51 - 60 □ Above 60
3. Highest educational level □ Secondary □ Pre-University □ Diploma □ Professional Qualification, eg. LCCI, ACCA, etc. □ Bachelor's degree □ Master's degree □ Doctoral degree
4. Employment status □ Freelancer, gig worker □ Employed as a full-time employee □ Employed as a part-time employee
5. What is your current position? □ Non-management level (eg. does not involve in any decision making of the company) □ Management-level employee (eg. does involve in any decision making of the company)
6. Type of industry □ Non-serviced based, eg., manufacturing, agriculture, construction, quarry, etc.

□ Service-based, eg. Finance, IT, healthcare, hospitality, restaurant café, etc.
7. Size of company □ Less than 5 employees □ 5 to less than 30 employees □ 30 to less than 75 employees □ More than 75 employees
8. Year(s) of establishment □ Less than 1 year □ 1 to 3 years □ More than 3 years, less than 5 years □ More than 5 years, less than 10 years □ More than 10 years

Appendix 3.3: Ethical Clearance Approval Letter

UNIVERSITI TUNKU ABDUL RAHMAN DU012(A)
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Re: U/SERC/78-352/2024

9 September 2024

Dr Fitriya Binti Abdul Rahim
Head, Department of International Business
Faculty of Accountancy and Management
Universiti Tunku Abdul Rahman
Jalan Sungai Long
Bandar Sungai Long
43000 Kajang, Selangor

Dear Dr Fitriya,

Ethical Approval For Research Project/Protocol

We refer to your application for ethical approval for your students' research project from Bachelor of International Business (Honours) programme enrolled in course UKMZ3016. We are pleased to inform you that the application has been approved under Expedited Review.

The details of the research projects are as follows:

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
1.	Strategic Approaches to Enhance Consumer Engagement and Traction Through Livestreaming Content: A Comparative Analysis of Effective Tactics and Best Practices	Adeline Kong Qing Qing	Pn Ezatul Emilia Binti Muhammad Arif	9 September 2024 – 8 September 2025
2.	Factors Influencing Customers Acceptance of Malaysian Traditional Bank's Digital Channels	Chan Huey Teng	Dr Tee Peck Ling	
3.	Relationship Marketing Affecting the Customer Experience in Using AI-Chatbot	Chan Pei Yee	Dr Yeong Wai Mun	
4.	Factors that Influence Employee Performance in the Workplace	Chen Kar Him	Dr Komathi a/p Munusamy	
5.	Social Media Advertising Format that Affect Consumer Behaviour in Malaysia	Cheong Yi Qian	Dr Fok Kuk Fai	
6.	Consumer Intentions to Switch Accommodations from Traditional Hotels to Airbnb	Chia Rong Wei	Dr Law Kian Aun	
7.	Engulfed by Recommendation Systems: Walking Away Empty-handed Becomes a Challenge	Chin Kai Ning	Pn Ezatul Emilia Binti Muhammad Arif	
8.	The Interrelations Between Artificial Intelligence (AI) Usage and Academic Performance	Chin Wie Jane	Dr Low Mei Peng	
9.	Factor Affecting University Students' Behavioural Intention to Use ChatGPT for Academic Purpose	Chock Yee Fai	Pn Farida Bhanu Binti Mohamed Yousoof	
10.	The Impact of ESG Initiatives on Green Product and Consumer Purchase Intentions	Choi Yoon Qi	Dr Foo Meow Yee	
11.	Factors Influencing Gender Entrepreneurial Intention Among Malaysian Undergraduate Students	Chong Chean You	Dr Kalaivani a/p Jayaraman	
12.	The Influence of Technological Infrastructure on the Success of Digital Reading Platforms Globally Among Students	Chong Li Xian	Dr Komathi a/p Munusamy	

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Tel: (603) 9086 0288 Fax: (603) 9019 8868
Website: www.utar.edu.my

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
13.	The Impact of Social Sustainability Awareness on Consumer Buying Behavior	Fang Yu Mei	Dr Komathi a/p Munusamy	9 September 2024 – 8 September 2025
14.	The Effect of Social Media Influencer Marketing on the Purchase Intention of Young Consumers in the Skincare Product Industry	Foh Zhi Hui	Ms Goh Poh Jin	
15.	University Student's Intention to Adopt Mobile Payments in Malaysia	Foo Yong Yi	Pn Farida Bhanu Binti Mohamed Yousoof	
16.	Modernisation and Transformation in SMEs: A Case Study Exploring Owner Perspectives on Process Transformation and Technological Adaptation	Grace Lim Wei Qi	Mr Lee Yoon Heng	
17.	Understanding the Influence of Greenwashing on Green Brand Equity and Green Purchase Intention Among Electric Vehicle Consumers in Klang Valley	Heng Xian Wei	Dr Tan Pei Meng	
18.	Adoption of Digital Marketing on SME Service Sector in Klang Valley	Jordan Wue Bin Hassan Wue	Ms Puvaneswari a/p Veloo	
19.	Exploring Determinants of Malaysian Purchase Intention for Electric Vehicles	Joyce Yap Jie Ni	Dr Malathi Nair a/p G Narayana Nair	
20.	Sustainable Shopper: Linking ESG with the Shopping Carts	Julia Look Hui Sian	Dr Abdullah Sallehhuddin Bin Abdullah Salim	
21.	Investigating Influential Factors on Female Consumers' Purchase Behavior or Organic Perfumes in Malaysia	Kang Karen	Dr Ooi Bee Chen	
22.	Factors Influencing Consumer Purchase Intention Towards Green Household Products	Kok ZiLi	Dr Ooi Bee Chen	
23.	Winning in Cross-border E-commerce: Factors That Influence Strategic Platform-based Product Selection Among Sellers	Lai Kah Shen	Pn Ezatul Emilia Binti Muhammad Arif	
24.	Employee Retention's Impact Factors Within the Retail Industry	Lee Yee Hong	Dr Foo Meow Yee	
25.	Factors Influencing the Employee Turnover Rate Among Fresh Graduate Employees	Leong Weng Kent	Dr Kalaivani a/p Jayaraman	
26.	The Factors Influencing the Purchase Intention of Electric Vehicles Among Malaysian Young Adults	Lew Hui Ching	Dr Foo Meow Yee	
27.	Exploring Factors Influencing Customer Loyalty in Malaysia's Traditional Coffee Shop (Kopitiam)	Lew Zhi Qing	Dr Malathi Nair a/p G Narayana Nair	
28.	Green Purchase Intention Towards Reusable Shopping Bag in Malaysia	Lim Khang Xian	Ms Tai Lit Cheng	
29.	What Type of E-commerce Advertising Method Impact Customer Purchase	Lim Qi Yi	Pn Ezatul Emilia Binti Muhammad Arif	
30.	Unlocking Cross-Border Growth: Exploring Digital Free Trade Zones' Impact on International Trade	Lim Ying Ze	Pn Ezatul Emilia Binti Muhammad Arif	
31.	Consumer Behavior Trends and Preferences in the Malaysia Car Spare Parts Market: A Case Study of Perodua Bezza	Loh Eng Kang	Dr Fok Kuk Fai	
32.	Impact of Sustainable Packaging on Consumer Buying Behaviour in Malaysia	Loh Yan Min	Dr Fok Kuk Fai	
33.	Explicating the Influence of Artificial Intelligence (AI) Literacy on Employee Performance	Loke Li Ying	Dr Low Mei Peng	
34.	Leveraging Artificial Intelligence (AI) Competencies for Organisational Performance	Loke Xin Yu	Dr Low Mei Peng	
35.	The Influence of Culture on Consumer's Intention to Purchase Personalized Products	Loo Ci Ting	Dr Choo Siew Ming	
36.	Exploring The Financial Benefits and Risks of Allocating Additional Income Towards Investment Opportunities	Loo Su Yu	Dr Choo Siew Ming	
37.	Factors Influencing Consumer's Purchase Behaviour Towards Organic Food Among Malaysian University Students in Klang Valley	Low Chan Guan	Dr Ooi Bee Chen	
38.	Adoption AI in Logistics Industry: Improved Efficiency and Fault Tolerance	Low Sam Yee	Mr Khairul Anuar Bin Rusli	

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Website: www.utar.edu.my

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
39.	Impact of Digital Marketing Strategy on Purchase Intention	Lum Jia Mei	Dr Komathi a/p Munusamy	9 September 2024 – 8 September 2025
40.	Unveiling the Elements of Employee Motivation for Thriving Workplaces in Malaysia	Michelle Tan Hui Shan	Dr Kalaivani a/p Jayaraman	
41.	Women's Entrepreneurship Success in the Technological Industry	Ooi Xin Yi	Dr Law Kian Aun	
42.	Social Media Strategies for Business Success Maximizing Impact through Navigating Channels and Engaging Audiences	Poon She Kei	Pn Ezatul Emilia Binti Muhammad Arif	
43.	Measuring the Impact of Organizational Factors on Turnover Intention of Fast-Food Industry Employees in Malaysia	Rachel Ong Pei Lyn	Ms Puvaneswari a/p Veloo	
44.	Impact of Transformational and Authentic Leadership on Innovation in Higher Education in Malaysia: The Contingent Role of Trust in Leader	Robin Wong Woon Ping	Ms Puvaneswari a/p Veloo	
45.	Social Media Influencers on Consumer Purchase Intention: The Sportswear Products	Sam Yu Xiang	Dr Sia Bee Chuan	
46.	The Influence of Customer Relationship Management on Customer Loyalty in Insurance Sector	Seah Chee Keong	Dr Komathi a/p Munusamy	
47.	Impact of Social Media Influencers (SMIs) on Purchase Intention of Young Adults in Malaysia	Seow Gin See	Dr Foo Meow Yee	
48.	Understanding University Student's Behavioral Intention in using 'Smart Technology'	Sin Chee Leong	Ms Goh Poh Jin	
49.	The Challenge of Consumer Adoption of Battery Electric Vehicle (BEV) in Malaysia	Siow Huang Ming	Dr Sia Bee Chuan	
50.	Customer Motivation in Choosing Preferred Courier Service	Syamini Syazwani Devi A/P Muraleidaran	Dr Komathi a/p Munusamy	
51.	Digital Platform: Do Data Privacy Concerns and Transparency Affect User's Trust and Loyalty?	Tai Buo Ting	Pn Ezatul Emilia Binti Muhammad Arif	
52.	A Study of the Impact of Flexible Work Arrangement on Employees' Turnover Intention Among Generation Z in Klang Valley	Teh Jia Chuen	Dr Lee Siew Peng	
53.	The Role of E-training, E-compensation and E-recruitment in Enhancing Employee Productivity in International Companies in Malaysia	Teo Wen Ping	Dr Omar Hamdan Mohammad Alkharabsheh	
54.	Factors Influencing the Sustainable Tourism Intentions Among Generation Z in Malaysia	Tey Xin Tong	Dr Tiong Kui Ming	
55.	Motivation Factors Impact the Employee Performance in the Retail Industry in Malaysia	Thiang Zhen Wu	Dr Law Kian Aun	
56.	Factors Motivating Malaysian Consumers' Intention Using QR Code Payment when Purchasing Movie Tickets	Wang Kean Seng	Pn Faridah Hanum Binti Amran	
57.	Entrepreneurial Orientation Relationship with Firm Performance Among F&B Industry: Perspective of Malaysian SME	Wong Chean Huai	Mr Mahendra Kumar a/l Chelliah	
58.	Resilience of Global Challenges: A Study of Manufacturing Resilience in Malaysian Manufacturing Industry	Wong Jin Mun	Dr Law Kian Aun	
59.	Impact of Customer Service Automation on the Performance of Customer Relationship Management in the Retail Sector	Yap Pui Man	Dr Law Kian Aun	
60.	The Influence of Social Media Marketing on Purchase Intention of Sportswear Among Malaysian Youth	Yap Seng Fui	Ms Cheah Lee Fong	
61.	Impact of Social Media Marketing on Consumer Purchase Intention in Food and Beverage Industry in Malaysia	Yee Kar Hung	Dr Sia Bee Chuan	
62.	Exploring the Relationship Between Organizational Culture and Customer Retention in E-commerce: A Study of Online Shoppers	Yeoh Chin Hui	Dr Choo Siew Ming	
63.	Factors Affecting Patient Satisfaction on Service Quality: An Investigation of Government Hospital in Klang Valley	Yoong Pooi Lim	Dr Tey Sheik Kyin	

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No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
64.	The Connection Between Gig-Economy Employees and Personal Well-Being	Yu Kay Ciek	Dr Law Kian Aun	9 September 2024 – 8 September 2025
65.	Role of Brand Communities in Building Brand Loyalty	Yuvarani a/p Suresh	Dr Komathi a/p Munusamy	

The conduct of this research is subject to the following:

(1) The participants' informed consent be obtained prior to the commencement of the research;

(2) Confidentiality of participants' personal data must be maintained; and

(3) Compliance with procedures set out in related policies of UTAR such as the UTAR Research Ethics and Code of Conduct, Code of Practice for Research Involving Humans and other related policies/guidelines.

(4) Written consent be obtained from the institution(s)/company(ies) in which the physical or/and online survey will be carried out, prior to the commencement of the research.

Should the students collect personal data of participants in their studies, please have the participants sign the attached Personal Data Protection Statement for records.

Thank you.

Yours sincerely,

Professor Ts Dr Faidz bin Abd Rahman
Chairman
UTAR Scientific and Ethical Review Committee

c.c Dean, Faculty of Accountancy and Management
Director, Institute of Postgraduate Studies and Research

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