THE IMPACT OF TASK-TECHNOLOGY FIT IN GENERATIVE AI ON UTILISATION AND EMPLOYEE OUTPUT

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DEPARTMENT OF INTERNATIONAL BUSINESS

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A final year project submitted in partial fulfilment of the requirement for the degree of

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(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.

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DEDICATION

This research project is mainly dedicated to:

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LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
B/ β	Beta
df	Degree of Freedom
DV	Dependent variable
IV	Independent variable
F	F ratio
H1	Hypothesis 1
H2	Hypothesis 2
H3	Hypothesis 3
H4	Hypothesis 4
H5	Hypothesis 5
H6	Hypothesis 6
TAC	Task Characteristics
TEC	Technology Characteristics
TTF	Task-Technology Fit
UT	Utilisation
SS	Supervisory Support
EO	Employee Output
SE	Standard Error
Sig.	Significance
SPSS	Statistical Package for Social Sciences

PREFACE

One of the most widely discussed developments in workplace technology is the rapid adoption of Generative AI (GenAI). With tools like ChatGPT and DALL·E being integrated into various job functions, organizations are beginning to explore how GenAI affects employee productivity and satisfaction. While existing literature acknowledges the potential of AI to enhance efficiency, research on the human and managerial factors influencing its effectiveness remains limited—particularly in the Malaysian context.

To address this gap, this research project was conducted to examine how task-technology fit, supervisory support, and technology utilisation influence employee output when using GenAI tools. This study seeks to provide valuable insights for both academic research and practical application in businesses that are transitioning into AI-supported work environments.

ABSTRACT

Generative AI (GenAI) is transforming workplace dynamics by enabling enhanced creativity, efficiency, and productivity. This study explores the impact of Generative AI on employee output, focusing on how task characteristics, technology characteristics, task-technology fit, supervisory support, and utilisation interact to influence performance and satisfaction. While GenAI promises increased efficiency and quality of work, concerns about cognitive overload and uneven productivity outcomes remain. Grounded in the Task-Technology Fit Theory and Social Learning Theory, this research develops a conceptual framework to investigate these dynamics.

A quantitative approach was adopted, involving a survey of full-time employees in Malaysian organisations. The findings are expected to reveal the relationships among the independent variables (task and technology characteristics, supervisory support), both dependent and independent variables (task-technology fit and utilisation), and the dependent variable (employee output). Results aim to offer actionable insights for business leaders to optimize GenAI integration and enhance employee output. By bridging gaps in current literature and addressing practical challenges, this study contributes to both academic discourse and strategic decision-making for organizational growth in the digital age.

Keywords: Generative AI, employee performance, task-technology fit, supervisory support, employee satisfaction

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

This chapter provides an overview of the research background related to using Generative AI in the workplace. It also outlines the problem statements, establishes the research objectives and questions, formulates the hypotheses, and highlights the significance of the research.

1.1 Research Background

Today's era is marked by revolutionary changes, driven largely by major advancements in digital technology, particularly in Artificial Intelligence (AI) (Naqbi et al., 2024). Two separate paradigms are defined in this discipline by classical AI and generative AI, each with its own set of guiding principles, methods, and procedures (Deltek, n.d.). Conventional AI, often called discriminative AI, which includes early-stage machine learning algorithms, uses preset data types and methods to carry out particular tasks like prediction and classification (Jovanovic & Campbell, 2022). Generative artificial intelligence (GenAI) is a rapidly advancing technology that has garnered significant global attention. Its emergence represents a critical moment, showcasing the transformative potential that transcends traditional AI applications (Jovanovic & Campbell, 2022). According to Daugherty et al. (2023), 97% of global executives believe GenAI will revolutionise AI by enabling seamless connections across diverse data types and industries. This innovation has fundamentally reshaped how businesses operate and engage with both customers and employees.

In contrast, the term "generative AI" refers to the use of machine learning models to produce creative content, including text, audio, video, photos, software code, and simulations, by using enormous datasets that have been used to train the models (Budhwar et al., 2023). Popular examples of Generative AI tools include ChatGPT, GPT-4, Playground, DALL·E 3, and Sora tools from OpenAI, Claude from Anthropic, Gemini (previously Bard) from Google, Stable Diffusion 3 from Stability AI, and Gen-2 from Runway (Law, 2024). GenAI can create fresh output data with comparable features after learning the statistical patterns and structures of enormous volumes of input training data (Hopkins & Gallagher, 2024).

According to Berşe et al. (2024), GenAI technologies can assist in a variety of domains, including visual identification, decision-making, and employee learning. They do this by simulating human cognitive and behavioural processes within machines. In reaction to user requests, or "prompts," GenAI models may generate a wide range of original material, including writing, graphics, code, music, molecular structures, robotic operations, and product ideas, far more quickly than professional knowledge workers alone (Hopkins & Gallagher, 2024). The quality of the input it gets determines the quality of its output, taking into account both the training data it has encountered and the user-provided prompts that specify the task they wish it to do (Budhwar et al., 2023). By enhancing work learning and enabling people to participate in creativity and innovation in management processes and functions, GenAI saves time and resources from repetitive activities and enhances talent (Malik et al., 2021).

1.2 Research Problem

Employee output is closely linked to performance and satisfaction. Performance reflects how effectively employees complete their tasks, directly impacting the volume and quality of output (Kuswati, 2020). Meanwhile, satisfied employees are more likely to maintain a positive attitude toward their work, contributing to sustained and improved output (Mishra et al., 2025). Therefore, assessing employee output provides a more comprehensive understanding of both performance levels and overall job satisfaction.

With the growing popularity of GenAI, it is crucial to explore its impact on employee performance and satisfaction, as its effects on productivity and overall performance remain poorly understood (Brynjolfsson et al., 2023). Goldman Sachs Research estimates that GenAI could boost productivity growth by 1.5% over ten years and raise global GDP by 7%, or US$7 trillion ("Generative AI Could Raise Global GDP," 2023). A more cautious forecast is offered by Acemoglu (2024), who projects GDP growth of just 0.9% to 1.1% during the ensuing ten years. According to Wamba-Taguimdje et al. (2020), GenAI can decrease errors while simultaneously increasing forecasting, efficiency, and an organisation's flexibility. Wijayati et al. (2022) emphasise how GenAI might improve worker performance and engagement.

However, the integration of GenAI into workplace environments presents notable challenges. Despite its promise, emerging evidence suggests that the use of GenAI tools can sometimes result in unintended productivity losses. Many users—including programmers—report more cognitive load, aggravation, and time spent on the tasks that GenAI is meant to assist with when utilising the new tools in practice (Simkute et al., 2024). Usability studies using GenAI-driven programming tools and user feedback from Copilot indicate that, in certain situations, utilising GenAI support may result in a loss of productivity (Simkute et al., 2024). Users' responsibilities have changed in the setting of GenAI from creating output to assessing it, frequently with limited situational awareness and contextual knowledge. This is made worse by the fact that GenAI techniques might generate outputs that are too demanding for proper evaluation, have poor explainability, and have uncertain reliability (Chen et al., 2023; Liao & Vaughan, 2023; Schellaert et al., 2023). This implies that the productivity-boosting potential of GenAI systems might not be completely realised, allocated fairly, or guaranteed (Simkute et al., 2024).

As a result, despite the growing adoption of GenAI tools, there remains insufficient clarity regarding the actual impact on employee productivity. Some findings suggest increased efficiency, while others point to challenges such as cognitive overload and uneven productivity outcomes. This disparity emphasises the need for a detailed investigation into how GenAI tools impact individual employee behaviour and output, particularly in varied industrial and organisational contexts.

Secondly, Malaysia's productivity performance in 2023 was consistent with its normalised 3.7% economic growth. In 2023, the nation's labour productivity per employee increased by 5.4%, although it moderated to 0.9% in 2022. In 2023, the nation's productivity level rose somewhat from RM95,858 in 2022 to RM96,692 per employee. Even with the slight increase, the development shows that productivity is resilient to economic shocks (Malaysia Production Corporation, 2024). Mid-Term Review of the Twelfth Plan remains optimistic in meeting its productivity target, aiming for an average annual growth rate of 3.7% from 2021 to 2025, with a projected productivity level of RM107,170 per employee by 2025 (Malaysia Production Corporation, 2024). However, with only a small increase recorded over the past year, a significant gap of over RM10,000 remains to be closed within the next two years. This shortfall is particularly relevant in the Malaysian context, emphasising the need for more substantial productivity improvements to achieve the nation’s economic goals. The adoption of GenAI presents a potential opportunity to bridge this gap by enabling more efficient workflows, enhancing employee performance, and driving overall economic growth (“Gen AI,” n.d.).

Thirdly, there is limited research on the role of supervisor support in influencing employees’ adoption of this technology (Sandelin, 2024). This gap in the literature presents a critical oversight, as supervisory support could play a key role in shaping employee attitudes, confidence, and willingness to engage with GenAI tools. In addition, research on task-technology fit within the context of GenAI remains scarce (Przegalinska et al., 2025), highlighting the need for deeper investigation into how effectively GenAI aligns with employee tasks to enhance performance outcomes.

1.3 Research Objectives

1.3.1 General Objective

The primary objective of this study is to evaluate the impact of generative AI on employee output by examining the interplay between key factors, including task characteristics, technology characteristics, task-technology fit in GenAI, supervisory support, and utilisation.

1.3.2 Specific Objective

I. To identify the relationship between task characteristics and task-technology fit in GenAI.

II. To identify the relationship between technology characteristics and task-technology fit in GenAI.

III. To identify the relationship between task-technology fit in GenAI and employee output in the workplace.

IV. To identify the relationship between task-technology fit in GenAI and the utilisation of GenAI.

V. To identify the relationship between supervisory support and the utilisation of GenAI.

VI. To identify the relationship between utilising GenAI and employee output in the workplace.

1.4 Research Questions

The study examines the impact of GenAI on employee output in the workplace. This research has generated several questions, which will be addressed as follows:

I. What is the relationship between task characteristics and task-technology fit in GenAI?
II. What is the relationship between technology characteristics and task-technology fit in GenAI?
III. What is the relationship between task-technology fit in GenAI and employee output in the workplace?
IV. What is the relationship between task-technology fit in GenAI and the utilisation of GenAI?
V. What is the relationship between supervisory support and the utilisation of GenAI?
VI. What is the relationship between the utilisation of GenAI and employee output in the workplace?

1.5 Research Significance

From an academic standpoint, this study adds to the body of knowledge already in existence by examining the connection between GenAI and employee output, with a specific emphasis on performance and satisfaction. While much of the current literature emphasises the potential of GenAI to improve efficiency, this study will critically examine how specific factors such as task-technology fit, supervisory support, and utilisation interact to influence employee output. This can provide a more balanced and evidence-based understanding of GenAI's impact in real-world organisational settings, while also highlighting the critical role of supervisory support in technology adoption. This study addresses significant gaps in the existing scholarly discourse, particularly through the extension of the Task-

Technology Fit (TTF) model and the incorporation of supervisory support as a key determinant in the adoption and effective utilisation of GenAI.

Furthermore, this research will enhance the theoretical understanding of human-computer interaction (HCI), particularly in the context of GenAI tools, by exploring how they impact employees' task performance. With the rise of these tools, HCI has evolved beyond traditional input-output interactions to encompass more complex and dynamic exchanges between users and intelligent systems. By addressing the conflicting perspectives on GenAI's impact on productivity, this study can also stimulate future research in the field of digital transformation and technology-driven organisational change.

From a practical perspective, this study provides actionable insights for business leaders, managers, and decision-makers aiming to integrate GenAI tools into their operations. Practitioners can gain a deeper understanding of how GenAI should be aligned with employee tasks and supported through effective supervision to maximise performance and satisfaction, thus making informed decisions about how to implement these technologies. Secondly, the findings serve as a guide for Malaysian organisations and policymakers working to close the nation's productivity gap and achieve economic targets outlined in national strategies. By strategically leveraging GenAI, stakeholders can improve operational efficiency and contribute to sustainable economic growth. Lastly, this research supports the development of best practices for training employees to use GenAI tools effectively, ensuring the technology complements human skills and workflows rather than overwhelming employees with additional complexity.

1.6 Conclusion

Chapter 1 discusses the research problems and significance that motivated the study on the impact of GenAI on employee output in the workplace. This chapter also outlines the research questions and objectives related to the topic.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This chapter presents a review and analysis of prior literature and secondary data, aligned with the research issues outlined in Chapter 1. Relevant journals, textbooks, and previous studies are utilised to support the variables of this research. Furthermore, this chapter provides an explanation and discussion of the theoretical model and conceptual framework.

2.1 Underlying Theories

2.1.1 Task-Technology Fit Theory (TTF)

By using the Task-Technology Fit (TTF) model, we can gain a deeper understanding of how the features of Gen AI align with employees' task requirements and how this alignment affects its utilisation, ultimately influencing employee output. TTF offers a way to measure how effective technology is in a company (Goodhue, 1998). The theory's goal is to verify and evaluate the premise that using information systems improves performance only when the capability of the technology matches the needs of the tasks that users must do (Goodhue & Thompson, 1995).

According to Zigurs and Khazanchi (2008), task-technology fit theories aim to help people understand how to match a new tool with a problem—in this case, a suitable set of collaboration technology capabilities with specific group work and context. TTF includes five constructs to explain the model: task characteristics, technology features, task-technology fit, technology use, and performance impact. While people's perspectives of task-technology fit are reflected in the overall task-technology fit factor, task characteristics and technology characteristics represent specific features of the technology and its application (Goodhue & Thompson, 1995; Goodhue, 1992).

The TTF model also incorporates three propositions. According to the first claim, both task and technology characteristics have an impact on the user's assessment of task-technology fit. The second proposition of the theory states that the perceived fit between information systems and user tasks determines an individual's adoption of those systems. According to the theory's third premise, a positive evaluation of task-technology fit not only forecasts usage but also favourably affects perceived performance, or an individual's completion of a portfolio of activities (Goodhue & Thompson, 1995).

TTF theory has been applied in various contexts in prior research, including healthcare wearable devices (Wang et al., 2020), information and communications technology (Kamdjoug et al., 2023), and mobile banking (Oliveira et al., 2014).

2.1.2 Social Learning Theory

Social Learning Theory helps explain how supervisory support—through modelling, guidance, and reinforcement—can shape employees' attitudes toward GenAI and enhance their willingness to adopt and utilise it, ultimately improving their employee output with the tools provided.

Albert Bandura (1977) proposed the Social Learning Theory as a novel explanation for why people act in certain ways. It contends that outside influences have an impact on human behaviour (Wood & Bandura, 1989). Bandura's study examined whether observing aggressive behaviour would cause other people to mimic the violent person's behaviour. It was discovered that this was the case. This makes it possible to draw a comparison between this example and a situation in an office setting, where a superior who exhibits a particular behaviour will influence their subordinates to follow suit.

According to the social learning theory, a leader who is hesitant to use new software or tools will have staff members who can follow suit. One might infer from the social learning theory that leaders' digital mentality and, consequently, their conduct, will be somewhat correlated with that of their employees. However, this idea takes into consideration how one person's actions can affect those of another. It is possible to argue that a leader with a specific mindset exhibits a specific kind of behaviour. The staff members may then observe this behaviour and be more inclined to follow suit. This suggests that the social learning theory may be applied to comprehend how a leader's actions impact their team members' behaviour (Hagen & Wibe, 2019).

2.2 Review of Variables

2.2.1 Task Characteristics

The definition of task characteristics is individuals' activities that transform inputs into outputs (Goodhue & Thompson, 1995). The physical nature of work is implied by the conversion of inputs into outputs. In an organisational context, the primary responsibility of the staff is to manage inputs and align them with business objectives to generate appropriate outputs, thereby addressing and resolving problems (Al-Maatouk et al., 2020). The construct, which was taken from Goodhue and Thompson (1995), is intended to assess two aspects of task characteristics: task routineness and task interdependence.

Task routineness can be divided into two categories: variation and difficulty. Task variety refers to the extent to which a wide range of operations or exceptions must be performed (Morgeson and Humphrey, 2006; Sims et al., 1976). According to Van de Ven and Delbecq (1974), task difficulty is the degree of analyzability of the work and the degree of knowledge of the procedures for carrying out the work. Therefore, an activity can be considered routine if it is analysable (i.e., not complex) and has few exceptions (i.e., low variability). Accordingly, task routineness describes how much time is spent on recurring and solvable problems (Goodhue and Thompson, 1995).

Task interdependence refers to the degree to which a person's task depends on the work of others (Wageman and Baker, 1997). The amount of information that must be processed by cooperating individuals to complete the work at a satisfactory level can alternatively be interpreted as interdependence (Hua et al., 2023). An interdependent task suggests that the knowledge and information needed to complete it successfully may be held by several people who must collaborate (Sosa, 2014).

2.2.2 Technology Characteristic

Technology characteristics are attributes or capabilities that are unique to a given technology. The technological functionality component refers to the tools that people use to accomplish tasks or to carry out activities. Technologies encompass computer systems and support services. This includes components like hardware, software, and data, along with services such as training, HR policies, and IT support. Hardware examples are Personal digital assistants, laptops, and personal computers. Software technologies that are commonly used include communicators (chat, IP phone), office applications (word processors, spreadsheets), email, information systems (HRM, inventory, administration), and online shared workspaces (Baas, 2010).

GenAI possesses various features, such as generating data that simulates real-world attributes, enabling data augmentation, anomaly detection, and creative content creation, all of which are crucial for organisations to accomplish their tasks effectively (Bandi et al., 2023).

2.2.3 Task-Technology Fit in Generative AI

The degree to which technology helps users complete their work duties is known as the TTF component (Goodhue & Thompson, 1995). A profile is a perfect scenario; the more an actual situation is like the profile, the better. Since everyone has a different ideal digital workspace, task-technology fit is a normative construct that is expressed in how well a user evaluates the alignment between the technological capabilities to support their tasks and the task needs (Fuller and Dennis, 2009).

Users can assess their level of task-technology fit, according to research by Goodhue (1995). Task-technology fit refers to the interconnection between the user, the technology they use, and the task they perform to achieve a specific objective. The degree to which a user's duties can be completed by technology depends on how well the technology's functions, task requirements, and individual talents align. Technology's usefulness is correlated with the goals it is designed to accomplish and the context in which it is employed. This is the moderating factor since people must use technology to complete the work to perform better (Goodhue & Thompson, 1995).

2.2.4 Utilisation

The utilisation component measures how often or in what ways the system is used (Davis, 1989; Thompson et al., 1994). Numerous elements related to beliefs and attitudes influence the use of technology, which is influenced by both required and optional settings. Social norms, behaviour attitudes, and anticipated outcomes are a few of these influences (Bagozzi, 1982; Fishbein & Ajzen, 1975). For instance, even when technology use is voluntary, it may nevertheless happen because of habits, societal conventions, ignorance, and other variables that impact the users. More often than not, the use of technology is mandated by the job function rather than because of its capabilities (Vendramin et al., 2021).

2.2.5 Supervisory Support

Supervisory support refers to how well managers understand and accept the technological capabilities of a new technology system (Maroufkhani et al., 2020). As part of their everyday tasks, immediate supervisors frequently interact directly and frequently with their subordinates. The basis for trust is established by the acts and behaviours of supervisors, which are crucial in affecting the attitudes of their subordinates (Myers, 2020). A good measure of the calibre of the exchange interactions between supervisors and employees is supervisory support (Stinglhamber & Vandenberghe, 2003).

According to Khayer et al.(2021), it is crucial to examine the role of the manager in the context of information systems for several reasons. First, in the 1990s, IT evolved from a support system to a strategic asset. Second, more complex technology-based communications, coordination, and control systems are needed as a result of growing global competitiveness, technological advancements, and organisational reorganisation. Effective leadership in managing the development and execution of technology is necessary if businesses are to use technology as a competitive weapon in this dynamic world.

2.2.6 Employee Output

Employee output will be examined in terms of performance and satisfaction in the workplace. The influence on performance pertains to the potential outcomes of completing the tasks in the portfolio. The effects on performance show how well a person completes a task. According to Goodhue and Thompson (1995), a higher performance depends on a mix of improved output quality overall and better efficacy and efficiency.

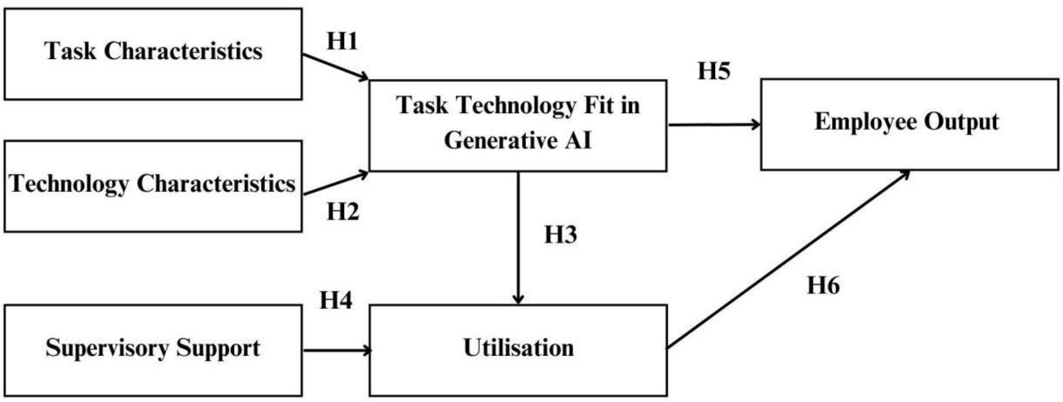
Performance, often known as job performance, is the quantity and quality of work that an employee completes in order to meet his given responsibilities (Darvishmotevali & Ali, 2020). Performance, as defined by Al Mehrzi and Singh (2016), is the result or level of achievement of a person over a given time period in carrying out tasks in relation to a number of options, including work standards, targets, or mutually agreed-upon predefined criteria. According to Shmailan (2016), employee performance is an activity that employees undertake when performing the tasks assigned by the organisation.

Rashidat and Akindele (2020) state that the extent to which one's requirements, desires, and wants are fulfilled is known as satisfaction. In essence, a person's level of satisfaction is determined by what he desires and receives from the world. Employee satisfaction assesses how happy workers are with their positions and work environment. It also refers to whether or not employees are satisfied, happy, and getting what they need and want at work (Sageer & Agarwal, 2012). It is the contentment employees feel about their jobs and workplace experiences (Anwar & Abdullah, 2021). An employee's emotional and cognitive assessment of their work is another definition (Schleicher et al., 2004; Tett & Meyer, 1993).

2.3 Conceptual Framework

The conceptual framework proposed for this study is presented in Figure 2.1. It is developed through the integration of the TTF model and Social Learning Theory. By combining elements from both frameworks, this model aims to offer a holistic understanding of the impact of GenAI on employee output in the workplace. The framework identifies task characteristics, technology characteristics, and supervisory support as independent variables; task-technology fit in GenAI and utilisation function as both independent and dependent variables; employee output is positioned as the dependent variable.

Figure 2.1: Proposed Conceptual Framework



Source: Developed for the research

2.4 Hypotheses Development

2.4.1 The relationship between task characteristics and task-technology fit in generative AI.

Several studies also show that task-technology fit is affected by task characteristics in various contexts; i. mobile banking (Oliveira et al., 2014), ii. social networking site (Lu & Yang, 2014), iii. chatbot (Tao et al., 2024). According to Wang et al. (2020), the study shows that task characteristics have a positive influence on task-technology fit, especially when tasks are highly demanding—such as those involving complexity and time sensitivity in health management. In such cases, healthcare wearable devices that meet general requirements may lead to a higher task-technology fit. Thus, this research proposes:

H1: Task characteristics have a significant positive relationship with task-technology fit in GenAI

2.4.2 The relationship between technology characteristics and task-technology fit in generative AI

Technology characteristics serve as the foundation for evaluating how information technology is used to determine how well it fits the user's daily tasks. Put another way, technology will seldom be able to match task demands as they get harder (Dishaw & Strong, 1999; Gebauer & Ginsburg, 2009; Junglas et al., 2008). Numerous prior studies have demonstrated that technological characteristics are key factors influencing task-technology fit in various contexts; i. Enterprise social media (Fu et al., 2020), ii. Cloud-based Collaborative Learning Technologies (Yadegaridehkordi et al., 2014), iii. Internet Banking (Rahi et al., 2021). For example, by making standard banking tasks like account management, broking, and financial enquiries both accessible and simple, technology makes mBanking appealing to consumers who are constantly on the go (Tam & Oliveira, 2019). Therefore, there is a greater task-technology fit as a result of the task characteristics and the technological characteristics of mBanking. A logical viewpoint on whether the technology being employed can maximise user labour or task is known as task-technology fit. The task's nature and the technology's suitability for doing it have an impact (Oliveira et al., 2014). Thus, this research proposes:

H2: Technology characteristics have a significant positive relationship with task-technology fit in GenAI

2.4.3 The relationship between task-technology fit in generative AI and its utilisation

According to the study by Goodhue and Thompson (1995), the use (utilisation) of information technology is influenced by how well the technology fits the purpose (task-technology fit). Numerous studies have also highlighted that task-technology fit impacts the use of information technology across various contexts; i. Blockchain technology (Alazab et al., 2021) ii. Cloud-based Collaborative Learning Technologies (Yadegaridehkordi et al., 2014), iii. Shopper-facing technologies (Wang et al., 2021).

Dishaw and Strong (1999) discovered that users' use of information technology is influenced by task-technology fit. Individual users must perceive the IS's capability as important for carrying out and finishing job activities for this specific behaviour to occur. Users' perceptions of the task-technology fit probably have an impact on their decision to continue exploring, adopting, using, and expanding the use of one or more of the IS's functionalities. Beliefs regarding the value, significance, and benefits of using information technology are determined by the technological suitability of the task (Morris & Venkatesh, 2000). Therefore, this research proposes:

H3: Task-technology Fit in GenAI has a significant positive relationship with its utilisation

2.4.4 The relationship between supervisory support and utilisation

According to studies, workers' adoption of newly introduced technology is influenced by their perceptions of the quality of their relationship with their leader and how these impressions heighten the idea that the new technology helps carry out one's job (Magni & Pennarola, 2008). Giving staff members the assistance they need to improve their skills with new technology can make the transition easier for everyone involved and potentially increase the advantages of technology use.

Besides, a supervisor often serves as a role model for employees, who tend to imitate and adopt the supervisor's behaviours and attitudes. If a supervisor with a fixed digital mindset is sceptical or reluctant to embrace new technology, employees may also adopt this mindset to some extent and become hesitant to use new technology themselves (Hagen & Wibe, 2019).

The studies have also highlighted that supervisory support impacts the use of information technology in the context of Industry 4.0 technology adoption (Dun & Kumar, 2023). Additionally, Yang et al. (2015) emphasised the supervisory influence in promoting the adoption of cloud computing and electronic business technologies in the field of information science. Hence, this research proposes:

H4: Supervisory support has a significant positive relationship with utilisation

2.4.5 The relationship between task-technology fit in generative AI and employee output

According to Kamdjoug et al. (2023), high performance reflects an effective and efficient integration of information systems in task execution. Individual performance refers to the degree to which ICT has enhanced workers' abilities, expertise, and production throughout the COVID-19 pandemic (Diamantidis & Chatzoglou, 2019).

Furthermore, the organisation's information technology operations can support users' everyday duties, then the technology's fit for the task will undoubtedly affect individual performance (Widagdo & Susanto, 2016). Numerous studies have also shown that the technology's fit for the task has an impact on people's performance when they use information technology in various contexts; i. Learning Management System (McGill & Klobas, 2009), ii. Internet of Things (Sinha et al., 2019). Thus, this research proposes:

H5: Task-technology fit in GenAI has a significant positive relationship with employee output

2.4.6 The relationship between utilisation and employee output

Individual performance is influenced by usage, aiming to demonstrate ways to enhance the information technology performance (Igbaria & Tan, 1997). The implication is that increased usage has a positive effect on individual performance outcomes. Previous studies have confirmed a positive correlation between the utilisation of information technology and its impact on individual performance in various contexts; i. Information and Management (Igbaria & Tan, 1997), ii. Technology System (Fitri et al., 2023). Further research has strengthened this connection by identifying the success of the model as a precursor to information systems, emphasising how individual use of these systems affects organisational performance in subsequent studies (DeLone & McLean, 2003).

Moreover, a positive experience with technology fosters satisfaction. This suggests that a remote worker whose job needs are efficiently fulfilled through the use of ICT is likely to feel satisfied (Issac et al., 2017). Therefore, this research proposes:

H6: Utilisation has a significant positive relationship with employee output

2.5 Conclusion

This chapter provides a detailed discussion of the variable definitions within the literature review section. Additionally, a research framework based on the TTF model has been developed to clearly illustrate the relationships among the independent variables (task characteristics, technology characteristics, and supervisory support), both independent variables and dependent variables (utilisation and TTF), and the ultimate dependent variable (employee output).

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter outlines the comprehensive methodology employed in this investigation. It covers the research design, sampling strategy, data collection techniques, and data analysis tools in detail.

3.1 Research Design

Research design serves as the overarching framework that links conceptual research problems to practical and achievable empirical investigation (Asenahabi, 2019). It establishes a structured approach that guides the researcher in planning procedures before data collection and analysis, ensuring that the research objectives are met validly (Creswell & Creswell, 2017). Essentially, it is a systematic process adopted to convert a research problem into analysable data, enabling the provision of accurate answers to research questions while minimising costs (Asenahabi, 2019). Research methodologies, as developed and proposed by various scholars, are broadly categorised into two main types: quantitative and qualitative methods (Pandey et al., 2023).

3.1.1 Quantitative Research

According to Kothari (2004), quantitative research design involves techniques and measurements that yield quantifiable values. Asenahabi (2019) describes quantitative research as an analytical approach to investigation. A key characteristic of many quantitative studies is the use of tools such as tests or surveys to gather data, along with the application of probability theory to test statistical hypotheses aligned with the research questions (Harwell, 2011).

3.1.2 Descriptive Research

Descriptive research aims to detail the characteristics of a sample and examine the relationships between observed phenomena, situations, and events (Siedlecki, 2020). Its purpose is to generate data that highlight fundamental relationships, thereby enhancing understanding of the research question (Tripodi & Bender, 2010). In this study, which evaluates the impact of GenAI on employee performance, a descriptive approach is well-suited for capturing and analysing the current state of these variables within the target population. Additionally, descriptive research serves as a foundation for generalising findings to similar contexts, providing valuable insights into how GenAI influences workforce productivity on a larger scale.

3.2 Sampling Design

Sampling is the process of choosing a representative portion from a larger population to assess the traits or attributes of the whole group. It entails choosing specific population units, such as individuals, cases, or data points, for analysis (Mujere, 2016). A well-constructed sampling design should, wherever possible, outline clear inclusion and exclusion criteria to define the parameters for selecting or omitting items from the study population (Mweshi & Sakyi, 2020).

3.2.1 Target population

The target population refers to a specific subgroup within the larger population that is the primary focus of a study, program, or marketing effort. It consists of individuals who share specific traits or meet particular criteria (Willie, 2023). The target population for this study comprises full-time employees across various industries in Malaysia who have had exposure to using GenAI tools in the workplace. Their insights are essential for understanding how GenAI influences employee performance, productivity, and overall work output.

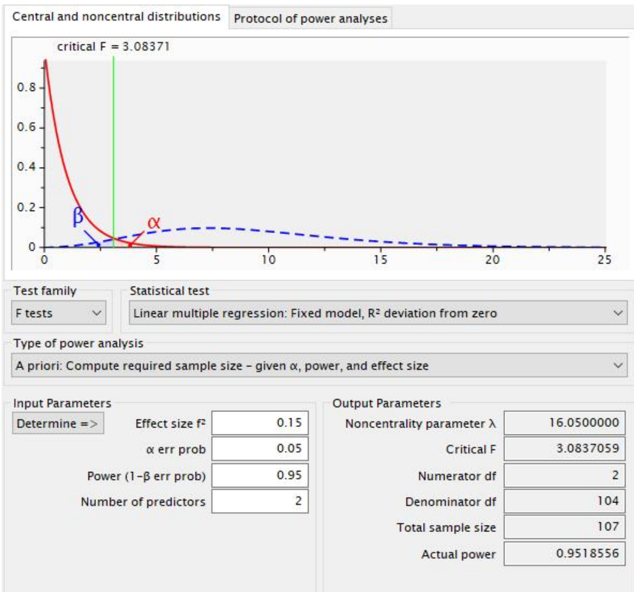
3.2.2 Sampling Technique

This study adopts a non-probability sampling method, where the likelihood of each individual in the population being selected for the sample is not predetermined (Bhardwaj, 2019). Specifically, convenience sampling is used, which allows researchers to choose participants based on their accessibility, availability, and proximity. This approach is efficient, as it involves selecting all eligible individuals from the target population until the required sample size is achieved (Mweshi & Sakyi, 2020). To facilitate data collection in a cost-effectively and efficient manner, the study will use Google Forms for survey distribution. The questionnaire link will be shared via various social media platforms, such as WhatsApp, Facebook, Instagram, WeChat, Telegram and others, targeting full-time employees in the workplace.

3.2.3 Sample Size

Sample size refers to a subset of a population that provides enough data to make informed conclusions (Memon et al., 2020). In this research, G*Power software was employed to conduct statistical analyses and identify the optimal sample size necessary to achieve the required statistical power for hypothesis testing. G*Power is a power analysis tool that helps researchers determine the sample size needed for a variety of statistical tests. It is widely acknowledged as a reliable and effective tool across numerous fields, including social and behavioural sciences (Faul et al., 2007).

Figure 3.1: Estimated Sample Size



Source: G*Power 3.1.9.7

Therefore, a sample size of 107 was initially calculated, based on a 95% confidence level (α) and a desired precision of 5%. A larger sample than needed will better represent the population, leading to more accurate results (Andrade, 2020). To minimise the risk of gathering inaccurate or unreliable data, this study plans to increase the sample size from the initially recommended 107 to 200 participants.

3.3 Data Collection Method

Data collection is the methodical process of gathering the information required to answer research questions, solve a particular research issue, or serve as a basis for approving or disapproving research hypotheses (Mwita, 2022).

3.3.1 Primary data

Primary data is the firsthand information collected directly by the researcher. It can be gathered through methods like surveys, observations, focus groups, case studies, and interviews (Ajayi, 2017). Information on the target audience can be gathered more accurately and efficiently with the use of primary data (Howard, 2021). An online survey was used to collect primary data for this study to gather quantitative data on specific items within the population. Thus, Google Forms is used as the main tool for data collection to gain a clear understanding and uncover the true relationship between variables for full-time employees who have exposure to GenAI in the workplace.

To maximise reach during data collection, a Facebook status post was published to encourage participation. The survey link was also shared through various platforms, including LinkedIn, Jobstreet, Facebook Messenger, and Microsoft Teams. In total, 222 questionnaires were distributed, and 204 were successfully returned, resulting in a high response rate of 91.89%.

3.4 Research Instruments

The tools the researcher uses to gather data are known as research instruments. An instrument's type is determined by its availability, character, function, and structure or format. Questionnaires are among the most commonly used tools for data collection, enabling the gathering of information about facts, views, attitudes, and knowledge (Sathiyaseelan, 2015). In this study, questionnaires are used as the research instrument, with Google Forms utilised for their design, distribution, and response collection.

3.4.1 Questionnaire design

According to Krosnick (2018), a questionnaire serves as a research tool designed to collect information from participants through a thoughtfully structured set of questions to ensure accurate data collection. For the layout of the questionnaire, the first page includes a cover page that outlines the research objectives, topic, and assures respondents of privacy and confidentiality. It also includes their acknowledgement of participation in the study. This is followed by the main body of the questionnaire, which is divided into three sections (Sections A, B, and C).

Section A includes a screening question designed to filter out respondents who are not full-time employees, ensuring greater accuracy and minimising irrelevant results and errors. Moreover, Section B focuses on demographic questions, covering aspects such as gender, age, ethnicity, industry, company size, work experience, job position, and individual monthly income level. This section aims to gather essential background information about the respondents.

Furthermore, Section C contains a total of 34 questions focused on the impact of GenAI on employee output. The independent variables (task characteristics, technology characteristics, and supervisory support), both independent and dependent variables (utilisation and task-technology fit in GenAI), and the dependent variable (employee output) are measured using a 5-point Likert scale, where 1 represents "strongly disagree" and 5 represents "strongly agree." A summary of the measures is presented in Table 3.1.

3.4.2 Instrument Development

Table 3.1 provides the details of the measurement items corresponding to the various constructs in the research.

Table 3.1: Survey Instrument

Construct	Source	Item	Statement
Task Characteristics	(Goodhue & Thompson, 1995)	TAC1	I frequently deal with ill-defined business problems.
		TAC2	I frequently deal with ad-hoc, non-routine business problems.
		TAC3	Many of the business problems I solve require new solutions.
Technology Characteristics	(Tam & Oliveira, 2016)	TEC1	Generative AI provides widely accessible support for my task.
		TEC2	Generative AI supports my tasks in real-time.
		TEC3	Generative AI provides quick support for my tasks.
		TEC4	Generative AI is secure to use.
Task-technology fit in Generative AI	(Huang & Chuang, 2016)	TTF1	Generative AI tools are easy to use.
		TTF2	Generative AI tools are user-friendly.
		TTF3	It is easy to get Generative AI tools to do what I want them to do.
		TTF4	My interactions with the

			Generative AI interface are clear and understandable.
		TTF5	I find the Generative AI interface easy to navigate.
		TTF6	Learning to use Generative AI tools is straightforward for me.
		TTF7	The output from Generative AI is presented in a useful format.
		TTF8	The information generated by Generative AI is accurate.
		TTF9	Generative AI provides up-to-date information.
		TTF10	I receive the information I need from Generative AI in time.
		TTF11	Generative AI produce output that aligns with what I need.
Utilisation	(Howard & Rose, 2019)	UT1	I often use Generative AI to perform tasks at work.
		UT2	I cannot imagine completing tasks without using Generative AI.
		UT3	More often than not, I use Generative AI to complete tasks.
		UT4	I almost always use Generative AI to complete tasks.
		UT5	I rarely perform tasks without using Generative AI.
Supervisory Support	(Maroufkhani et al., 2023)	SS1	My supervisor encourages the use of Generative AI.
		SS2	My supervisor provides support for Generative AI initiatives.
		SS3	My supervisor prioritises the

			adoption of Generative AI.
		SS4	My supervisor is interested in developments related to Generative AI adoption.
Employee Output	(Bader & Mohammad, 2019; Baas, 2010)	EO1	Utilising Generative AI helps me complete tasks more efficiently.
		EO2	Generative AI enhances the quality of my work.
		EO3	Using Generative AI improves my job performance.
		EO4	I would recommend this company to an acquaintance seeking employment.
		EO5	I personally feel fulfilled when I perform my job well.
		EO6	I proudly tell others that I am part of this organisation.
		EO7	This company is the ideal place for me to work.

Source: Developed for the research.

3.5 Measurement of Scale

3.1 Nominal Scale

Shukla (2023) states that the nominal scale does not have a natural order to its categories, and it involves collecting data that can be divided into two or more groups. In this study, the nominal scale was used to assess variables such as gender, ethnicity, industry, and job position. Additionally, nominal scaling was applied in the questionnaire's screening questions to identify full-time employment status.

3.5.2 Ordinal Scale

An ordinal scale function within structured ordered numerical sequences (Chiang & Bock, 2022). This type of scale is commonly used to collect important data about variables such as age, company size, work experience, and individual monthly income level.

3.5.3 Interval Scale

An interval scale is one where the numbering system not only indicates the order of data points but also the size of the intervals between them (Zumba, 2024). According to Carifio and Perla (2008), Likert scales are considered interval scales. In this study, a 5-point Likert Scale ranging from "1 - Strongly Disagree" to "5 - Strongly Agree" was used to assess the dependent (e.g., employee output) and independent variables (e.g., task characteristics) by measuring the respondent's level of agreement with statements related to GenAI.

Table 3.2: Summary of Measurement Scales based on the Questionnaire Section

Section	Title	Items	Measurement Scale
A	Screening	Full-time employee	Nominal
B	Demographic Profile	Gender	Nominal
		Age	Ordinal
		Ethnicity	Nominal
		Industry	Nominal
		Company size	Ordinal

		Work Experience	Ordinal
		Position	Nominal
		Individual Monthly Income Level	Ordinal
C	Variables	Task Characteristics	Interval
		Technology Characteristics	Interval
		Task-technology fit in Generative AI	Interval
		Utilisation	Interval
		Supervisory Support	Interval
		Employee Output	Interval

Source: Developed for the research

3.6 Data Processing

Data processing is a systematic approach to collecting and transforming raw data into valuable and meaningful information. This process includes reviewing responses, cleaning, coding, and editing the data to ensure accuracy and reliability.

3.6.1 Data Checking

The data collected in this study must be reviewed to ensure its relevance and validity for the research. Responses were reviewed to ensure all required questions were answered and that there were no duplicated entries. Any incomplete or irrelevant responses were flagged for removal.

3.6.2 Data Cleaning

Data cleaning was then performed to eliminate errors or inconsistencies. If straight-line responses or inaccurate data from participants are found to potentially compromise the integrity of the overall findings, they will be excluded. This process helps maintain the quality of the research by minimising the risk of errors.

3.6.3 Data Coding

Quantitative data should generally be recorded using numerical codes to allow for faster entry with fewer errors (Saunders et al., 2024). For example, in Section A of the questionnaire, males are assigned the code 1, while females are assigned 2. Similarly, respondents' agreement levels with statements in Section B are categorised on a scale from strongly disagree to strongly agree, with 1 to 5 reflecting each level.

3.6.4 Data Editing

Data editing was conducted to check for consistency and accuracy before analysis. Any errors in coding or entry were corrected. Variables were properly labelled accordingly to maintain consistency in interpretation.

3.6 Pre-Test

Pre-testing involves evaluating a tool or process prior to the official data collection phase and should be conducted before the pilot stage (Ruel et al., 2016). It can be carried out with the help of experts or respondents. This step is crucial for detecting problematic questions or sections, minimising measurement errors, and lessening the burden on participants (Ruel et al., 2016). In this study, the survey will be administered to a small group, including three academic experts and three employees from various levels and industries, to gather valuable feedback.

3.7 Pilot Test

A pilot study is a brief feasibility study carried out to assess several aspects of the methods meant for a more thorough, precise, or confirmatory investigation (Lowe, 2019). Conducting a pilot test is crucial for identifying potential flaws early, allowing necessary adjustments to the instrument while enhancing the research's credibility and value (Gani et al., 2020). A small sample size of fewer than 30 participants is usually sufficient to assess the reliability of a questionnaire (Bujang et al., 2024). Thus, a pilot test was conducted with 30 respondents, and the results are presented in the table below:

Table 3.3: Reliability Scores for Pilot Test (N=30)

Variables	Items	Cronbach's Alpha
Task Characteristics	3	0.711
Technology Characteristics	4	0.732
Task-technology fit	11	0.851
Utilisation	5	0.758
Supervisory Support	4	0.934
Employee Output	7	0.869

Source: Developed for the research

The reliability test indicated that task characteristics, technology characteristics, task-technology fit, utilisation, supervisory support and employee output, all achieved Cronbach's Alpha values of 0.711, 0.732, 0.851, 0.758, 0.934 and 0.869, respectively. The results indicate that the variable Supervisory Support (SS) demonstrates excellent reliability, while the other five variables (TAC, TEC, TTF, UT, and EO) exhibit high reliability.

3.8 Data Analysis Technique

The process of gathering, classifying, and arranging program data most efficiently is known as data analysis (Maryville University, 2021). The data collected for this study were examined using the Social Science Statistical Package (SPSS). The results of this study will also be used to test the six research hypotheses. This study will be developed using multiple linear regression, descriptive statistics, and inferential analysis. Descriptive analysis and inferential analysis are two different categories of data analysis techniques (Zikmund et al., 2013).

3.8.1 Descriptive Analysis

Descriptive statistics show the relationship between variables within a population to give an organised summary of data (Pyzdek, 2021). Frequency distribution analysis was used in the current study to transform the data into tabular or graphical representations, such as pie charts and bars. Frequency distribution analysis involves analysing the data collected in Section A, which includes the demographic and general characteristics of the respondents, using frequency and percentage measurements. Additionally, metrics of central tendency (i.e., mean) and degree of dispersion (i.e., range, standard deviation, and variance) were used to analyse the data gathered in Section B. Additionally, it simplifies the investigation of correlations between variables and helps identify mistakes and abnormalities (Loeb et al., 2017).

3.8.2 Reliability test

A reliability test is a measure used to evaluate internal consistency, referring to how free measurements are from random errors and, as a result, yield consistent results. Passing the reliability test improves transparency and reduces the potential for bias (Livingston et al., 2018). According to Yun et al. (2023), Cronbach's alpha coefficient is used to assess internal consistency and determine the reliability of multi-item scales. Cronbach's alpha can be used to determine how reliable a collection of items, measures, or ratings is. Better values of the coefficient, which range from 0 to 1, signify a better degree of internal consistency. The more closely the survey items measure the same construct, the closer the alpha value is to 1. Additionally, Cronbach's Alpha must have a minimum acceptable value of 0.7. Table 3.4 below presents the rules of thumb for Cronbach's Alpha.

Table 3.4: Cronbach's Alpha Rule of Thumb

Cronbach's Alpha	Internal Consistency
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

Source: Sharma, B. (2016). A focus on reliability in developmental research through Cronbach's Alpha among medical, dental and paramedical professionals. *Asian Pacific Journal of Health Sciences*, *3*(4), 271-278.

3.6.3 Inferential Analysis

According to Hamzani et al. (2023), inferential analysis is typically used for population value estimation and hypothesis testing. By evaluating the correlation between the variables, this study applies inferential analysis to assess the validity of the hypothesis.

3.6.3.1 Multiple Linear Regression Analysis

Multiple regression analysis is a methodological technique used to investigate the linear relationship between a dependent variable and numerous independent variables. When both the dependent and independent variables can be measured with a standard scale, multiple regression analysis is considered appropriate (Uyanık & Güler, 2013).

The formula equation for multiple regression analysis is as below:

$Y = \beta 1x1 + \beta 2x2 + \ldots + \beta nxn + c$

In this research, three equations are proposed:

$TTF=\beta 1(TAC)+\beta 2(TEC)+c$
$UT=\beta 1(TTF)+\beta 2(SS)+c$
$EO=\beta 1(TTF)+\beta 2(UT)+c$

Whereby,
TAC = Task Characteristics
TEC = Technology Characteristics
UT = Utilisation
TTF = Task-technology fit
SS = Supervisory Support
EO = Employee Output

$\beta 1, \beta 2$ = The slope of the coefficient

c = Intercept

*c is a constant value, and $\beta 1$ and $\beta 2$ are the coefficients relating to dependent variable to the independent variable of interest.

3.9 Conclusion

Chapter 3 outlined the research methodology employed in the study. Both quantitative and descriptive research approaches were applied to investigate the proposed objectives. A convenience sampling technique was used to collect primary data, allowing for the examination of internal reliability and the testing of hypothesised relationships. A pre-test and pilot study were conducted, and the results confirmed acceptable Cronbach's alpha values, indicating reliable measurement constructs. The following chapter presents both the descriptive and inferential analyses of the collected data.

CHAPTER 4: DATA ANALYSIS

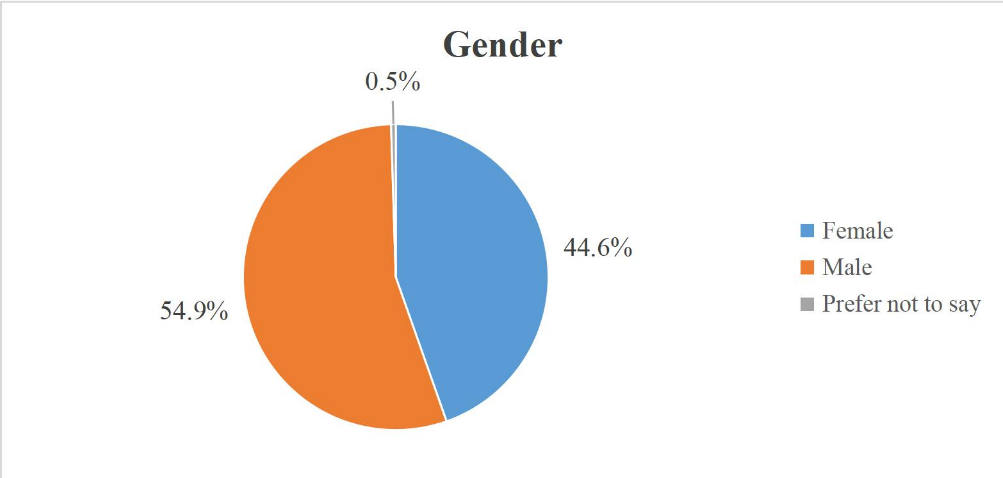
4.0 Introduction

This chapter presents the results of the analyses conducted. A total of 204 questionnaire responses were utilised and analysed using SPSS Version 29.0 and Microsoft Excel. Additionally, this chapter includes demographic information and details about the respondents. The Cronbach's Alpha reliability analysis is also presented to assess the internal consistency of the scale and its inter-item reliability. Furthermore, statistical analyses are conducted to examine the relationships between variables.

4.1 Respondent Demographic Profile

4.1.1 Gender

Figure 4.1: Gender (N=204)



Source: Developed for the research

Table 4.1: Gender (N=204)

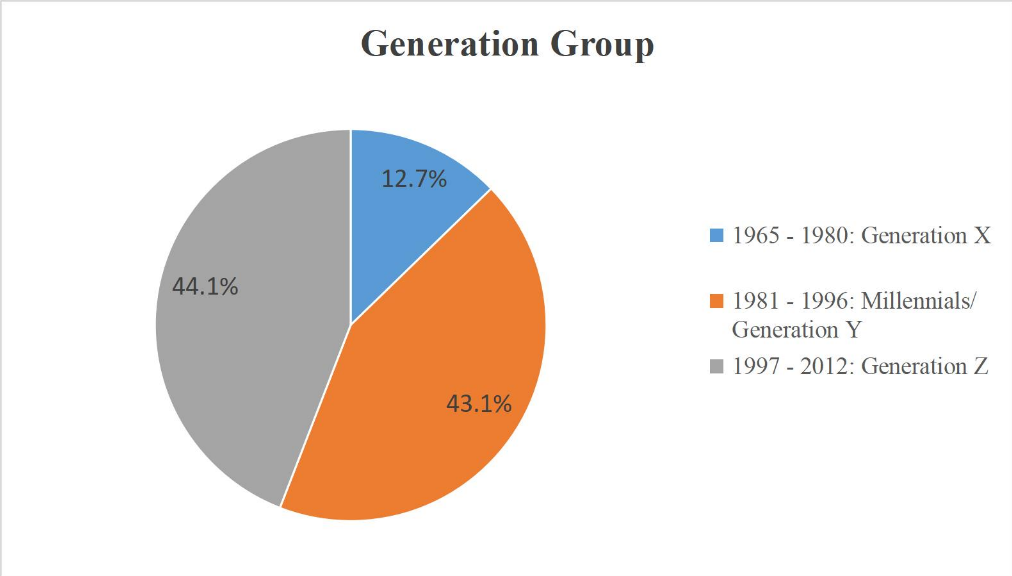
Gender	Frequency	Percentage(%)
Female	91	44.6
Male	112	54.9
Prefer not to say	1	0.5
Total	204	100.0

Source: Developed for the research

Figure 4.1 and Table 4.1 above display the gender of respondents. This study had 204 respondents. The data above shows that 44.6% of respondents were females and 54.9% were males.

4.1.2 Generation Group

Figure 4.2: Generation Group (N=204)



Source: Developed for the research

Table 4.2: Generation Group (N=204)

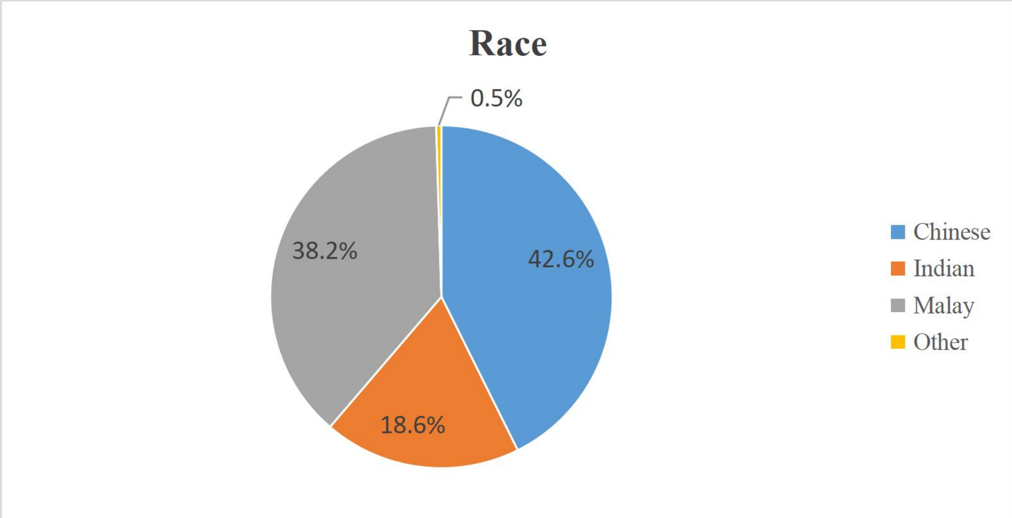
Generation Group	Frequency	Percentage(%)
1965 - 1980: Generation X	26	12.7
1981 - 1996: Millennials/ Generation Y	88	43.1
1997 - 2012: Generation Z	90	44.1
Total	204	100.0

Source: Developed for the research

Figure 4.2 and Table 4.2 show the ages of the respondents. 43.1% are Generation Y, followed by 44.1% are Generation Z, and 12.7% are Generation X. No respondents were Baby Boomers.

4.1.3 Race/Ethnicity

Figure 4.3: Race (N=204)



Source: Developed for the research

Table 4.3: Race (N=204)

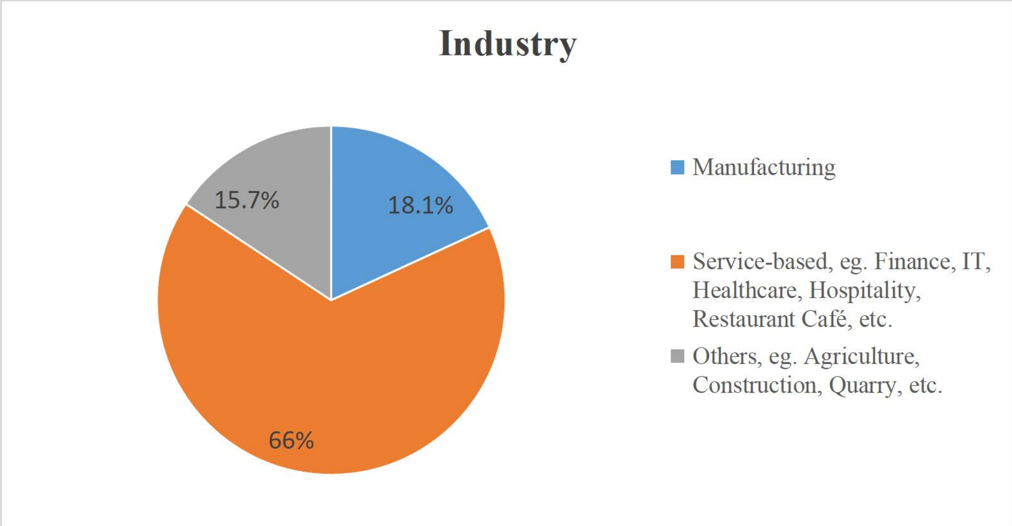
Race	Frequency	Percentage(%)
Chinese	87	42.6
Indian	38	18.6
Malay	78	38.2
Other	1	0.5
Total	204	100.0

Source: Developed for the research

Figure 4.3 and Table 4.3 demonstrate the race of the respondents. The data above shows that 42.6% are Chinese, followed by 38.2% are Malay, and 18.6% are Indian. Whereas only one respondent is Iban.

4.1.4 Industry

Figure 4.4: Industry (N=204)



Source: Developed for the research

Table 4.4: Industry (N=204)

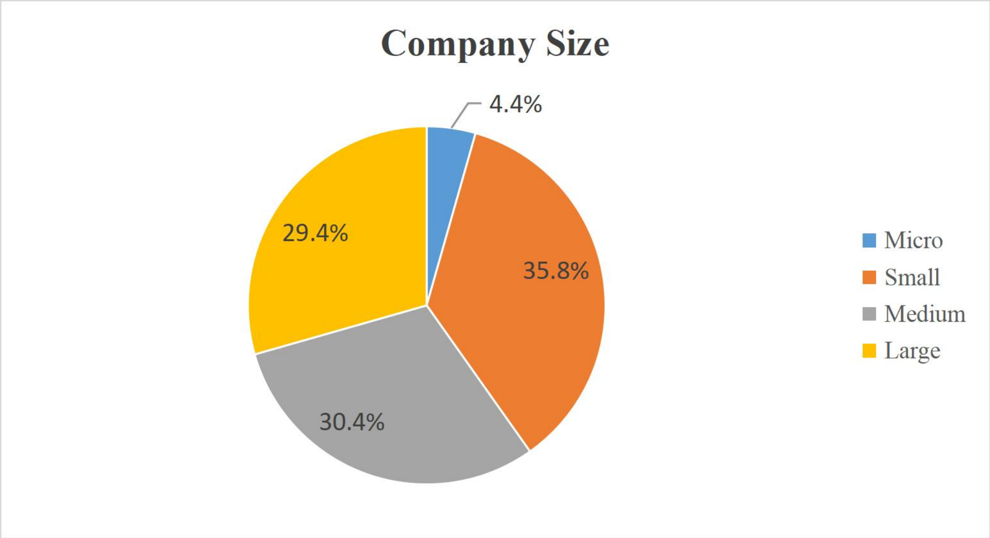
Type of Industry	Frequency	Percentage(%)
Manufacturing	37	18.1
Services and other sectors	167	81.9
Total	204	100.0

Source: Developed for the research

Figure 4.4 and Table 4.4 show the distribution of respondents across various industries. The majority, 81.9%, are employed in service-based sectors, including finance, IT, healthcare, hospitality, restaurants, and other sectors like agriculture, construction, and quarrying. A smaller proportion, 18.1%, work in the manufacturing sector.

4.1.5 Company Size

Figure 4.5: Company Size Based on Number of Employees (N=204)



Source: Developed for the research

Table 4.5: Company Size Based on Number of Employees (N=204)

Company Size *	Manufacturing	Service and other sectors	Total	Percentage (%)
Micro	1	8	9	4.41
Small	22	51	73	35.78
Medium	10	52	62	30.39
Large	4	56	60	29.41
Total	37	167	204	100

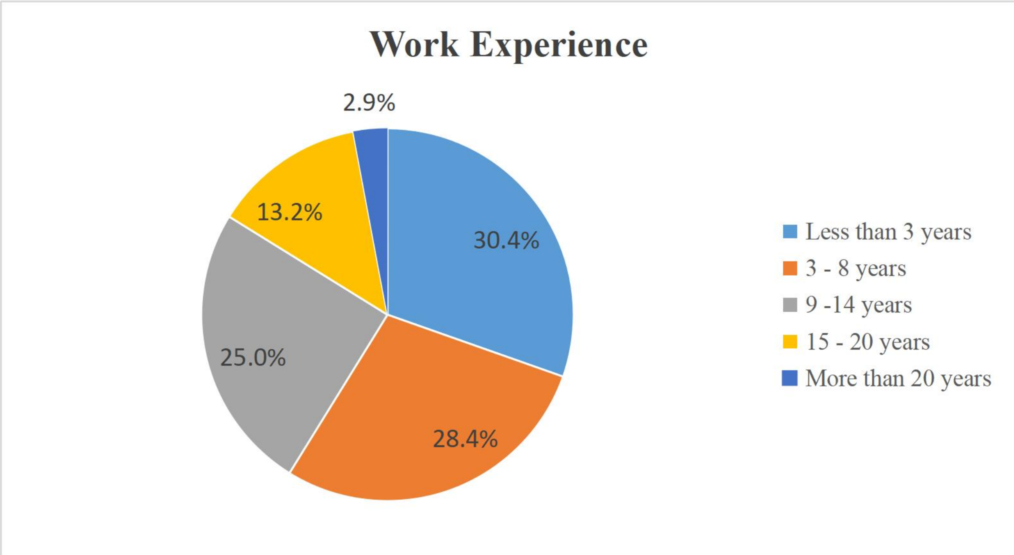
**Note: Company size is classified based on SME Corp definitions. For manufacturing, micro (<5 employees), small (5–75 employees), medium (76–200 employees), and large (>200 employees). For services and other sectors: micro (<5 employees), small (5–30 employees), medium (31–75 employees), and large (>75 employees).*

Source: Developed for the research

Figure 4.5 and Table 4.5 reveal that small enterprises make up the largest portion of the sample (35.78%), followed by medium (30.39%) and large enterprises (29.41%), with micro enterprises forming only a small fraction (4.41%).

4.1.6 Work Experience

Figure 4.6: Work Experience (N=204)



Source: Developed for the research

Table 4.6: Work Experience (N=204)

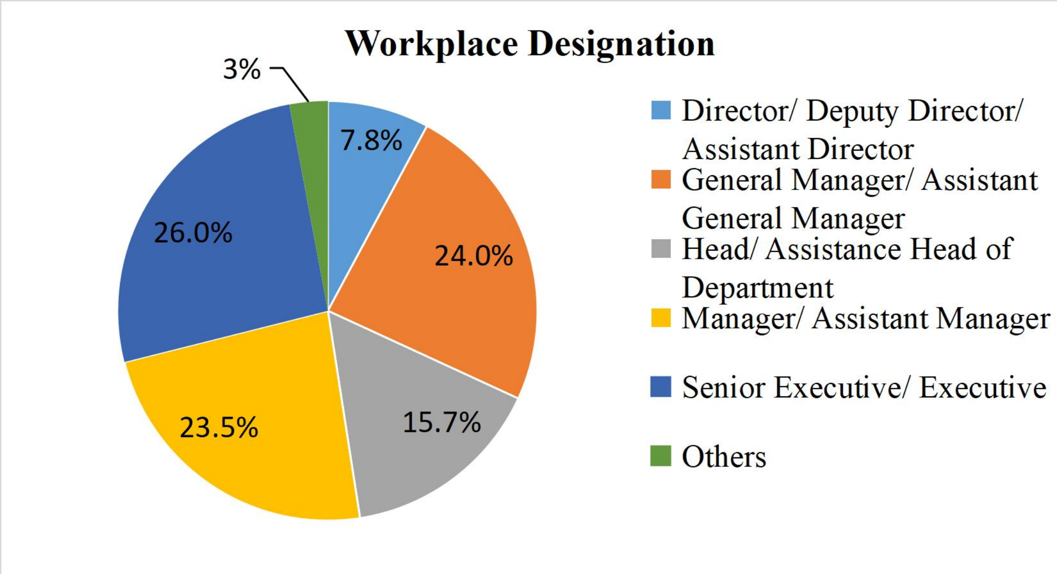
Work Experience	Frequency	Percentage(%)
Less than 3 years	62	30.4
3 - 8 years	58	28.4
9 -14 years	51	25.0
15 - 20 years	27	13.2
More than 20 years	6	2.9
Total	204	100.0

Source: Developed for the research

Figure 4.6 and Table 4.6 present the respondents' varying levels of work experience. The largest group, accounting for 30.4%, consists of individuals with less than three years of experience, followed closely by those with 3 to 8 years at 28.4%. Additionally, 25.0% have between 9 and 14 years of experience. Meanwhile, 13.2% fall within the 15 to 20-year range, and only 2.9% have over 20 years of experience.

4.1.7 Workplace Designation

Figure 4.7: Workplace Designation (N=204)



Source: Developed for the research

Table 4.7: Workplace Designation (N=204)

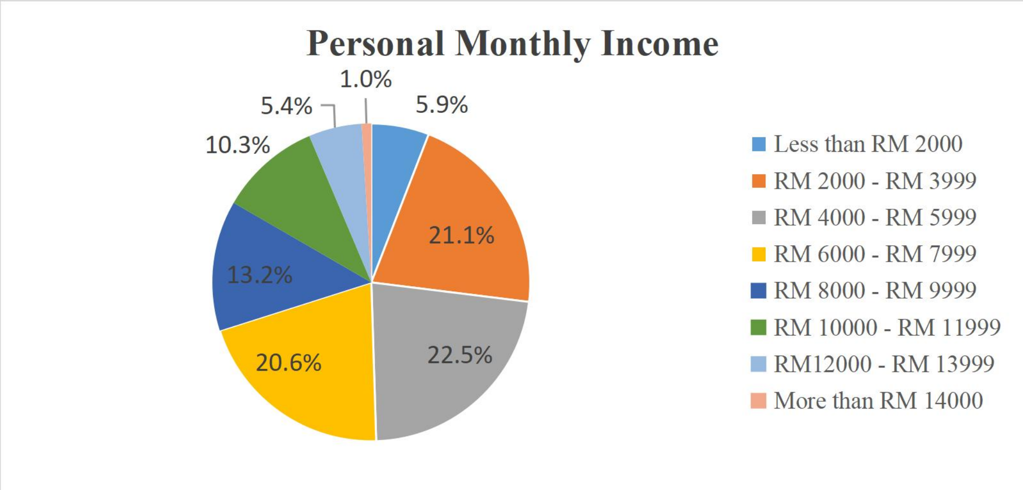
Workplace Designation	Frequency	Percentage(%)
Director/ Deputy Director/ Assistant Director	16	7.8
General Manager/ Assistant General Manager	49	24.0
Head/ Assistant Head of Department	32	15.7
Manager/ Assistant Manager	48	23.5
Senior Executive/ Executive	53	26.0
Others	6	3
Total	204	100.0

Source: Developed for the research

Figure 4.7 and Table 4.7 demonstrate the various workplace designations of the respondents. The largest group consists of Senior Executives/Executives, making up 26.0%, followed closely by General Managers/Assistant General Managers at 24.0%, and Managers/Assistant Managers at 23.5%. Additionally, 15.7% serve as Heads or Assistant Heads of Departments, while 7.8% hold senior positions such as Director, Deputy Director, or Assistant Director. The remaining 3% include roles such as Junior, Engineers, and IT Consultants.

4.1.8 Personal Monthly Income

Figure 4.8: Personal Monthly Income (N=204)



Source: Developed for the research

Table 4.8: Personal Monthly Income (N=204)

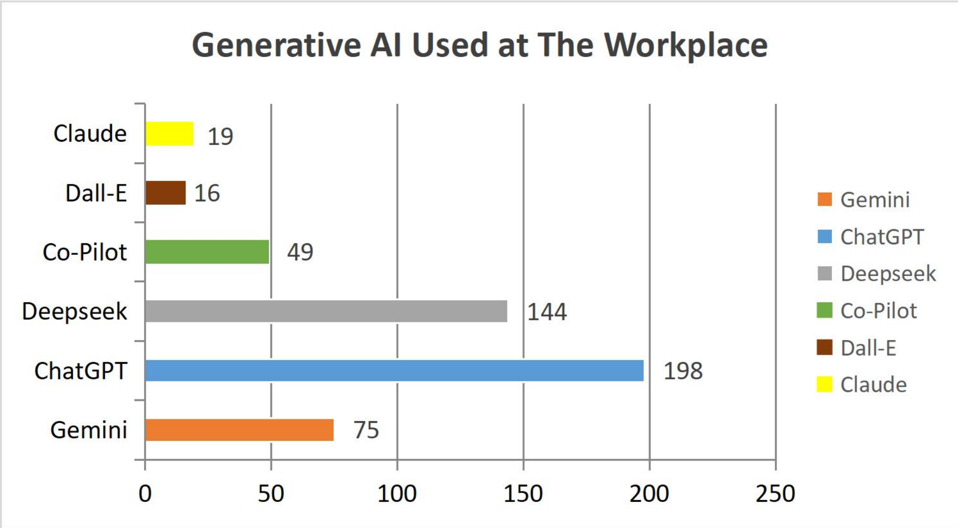
Personal Monthly Income	Frequency	Percentage(%)
Less than RM 2000	12	5.9
RM 2000 - RM 3999	43	21.1
RM 4000 - RM 5999	46	22.5
RM 6000 - RM 7999	42	20.6
RM 8000 - RM 9999	27	13.2
RM 10000 - RM 11999	21	10.3
RM12000 - RM 13999	11	5.4
More than RM 14000	2	1.0
Total	204	100.0

Source: Developed for the research

Figure 4.8 and Table 4.8 illustrate the respondents' personal monthly income levels. A total of 5.9% earn less than RM 2,000, while 21.1% fall within the RM 2,000–RM 3,999 range. The largest proportion, 22.5%, earn between RM 4,000 and RM 5,999, followed by 20.6% who earn between RM 6,000 and RM 7,999. Additionally, 13.2% report earnings within the RM 8,000–RM 9,999 range, while 10.3% earn between RM 10,000 and RM 11,999. About 5.4% receive salaries in the RM 12,000–RM 13,999 range, and only 1% earn more than RM 14,000.

4.1.9 Generative AI Used at The Workplace

Figure 4.9: Generative AI Used at The Workplace



Source: Developed for the research

Table 4.9: Generative AI Used for Workplace

Type of GenAI	Frequency	Percentage (%)
Gemini	75	15.0
ChatGPT	198	39.5
Deepseek	144	28.7
Co-Pilot	49	9.8
Dall-E	16	3.2
Claude	19	3.8
Total	501	100.0

Source: Developed for the research

Figure 4.9 and Table 4.9 present the frequency of GenAI tools used by respondents in the workplace. ChatGPT is the most frequently used, with 198 respondents incorporating it into their work. Deepseek follows with 144 users, while Gemini is used by 75 respondents. Co-Pilot is mentioned by 49 respondents, whereas Claude and DALL-E have the lowest usage, with 19 and 16 respondents, respectively.

4.2 Central Tendencies Measurement of Constructs

Table 4.10: Measurement of Constructs (N=204)

Items	Mean	Std. Deviation
TAC	4.10	0.8557
TEC	4.2623	0.7814
TTF	4.2664	0.8022
UT	4.0333	0.9597
SS	3.9301	1.0212
EO	4.2115	0.8068

Source: Developed for the research

The study employed a 5-point scale to assess agreement on employee performance and associated workplace factors. The scores ranged from 3.93 to 4.26, reflecting generally positive responses from participants. TTF achieved the highest mean of 4.2664, indicating strong agreement. TEC closely followed with a mean of 4.2623, underscoring its importance. EO showed considerable significance with a mean of 4.2115, while TAC and UT had means of 4.1 and 4.0333, respectively. SS recorded the lowest mean at 3.93.

4.3 Internal Reliability Test

Table 4.11: Reliability Statistic for Actual Result (N=204)

Variable	No of Items	Cronbach's Alpha
Task Characteristics	3	0.730
Technology Characteristics	4	0.726
Task-technology fit	11	0.857
Utilisation	5	0.836
Supervisory Support	4	0.888
Employee Output	7	0.845

Source: Developed for the research

Table 4.11 exhibits the Cronbach's alpha values for each variable. The results showed that all variables exceeded the value of 0.7, which is indicative of reliable results. It has been found that the variables of task-technology fit, utilisation, supervisory support and employee output possess Cronbach's Alpha values of 0.857, 0.836, 0.888, and 0.845, respectively. These variables are being regarded as highly reliable. Meanwhile, task characteristics (0.730) and technology characteristics (0.726) fall under the acceptable reliability range.

4.3 Multiple Linear Regression Analysis

4.3.1 Regression Analysis for Predicting Task-Technology Fit

Table 4.12: Coefficients for Predicting Task-Technology Fit

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	17.329	2.400		7.221	<.001		
	TAC	.405	.159	.148	2.547	.012	.821	1.219
	TEC	1.445	.142	.591	10.178	<.001	.821	1.219

a. Dependent Variable: TTF

Source: SPSS Version 29.0

Table 4.13: Model Summary for Predicting Task-Technology Fit

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.667[a]	.445	.439	4.24405	.445	80.440	2	201	<.001	1.738

a. Predictors: (Constant), TEC, TAC

b. Dependent Variable: TTF

Source: SPSS Version 29.0

Table 4.14: ANOVA for Predicting Task-Technology Fit

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2897.762	2	1448.881	80.440	<.001[b]
	Residual	3620.410	201	18.012		
	Total	6518.172	203			

a. Dependent Variable: TTF

b. Predictors: (Constant), TEC, TAC

Source: SPSS Version 29.0

Task-technology fit = 17.329 + 0.405 (Task Characteristics) + 1.445 (technology characteristics)

According to this equation, every one unit increase in TAC leads to a 0.405 unit increase in TTF, while every one unit increase in TEC results in a 1.445 unit increase in TTF, assuming all other variables remain constant.

Table 4.13 presents the value of R2 as 0.445. This indicates that 44.5% of the variance in task-technology fit can be explained by the task characteristics and technology characteristics. However, the remaining 55.5% is influenced by other factors not explained in this research model.

The statistical results show that both independent variables significantly influence task-technology fit in this regression model ($F = 80.44$, $p<0.001$). Task characteristics have a significant positive impact on task-technology fit ($t = 2.547$, $p < 0.05$). This suggests that as task characteristics become more complex or varied, the task-technology fit increases, implying that more demanding or complex tasks may align with the technology. Thus, H1 is being supported.

Moreover, technology characteristics have a strong positive influence on task-technology fit ($t = 10.178$, $p < 0.05$). This indicates that the suitability of the technology improves, and then the fit between the technology and the tasks being performed also increases. Hence, H2 is also supported.

4.3.2 Regression Analysis for Predicting Utilisation

Table 4.15: Coefficients for Predicting Utilisation

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	2.361	1.706		1.384	.168		
	TTF	.244	.040	.371	6.169	<.001	.819	1.220
	SS	.404	.063	.383	6.365	<.001	.819	1.220

a. Dependent Variable: UT

Source: SPSS Version 29.0

Table 4.16: Model Summary for Predicting Utilisation

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.636[a]	.405	.399	2.89141	.405	68.295	2	201	<.001	1.851

a. Predictors: (Constant), SS, TTF

b. Dependent Variable: UT

Source: SPSS Version 29.0

Table 4.17: ANOVA for Predicting Utilisation

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1141.921	2	570.960	68.295	<.001[b]
	Residual	1680.413	201	8.360		
	Total	2822.333	203			

a. Dependent Variable: UT

b. Predictors: (Constant), SS, TTF

Source: SPSS Version 29.0

Utilisation= 2.361 + 0.244 (Task-Technology Fit) + 0.404 (Supervisory Support)

According to this equation, every one-unit increase in TTF leads to a 0.244 unit increase in UT, while every one unit increase in SS results in a 0.404 unit increase in TTF, assuming all other variables remain constant.

Table 4.16 shows that the value of R2 is 0.405. This indicates that 40.5% of the variance in utilisation can be explained by the task-technology fit and supervisory support. However, the remaining 59.5% is influenced by other factors not explained in this research model.

The statistical result demonstrates that both independent variables have a significant effect on utilisation in this regression model ($F = 68.295$, $p<0.001$). Task-technology fit significantly influences the utilisation of GenAI ($t = 6.169$, $p < 0.05$). This suggests that the higher the task-technology fit, the higher the utilisation of GenAI. Therefore, H3 is being supported.

Furthermore, supervisory support shows a significant impact on utilisation ($t = 6.365$, $p < 0.05$). This indicates that the greater the supervisory support, the higher the utilisation of GenAI. Thus, H4 is also supported.

4.3.3 Regression Analysis for Predicting Employee Output

Table 4.18: Coefficients for Predicting Employee Output

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	6.049	1.700		3.559	<.001		
	TTF	.349	.042	.487	8.301	<.001	.715	1.398
	UT	.349	.064	.320	5.452	<.001	.715	1.398

a. Dependent Variable: EO

Source: SPSS Version 29.0

Table 4.19: Model Summary for Predicting Employee Output

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.711[a]	.505	.500	2.87422	.505	102.676	2	201	<.001	2.004

a. Predictors: (Constant), UT, TTF

b. Dependent Variable: EO

Source: SPSS Version 29.0

Table 4.20: ANOVA for Predicting Employee Output

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1696.436	2	848.218	102.676	<.001[b]
	Residual	1660.485	201	8.261		
	Total	3356.922	203			

a. Dependent Variable: EO

b. Predictors: (Constant), UT, TTF

Source: SPSS Version 29.0

Employee Output = 6.049 + 0.349 (Task-Technology Fit) +0.349 (Utilisation)

According to this equation, every one-unit increase in TTF or UT leads to a 0.349-unit increase in EO, assuming all other variables remain constant.

Table 4.19 presents the value of R2 as 0.505. This indicates that 50.5% of the variance in employee output can be explained by the task-technology fit and utilisation. However, the remaining 49.5% is influenced by other factors not explained in this research model.

The statistical results reveal that both independent variables have a significant influence on employee output in the regression model ($F = 102.676$, $p<0.001$). Task-technology fit has a significant effect on employee output ($t = 8.301$, $p < 0.05$). This means that the higher the task-technology fit, the higher the employee output. Hence, H5 is being supported.

Additionally, utilisation also significantly influences employee output ($t = 5.452$, $p < 0.05$). This indicates that the higher the utilisation of GenAI, the higher the employee output. Therefore, H6 is also supported.

4.4 Hypotheses Testing

Table 4.21 shows the summary of the hypothesis testing results for the six proposed hypotheses (H1, H2, H3, H4, H5, and H6).

Table 4.21: Summary of Hypotheses Testing Results

Hypotheses	Path	Outcome	Result
H1	TAC → TTF	Multiple Linear Regression β=-0.148 p=0.012	Supported
H2	TEC → TTF	Multiple Linear Regression β=0.591 p=0.000	Supported
H3	TTF →UT	Multiple Linear Regression β=0.371 p=0.000	Supported
H4	SS → UT	Multiple Linear Regression β=0.383 p=0.000	Supported
H5	TTF → EO	Multiple Linear Regression β=0.487 p=0.000	Supported

H6	UT → EO	Multiple Linear Regression β=0.320 p=0.000	Supported

Source: Developed for the research.

4.5 Conclusion

The chapter concludes with a descriptive analysis of the respondents' demographic information. A reliability test was conducted on all variables using SPSS software. In addition, a multiple linear regression analysis was also conducted using SPSS to carry out the inferential analysis.

CHAPTER 5: DISCUSSION, CONCLUSION AND IMPLICATIONS

5.0 Introduction

Chapter 5 presents key findings that support the study's objectives and hypotheses. It also outlines the research limitations, discusses the theoretical and practical implications, and offers suggestions for future studies.

5.1 Demographic Profile

The study's findings reveal that a total of 204 Malaysian employees are adopting GenAI. Among them, 91 respondents were female, 112 were male, and the gender of one respondent was not specified. The majority of respondents belonged to Generation Y and Generation Z, with 88 respondents (43.1%) and 90 respondents (44.1%) respectively. The data shows that a significant portion of respondents are 30.4% having less than 3 years of work experience and 28.4% having between 3 to 8 years. This suggests that the adoption of GenAI is most prominent among younger professionals who are typically more tech-savvy, adaptable, and open to using emerging technologies in their work environments.

Furthermore, Senior Executives/Executives (26.0%), General Managers/Assistant General Managers (24.0%) and Managers/Assistant Managers (23.5%) make up 73.5% of the total respondents; the utilisation of GenAI is largely driven by individuals in leadership and decision-making positions. Most of the respondents are from small companies (35.78%). ChatGPT (39.5%) and Deepseek (28.7%) are the most common GenAI used in their workplace. Moreover, most of the Malaysian employees are working in the service-based sector (66.2%). The income distribution of the respondents reveals that the majority earn between RM

2000 and RM 7999, with the highest concentration in the RM 4000–RM 5999 range (22.5%), followed closely by RM 2000–RM 3999 (21.1%) and RM 6000–RM 7999 (20.6%). Together, these three income groups account for 64.2% of the total respondents, indicating that most individuals using GenAI fall within the lower to middle-income bracket.

5.2 Discussion of Major Findings

Table 5.1 Major Findings

Hypotheses	β-value/p-value	Result
H1: Task characteristics have a significant positive relationship with Task-technology fit in generative AI	β=0.148 p=0.012	Supported
H2: Technology characteristics have a significant positive relationship with Task-technology fit in generative AI	β=0.591 P<0.001	Supported
H3: Task-technology fit in generative AI has a significant positive relationship with its utilisation	β=0.371 p<0.001	Supported
H4: Supervisory support has a significant positive relationship with utilisation	β=0.383 p<0.001	Supported
H5: Task-technology fit in generative AI has a significant positive relationship with employee output	β=0.487 p<0.001	Supported
H6: Utilisation has a significant positive relationship with employee output	β=0.320 p<0.001	Supported

Source: Developed for research

5.2.1 Relationship between Task Characteristics and Task-Technology Fit in Generative AI.

Table 5.1 shows a significant relationship between task characteristics and task-technology fit with a p-value of 0.012. This suggests that the nature of the task plays a critical role in determining how well GenAI aligns with and supports task performance. Tasks that are ill-defined, ad-hoc, non-routine, and require new solutions often involve high levels of uncertainty; therefore, technologies that are well-suited to support such tasks can significantly improve the overall task-technology fit.

This is also supported by earlier studies, such as those on healthcare wearable devices (Wang et al., 2020), mobile banking (Oliveira, 2014), social networking sites (Lu & Yang, 2014), and chatbots (Tao et al., 2024), which have demonstrated that task characteristics significantly affect task-technology fit.

5.2.2 Relationship between Technology Characteristics and Task-Technology Fit in Generative AI.

Table 5.1 reveals a significant association between the technology characteristics and task-technology fit, with a p-value below 0.001. This indicates that when the features and functionalities of a technology are well-aligned with task demands, the overall task-technology fit improves. For instance, previous research done by Tripathi and Jigeesh (2015) found that when cloud computing technology meets users' task requirements, it enhances the perceived TTF.

In non-routine and uncertain situations, GenAI often plays a more analytical and supportive role, enhancing human problem-solving in both work and decision-making processes. Individuals who integrate GenAI into their tasks report improved capabilities in creativity, analysis, technical skills, planning, and evaluation, resulting in stronger alignment with task requirements (Sandelin, 2024).

This relationship is further supported by studies in various technological contexts. Research on enterprise social media (Fu et al., 2020), cloud-based collaborative learning tools (Yadegaridehkordi et al., 2014), and internet banking systems (Rahi et al., 2021) consistently demonstrates that technology characteristics play a vital role in shaping task-technology fit.

5.2.3 Relationship between Task-Technology Fit in Generative AI and Its Utilisation

Table 5.1 reveals a significant relationship between task-technology fit in GenAI and its utilisation, with a p-value below 0.001. This indicates that when GenAI aligns well with task requirements, its usage in the workplace increases. Shakeel and Siddiqui (2021) support this notion, stating that the task-technology fit of AI plays a crucial role in determining its actual application in talent acquisition processes. When GenAI tools are well-suited to specific task needs, employees are more likely to adopt and trust the technology.

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This finding aligns with prior studies on blockchain technology (Alazab et al., 2021), cloud-based collaborative learning technologies (Yadegaridehkordi et al., 2014), and shopper-facing technologies (Wang et al., 2021), all of which highlight the impact of task-technology fit on utilisation of technology.

5.2.4 Relationship between Supervisory Support and Utilisation

Table 5.1 highlights a significant relationship between supervisory support and the utilisation of technology, with a p-value below 0.001. This underscores the vital role that supervisors play in encouraging the effective use of technology in the workplace. The finding is consistent with prior research (Yang et al., 2015; Dun & Kumar, 2023), which stresses the importance of supervisory support in facilitating technology adoption.

Besides, Sugandini et al. (2019) state the positive influence of managerial support on the adoption of digital technology. This is largely because supportive management helps employees overcome adoption challenges, creates a positive and encouraging environment, and provides the motivation and resources needed to fully leverage the technology (Anam & Haque, 2023).

5.2.5 Relationship between Task-Technology Fit in Generative AI and Employee Output

Table 5.1 highlights a significant relationship between task-technology fit in GenAI and employee output, with a p-value below 0.001. This finding emphasises the importance of aligning technology capabilities with job requirements to enhance employee performance. Previous research done by Widagdo and Susanto (2016) suggested that when information technology effectively supports daily tasks, it enhances the alignment between technology and job demands, thereby improving individual performance.

Similarly, Kamdjoug et al. (2023) emphasised that strong employee performance is a clear indicator of successful technology integration into task execution. Additionally, Diamantidis and Chatzoglou (2019) found that ICT significantly boosted employees' productivity, skills, and efficiency during the COVID-19 pandemic. This aligns with previous research conducted in the context of Learning Management Systems (McGill & Klobas, 2009) and the Internet of Things (Sinha et al., 2019), both of which emphasise the positive relationship between task-technology fit and employee performance.

5.2.6 Relationship between Utilisation and Employee Output

Table 5.1 highlights a significant relationship between utilisation and employee output, with a p-value below 0.001. This suggests that the more GenAI is effectively used in the workplace, the greater the impact on employee performance. Sinha et al. (2024) found that adopting technology for routine cognitive and manual tasks enhances employee performance in non-routine problem-solving and complex communication activities.

Additionally, the greater utilisation of technology leads to greater satisfaction. Isaac et al. (2017) also noted that remote workers whose job requirements are effectively met through ICT tend to experience greater satisfaction. Kamdjoug et al. (2023) show the positive relationship between the use of ICT and individual performance. This is consistent with prior studies (Igbaria & Tan, 1997; Fitri et al., 2023; DeLone & McLean, 2003) that have similarly highlighted the influence of technology usage on employee performance.

5.3 Implications of the study

5.3.1 Theoretical Implications

This study makes several key theoretical contributions by extending existing knowledge on the impact of GenAI in workplace settings. Grounded in the Task-Technology Fit (TTF) theory, the research confirms that both task characteristics and technology characteristics play a significant role in shaping the task-technology fit of GenAI (Sandelin, 2024). Furthermore, it establishes that task-technology fit significantly influences the utilisation of GenAI tools (Alazab et al., 2021), which in turn positively impacts employee output, specifically in terms of job performance and satisfaction (Kamdjoug et al., 2023). These findings validate and extend the TTF model by demonstrating its applicability in the context of emerging technologies, such as GenAI, an area that remains underexplored in current literature (Wang et al., 2020; Kamdjoug et al., 2023; Oliveira et al., 2014).

Building upon the existing conceptual framework, this study has developed a new comprehensive framework that incorporates the factors of supervisory support that could influence the utilisation of Gen AI (Dun & Kumar, 2023). The study offers new insights into the social and behavioural factors that influence technology adoption. These theoretical contributions pave the way for further research exploring other organisational dynamics.

Additionally, the study also advances the field of human-computer interaction (HCI) by analysing the evolving nature of user engagement with intelligent systems. Unlike conventional tools, GenAI introduces dynamic and generative exchanges, which this research explores in terms of their effects on employee performance and satisfaction. This perspective provides a foundation for future research on AI-enabled work environments, digital transformation, and the balance between human agency and machine intelligence (Przegalinska et al., 2025).

5.3.2 Practical Implications

The insights from this study can benefit both business practitioners and organisations in Malaysia. For business practitioners, this research offers strategic guidance on how to integrate GenAI tools in ways that enhance, rather than hinder, employee productivity. By exploring how GenAI influences employee satisfaction and productivity, leaders can establish clear task requirements that align with the technology's features and capabilities, ultimately fostering greater job fulfilment.

Additionally, the study highlights the critical role of supervisory support, offering a roadmap for helping employees adopt and utilise GenAI tools effectively. Supervisors play a key role not only in facilitating access to these technologies but also in shaping employees' attitudes and confidence toward their use (Holland et al., 2017). By providing continuous guidance, constructive feedback, and tailored support, supervisors can help bridge knowledge gaps and reduce resistance to technological change. This creates a more supportive learning environment where employees feel encouraged to experiment with GenAI tools, adapt their workflows, and gradually develop the digital competencies required to fully harness the benefits of AI-assisted productivity. As such, supervisory support functions as a critical enabler of both technology adoption and sustained performance improvement.

For organisations in Malaysia, this study is especially relevant given the nation's economic agenda focused on improving labour productivity. Policymakers can draw on these findings to develop forward-looking labour policies and digital transformation strategies that ensure GenAI adoption contributes to economic growth while minimising skill disparities (Young, 2025). The study's sector-specific recommendations can inform targeted initiatives in industries where GenAI has the highest potential for productivity gains. Moreover, the findings support the development of public-private partnerships aimed at enhancing digital literacy, promoting lifelong learning, and encouraging the ethical use of AI technologies across the workforce.

5.4 Limitations of the Study

The study has a few limitations in different areas that should be considered. The study utilised a cross-sectional design, which involves collecting data at a single point in time (Cvetkovic et al., 2021). While this approach is efficient and useful for identifying relationships among variables, it restricts the ability to draw conclusions about causality (Wang & Cheng, 2020). That is, even though the study finds that variables like task-technology fit and utilisation are significantly associated with employee output, it cannot confirm whether the relationship changes over time.

Besides, the data collected for this study were based on self-administered questionnaires, which depend on respondents' own perceptions and honesty. Although reliability and validity checks were conducted, self-reporting inherently introduces potential biases. Respondents might overstate positive behaviours or underreport negative experiences due to social desirability bias (Ross & Bibler, 2019). Additionally, some may misinterpret questions or inaccurately assess their own performance or AI usage, which can affect the accuracy of the findings.

Moreover, the study concentrated on a narrow set of variables—specifically, task characteristics, technology characteristics, task-technology fit, supervisory support, utilisation, and employee output. While these factors were carefully selected based on relevant literature and theoretical frameworks, they do not encompass the full range of elements that could influence the utilisation of GenAI and its impact on employee performance.

5.5 Recommendations for Future Research

This research includes several recommendations for future studies to address some of the limitations mentioned in this study. Given the limitations of the cross-sectional approach used in this study, longitudinal research is recommended for future studies. A longitudinal design would allow researchers to track changes in the utilisation of GenAI and its impact on employee output over time. This approach would help uncover causal relationships and provide deeper insights into how the adoption of GenAI evolves and how its long-term impact can be measured, especially in rapidly changing technological environments (Bala, 2020).

Furthermore, a mixed-methods strategy that incorporates both qualitative insights (such as interviews) and quantitative data (such as surveys) may prove advantageous for future research. This approach would provide a richer understanding of employee experiences, uncover challenges not captured in quantitative surveys, and add depth to the interpretation of data. Qualitative insights could explore employees' personal perceptions of AI tools, their hesitations, and the complexities of how they interact with the technology in their daily work (Gregar, 2023).

Moreover, future research is recommended to broaden the range of variables by incorporating constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT) model. This approach could offer a more holistic view of the factors influencing employees' acceptance and utilisation of GenAI in the workplace. Specifically, including variables like social influence, performance expectancy, effort expectancy, and facilitating conditions could significantly deepen the understanding of user behaviour (Bader & Mohammad, 2019). By expanding the theoretical framework with these constructs, future studies would be able to capture not only the technical alignment and managerial support aspects but also the psychological, social, and infrastructural factors that drive or hinder the adoption of GenAI technologies.

5.6 Conclusion

To summarise, this research aims to deepen the understanding of employee output in the workplace by exploring the factors of task characteristics, technology characteristics, task-technology fit, utilisation of GenAI, and supervisory support. The study successfully achieved its objectives by evaluating the relationships among these factors and assessing the impact of GenAI on employee output. Additionally, this chapter outlines the study’s limitations and provides recommendations for future research to enhance subsequent studies. In doing so, this research contributes valuable insights into the impact of GenAI on employee output, offering a foundation for future analysis.

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APPENDICES

Appendix A: Survey Questionnaire

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UNIVERSITI TUNKU ABDUL RAHMAN
FACULTY OF ACCOUNTANCY AND MANAGEMENT

BACHELOR OF INTERNATIONAL BUSINESS
FINAL YEAR PROJECT

The Impact of Generative AI on Employee Output

Survey Questionnaire

Dear Participants, Greetings! I am Lim Qi Fei, student from Universiti Tunku Abdul Rahman (UTAR), pursuing a degree in Bachelor of International Business (HONS). I'm currently conducting a research on **"Impact of Generative AI on Employee Output"** for my final year project.

This questionnaire consists of THREE (3) sections that should take approximately **5 – 10 minutes** to complete. Your involvement is crucial to the success of this research. Your effort and time taken to complete this survey are highly appreciated. Your answers will be kept **PRIVATE & CONFIDENTIAL** and used only for academic purposes.

For any further inquiries, please contact qfeilim03@1utar.my. Thank you for your participation!

Personal Data Protection Notice

In accordance with the Personal Data Protection Act 2010 (PDPA), Universiti Tunku Abdul Rahman (UTAR) requires notice and consent for the collection, storage, usage, and retention of personal and research data. This data may be used for purposes such as administration and research. UTAR may disclose these data to third parties when necessary to comply with legal requirements. Data will be securely maintained and deleted per UTAR's retention policy. UTAR ensures confidentiality, security, and accuracy of personal data, which will not be used for political or commercial purposes. By submitting personal data, individuals consent to its use per UTAR's policies. For data access or updates, individuals may contact qfeilim03@1utar.my.

Acknowledgment of Notice

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

(   ) I disagree, my personal data will not be processed.

SECTION A: SCREENING

Instruction: Please complete the following screening question by choosing your preferred response.

Are you in full time employment?

(   ) Yes.

(   ) No.

SECTION B: DEMOGRAPHIC PROFILE

Instruction: Please complete the following question by choosing the relevant option.

1. Gender

(   ) Male

(   ) Female

(   ) Prefer not to say

2. Birth Year/ Generation Group

(   ) 1946 - 1964: Baby Boomers

(   ) 1965 - 1980: Generative X

(   ) 1981 - 1996: Millennials/ Generative Y

(   ) 1997 - 2012: Generative Z

3. Race

(   ) Malay

(   ) Chinese

(   ) Indian

(   ) Other (please specify)

4. Size of company

(   ) Less than 5 employees

(   ) 5 to less than 30 employees

(   ) 30 to less than 75 employees

(   ) 75 to less than 200 employees

(   ) More than 200 employees

5. Work Experience

(   ) Less than 3 years

(   ) 3 - 8 years

(   ) 9 -14 years

(   ) 15 - 20 years

(   ) More than 20 years

6. Position

(   ) Director/ Deputy director/ Assistant Director

(   ) General Manager/ Assistant General Manager

(   ) Head/ Assistant Head of Department

(   ) Manager/ Assistant Manager

(   ) Senior Executive/ Executive

(   ) Other (please specify)

7. Industry

(   ) Manufacturing,

(   ) Service-based, eg. Finance, IT, Healthcare, Hospitality, Restaurant Café, etc.

(   ) Others, eg. Agriculture, Construction, Quarry, etc.

8. Monthly income (personal)

(   ) Less than RM 2000

(   ) RM 2000 - RM 3999

( ) RM 4000 - RM 5999

( ) RM 6000 - RM 7999

( ) RM 8000 - RM 9999

( ) RM 10000 - RM 11999

( ) RM12000 - RM 13999

( ) More than RM 14000

9. Type of Generative AI that I use for my workplace (You may choose more than one)

( ) Gemini

( ) ChatGPT

( ) Deepseek

( ) Co-Pilot

( ) Dall-E

( ) Claude

( ) Other (please specify)

SECTION C: FACTORS

This section examines the factors influencing employee output in the workplace. Please indicate your level of agreement with each statement using a 5-point Likert scale, ranging from 1 (=strongly disagree) to 5 (=strongly agree).

Factor 1 : Task Characteristics

Measurement Items	Strongly Disagree				Strongly Agree
1. I frequently deal with ill-defined business problems.	1	2	3	4	5
2. I frequently deal with ad-hoc, non-routine business problems.	1	2	3	4	5
3. Many of the business problems I solve require new solutions.	1	2	3	4	5

Factor 2 : Technology Characteristics

Measurement Items	Strongly Disagree				Strongly Agree
1. Generative AI provides widely accessible support for my task.	1	2	3	4	5
2. Generative AI supports my tasks in real-time.	1	2	3	4	5
3. Generative AI provides quick support for my tasks.	1	2	3	4	5
4. Generative AI is secure to use.	1	2	3	4	5

Factor 3 : Task-Technology fit

Measurement Items	Strongly Disagree				Strongly Agree
1. Generative AI tools are easy to use.	1	2	3	4	5
2. Generative AI tools are user-friendly.	1	2	3	4	5
3. It is easy to get Generative AI tools to do what I want them to do.	1	2	3	4	5
4. My interactions with the Generative AI interface are clear and understandable.	1	2	3	4	5
5. I find the Generative AI interface easy to navigate.	1	2	3	4	5
6. Learning to use Generative AI tools is straightforward for me.	1	2	3	4	5
7. The output from Generative AI is presented in a useful format.	1	2	3	4	5

8. The information generated by Generative AI is accurate.	1	2	3	4	5
9. Generative AI provides up-to-date information.	1	2	3	4	5
10. I receive the information I need from Generative AI in time.	1	2	3	4	5
11. Generative AI produce output that aligns with what I need.	1	2	3	4	5

Factor 4 : Utilisation

Measurement Items	Strongly Disagree				Strongly Agree
1. I often use Generative AI to perform tasks at work.	1	2	3	4	5
2. I cannot imagine completing tasks without using Generative AI.	1	2	3	4	5
3. More often than not, I use Generative AI to complete tasks.	1	2	3	4	5
4. I almost always use Generative AI to complete tasks.	1	2	3	4	5
5. I rarely perform tasks without using Generative AI.	1	2	3	4	5

Factor 5 : Supervisor Support

Measurement Items	Strongly Disagree				Strongly Agree
1. My supervisor encourages the use of Generative AI.	1	2	3	4	5
2. My supervisor provide supports for Generative AI initiatives.	1	2	3	4	5
3. My supervisor prioritises the adoption of Generative AI.	1	2	3	4	5
4. My supervisor is interested in developments related to Generative AI adoption.	1	2	3	4	5

Employee output

Measurement Items	Strongly Disagree				Strongly Agree
1. Utilizing Generative AI helps me complete tasks more efficiently.	1	2	3	4	5
2. Generative AI enhances the quality of my work.	1	2	3	4	5
3. Using Generative AI improves my job performance.	1	2	3	4	5
4. I would recommend this company to an acquaintance seeking employment.	1	2	3	4	5
5. I personally feel fulfilled when I perform my job well.	1	2	3	4	5
6. I proudly tell others that I am part of this organization.	1	2	3	4	5
7. This company is the ideal place for me to work.	1	2	3	4	5

Appendix B: Ethical Clearance Form

UNIVERSITI TUNKU ABDUL RAHMAN DU012(A)
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Re: U/SERC/78-420/2024

23 December 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 projects 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.	The Factors that Impact Women's Intention to Purchase Luxury Handbags in Malaysia	Lee Wen	Dr Mahendra Kumar a/l Chelliah	23 December 2024 – 22 December 2025
2.	Evaluating Customer Satisfaction in International Coffee Chains in Malaysia By Using SERVQUAL Model	Wong Xuan	Dr Malathi Nair a/p G Narayana Nair	
3.	Integrated Marketing Communication (IMC) Motivates Student's eWoM Intentions and Choice of University Through Brand Equity	Oo Kai Shi	Dr Tang Kin Leong	
4.	Exploring the Impact of Social Media Marketing on Consumer Brand Engagement in Fashion Branded Jewellery	Leow Yi Ling	Dr Malathi Nair a/p G Narayana Nair	
5.	Factors Influencing Women's Barriers to Career Advancement Within Malaysian Workplaces	Chia Xin Rou	Dr Kalaivani a/p Jayaraman	
6.	Factor Affecting Customers' Trust in E-commerce	Lai Yen Ee	Mr Low Choon Wei	
7.	Factors of Students' Behavioral Intention to Adopt Artificial Intelligence (AI) Chatbots in Higher Education	Seow Jia Ling	Dr Foo Meow Yee	
8.	The Influence of Green Marketing Strategies on Consumer Purchase Intention for Electric Vehicles	Ng Chang Da	Dr Yeong Wai Mun	
9.	Factors Influencing Job Satisfaction in Malaysia's Hospitality Industry	Janice Tan	Mr Khairul Anuar Bin Rusli	
10.	Factors Influencing Malaysian Consumers' Impulse Buying Behaviour in Live Streaming Commerce	Tan Zhi Wei	Dr Corrinne Lee Mei Jyin	
11.	How Working Abroad Affects Consumer Behaviour: A Study on Factor Influencing Consumers' Purchasing Behaviour When Working Abroad	Li Wen Kee	Mr Khairul Anuar Bin Rusli	

Kampar Campus : Jalan Universiti, Bandar Barat, 31900 Kampar, Perak Darul Ridzuan, Malaysia
Tel: (605) 468 8888 Fax: (605) 466 1313
Sungai Long Campus : Jalan Sungai Long, Bandar Sungai Long, Cheras, 43000 Kajang, Selangor Darul Ehsan, Malaysia
Tel: (603) 9086 0288 Fax: (603) 9019 8868
Website: www.utar.edu.my

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
12.	The Linkage Between Entrepreneurial Motivation Towards Their Business Strategy Choices in Malaysian SMEs	Pua Shue Ling	Dr Mahendra Kumar a/l Chelliah	23 December 2024 – 22 December 2025
13.	Exploring the Motives of Generation Z's Purchase Intention for Branded Sport Shoes	Jeow Bin Hong	Dr Malathi Nair a/p G Narayana Nair	
14.	The Effectiveness of Live-Streaming Commerce in Driving Consumer Engagement and Purchasing Intention	Leong Ze Qi	Dr Fok Kuk Fai	
15.	The Impact of Generative AI on Employee Output	Lim Qi Fei	Dr Corrinne Lee Mei Jyin	
16.	Analyzing The Effects of Workplace Culture on Employee Retention Rate Among SME Companies in Malaysia	Yaw Wei Jian	Mr Khairul Anuar Bin Rusli	
17.	The Perception of Youths on The Board of Directors' Performance towards Sound Governance	Lee Xing Jia	Dr Abdullah Sallehhuddin Bin Abdullah Salim	
18.	Evaluating the Influence of Monetary and Non-Monetary Rewards in Enhancing Employee Performance	Geetha Kaurr Chandi A/P Stevender Singh	Dr Komathi a/p Munusamy	
19.	Analyzing the Adoption of Mobile Payment Systems Among Malaysian University Students	Samuel Rinaldo		
20.	The Comparative Influence of Traditional Celebrities and Digital Influencers in Fashion Industry for Generation Z	Lai Pei Xuan	Pn Ezatul Emilia Binti Muhammad Arif	
21.	Analysing the Effectiveness of Real-time Inventory Technology in Optimising Central Kitchen Operations	Sim Kah Khai		
22.	Analyzing the Key Challenges that Demotivates Women Entrepreneurs to Execute Online Business in Malaysia	Yeo Yee Shen		
23.	Influencer Marketing Effectiveness: Analyzing the Impact of Influencers in Driving Consumer Purchase Intention Among Generation Z	Foo Yen Thung	Dr Choo Siew Ming	

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

Appendix C: Pilot Test

Scale: Task Characteristics

Case Processing Summary

		N	%
Cases	Valid	30	100.0
	Excluded[a]	0	.0
	Total	30	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.711	.703	3

Item Statistics

	Mean	Std. Deviation	N
TAC1	3.77	1.073	30
TAC2	3.73	1.230	30
TAC3	3.90	1.029	30

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TAC1	7.63	3.689	.543	.480	.606
TAC2	7.67	2.644	.730	.565	.329
TAC3	7.50	4.466	.357	.215	.807

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
11.40	7.076	2.660	3

Scale: Technology Characteristics

Case Processing Summary

		N	%
Cases	Valid	30	100.0
	Excluded[a]	0	.0
	Total	30	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.732	.766	4

Item Statistics

	Mean	Std. Deviation	N
TEC1	4.33	.711	30
TEC2	4.30	.596	30
TEC3	4.23	.728	30
TEC4	3.87	.937	30

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TEC1	12.40	3.007	.615	.474	.620
TEC2	12.43	3.220	.680	.532	.608
TEC3	12.50	3.017	.586	.445	.635
TEC4	12.87	3.085	.324	.112	.824

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
16.73	5.030	2.243	4

Scale: Task-technology Fit

Case Processing Summary

		N	%
Cases	Valid	30	100.0
	Excluded[a]	0	.0
	Total	30	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.851	.851	11

Item Statistics

	Mean	Std. Deviation	N
TTF1	4.43	.504	30
TTF2	4.47	.571	30
TTF3	4.23	.728	30
TTF4	4.37	.556	30
TTF5	4.20	.407	30
TTF6	4.50	.572	30
TTF7	4.20	.664	30
TTF8	4.03	.890	30
TTF9	4.03	.850	30
TTF10	4.30	.535	30
TTF11	4.20	.664	30

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TTF1	42.53	17.913	.502	.593	.842
TTF2	42.50	17.569	.504	.694	.841
TTF3	42.73	15.857	.676	.697	.826
TTF4	42.60	17.628	.508	.669	.841
TTF5	42.77	19.289	.239	.689	.856
TTF6	42.47	18.257	.352	.627	.851
TTF7	42.77	16.737	.576	.466	.835
TTF8	42.93	15.168	.627	.651	.832
TTF9	42.93	15.582	.597	.813	.835
TTF10	42.67	16.989	.688	.746	.829
TTF11	42.77	16.392	.646	.583	.829

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
46.97	20.309	4.507	11

Scale: Utilisation

Case Processing Summary

		N	%
Cases	Valid	30	100.0
	Excluded[a]	0	.0
	Total	30	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.758	.781	5

Item Statistics

	Mean	Std. Deviation	N
UT1	4.17	.747	30
UT2	3.83	.986	30
UT3	4.03	.850	30
UT4	3.83	1.020	30
UT5	3.57	1.135	30

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
UT1	15.27	8.340	.634	.614	.690
UT2	15.60	7.559	.573	.580	.697
UT3	15.40	7.903	.629	.687	.683
UT4	15.60	7.007	.664	.530	.660
UT5	15.87	8.671	.250	.256	.827

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
19.43	11.633	3.411	5

Scale: Supervisory Support

Case Processing Summary

		N	%
Cases	Valid	30	100.0
	Excluded[a]	0	.0
	Total	30	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.934	.934	4

Item Statistics

	Mean	Std. Deviation	N
SS1	3.47	1.042	30
SS2	3.63	1.066	30
SS3	3.53	1.106	30
SS4	3.83	1.053	30

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SS1	11.00	8.966	.829	.811	.920
SS2	10.83	8.695	.857	.802	.911
SS3	10.93	8.409	.872	.834	.906
SS4	10.63	8.930	.824	.790	.921

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
14.47	15.223	3.902	4

Scale: Employee Output

Case Processing Summary

		N	%
Cases	Valid	30	100.0
	Excluded[a]	0	.0
	Total	30	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.869	.870	7

Item Statistics

	Mean	Std. Deviation	N
EO1	4.40	.563	30
EO2	4.33	.606	30
EO3	4.33	.661	30
EO4	4.33	.547	30
EO5	4.10	.607	30
EO6	4.17	.699	30
EO7	4.17	.699	30

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
EO1	25.43	8.668	.557	.402	.861
EO2	25.50	7.983	.724	.652	.839
EO3	25.50	7.845	.689	.668	.844
EO4	25.50	8.534	.626	.479	.853
EO5	25.73	8.202	.650	.509	.849
EO6	25.67	7.678	.688	.567	.844
EO7	25.67	8.023	.586	.456	.859

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
29.83	10.833	3.291	7

Appendix D: Internal Reliability Test

Scale: Task Characteristics

Case Processing Summary

		N	%
Cases	Valid	204	100.0
	Excluded[a]	0	.0
	Total	204	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.730	.732	3

Item Statistics

	Mean	Std. Deviation	N
TAC1	4.04	.818	204
TAC2	4.01	.865	204
TAC3	4.25	.883	204

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TAC1	8.26	2.193	.586	.347	.606
TAC2	8.29	2.118	.561	.325	.633
TAC3	8.05	2.165	.514	.265	.691

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
12.30	4.280	2.069	3

Scale: Technology Characteristics

Case Processing Summary

		N	%
Cases	Valid	204	100.0
	Excluded[a]	0	.0
	Total	204	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.726	.731	4

Item Statistics

	Mean	Std. Deviation	N
TEC1	4.33	.759	204
TEC2	4.26	.766	204
TEC3	4.39	.745	204
TEC4	4.07	.851	204

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TEC1	12.72	3.434	.482	.266	.685
TEC2	12.79	3.221	.566	.328	.636
TEC3	12.66	3.222	.595	.367	.621
TEC4	12.98	3.300	.434	.202	.719

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
17.05	5.367	2.317	4

Scale: Task-technology Fit

Case Processing Summary

		N	%
Cases	Valid	204	100.0
	Excluded[a]	0	.0
	Total	204	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.857	.861	11

Item Statistics

	Mean	Std. Deviation	N
TTF1	4.39	.751	204
TTF2	4.42	.687	204
TTF3	4.29	.801	204
TTF4	4.38	.680	204
TTF5	4.31	.693	204
TTF6	4.34	.709	204
TTF7	4.32	.718	204
TTF8	3.95	.981	204
TTF9	4.00	1.048	204
TTF10	4.28	.828	204
TTF11	4.25	.836	204

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TTF1	42.55	27.293	.542	.397	.846
TTF2	42.51	28.044	.494	.332	.849
TTF3	42.64	26.418	.613	.446	.840
TTF4	42.56	27.745	.544	.422	.846
TTF5	42.63	28.058	.486	.270	.850
TTF6	42.59	27.504	.552	.396	.845
TTF7	42.61	27.490	.545	.374	.846
TTF8	42.99	26.182	.494	.404	.851
TTF9	42.93	25.040	.569	.465	.846
TTF10	42.66	26.394	.591	.468	.842
TTF11	42.69	25.899	.648	.524	.837

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
46.94	32.109	5.666	11

Scale: Utilisation

Case Processing Summary

		N	%
Cases	Valid	204	100.0
	Excluded[a]	0	.0
	Total	204	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.836	.841	5

Item Statistics

	Mean	Std. Deviation	N
UT1	4.28	.811	204
UT2	3.96	1.042	204
UT3	4.13	.864	204
UT4	4.00	.962	204
UT5	3.79	1.090	204

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
UT1	15.88	9.927	.649	.439	.803
UT2	16.21	9.005	.609	.372	.812
UT3	16.03	9.659	.652	.452	.801
UT4	16.17	8.957	.698	.496	.786
UT5	16.37	8.767	.611	.382	.814

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
20.17	13.903	3.729	5

Scale: Supervisory Support

Case Processing Summary

		N	%
Cases	Valid	204	100.0
	Excluded[a]	0	.0
	Total	204	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.888	.889	4

Item Statistics

	Mean	Std. Deviation	N
SS1	3.97	.957	204
SS2	3.93	1.000	204
SS3	3.84	1.125	204
SS4	3.98	.995	204

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SS1	11.75	7.676	.733	.538	.864
SS2	11.79	7.389	.752	.576	.856
SS3	11.88	6.778	.757	.579	.857
SS4	11.75	7.284	.783	.618	.845

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
15.72	12.478	3.532	4

Scale: Employee Output

Case Processing Summary

		N	%
Cases	Valid	204	100.0
	Excluded[a]	0	.0
	Total	204	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.845	.846	7

Item Statistics

	Mean	Std. Deviation	N
EO1	4.32	.711	204
EO2	4.21	.786	204
EO3	4.25	.841	204
EO4	4.12	.907	204
EO5	4.31	.714	204
EO6	4.14	.831	204
EO7	4.14	.839	204

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
EO1	25.16	13.158	.557	.389	.830
EO2	25.27	12.604	.594	.423	.825
EO3	25.24	11.984	.660	.469	.814
EO4	25.36	12.242	.547	.354	.834
EO5	25.17	13.246	.535	.334	.833
EO6	25.34	12.158	.637	.487	.818
EO7	25.34	11.851	.689	.526	.810

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
29.48	16.537	4.067	7

Appendix E: Regression Analysis for Predicting Task-Technology Fit

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	TEC, TAC[b]	.	Enter

a. Dependent Variable: TTF
b. All requested variables entered.

Model Summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.667[a]	.445	.439	4.24405	.445	80.440	2	201	<.001	1.738

a. Predictors: (Constant), TEC, TAC
b. Dependent Variable: TTF

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2897.762	2	1448.881	80.440	<.001[b]
	Residual	3620.410	201	18.012		
	Total	6518.172	203			

a. Dependent Variable: TTF
b. Predictors: (Constant), TEC, TAC

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	17.329	2.400		7.221	<.001	12.597	22.061
	TEC	1.445	.142	.591	10.178	<.001	1.165	1.724
	TAC	.405	.159	.148	2.547	.012	.091	.718

a. Dependent Variable: TTF

Appendix F: Regression Analysis for Predicting Utilisation

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	SS, TTF[b]	.	Enter

a. Dependent Variable: UT
b. All requested variables entered.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.636[a]	.405	.399	2.89141	.405	68.295	2	201	<.001	1.851

a. Predictors: (Constant), SS, TTF
b. Dependent Variable: UT

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1141.921	2	570.960	68.295	<.001[b]
	Residual	1680.413	201	8.360		
	Total	2822.333	203			

a. Dependent Variable: UT
b. Predictors: (Constant), SS, TTF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.361	1.706		1.384	.168	-1.002	5.725
	TTF	.244	.040	.371	6.169	<.001	.166	.322
	SS	.404	.063	.383	6.365	<.001	.279	.529

a. Dependent Variable: UT

Appendix G: Regression Analysis for Predicting Employee Output

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	UT, TTF[b]	.	Enter

a. Dependent Variable: EO
b. All requested variables entered.

Model Summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.711[a]	.505	.500	2.87422	.505	102.676	2	201	<.001	2.004

a. Predictors: (Constant), UT, TTF
b. Dependent Variable: EO

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1696.436	2	848.218	102.676	<.001[b]
	Residual	1660.485	201	8.261		
	Total	3356.922	203			

a. Dependent Variable: EO
b. Predictors: (Constant), UT, TTF

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	6.049	1.700		3.559	<.001	2.698	9.400
	TTF	.349	.042	.487	8.301	<.001	.266	.432
	UT	.349	.064	.320	5.452	<.001	.223	.475

a. Dependent Variable: EO