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***Title: The Impact of AI Adoption on Operational Efficiency: The
Mediating Role of Employee Competence***

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Declaration

I have written this Dissertation, entitled The Impact of AI Adoption on Operational Efficiency: The Mediating Role of Employee Competence, entirely myself and have complied with the academic requirements of the programme. I have completed this research with honesty and in an ethical manner and all sources, information, ideas and evidence which have been used have been acknowledged and referenced. I certify that the data herein given in this dissertation have been analyzed and reported for the purposes of this dissertation. This dissertation has not been written for any other degree or qualification, nor has it been published in any other form.

Abstract

Purpose

The objective of this dissertation is to discuss the influence of adopting AI on efficiency and to investigate the correlation between employee competence and efficiency in the context of AI. It emphasises the rising prominence of AI in businesses and its impact on employee skills and capabilities as well as how it can enhance the efficiency of operations. The study draws on the Technology–Organisation–Environment (TOE) model and the Resource-Based View (RBV) to give a base to explain the conditions of the organisation for adopting AI and the strategic importance of employee skill for implementing AI.

Method

The quantitative research approach was used with a positivist philosophy and a deductive approach. Structured questionnaire was used for the primary data collection which was analyzed using SPSS. Descriptive analysis, reliability testing, correlation analysis and regression analysis were used to analyze the relationship between the use of AI, employee competence, and operational efficiency.

Findings

Results showed that all the primary variables had strong positive relationships. AI adoption had a significant positive influence on operational efficiency, supporting H1. AI use likewise was associated with a positive connection with employee competence, and created substantial support for H2. Additionally, employee competence played a significant and positive influence in operational efficiency, thus, supporting H3. The results reveal that employee competence is the one of organisational competence, which includes operational performance.

Conclusion

The study concludes that for successful implementation of AI in an organisation, they must take a “people-first” approach alongside the technology. The introduction of AI in workplaces can be supported by suitable training, permanent retraining, competence evaluation and organizational

assistance, ensuring that employees are able to adjust to the changing task environments and participate in the improvement of the work operations. Based on the above, future studies should employ larger sample sizes, longitudinal study designs, sophisticated mediation models to further investigate the relationships between the adoption of AI and competence and operational efficiency of employees.

Keywords: Artificial Intelligence (AI), AI Adoption, Operational Efficiency, Employee Competence, Technology–Organisation–Environment (TOE), Resource-Based View (RBV), Employee Skills, Organisational Performance.

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Chapter One: Introduction

1.1 Introduction

Artificial Intelligence (AI) is one of the most revolutionary technologies to impact contemporary organisations. From healthcare and finance to logistics and service sectors, the use of AI is growing in various industries designed to boost productivity, eliminate repetitive tasks, assist with decision-making, and optimise resource utilisation. Technologies like machine learning, predictive analytics, Robotic Process Automation (RPA) and generative AI are helping businesses to adapt to dynamic market scenarios and increase their efficiency (Singh and Pandey, 2024). Based on the estimates of Treat (2026), by 2030, AI will add somewhere between 11 and 15.6 trillion dollars to the global economy via improvements to productivity and innovation as well as digital transformation.

While AI adoption has significantly ramped up, there has been varied success among organisations with regard to operational efficiency. Some companies see significant benefits in productivity and process optimisation; others struggle to see the organisational benefits they had hoped for. There is a growing body of evidence indicating that using technology is not enough to enhance organisational performance. On the other hand, employee competence such as AI literacy, digital competencies, technical knowledge and creativity in problem-solving are directly involved in enhancing operational efficiency in the process of implementing AI (Zirar, Ali and Islam, 2023). By examining the case of applying AI in service to operational efficiency, this dissertation explores the mediating role of employee competence and how to effectively leverage AI in service to enhance operational efficiency.

1.2 Background of the Study

AI has transitioned from being a niche technological advancement to a business strategy. Organisations have been increasingly leveraging AI technologies over the last ten years to boost operational performance, cut operational expenses, provide better customer experiences, and enable intelligent data-driven decision-making. AI is becoming increasingly important and is seen in more and more organisations as more of them implement AI in at least one business function (McKinsey & Company, 2025).

Numerous organisational aspects like finance, marketing, customer service, operations management and human resource management are now using AI applications. Predictive analytics and automated technologies like RPA help organisations to predict customer demand patterns and provide time-saving benefits by automating repetitive tasks. Likewise, generative AI aids in knowledge management, content generation and decision support, allowing organisations to be more agile and innovative (Singh and Pandey, 2024).

Despite all these advances, AI adoption doesn't just lead to organisational success, as research shows. Implementation is a problem at many organisations because of non-completion of digital competences, non-acceptance of technological change and insufficient skills of the employees. Further, there are situations where, for organizations that focus on investing in AI, they may not be gaining the desired productivity gains if their employees lack the skill sets to optimally use AI systems (Zirar, Ali and Islam, 2023).

The capability of the employees, as a resource of the organisation, has thus become relevant. Competence includes knowledge, digital literacy, capabilities with AI, capability to learn and solve problems. When employees face technical changes, they will be better prepared to adapt to them; otherwise, they can be innovators and contribute to the increase in organisational performance (Wijayanti and Sari, 2023). Moreover, companies with high-tech AI systems and highly skilled staff are more likely to gain a sustainable competitive advantage, as above is supported by the Resource-Based View theory (RBV) (Beamish and Chakravarty, 2021).

Another way of understanding reasons for successful uptake of AI is through the Technology–Organisation–Environment (TOE) framework, which points to the importance of organisational resources and environmental conditions in addition to technological readiness (Chong and Olesen, 2017). Thus, the challenge of how the competence of employees affects working efficiency and the connection between AI adoption and working efficiency is an essential research topic that has practical relevance for companies embarking on digital transformation.

1.3 Problem Statement

Even though Artificial Intelligence has emerged as a significant catalyst of an organisation's digital transformation, numerous organisations have reported that efficiency hasn't necessarily improved exponentially after they adopt AI. Previous studies have mainly addressed technological infrastructure, AI capabilities, and system implementation, with relatively limited attention paid to human factors that impact the success of the implementation.

Research from various sources shows that employee competence plays a significant role in enhancing the performance of an organisation, as employees who are competent will be able to effectively apply artificial intelligence (AI) in performing daily tasks in an organisation (Kim and Jung, 2022; Wijayanti and Sari, 2023). Empirical evidence, however, that looks at employee competence as a mediating variable between employee adoption and operational efficiency is still limited. As a result, organisations can also be spending large amounts of money on AI technologies, but about how they can embed the capability of the staff in successful deployment and operational improvement.

The present study fills this gap in knowledge by examining whether the impact of employee competence on operational efficiency is mediated by AI adoption. The findings will inform the literature and be used to guide organisations on how to get the most value from AI investments.

1.4 Scope of the Study

1.4.1 Research Aim

To investigate the impact of Artificial Intelligence adoption on operational efficiency and examine the mediating role of employee competence.

1.4.2 Research Objectives

- To examine the effect of Artificial Intelligence (AI) adoption on operational efficiency.
- To evaluate the relationship between AI adoption and employee competence.
- To analyse the influence of employee competence on operational efficiency.

- To investigate the mediating role of employee competence between AI adoption and operational efficiency.

1.4.3 Research Question

Main Research Question

How does Artificial Intelligence (AI) adoption influence operational efficiency in organisations through employee competence?

Sub-questions

RQ1.1: How does AI adoption affect employee competence in organisations?

RQ1.2: How does employee competence influence operational efficiency?

RQ1.3: To what extent does employee competence mediate the relationship between AI adoption and operational efficiency?

1.5 Outline of the Methodology

The methodology in this study was quantitative, and the philosophy of this study was positivist. The research method used is deductive research because the research starts from the hypothesis of previous research studies that have been established, namely the Technology–Organization–Environment (TOE) framework and Resource-Based View (RBV) theory (Chong and Olesen, 2017; Beamish and Chakravarty, 2021).

The data for the study will be obtained through a cross-sectional survey design, which will involve primary data collection from respondents, such as employees, who work in organizations using AI technologies. The data will be collected through a structured online questionnaire, which will be sent via Google Forms. Around 100–150 respondents with experience of AI implementation in their workplaces will be recruited using the purposive sampling method.

IBM SPSS Statistics will be used to analyse the collected data. To describe the characteristics of the respondents, descriptive statistics will be used, and to assess reliability, Cronbach's Alpha

will be used. Correlation analysis, multiple regression and mediation analysis will be performed to analyse the relationships between the use of AI and employee competency and operational efficiency. The ethical considerations, such as voluntary participation, informed consent, confidentiality and anonymity, will be upheld during the research process.

1.6 Significance of the Study

This study is of benefit for the general academic subject, knowledge of society and for the making of praxis. In an academic context, it builds upon the existing literature by analysing the competence of the employees as an intervening construct between the adoption of AI and operational efficiency. Exploring the link between employee competence and firm performance, previous research has focused on the subject of AI adoption or organisational performance separately, yet few have delved into the impact of employee competence (Kassa and Worku, 2025).

On the practical side, the results will help managers and organisational leaders to gain a deeper understanding of the importance of investing in capability development as well as technology to make AI work. The study can aid in the decision-making process for employee training, AI literacy initiatives, and digital transformation plans, helping organisations ensure sustainable enhancements.

In addition, the results could feed into the terms of the policy and practice of workforce development, in order to highlight the need for developing digital skills in relation to technological innovations.

1.7 Thesis Structure

The dissertation is organised into five chapters. Chapter One starts with the background of the research, which includes the research problem, aim, objectives and research questions, methodology, significance of the study and overall structure of the research. Chapter Two critically examines the literature surrounding the adoption of Artificial Intelligence, employee competence and operational efficiency of the firm to discuss the TOE framework, Resource-Based View theory and discuss research problems. Chapter Three presents the research

methodology, including the research philosophy, approach, design, sampling strategy, data collection procedures, analytical techniques and ethical considerations. The results of the statistical analysis, along with the interpretation of the relationships between the variables of the study, are presented in Chapter Four. Finally, findings of the study are presented and discussed with the existing literature in Chapter Five, conclusions are drawn, the study limitations are discussed, and recommendations are made for future research.

Chapter Two: Literature Review

2.1 Introduction

Artificial Intelligence (AI) has evolved from a nascent technology to a strategic organisational capability, as more companies are now embracing AI to further assist in areas such as automation, business decisions, and resource optimisation. Organisations are beginning to deploy AI throughout business processes, and the proposal estimates that by 2030, there will be \$15.7 trillion in economic value generated globally by productivity and innovation. But technology can't do everything – getting the best out of AI requires employees to be able to make the best use of it. Based on the TOE framework and RBV theory, this study sets the hypotheses: viewed critically, AI adoption as the independent variable is mediated by employee competence, which in turn acts on the dependent variable, operational use as the desired end.

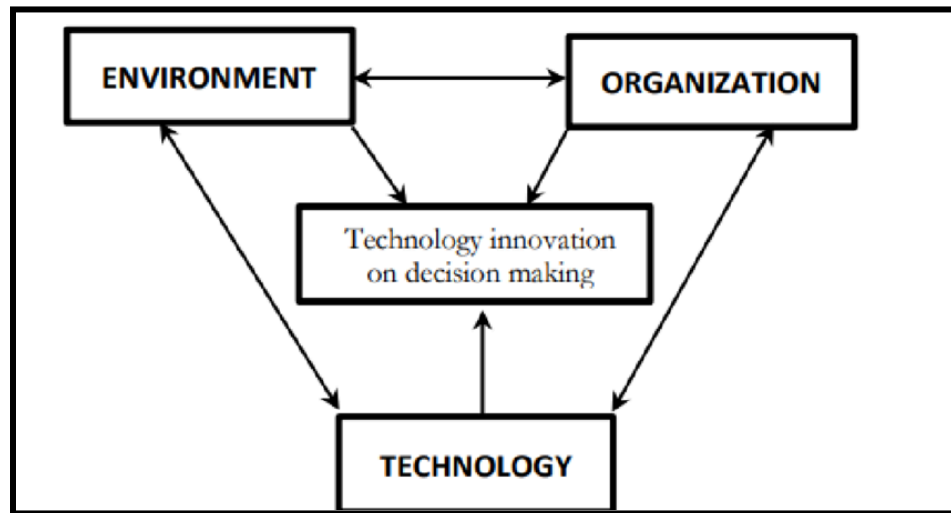
2.2 Theoretical Framework

2.2.1 Technology–Organisation–Environment (TOE) Framework

Yet, the TOE framework provides a behind-the-scenes analysis of technology adoption, considering technological, organisational and environmental contexts, rather than focusing only on technology. Horani *et al.* (2023) respondents (307) provided valid answers on a sample comprised of Jordanian commercial banks using TOE and RBV, and obtained a positive correlation between the usage of Business Analytics and bank performance. Likewise, Nguyen, Le and Vu (2022) obtained results from an analysis of 325 usable answers submitted by Vietnamese online retailers, which showed that technology factors such as relative advantage ($\beta = 0.105$), compatibility ($\beta = 0.119$) and observability ($\beta = 0.141$) had a significant impact on adoption. Other factors were also important in the organisational context (such as top-management support) and the environment (such as government support and legal frameworks), but not the competition of other firms, which turned out to be less important than expected. Notably, these results indicate that TOE is useful in accounting for adoption as a process of a contextual nature and not one strictly technological. TOE, on the other hand, defines the adoption conditions and doesn't actually capture the relationship between employee

competence and operational efficiency. Thus, this study is more meaningfully underpinned by the theory of TOE in combination with RBV.

Figure 2.1 Technology–Organisation–Environment (TOE) Framework



Source: Adapted from: Horani *et al.* (2023)

2.2.2 Resource-Based View (RBV) Theory

The Resource-Based View (VB) is the concept that one's competitive advantage comes about as a result of building and utilising valuable organisational resources and capabilities. The systematic literature review by Mailani *et al* in the year 2024 emphasises the importance of internal resources to sustain competitive advantage in the context that the resources are strategically developed and challenging to be replicated by other competitors. While doing this, Oria *et al.* (2021) perform a meta-analytical integration of the strategic resources–actions–performance pathway, which shows that resources do not automatically translate into performance, but instead do so through organisational actions. This separation is crucial for the adoption of AI: AI technology can be a valuable tool, but its operational value relies on the level of knowledge, digital skill and, AI literacy, and problem-solving skills of employees (Oyekunle and Boohene, 2024). So, two groups that have invested in parallel AI resources could end up with efficiency results that are quite different due to other human factors. But, crucially, in RBV, employee competence is thus seen as a complementary organisational

capability which helps in the effective use of AI resources. It sets a foundation for discussion of the relationships suggested in H2 and H3, and acknowledges that resources need to be put to efficient use in an organisation to generate value.

2.3 Artificial Intelligence Adoption

2.3.1 Concept and Definition of AI Adoption

Adoption of AI is not confined to the availability of the technology, but represents activities that are continuous within the organisation. However, the authors Reyes-Reina, Sánchez-Torres and Rueda-Cáceres (2026) review 25 peer-reviewed studies and, in their review, find that the adoption process is often treated as mere tools for use, which does not imply a strong conceptual standardisation. Fitriani *et al.* (2025), on the other hand, create a framework based on two case studies, which connects AI technology to the organisational capability, information streams and value streams. Thus, it is essential to view the adoption of AI as an organisational transformative journey involving the integration of technology, staff capabilities, and strategic planning to maximise operational value and sustainability. (Kassa and Worku, 2025). In this way, effective implementation goes beyond just implementation and, in fact, includes strategy and alignment to organisational goals.

Figure 2.2 AI for Marketing



Source: Adapted from Haleem *et al.* (2022)

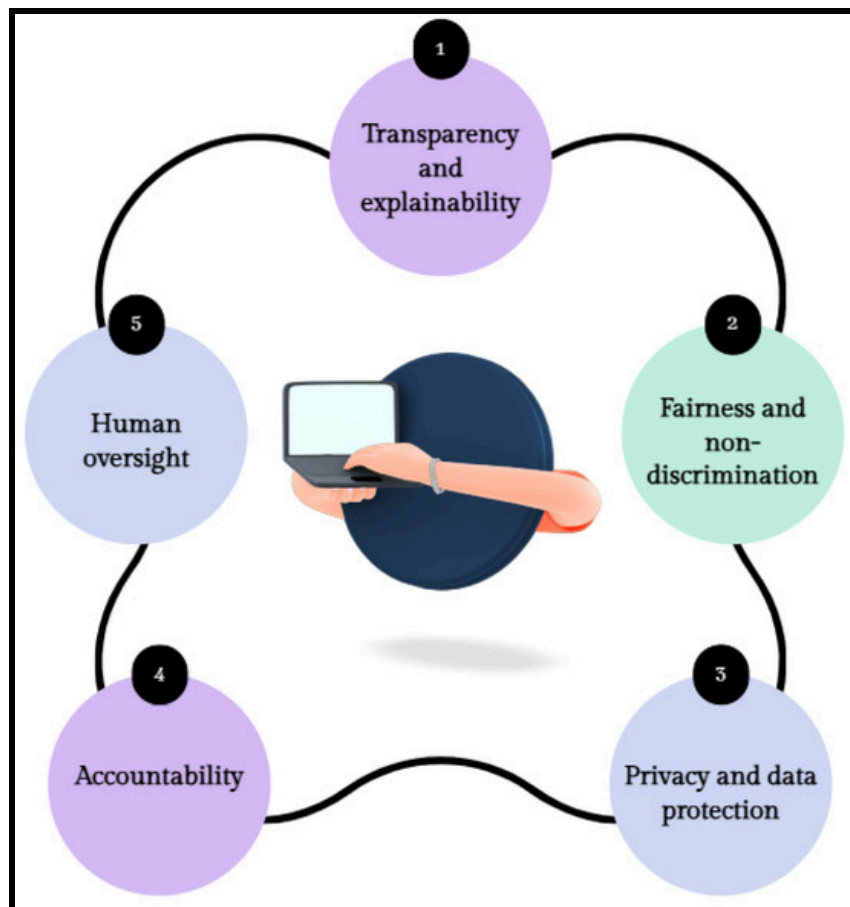
2.3.2 Types and Applications of AI

AI solutions span various business activities. AI has a significant impact on real-time pricing, targeting, promotion, product management, and demand analysis, as outlined by Haleem *et al.* (2022), who show its potential to assist decision-making based on data and cater for customer responsiveness. In comparison, Ofosu-Ampong (2024) summarises 85 peer-reviewed papers spanning the years 2020-2023 to show that the literature about AI research is predominantly technology-centric, with comparatively little focus on application contexts. In fact, the potential of AI is also deeply rooted in the way it can be adopted within the organisation, this requires contextual adaptation to the organisational processes, employees' needs and goals (Naoum, Szakadáti and Balogh, 2026). AI's operational utility is not just about its technology but rather its ability to integrate seamlessly into specific contexts, thereby improving automation and decision-making processes.

2.3.3 Organisational Drivers and Barriers to AI Adoption

There are lines of productivity, cost saving, and improved decision-making in support of the adoption of AI; however, this evidence offers a few challenges to the optimistic expectations. After synthesising 30 systematic reviews of 2,021 primary studies, Cubric (2020) identified technical and economic advantages as important elements, with comparatively limited practical validation and potential for job displacement as concerns. A similar finding was found by Kar, Kar and Gupta (2022), which highlighted eight drivers and nine barriers, including AI decision accuracy being one of the most potent drivers, while limited AI talent, strategy and leadership commitment being one of the most potent barriers. In addition to digital leadership and digital culture, Madanchian and Taherdoost (2025) highlight data security and integration costs.

Figure 2.3 Barriers and Enablers of AI Adoption



Source: Adapted from Madanchian and Taherdoost (2025)

2.4 Operational Efficiency

2.4.1 Concept of Operational Efficiency

Operational efficiency consists of how an organisation can achieve the most output with the least use of resources, cost, and operational waste. It is important to note that equipment performance, age, location, and the clustering of equipment are significant and do impact productivity and operating costs, as Febrianto *et al.* (2025) show. Li *et al.* (2022) compared 32 Chinese CT firms between 2017 and 2020, relying on DEA-SBM and Malmquist methods for separating efficiency and TFP for the CT firms. Handoyo *et al.* (2023) also discovered that operational efficiency was a significant determinant of manufacturing performance with $p < 0.001$, indicating that operational efficiency is an intervening variable that is involved in manufacturing performance. Hence, there are several aspects of the operational efficiency: productivity, the speed of the process, reduction in costs, improvement in the quality of output and effective use of resources (Jeong and Phillips, 2001).

2.4.2 Dimensions of Operational Efficiency

Operational efficiency is about more than just cost minimisation. Panduru, Simion and Ioanid (2024) identify, through functional analysis of core and non-core activities, opportunities for resource optimisation in one of the largest oil and gas retailers from Romania. By comparison, Imron and Dharmajaya (2026) separate labour productivity from capacity productivity, and find that relationships between the two productivities depend on strategic orientations, with an adjusted R^2 of at most 0.518 achieved with the model based on U.S. airline panel data. Therefore, considering the notion of operational efficiency, investors should take into account productivity, process speed, cost control, quality outcomes, and the utilisation of resources rather than only reduction in the cost of operation (Alkhatib *et al.*, 2026). So, if we need to assess productivity, speed, cost, quality, and resource utilisation is a better option.

2.4.3 Technological Innovation and Operational Efficiency

The positive impact of technological innovation depends on the context: automation can and does improve operational efficiency and speed up processes and resource allocation. This was shown to be quite competitive, with technological innovation and operational efficiency being high and able to explain 56.9% of the competitive advantage by An *et al.* (2026) for 100 airport users. Conversely, Berlianto, Suhud and Hamidah (2024) assert that the impacts of automation and digitalisation on port logistics are fast, while improving efficiency minimises the cost of resources. Thus, technological innovation presents opportunities for operational efficiency improvement, but it relies on organisational context, implementation quality and the technological ability to combine technology with the ongoing operational processes (Prince, 2024). Therefore, technology can best support the effectiveness of operational and service capabilities, thereby achieving the most valuable efficiency.

2.4.4 Factors Limiting Operational Efficiency

Technology does not influence operational efficiency; rather, operational efficiency is influenced by operating and technological factors. Bhosale, J. and Jadhav, A. (2025) argue that real-time manufacturing data can be substantially used in shaping the efficiency of the process, which is why process-level control is necessary. Similarly, compared with these, Sarkis and Xue (2024) enhanced operational efficiency and effectiveness by making the process more transparent and by securing the reliability of the information provided. Blockchain can, however, only enhance operational efficiency and effectiveness when it is effectively implemented, thereby ensuring transparency and reliability of the information provided (Rahman, Yeoh and Pal, 2026). Hence, further efficiency-improving capabilities of employees, process conditions, etc., as well as infrastructure and organisational alignment are key limitations.

2.5 Employee Competence

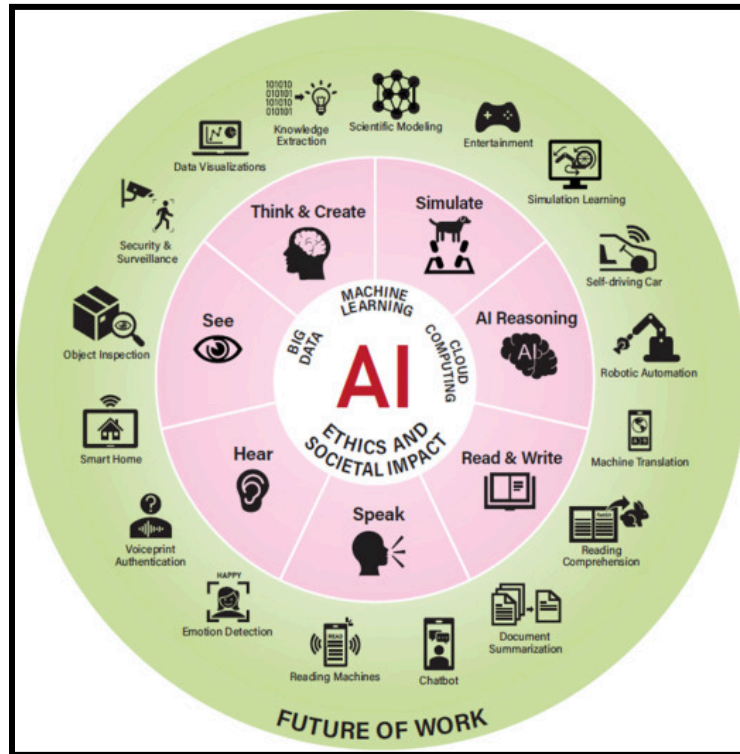
2.5.1 Concept and Definition of Employee Competence

Competence is a multi-faceted concept that encompasses knowledge, skills, resources, and behavioural capacities of the employee that enable them to perform in the workplace. Salman, Ganie and Saleem (2020), in a thematic review, suggest that competence is not limited to the technical aspects of the job but also includes other forms of behaviour and context. In comparison, Daniali *et al.* (2022), in developing an employee competency model for a welfare organisation, focus on competencies required for the jobs within the organisation and how to measure organisational outputs. So, employee competence must be considered as an organisational competence that helps employees to adapt themselves to technological advancements and teach knowledge and skills efficiently in AI-based working environments (Amayreh *et al.*, 2025). Competency is therefore not a mere qualification but more of a performance of technical skills, digital skills, learning, and problem-solving.

2.5.2 AI Literacy and Digital Competence

AI literacy is essential for grasping, engaging with, and assessing AI systems, whereas digital competence is crucial for absorbing and evolving across the organisation. Rather than conceiving of AI literacy as a mere ability to familiarise themselves with tools, Chiu *et al.* advocate for a broad spectrum of competencies and knowledge that denotes responsible use of AI systems and a grasp of their workings. In comparison, Dringó-Horváth, Rajki and Nagy (2025) conclude from their research on university teachers that these factors, such as gender, age, experience and discipline, moderate the level of competence. So, integrating AI into organisations is a process that requires ongoing staff learning and development – something technology investments alone will not meet if employees lack the digital competence and adaptability (also AI literacy) required to make the technology work for them and their company (Bautista and Ivy, 2025). Thus, investment in AI could be of minimal benefit where capabilities and contextual adaptability are still limited in the workforce.

Figure 2.4 AI Literacy

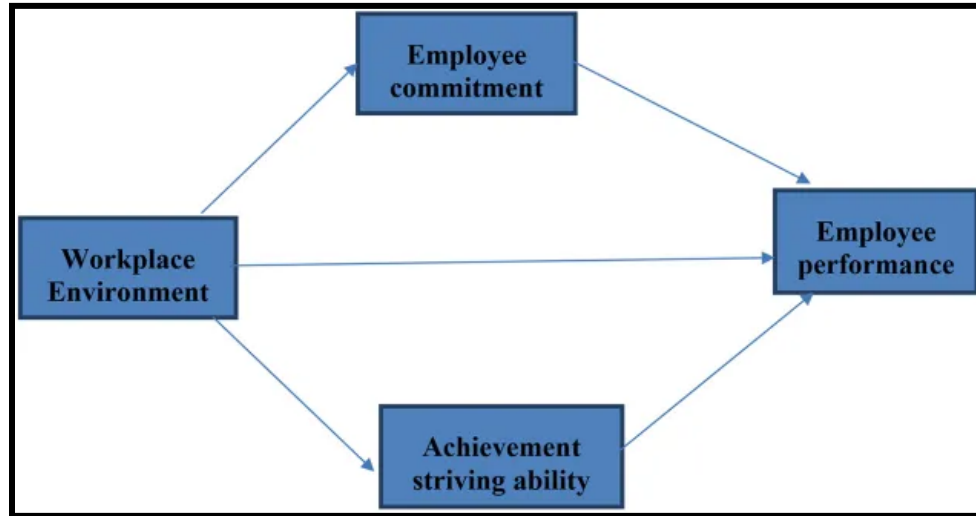


Source: Adapted from Chiu *et al.* (2024)

2.5.3 Employee Competence and Employee Performance

In general, employee competence has a positive effect on task performance and productivity that employees can adapt to. After studying 12 empirical studies, Wijayanti and Sari (2023) concluded that the competency–performance relationship was mostly positive, with some studies reporting insignificant results. In comparison, Zhenjing *et al.* (2022) assert that workplace factors act through employee commitment and capability to achieve performance, and it is not only about competence. Thus, employee competence, with a supportive working environment, can create productive results; yet the involvement of employee competence in organisational performance is dependent on organisational culture and employees' competency in using their competence effectively (Kim and Jung, 2022). Hence, organisational culture/products and work environment can affect whether employee capabilities are correlated with superior performance.

Figure 2.5 Impact of Employees in the Workplace



Source: Adapted from Zhenjing *et al.* (2022)

2.5.4 Competence as an Organisational Capability

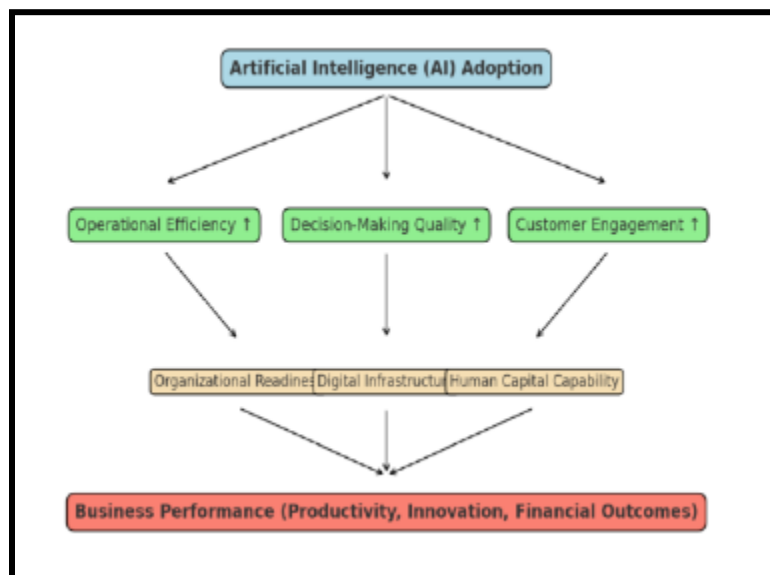
Where it is valuable to the organisation, hard to imitate, and successfully integrated to a good level with the organisation's processes, then competence can be regarded as a form of potential strategic capability that an employee can contribute. Rather, Lee, Wu and Jong (2022) supported the strategic value of core competency from 220 valid SME responses, as it had a significantly positive correlation with alliance performance. In contrast, Edgar and Lockwood (2021) suggest that there is a lack of unity in the concept of core competencies in the literature, and it should be avoided to assume that all core competencies are equally valuable. Hence, employee competence can be strategically valued in an organisation where AI is integrated, and firms put the required resources in place to help leverage competence to generate performance benefits. So, while skilled workers can support AI efforts, it's not competitive by itself; it's competitive when incorporated into the organisation and applied properly.

2.6 Relationship Between AI Adoption and Operational Efficiency

2.6.1 Positive Effects of AI Adoption

AI adoption has the potential to enhance efficiency, decision-making, and productivity, but the advantages will be seen when organizations are ready for it. In a global survey of 312 businesses in 4 countries in Southeast Asia, Savandha (2025) reports AI adoption to have a statistically significant positive impact on decision quality ($\beta=0.42$, $p<0.01$), and sees a 10-20% reduction in operational costs, 10-18% faster production, and 10-22% faster customer service. In comparison, Yuan, Zhou and Rajaram (2025) summarise 43 peer-reviewed pieces of research, which include both gains and losses, namely productivity, efficiency and skill development of employees, as well as job displacement and skill gaps. As such, gains achieved through the adoption of AI may be measurable, but they are not certain unless the organisation is ready to implement AI, employees have the necessary technology skills, and the management of technological change is effective (Behera, Behera and Bala, 2025).

Figure 2.6 AI Adoption



Source: Adapted from Savandha (2025)

2.6.2 Limitations and Contradictory Evidence

Technology on its own can limit effective decision-making, in terms of evidence quality and/or organisational context. Ouèlard and Steffick (2014) found that fragmented institutions, lack of adequate data infrastructure, and political resistance are among the main factors hindering evidence-informed decisions when analysing 119 peer-reviewed research papers from 32 countries. In contrast, Loeffelholz (2026) debunks the notion that evidence always leads to rational rethinking and demonstrates that people's beliefs can be stable in the face of disconfirming evidence. While neither study specifically focuses on AI adoption, both organizations stress the importance of considering evidence, infrastructure, and organisational conditions to constrain the gains in efficiency gained by the use of technology (Mikalef *et al.*, 2023).

2.6.3 Critical Synthesis

On the whole, there is evidence of a positive efficiency–AI relationship, but effects are contingent. Ngabalin (2025) finds that automation, decision-making and resource utilisation have improved, and Saif-Alyousfi and Alshammari (2026) found that the institutional quality and digital infrastructure affect the value generated by AI. Hence, there is a predicted positive correlation between artificial intelligence's adoption in the business and operational efficiency, assuming readiness, digital infrastructure, and employee skills (Wang *et al.*, 2026). This is in contrast to evidence that weak implementation and limited capacities can limit benefits. Therefore, AI adoption is likely to increase operational efficiency, as long as the necessary organisational capability and human capacity exist, which aligns with the justification for H1.

H1: Artificial Intelligence adoption has a positive and significant influence on operational efficiency.

2.7 Relationship Between AI Adoption and Employee Competence

2.7.1 AI as a Driver of Employee Capability

Digital skills, AI literacy, technical knowledge, analytical thinking, problem-solving, and continuous learning are all areas where employees need to demonstrate their skills when implementing AI, enabling AI adoption to help build employee capability. Amayreh *et al.* (2025) concluded that the use of AI tools has a significant positive effect on the self-competence of the pharmaceutical manufacturers in Jordan, with $\beta=0.346$ ($p=0.006$) for AI experience, $\beta=0.225$ ($p=0.027$) for utilisation, and $\beta=0.535$ ($p=0.006$) for technical capability. In comparison, Tariq *et al.* (2021), in a study of 53 studies, point to employee skills as a huge hurdle. This means that AI can be capable of learning ability – but only if there is an enabling capacity for organisational learning and skills development.

Figure 2.7 Operational Exchange



Source: Adapted from Tariq, Poulin and Abonamah (2021)

2.7.2 AI Adoption and Workforce Adaptation

Adopting AI changes, the nature of work and presents an opportunity for upskilling workers, as well as obsolescence and risk of displacement. They cite stress (92 articles), autonomy (25 studies), and mental health as themes; yet, through thematic analysis, Soulami, Benchekroun, and Galiulina (2024) uncover the assumptions made by purely positive adaptation, which contradict the findings of this study. In comparison, Babashahi *et al.* (2024) perform a review of AI-driven changes to skills in various sectors, emphasising the need for AI's impact on adaptive technical and human skills. However, AI's potential for strengthening employee competence, through upskilling and adaptive capabilities, relies on a commitment to training and reskilling employees to ensure the workforce can adapt effectively to meet changing skill needs (Tariq, 2024). However, constant reskilling is necessary for successful adaptation of the workforce.

2.7.3 Critical Synthesis

In general, the evidence points to AI adoption having a positive impact on employee competence, which relies on organisational support. Amayreh *et al.* (2025) noted that technical ability improves self-competence significantly ($\beta=0.535$, $p=0.006$), but Soulami, Benchekroun and Galiulina (2024) pointed out that stress or challenges of adjustment among employees cannot be considered as a consequence or effect of exposure. Thus, whether AI becomes a tool for capability building depends on the skills learned, organisational support, and adaptability of employees. This is evidence to support H2.

H2: Artificial Intelligence adoption has a positive and significant influence on employee competence.

2.8 Relationship Between Employee Competence and Operational Efficiency

2.8.1 Employee Skills and Productivity

Becoming more productive means better task execution, knowledge application, problem-solving, and process improvement, as these activities rely upon the knowledge and

skills of employees. Research on the employees of a manpower department by Nishu and Lalrinzuala (2021) revealed that knowledge and skills have a significant effect on work productivity, thus contributing to human capability. So, employee competence plays a role in operational efficiency by being able to carry out the work, solve problems and improve the process, technically, behaviorally and practically (Abhari, 2025). Results in comparison show that soft skills, together with employee productivity and organisational performance, are far from being a trivial yet standard skill to practice in the workplace, and were expanded in terms of the relationship deepened by Muñoz-Peña and Pulido-Reina (2025) in their study on the relationship between soft skills, employee productivity and organisational performance. Therefore, the key to being productive is to have knowledge, behavioural skills, and practical skills within the process of the organisation.

2.8.2 Employee Competence in Technology-Enabled Workplaces

The effectiveness of technology's translation to the workplace depends on the skill of the employee. Barbu *et al.* (2025) studied employees' attitudes toward workplace technologies, suggesting that although they believe that their continued use will boost satisfaction and performance in their jobs, the perceptions of the employees affect the results. In comparison, Huu (2023), in a systematic review, considers digital competence an important link between digital autonomy and innovative work behaviour. Thus, employee competence becomes a crucial mechanism by which AI can create operational value, with employees interpreting and identifying inaccuracies within the AI's output and being able to incorporate the technology into their decision-making processes, as explained by James and Ashokkumar (2025). The presence of technically competent workers, therefore, would only strengthen their ability to leverage AI, deciphering its results and identifying inaccuracies, as well as sustaining organisational autonomy and support for implementing AI technologies into daily decisions.

2.8.3 Critical Evaluation

The competence of the employees can have direct positive impacts on their operational efficiency, in the sense of these employees having better problem-solving skills, performing their tasks, and using the technology, etc., but without independence of their organisational conditions.

A focus on digital competence is regarded as relevant for fostering innovative behaviour in this shift to autonomy (Huu, 2023), and the outcomes of workplace technology use utilise and draw on the perceptions of digital technology use and organisational context of the employees (Barbu *et al.*, 2025). Thus, the success of a Competence to measurable efficiency depends on how well training, management support, appropriate culture, infrastructure, and effective Implementation are achieved. This supports H3.

H3: Employee competence has a positive and significant influence on operational efficiency.

2.9 Employee Competence as a Mediator

Employee competency can serve as a link between the impact of AI adoption on operational efficiency: AI impacts work, and employee competence decides how successful AI is in application. By employing 85 BPBD employees, Gwijangga, Rina and Adi (2026) identified that actual competence was highly attributed to supervision and training; and competence further facilitated the connection between these two and employee effectiveness, thus reinforcing the general notion that actual competence can be "transmitted" as a single process that transforms external inputs into the organisation's outputs. In comparison, Gede (2025), in an analysis of 365 respondents from three educational institutions in Ethiopia, noted that employee engagement completely mediated between strategic alignment and organisational performance, meaning that human factors can account for the conversion of organisational resources into outcomes. Both studies fail to study the relationship between the adoption of AI and employees' competence and operational efficiency, leaving an important gap in both the contextual and empirical contexts. Based on this, this dissertation builds on previous mediation research by testing whether the effect of AI adoption on operational efficiency is mediated through employee competence; whereas H1–H3, the direct relationships, remain the same.

2.10 Research Gap

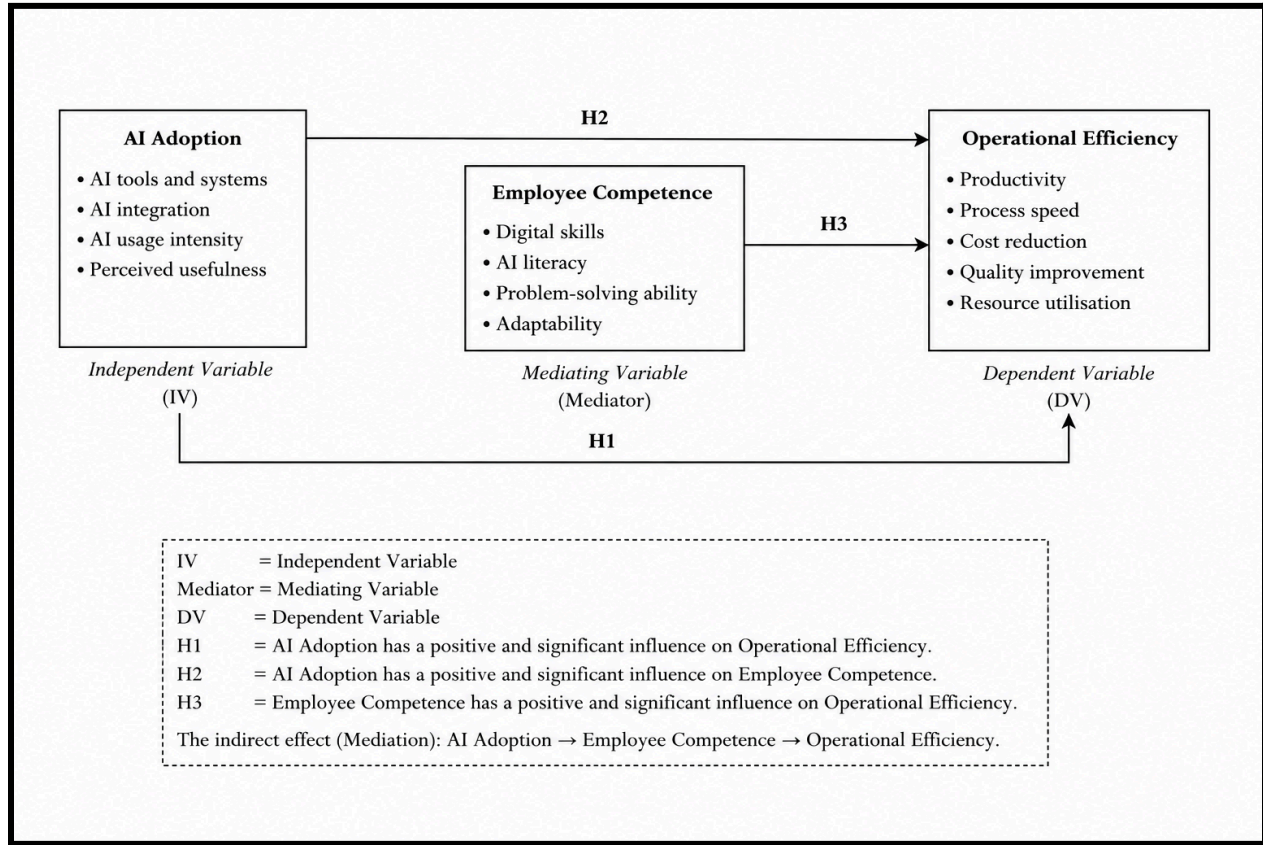
While the existing literature shows that AI can have positive impacts on the outcomes of an organisation, there are significant gaps to be recognised. Empirically, some research correlates the use of AI with efficiency (Ngabalin, 2025), and other research primarily covers employee

competence and efficiency (Wijayanti and Sari, 2023); however, not much research has been conducted to analyse the relationship between employee competence and AI adoption towards operational efficiency in one comprehensive model. The essence of the proposal is thus to stimulate the study of employee competence as a relatively unexploited mechanism. In the relational approach, Kassa and Worku (2025) show a noticeable route that involves the relationship between AI and productivity and then onto AI and performance. In this case, they include productivity as a mediator, but not competence, and thus the approach they propose isn't sufficiently tested in the context of human participation. Theory-wise, TOE deals with the conditions of technological, organisational, and environmental adoption, while RBV deals with how internal capabilities generate value; integration of these two theories around the employees' competence is weak. Methodologically, previous studies were done in various contexts and designs, but this study was conducted with a quantitative questionnaire method of correlation, regression, and mediation analysis. This research directly addresses the gap identified by testing whether competence is a conduit for the impact of AI adoption on operational efficiency in a real-world setting.

2.11 Conceptual Framework

The conceptual framework recommends that the independent variable is AI adoption, a mediating variable is at the level of employee competence, and the dependent variable is operational efficiency. It hypothesises that implementation of AI directly contributes to increased operational efficiency (H1), and that the development of competence of the employees (H2), an increase in operational efficiency (H3). So, the potential value of AI adoption could be explained via Employee Competence. Most importantly, the framework acknowledges that achieving efficiency cannot be accomplished solely through AI investments, as the success of the technology needs to rely on employee abilities. Productivity, process speed, cost reduction, quality improvement and resource utilisation are measures of operational efficiency in line with the proposed.

Figure 2.8 Conceptual Framework



Source: Self-Created

2.12 Chapter Summary

This chapter critically identified the potential of AI to advance operational efficiencies by boosting automation, productivity optimisation and resource efficiency, acknowledging that while investing in technology can help deliver better results, it isn't substantial enough on its own. In contrast, the literature provides examples of employee competence shaping the effectiveness of workplace capabilities through the use of AI. The TOE framework is used to describe the technological, organisational and environmental conditions influencing technological adoption, and RBV adds this by seeing employee competence as a valuable capability within their work organisation. Generally, there is evidence supporting the proposed positive relationships between AI use, both employee competence and operational efficiency, but there is only limited research that specifically investigates competence as a mediator. This

empirical and theoretical gap identified in the literature, therefore, justifies the testing of the proposed conceptual model of H1, H2 and H3 as well as the indirect mediation pathway.

Chapter Three: Research Methodology

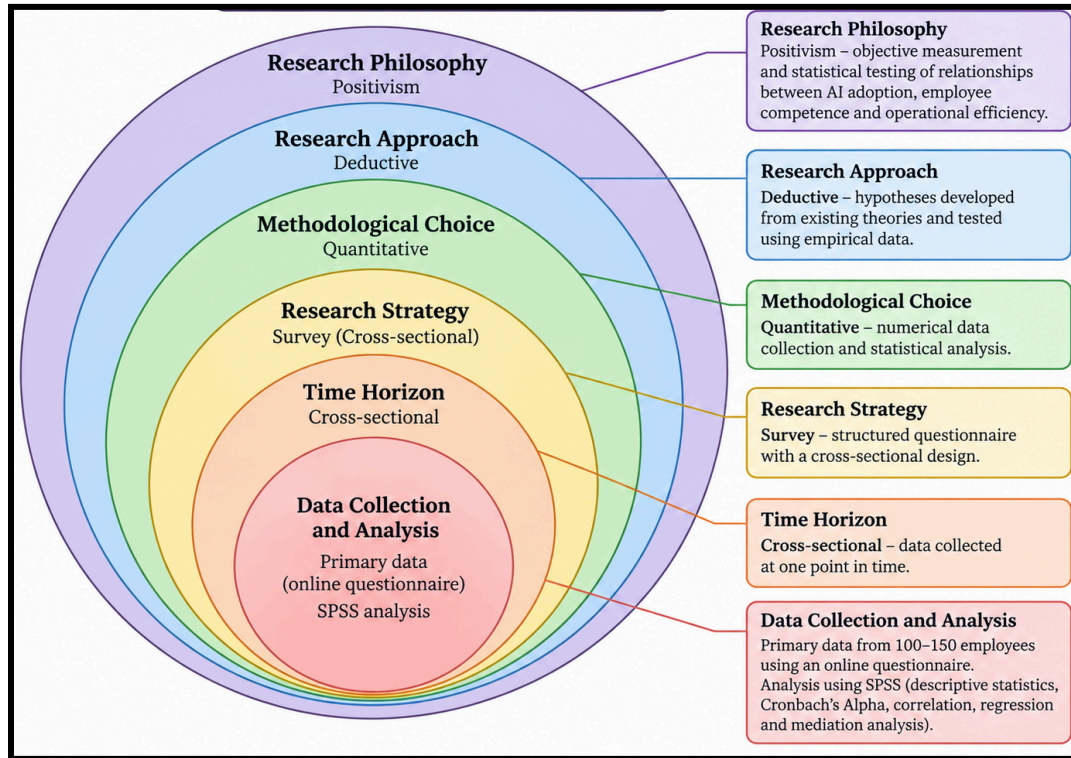
3.1 Introduction

This chapter gives a critical explanation of the methodological decisions made to explore the effect of the use of Artificial Intelligence (AI) on Employee competence and operational efficiency. According to the study method, it follows a quantitative and positivist approach, which is also deductive, that allows one to make an objective effort to measure and test the relationship proposed by the study statistically. The primary data for the study will be gathered from approximately 100-150 employees, based on organisations employing AI technologies, using purposive sampling and an online structured questionnaire. Descriptive statistics, Cronbach's Alpha, correlation, multiple regression and mediation analysis will be used to analyse the data in IBM SPSS Statistics. These methods implicitly and explicitly map to the study's conceptual framework and hypotheses about how and why employees would adopt AI, and whether this leads to improvements in their competence and operational efficiency.

3.2 Research Onion

This study follows the positivism research approach, allowing for the objective measurement of the level of AI use and the competencies of employees and the efficiency of the operation. The deductive method is used to verify hypotheses that have been generated from already known theories. The research methodology used was quantitative methodology and adopted design was a cross-sectional survey with the data collection technique used was a structured online questionnaire. Purposive sampling will be used for sampling with a sample size of c. 100-150 for employees who have a workplace experience of AI technologies. IBM SPSS will be used for data analysis including descriptive statistics, Cronbach's alpha, correlation, multiple regression and mediation analysis. The consideration of the proposed relations and the mediating between them and employee competence is facilitated through this method.

Figure 3.1 Research Onion



3.3 Research Philosophy

This study used a positivism approach because it allows the measurement of AI adoption to be done numerically based on operational efficiency and the competence of employees. With a statistical basis, positivism helps to test the hypotheses, minimise researcher subjectivity and apply statistical evidence in the test (Park, Konge and Artino, 2020). This is a suitable approach as this study aims to examine a set of pre-established relationships that are taken from the two theories TOE and RBV, and not isolate individual experiences. While interpretivism might offer a deeper understanding of how employees perceive AI, it is less well suited for assessing the measurable relationship and mediation effects of AI (Zhao *et al.*, 2025). Thus, positivism can be more suitable as the research method for the study, which is a quantitative survey, e.g. correlation, regression, and mediation analysis with SPSS software.

3.4 Research Approach

The method employed in the research is deductive and systematic, from theory, hypotheses, empirical data and statistical conclusions. Theories of TOE and RBV support hypotheses about

workforce competence and efficiency and how they will relate to the adoption of AI technology. The method is suitable as it is a study on the predefined relationships instead of developing theory based on the experiences that respondents gave. (Neupane *et al.*, 2026) H2 and H3 focus on the effect of AI on employee competence and efficiency; H1 focuses on operational efficiency. The proposed mediation pathway is then statistically tested for verification. This deductive sequence provides consistency and supports the theory-testing hypothesis testing using the SPSS questionnaire measurement.

3.5 Research Method and Research Design

This study can be called quantitative research to measure the relationship between AI adoption, employee competence and operational efficiency, as the research method used in this study is quantitative and the design of the research is a cross-sectional survey. The quantitative data allows them to be standardised and analysed in a statistically meaningful way across subjects responding, to facilitate objective testing of the hypotheses (Ma and Lee, 2026). The cross-sectional design type would be appropriate as data would be collected at one point in time from employees who have experience with the use of AI technologies in their organisations (i.e. 100-150 individuals will be targeted). The use of a structured web-based questionnaire helps to ensure consistency and efficiency in collection. Temporal causality cannot be inferred from cross-sectional data, and self-reported responses can also lead to common-method bias and perceptual (common) bias (Guerrero *et al.*, 2024). However, the design is suitable for the study's real-time and resource limitations, while addressing the proposed relationships and mediation pathway.

3.6 Research Population and Sampling

The group of target population includes employees in organisations that either have incorporated AI technologies or are actively using them, with the aim of ensuring that the respondents have relevant experience in their workplaces. Eligibility includes being 18 or older, in work, and with experience of AI-driven systems, either directly or indirectly. People not exposed to AI in the workplace will not be included, since their answers may not be reliably used to measure the study variables. Purposive sampling is suitable as it focuses on searching for those

information-rich people who fall within the information criteria and parts of the study. The proposed sample of 100-150 that has been devised for the study is in accordance with the methodology set in Chapter 1. The number of observations in this sample will be adequate for descriptive, correlation, regression and mediation analyses, and will be reasonable to the dissertation constraints. However, purposive sampling is non-probabilistic, and the representation of industry may introduce some selection bias, and the relatively small sample size restricts generalisability across industries. However, this methodology still emphasises the relevance of the respondents involved, which is crucial for tackling topics such as adoption of AI and competence and efficiency of employees.

3.7 Data Collection Method

Data will be gathered from a structured online questionnaire on Google Forms with the participation of employees with AI in the workplace experience. This method helps to ensure standardised responses, timely delivery and mass collection from geographically distributed participants. The link to the questionnaire will be sent out via professional networks and/or appropriate online media to reach 100-150 suitable target groups. Before providing informed consent to participate in this study, participants will be provided with an information statement that explains the purpose of the study, the confidentiality of the information, and the voluntary nature of participation. There is no penalty if a response is withdrawn before recording. Representativeness might, however, be limited due to self-selection and coverage bias introduced through the online recruitment. However, the approach used is commendable for the study and is designed as a cross-sectional study of quantitative type.

3.8 Questionnaire Design and Measurement

The questionnaire is designed to be divided into four sections, with systematic measurement of the four constructs of this study. The sections of the questionnaire will request some demographic data (age, gender, organisational experience, industry). Section B will assess the use and uptake of AI, including levels of integration and usage of AI tools into workplace activities. In Section C, employee competence will be evaluated, including AI literacy, digitisation skills, technical knowledge, flexibility and problem-solving. To determine the

operational efficiency based on the conceptual framework, Section D will let you know operational indicators to consider, such as productivity, process speed, cost reduction, quality and use of resources.

The five-point Likert scale will be used with 1=Strongly Disagree and 5 =Strongly Agree, allowing the perceptions of the respondents to be quantified and compared statistically. Items in the measures will be taken from existing literature, which will increase content validity and the connection with theory. Wording will be simplified; however, with contextual differences in interpretation expected with adaptation, a pilot testing process will be undertaken. The use of standardised questions has been helpful in obtaining greater consistency of results (but Likert responses are subjective and may incorporate response bias).

3.9 Operationalisation of Variables

In this study, three constructs are implemented in the proposed mediation model. Indicator measures of AI adoption (X): AI tools and systems used, AI organisational integration, extent of use (think about how often you use AI), perceived usefulness. Employee competence (mediating variable) will include digital skills, AI literacy, technical knowledge, problem-solving, and adaptability, which represent competences as a multi-dimensional organisational competence (Cetindamar *et al.*, 2022). Operational efficiency (dependent variables) will be analysed based on productivity, process speed, cost reduction, quality improvement and resource utilisation, which is consistent with the conceptual framework (Wei and Wang, 2025). Multiple items based on a Likert scale will be used to measure each construct with a high level of measurement reliability. The operationalisation allows for statistically valid assessment of the data, but perceptual measures could lead to common method bias, so results need to be interpreted with caution.

3.10 Pilot Testing, Reliability and Validity

The small-scale test will be used to evaluate the clarity, relevance, wording and time to complete the questionnaire before the main questionnaire test. Ambiguous or repeated items will be further modified, and work experience with workplace AI will be enhanced based on feedback collected from pilot participants. Cronbach's alpha will then evaluate the internal

consistency between the items measuring ADI and employee competence in operational efficiency, with $\alpha \geq 0.70$ being a reliable point for data. Items will be drawn from previously published sources and adjusted for content validity and congruence with the conceptual framework. Face and construct validity will be supported by measuring each of the variables with more than one indicator that is theoretically relevant. Validity is not assumed from high alpha values, though; so, reliability evidence will also be taken into account in addition to the alignment of theory and measurement.

3.11 Data Analysis Procedures

Data collected will be analysed using IBM SPSS Statistics. Preliminary analysis will be conducted for data that appear incomplete, may lack data, duplicate cases, and inconsistent input to increase the validity of data for analysis. Demographic characteristics will be summarised using frequencies and percentages, and responses will be summarised across main variables (Ivankova, 2015) using means and standard deviations. This is a description of the characteristics of the respondents and data distribution, which will help to identify them before inferential testing. It is a method that matches the proposed methodology that first specifies awareness of SPSS and descriptive analysis, with correlation and regression and mediation testing to follow. But descriptive statistics alone cannot define relationships, and inferential analysis is necessary.

3.12 Inferential and Mediation Analysis

The relationship between the proposed variables will be tested using inferential analysis, which includes Pearson correlation and multiple regression in SPSS. Correlation will determine the strength and direction of associations to test hypotheses H1, H2, and H3. In accordance with the proposed indirect pathway in this study, the mediation hypothesis (H4) will be evaluated to determine whether the competence of employees mediates the link between the use of AI in work and operational efficiency. Mediation analysis will be tested using the use of PROCESS Macro with bootstrapping, reporting direct, indirect and total effects with 95% Confidence Intervals. If the confidence interval for the indirect effect does not contain zero, then there is an indirect effect, and this effect is considered significant. These methods can detect statistical

relationships, but a cross-sectional study does not allow for definite causal conclusions to be drawn.

3.13 Ethical Considerations

Research will be conducted consistent with ethical considerations. Participants will be fully informed about the study and provide informed consent before participating. Participation will be voluntary, and anyone who chooses to end participation before the time they submit the questionnaire will have the right to do so without penalty (Gordon and Prohaska, 2006). No personal/identifying information will be collected unnecessarily, which will help ensure anonymity and confidentiality. The data from the surveys will be stored and used for academic purposes only. The reasons outlined above for using these safeguards are especially relevant, as workers can share perceptions about their organizations and how AI tools are used in the workplace. While anonymity greatly narrows privacy concerns, data collection online will not rule out confidentiality or response-identification concerns; these will be addressed via secure storage and limited data access.

3.14 Methodological Limitations

There are several methodological issues to be noted. There may be restricted representativeness and generalisation given the method (purposive sampling) and size (100-150 respondents). Both self-reported and online questionnaires have the potential of introducing common-method and self-selection bias, and social-desirability bias. This is a cross-sectional design, which means that it measures perceptions only at a single point in time and thus does not allow for causal relationships to be drawn. Therefore, regression and mediation analysis results should only be viewed as statistical relationships and not causal effects.

3.15 Chapter Summary

The study was built on the positivist philosophy and deductive approach with the quantitative cross-sectional survey design set in this chapter. Located in the field of health administration and management, the study will use purposive sampling (with 100 to 150 health administration and

management employees who are familiar with AI) and a structured questionnaire to gather primary data. SPSS will be used for reliability, correlation, regression and mediation analysis, and ethical precautions will be taken for participants. The results from the empirical analyses and the results of the hypothesis testing will be presented in Chapter Four.

Chapter Four: Findings and analysis

4.1 Introduction

This chapter is the quantitative results of the studies conducted on AI adoption, competence of employees and operational efficiency. The data were also determine through a structured question and were analysed by means of SPSS Statistics. The chapter starts with demographic analysis, reliability testing, Pearson correlation tests and Pearson regression tests to predict the relationships amongst the key variables. Lastly, is the mechanism of employees became competent an intervening step between the use of AI and operational efficiency? Finally, does employee competence mediate between AI adoption and operational efficiency? The results are discussed in terms of research goals and research questions.

4.2 Background industry

The study authors examine the context in which the digital technologies are employed – the organisational context, in this instance, relating to health administration and management – where these technologies increasingly assist in the performance of the organisation. AI is integrated in various sectors like healthcare, finance, logistics, and services for increased productivity, automation of repeated tasks, improved decision-making, and optimising resources, with the application of machine learning, predictive analytics, RPA, and generative AI (Singh and Pandey, 2024). But the key to doing it well is employee knowledge, digital literacy, AI skills, adaptability, and problem-solving abilities. Even with the use of Artificial Intelligence, small-scale competency issues and resistance to change can limit the benefits from implementation, which is why efficiency in the operation of your business is not a foregone conclusion. Thus, it is important to have employee competence in order to convert the investment in AI into productivity and improvements in the business stream (Zirar, Ali and Islam, 2023).

4.3 Demographic analysis

The analysis of the demographics is based on questions 1 – 6 which cover the job role, time spent in the current position, size of the organisation, industry sector, usage frequency of AI, and

types of AI technologies deployed. Respondents' roles and experiences in the workplace could affect their perception and utilization of AI tools, making these characteristics relevant. The sample is specifically defined as sampling those employees that have had experience with using or dealing with AI in their organizations. The results of the demographic analysis provide a useful basis for the interpretation of the three primary research constructs. AI Adoption is measured by Questions 7-11, Employee Competence by Questions 12-17, Operational Efficiency by Questions 18-23. Highly structured separations allows for respondent characteristics to be taken into account prior to exploring relationships between study variables and then correlation, regression and mediation analyses.

Question	Category	Purpose
Q1	Job role	Identifies respondents' workplace positions
Q2	Length in role	Measures relevant work experience
Q3	Organisation size	Identifies organisational context
Q4	Industry sector	Establishes sector representation
Q5	AI usage frequency	Measures level of AI engagement
Q6	AI technology used	Identifies technologies encountered
Q7–Q11	AI Adoption	Measures AI adoption
Q12–Q17	Employee Competence	Measures employee competence
Q18–Q23	Operational Efficiency	Measures operational efficiency

4.4 Reliability test analysis

Reliability Statistics	
Cronbach's Alpha	N of Items
.771	5

Figure 4.1: Reliability analysis of Q7- Q11 as AI Adoption

(Source: Self-created in SPSS)

Cronbach's Alpha was used to test the reliability of the five items measuring AI Adoption (Q7 – Q11). The Cronbach's α for the five items is 0.771. This reflects a good internal consistency of the items measuring AI adoption. The value goes beyond the usual value of 0.70, which allows the scale to be used for further statistical analysis. Hence, Q7-Q11 offer a uniform indicator of AI adoption, and these variables can be aggregated to obtain the totality of AI adoption (AIA), which was then correlated, regressed, and mediated later.

Item-Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
7. My organisation has integrated AI technologies into its business operations.	15.58	11.489	.237	.831
8. AI technologies are regularly used to support work-related activities in my organisation.	15.32	9.267	.605	.707
9. My organisation has increased its use of AI technologies in recent years.	15.17	9.348	.676	.685
10. AI technologies are integrated into existing organisational processes rather than being used only for occasional tasks.	15.24	9.447	.638	.697
11. AI technologies are useful for supporting employees in completing their work.	15.23	9.325	.612	.705

Figure 4.2: Item total statistics of Q7- Q11

(Source: Self-created in SPSS)

The item-total statistics show that most items of the AI adoption scale show Grade A to Grade B external relationship to the total. Reliability values for corrected item-total correlations are in the

range of 0.237 to 0.676. There is good consistency among the constructs, with the highest correlation between Q9 and the overall construct (0.676), followed by Q10 (0.638), Q11 (0.612), and Q8 (0.605). But the correlation for Q7 is relatively low (0.237). Cronbach's alpha would increase from 0.771 to 0.831 if question Q7 were removed, therefore indicating better internal consistency if it were removed. However, conceptually speaking, Q7 is relevant to the subject of AI uptake and can be kept and analysed.

Reliability Statistics	
Cronbach's Alpha	N of Items
.771	6

Figure 4.3: Reliability stats Q12–Q17 as Employee Competence

(Source: Self-created in SPSS)

The reliability analysis of employee competence items (Q12–Q17) of the questionnaire yielded a Cronbach's Alpha of 0.771 with six items. A good level of internal consistency among the 6 items of employee competence. Because its alpha is higher than the usual criteria (0.70), the scale can be applied for use in subsequent statistics. The results indicate that the competencies of knowledge, ability to use AI, critical evaluation, problem solving, and adaptability were consistently found in Q12–Q17. Therefore, the six items can be combined to form the Employee Competence (EC) construct.

Item-Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
12. I have sufficient digital skills to work effectively with AI technologies.	19.64	12.475	.476	.747
13. I understand the basic functions and capabilities of the AI technologies I use at work.	19.67	11.819	.618	.712
14. I can critically evaluate the information or recommendations generated by AI systems.	19.78	11.810	.576	.722
15. I can use AI technologies to solve work-related problems effectively.	19.68	12.482	.535	.733
16. I can adapt my work practices when new AI technologies or systems are introduced.	19.68	12.159	.504	.740
17. My organisation provides sufficient training to develop employees' ability to use AI technologies effectively.	19.85	12.513	.404	.768

Figure 4.4: Item Total Statistics Q12–Q17

(Source: Self-created in SPSS)

A factor analysis with item-total correlation statistics indicates that the corrected item-total statistics are satisfactory for all the items (ranging from 0.404 to 0.618) in the Employee Competence dimension. The highest correlations with the overall scale are with items Q13 (0.618), Q14 (0.576), and Q15 (0.535). The Q17 closest to the original is the one that has the lowest accuracy (0.404), which is still acceptable. The Cronbach's Alpha if Item Deleted is between 0.712 and 0.768 for all these items, which are lower than the overall alpha coefficient of

0.771. So there's no reason why deleting a single element would have much impact on the score of reliability. All six items can then be kept for further analysis.

Reliability Statistics	
Cronbach's Alpha	N of Items
.838	6

Figure 4.5: Reliability stats Q18–Q23 Operational Efficiency

(Source: Self-created in SPSS)

For Operational Efficiency (Q18- Q23), there were six questionnaire items with a Cronbach's Alpha value of 0.838. The high internal consistency among the items used to measure operational efficiency is reflected by this. The alpha coefficient (0.70) is much higher than the recommended value of 0.70; thus, the scale is reliable for statistical analysis. Overall, the data indicate that the six items actually tap the major dimensions of operational efficiency, productivity, process speed, cost reduction, quality, accuracy, and resource utilisation. Hence, Q18–Q23 can remain as such and be added together to make the Operational efficiency (OE) construct.

Item-Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
18. AI adoption has improved productivity in my organisation.	19.33	21.776	.445	.842
19. AI technologies have reduced the time required to complete routine work processes.	19.59	19.429	.611	.813
20. AI adoption has helped my organisation reduce unnecessary operational costs.	19.46	18.892	.734	.788
21. AI technologies have improved the quality and accuracy of organisational processes.	19.59	18.750	.700	.794
22. AI adoption has improved the efficient use of organisational resources.	19.56	18.968	.663	.802
23. Overall, AI adoption has improved operational efficiency in my organisation.	19.60	20.010	.541	.827

Figure 4.6: Item total statistics Q18–Q23

(Source: Self-created in SPSS)

The item-total statistics reveal acceptable to highly corrected item-total reliability of all six items in the Operational Efficiency section, ranging from 0.445 to 0.734. The highest correlation is found with Q20 (0.734), followed by Q21 (0.700) and Q22 (0.663), showing good consistency among the scale items. The lowest correlation is in question Q18 (0.445), but still acceptable. The Cronbach's Alpha if Item Deleted ranges from 0.788 to 0.842, and the overall Cronbach's Alpha is 0.838. Rather, deleting Q18 will make alpha 0.842, only a little better. Thus, both items 1 and 2 are excluded, and items 3-6 are retained for further analysis.

4.5 Hypotheses testing

4.5.1 Correlation analysis

		Correlations			
		Timestamp	AI_Adoption	Employee_C ompetence	Operational_ Efficiency
Timestamp	Pearson Correlation	1	-.078	-.088	-.122
	Sig. (2-tailed)		.433	.375	.217
	N	104	104	104	104
AI_Adoption	Pearson Correlation	-.078	1	.585**	.524**
	Sig. (2-tailed)	.433		<.001	<.001
	N	104	104	104	104
Employee_Competence	Pearson Correlation	-.088	.585**	1	.664**
	Sig. (2-tailed)	.375	<.001		<.001
	N	104	104	104	104
Operational_Efficiency	Pearson Correlation	-.122	.524**	.664**	1
	Sig. (2-tailed)	.217	<.001	<.001	
	N	104	104	104	104

** . Correlation is significant at the 0.01 level (2-tailed).

Figure 4.7: Correlation analysis

(Source: Self-created in SPSS)

Data from 104 respondents were used in Pearson's correlation analysis in order to look into the relationships between AI Adoption, Employee Competence and Operational Efficiency. Employee Competence ($r = .585$, $p < .001$) and Operational Efficiency ($r = .524$, $p < .001$) had a moderate positive correlation with AI Adoption. There was a significant positive correlation between Employee Competence and Operational Efficiency ($r = .664$, $p < .001$), as the strongest positive relationship is observed and measured between the two constructs. All the relationships were found significant at the 0.01 level (2-tailed), which gives a preliminary basis for the hypotheses of H1, H2, and H3 and thus supports regression analysis.

4.5.2 Regression analysis for each hypothesis

H1: AI Adoption and Operational Efficiency

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.524 ^a	.275	.268	.74648

a. Predictors: (Constant), AI_Adoption

Figure 4.8: Model summary

(Source: Self-created in SPSS)

The results of this provide a correlation coefficient (r) of .524 with a value of moderate positive relationship between the two variables. R Square value is .275, which indicates that 27.5% of the variance in Operational Efficiency is explained by AI Adoption. The adjusted R Square is .268, which means some of the variation has not been accounted for after the adjustment. The following indexes show the standard error of the estimate is .74648. The scores suggest that AI Adoption is a meaningful contributor toward the explanation of the differences in Operational Efficiency in this sample.

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21.534	1	21.534	38.645	<.001 ^b
	Residual	56.837	102	.557		
	Total	78.372	103			

a. Dependent Variable: Operational_Efficiency

b. Predictors: (Constant), AI_Adoption

Figure 4.9: ANOVA Test

(Source: Self-created in SPSS)

The results of the ANOVA tests are used to determine if the "Predictor" (AI Adoption) significantly explains the 'Predicted' (Operational Efficiency). The sum of squares of the regression was 21.534 and the sum of squares of the residuals was 56.837, totalling 78.372. The model was found to have an F-value of 38.645 and 102 d.f. The value for significance was $p < .001$, showing that the regression model was statistically significant. Hence, AI Adoption was found to give good predictive power for Operational Efficiency, affirming a positive relationship between the aforementioned variables, statistically.

H2: AI Adoption and Employee Competence

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.585 ^a	.343	.336	.56328

a. Predictors: (Constant), AI_Adoption

4.10: Model summary

(Source: Self-created in SPSS)

The results of the regression analysis of predicting Employee Competence for H2 are discussed in the Model Summary. As depicted in the results, the measured R value is .585, which signifies a medium level of positive relationship between AI Adoption and Employee Competence. The R Square value is .343 or one can say the R Square value is 34.3%. Employee Competence is explained what percent of the variance by AI Adoption is 34.3% or the R Square value. The correlation coefficient is also adjusted to obtain an Adjusted R Square of 0.336, which indicates that around 33.6% of the variation has been explained after the adjustment. The standard error of estimate is: .56328 Overall, the results show that the contribution made by AI Adoption to the differences between the respondents' Employee Competence scores is meaningful.

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	16.878	1	16.878	53.196	<.001 ^b
	Residual	32.363	102	.317		
	Total	49.242	103			

a. Dependent Variable: Employee_Competence

b. Predictors: (Constant), AI_Adoption

4.11: Anova Test

(Source: Self-created in SPSS)

The ANOVA table allows you to determine if the regression model used for predicting Employee Competence by AI Adoption is statistically significant. The regression sum of squares is 16.878, and the residual sum of squares is 32.363; the total sum of squares is 49.242. The model would have an F value of 53.196 for 102 and 1 degree of freedom. The F value of the regression model is 446.32 with a significance value of $p < .001$, indicating that the regression model is statistically significant. Hence, AI Adoption is highly foreseen to affect Employee Competence. H2 supports a hypothesis that AI Adoption positively and significantly affects Employee Competence, which is supported by these findings.

H3: Employee Competence and Operational Efficiency

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.664 ^a	.441	.436	.65521

a. Predictors: (Constant), Employee_Competence

4.12: Model summary

(Source: Self-created in SPSS)

The Model Summary provides the regression results for H3, which is whether Employee Competence predicts Operational Efficiency. Results show that there is a strong positive relationship between Employee Competence(EC) and Operational Efficiency(OE), with an R value as .664. The R-squared value of .441 signifies that 44.1% of the variation in Operational Efficiency can be accounted for by Employee Competence. The Adjusted R Square is .436, which means about 43.6% of the variance is still unexplainable after the adjustments. The standard error of the estimate is .65521. The overall findings show that Employee Competence contributes significantly to the variations of Operational Efficiency amongst the respondents.

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	34.583	1	34.583	80.557	<.001 ^b
	Residual	43.789	102	.429		
	Total	78.372	103			

a. Dependent Variable: Operational_Efficiency

b. Predictors: (Constant), Employee_Competence

4.13: Anova Test

(Source: Self-created in SPSS)

The ANOVA results test the overall statistical significance of the regression model used in the analysis to test whether Employee Competence is a statistically significant predictor of Operational Efficiency. The sum of squares due to the regression is 34.583, the sum of squares due to the residual is 43.789, and the total sum of squares is 78.372. An F-value of 80.557 is reported for 1 and 102 degrees of freedom for the model. Results show that the regression model is significant, given the significance value = $p < .001$. Thus, it can be said that Employee Competence is an important predictor for Operational Efficiency. The results support H3, which states that Employee Competence has a positive, significant impact on Operational Efficiency.

4.5.3 Summary of Hypothesis Testing

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	22.353	2	11.176	30.367	<.001 ^b
	Residual	37.172	101	.368		
	Total	59.525	103			

a. Dependent Variable: AI_Adoption

b. Predictors: (Constant), Operational_Efficiency, Employee_Competence

Figure 4.14: Anova test for all Hypothesis variables

The ANOVA test shows a significant fit for the regression model to explain variation of AI Adoption. The sum of squares was 37.172 while the regression sum of squares was 22.353 and the total sum of squares was 59.525. The analysis reported a mean square of 30.367 and significant level < .001. This indicates that the two predictors (Employee Competence and Operational Efficiency) have considerable predictive power over AI Adoption. Thus, the regression model is found to be statistically significant, and it suggests the relationships between the difference in employee competence and the difference in operational effectiveness to the difference in the level of AI adoption.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.613 ^a	.376	.363	.60666

a. Predictors: (Constant), Operational_Efficiency, Employee_Competence

Figure 4.15: Model Summary for all Hypothesis variables

There is a positive relationship between both of the predictors and AI Adoption as illustrated in the model summary. The multiple correlation coefficient (R) is .613, a moderately strong positive correlation. The R Square value of .376 indicates that the model accounts for 37.6% of the

variance in AI Adoption, with Employee Competence and Operational Efficiency being responsible for that variance. The Adjusted R Square is .363 which is the percentage of the variation that is not accounted for by the number of predictors. The prediction error (or the standard error of the estimate) is .60666. In general, the model has significant explanatory ability and suggests that both predictors together explain the phenomenon of AI Adoption.

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.163	.350		3.320	.001
	Employee_Competence	.467	.116	.425	4.037	<.001
	Operational_Efficiency	.211	.092	.242	2.302	.023

a. Dependent Variable: AI_Adoption

Figure 4.16: Coefficients for all Hypothesis variables

The coefficients table displays that both Employee Competence and Operational Efficiency are significant positive contributors of the AI Adoption. Employee Competence occurred with an unstandardized coefficient of .467, a standardized Beta of .425, a t-value of 4.037, and the standardized significance of less than .001, where it is the greatest contributor. Operational Efficiency also has a positive effect, with B = .211, Beta = .242, t = 2.302 and p = .023. It is statistically significant (p = .001) with a constant of 1.163. The results reflect that increased employee skills and improved operational effectiveness can be linked to increased AI Adoption in this model.

Hypothesis	Relationship Tested	Statistical Result	Decision
H1	AI Adoption to Operational Efficiency	$R^2 = .275$; $F = 38.645$; $p < .001$	Supported

H2	AI Adoption to Employee Competence	$R^2 = .343$; $F = 53.196$; $p < .001$	Supported
H3	Employee Competence to Operational Efficiency	$R^2 = .441$; $F = 80.557$; $p < .001$	Supported

The hypothesis testing table collates the strength of the three expected relationships in this study. There is support for H1 as the regression model indicated that there is a significant positive relationship between AI Adoption and Operational Efficiency. Similarly, the influence of AI Adoption on Employee Competence (H2) is also supported, with a significant positive regression result. There was a great positive correlation for H3, Employee Competence on Operational Efficiency. Based on the overall findings, all three hypotheses are accepted, meaning that it found that there is a positive interconnection between the three variables of the study (AI Adoption, Employee Competence and Operational Efficiency) and consequently, they have been found to sustain the proposed research model in the sample.

4.6 Discussion of Findings

The empirical results show that the proposed relationships between employee competence and operational efficiency, and the others, are supported empirically with consistency. Pearson correlation was used, and the collected data were analysed to determine the correlation between the three core variables, which showed positive and statistically significant relationships, based upon a correlation of $r=0.01$ up to $r=6.81$ for the 104 respondents. Employee Competence was positively correlated with AI Adoption ($r = .585$, $p < .001$) and Operational Efficiency ($r = .524$, $p < .001$); within this, Operational Efficiency had the strongest correlation with Employee Competence ($r = .664$, $p < .001$). These relationships were confirmed by the regression results as well. These empirical results are then compared with those from the literature reviewed in Chapter Two in the discussion below.

4.6.1 H1: AI Adoption and Operational Efficiency

The results confirm H1, showing that the use of AI has a positive and significant impact on the efficiency of operations. The regression equation obtained was $R = .524$, and the significance of R^2 was .275, showing that 27.5% of the variance in operational efficiency can be explained by the adoption of AI, and ANOVA was significant ($F = 38.645$ and $p < .001$). These are consistent with Ngabalin (2025) who highlighted the advantages of the automation, decision making and the use of resources and Wang et al. (2026) who highlighted the capability of the employees, infrastructure and the readiness of the organisation. But, using AI technology doesn't necessarily lead to efficient automation. Limited implementation and capability may limit benefits. The conclusions therefore reinforce the TOE approach, looking at the wider organisation.

4.6.2 H2: AI Adoption and Employee Competence

The results support H2, showing that AI adoption positively and significantly influences employee competence. An R value of .585 and an R^2 value of .343 suggest that 34.3% of the variance in competence of employees could be explained by their adoption of AI, and the ANOVA was significant ($F = 53.196$, $p < .001$). This result is consistent with Amayreh et al. (2025), who discovered positive relationships between AI experience, utilisation, and technical competence. However, Soulami et al. (2024) noted that employee stress and adaptation issues were evident, and Babashahi et al. (2024) pointed to technical and human skills that need to be adaptable. So, the adoption of AI can enable competence building, but training, reskilling, and building human competence will always be needed.

4.6.3 H3: Employee Competence and Operational Efficiency

The best result that was found is for Employee Competence and Operational Efficiency, which supports H3. There was found to be a strong positive correlation ($r = .664$, $p < .001$) and regression yielded $R = .664$ with R^2 of .441, which means competence accounted for 44.1% of operational efficiency. The ANOVA was also significant ($F = 80.557$, $p < .001$). This supports Nishu and Lalrinzuala (2021), who associated EE knowledge and skills with EE productivity, and Abhari (2025), who suggested that competence in task performance and process

improvement is significant. Like Wijayanti and Sari (2023), the competences-competency relations were overwhelmingly positive. Other studies also covered different aspects of the perceptions of technology and digital competence, as stated in the work of Barbu et al. (2025) and Huu (2023). The results highlight the dissertation's focus on investing in and building human capabilities.

4.6.4 Overall discussion

The results overall support the proposed relationships between the constructs of AI Adoption and Employee Competence and Operational Efficiency. Positive relationships were concluded between the three variables using the Pearson correlation coefficient and the results revealed that the relationships were assumed to be statistically significant. The highest correlation among the block of variables was between AI Adoption and Employee Competence ($r = .585$, $p < .001$) and Operational Efficiency ($r = .524$, $p < .001$), with both variables displaying positive values. Employee Competence had the strongest positive correlation with Operational Efficiency ($r = .664$, $p < .001$). The relationships were also supported by the regression results, which supported H1, H2 and H3. For H1, the findings indicate that there is a significant relationship between AI adoption and operational efficiency, as the variance in operational efficiency is accounted for by AI adoption is 27.5% ($R^2 = .275$) with a significant ANOVA ($F = 38.645$, $p < .001$). This aligns with Ngabalin (2025), who found that benefits of automation, decision-making and resource utilisation and Wang et al. (2026) who found that organisational readiness, infrastructure and employee capabilities were important. The findings, however, also suggest that the adoption of AI is not enough to explain operational efficiency, thus highlighting the impact of larger organisational factors on technological outcomes in line with the TOE perspective.

The measure of employee competence was explained by 34.3% ($R^2 = .343$; $F = 53.196$, $p < .001$) of variance in H2 as a result of AI adoption. Amayreh and his team (2025) noted a positive correlation between AI experience and technical capability, AI usage and technical capability, as well as AI usage with experience. However, Souلامي et al., (2024) identified employee stress and adaptation challenges and Babashahi et al., (2024) called for technical and human adaptation skills. As a result, while the adoption of AI can help in the development of competence, the need for training and reskilling is crucial. Finally, H3 had the largest result value with an R^2 of .441,

Operational Efficiency was compared with Employee Competence, which resulted in an F-Value of 80.557 ($p < .001$); this was also preceded by a significant model. This supports Nishu and Lalrinzuala (2021), Abhari (2025), Wijayanti and Sari (2023), Barbu et al. (2025) and Huu (2023). Overall the results highlight that with AI investments training employees on the subject, along with digital competence, and problem-solving abilities are crucial elements for implementing operational gains.

4.7 Conclusion

The discussion and interpretation of the study findings have been done in relation to the current study evidence on the literature and AI adoption, employees' competence, and employees' operational efficiency. The results for each of the three hypotheses were all positive and significant, showing that there was a significant positive relationship between AI adoption and operational efficiency, AI adoption and employee competence, and employee competence and operational efficiency. The competency of personnel was the strongest correlate to operational efficiency, further supporting the human power's role in the amount of benefit that could be derived from an AI investment. The overall results support the TOE and the RBV view and prove that AI technology is not enough, but that the skills of the staff and their adjustability to the organisational support will be necessary parameters to have better operational efficiency.

Chapter Five: Conclusion and Recommendations

5.1 Conclusion

The purpose of this study is to explore how the use of Artificial Intelligence Technologies (AIT) affects operational efficiency, focusing especially on the competences of the employees. The results indicate a positive correlation between the use of AI in the workplace and increased operational efficiency, as well as a connection between employee competence and organizational capacity in AI contexts. The findings of the regression analysis also validate H1, because there was a significant relationship between AI Adoption and Operational Efficiency with the model explaining 27.5% of the variance. H2 was also supported, showing strong evidence of a positive

correlation between AI Adoption and Employee Competence, whereas H3 had been supported because of the significant role of Employee Competence in predicting Operational Efficiency. The results align with the case outlined in Chapter 2 that AI contributes to the organisation through the combination of technological resources and knowledge, digital skills and adaptability of employees (Ngabalin, 2025; Amayreh et al., 2025). The results hence justify the use of the Technology–Organisation–Environment (TOE) theoretical framework and the Resource-Based View (RBV) theory used in this dissertation simultaneously. The operational value of AI is not solely about the technology, but also on how well the employees can utilise it and how the organisations are ready for it. Organisations looking to be more efficient and sustainable must therefore build the skills of employees in tandem with the rollout of AI.

5.2 Linking with the Objectives

The first goal was to explore the impact of AI adoption on increased operational efficiency. This objective is also well supported by the findings as indicated from the regression analysis which showed a positive relationship statistically significant between AI Adoption and Operational Efficiency ($R^2 = .275$, $F = 38.645$, $p < .001$). This means that the number of those differences between the respondents can be accounted for by the way that AI is adopted. The results align with Ngabalin (2025), who correlated the use of AI with better automation, decisions and resource use. It further reaffirms the findings of Wang et al. (2026) which identified organisational readiness, infrastructure and employee skills as prerequisites for the realization of benefits from AI utilization in business. Thus, the results indicate that AI can contribute to operational efficiency but that it does not necessarily do so when technology is the limiting factor but when the wider constructs of the organisation are. This is a TOE interpretation, which is congruent with the TOE perspective used in the dissertation.

The second goal was to investigate the correlation between the use of AI and the competences of the employees. A significant positive relationship between the two variables was obtained during the analysis and this was the objective that has been met. The regression model was significant ($R^2 = .343$, $F = 53.196$, $p < .001$) accounting for the 34.3% variance in the dependent variable, Employee Competence. This discovery aligns with the results of the study carried out by Amayreh et al. (2025) which reported positive correlation between AI experience and AI

utilisation and technical competence. Likewise, Tariq et al. (2021) highlighted the significance of employee skills to a successful AI implementation. The dissertation also acknowledges that there might be adaptation challenges when using AI. Soulamy et al (2024) found stress faced by employees in the company, and adaptation problems, and Babashahi et al (2024) presented the importance of both technical and human adaption skills. Therefore, there is a need to undertake training, reskilling and organisational support to ensure the right implementation of AI adoption.

The third aim was to examine how employee competence impacts on operational efficiency. The results are very strong with regard to this objective, and in this case, Employee Competence accounted for 44.1% of the variance in Operational Efficiency ($R^2 = .441$; $F = 80.557$; $p < .001$). This is the best explanatory association amongst the three direct associations tested. The finding is consistent with Nishu and Lalrinzuala (2021), Abhari (2025), Wijayanti and Sari (2023), Barbu et al. (2025) and Huu (2023) as the research that consolidates the role of employee knowledge, skills, competence and digital capabilities in workplace performance. It thus supports the RBV in showing that employee competence may become an important organisational capability to utilize technological investments for operational benefits.

The fourth objective was about how employee competence mediates the relationship of employee competency to operational efficiency (OPEFF). The conceptual framework established a link between employee competence as the driver delivering operational value and the deployment of AI, acknowledging that achieving efficiency is more about the individual and their ability than merely about technology. Previous literature has studied either AI and efficiency, or employee competence and efficiency, separately, and there has been a lack of research that explores employee competence as the element between AI and operational efficiency. In a model explored by Kassa & Worku (2025), the relationship between AI and productivity and organisational performance was researched but the mediator was productivity instead of competence of employees. Likewise, Gede (2025) and Gwijangga, Rina and Adi (2026) illustrate general significance of human factors and competence to become organizational resources with output in the form of organizational performance. Some relations found in this study, and specifically between the adoption of AI in the Euro NCAP document and the competence of employees, and then between the competence of employees and operational

efficiency, were therefore particularly significant to the proposed mediation logic, and can thus be supported by an empirical basis. The reported Chapter 4 analysis does not report an indirect-effect coefficient or an indirect-effect (bootstrapped) coefficient, however. Hence, it is unsuitable to make a statistically substantiated inference of mediation in the study.

5.3 Recommendations

5.3.1 Employee Training and AI Competence Development

First, employee training must be included in the process of implementing AI technology — it should not be viewed as an AI investment in isolation. The results have confirmed that there is a significant relationship between both variables (Employee Competence and Operational Efficiency), indicating that employees' knowledge, digitization capabilities, problem-solving skills, and application of AI should not be ignored with technological implementation. Structured AI-literacy initiatives need to be integrated within the system by organisations, which should include practical AI application, data interpretation, critical evaluation of AI-generated content, and responsible technology use. Organisations need employees with digital competencies to effectively use and adopt AI, highlighting the need for suitable skills among the workforce, as underlined by Santana and Díaz-Fernández (2022). This backs up the call for investing in AI with ongoing competency development, not as a single, one-time technical course.

5.3.2 Continuous Reskilling and Professional Development

Second, managers should create continuous reskilling and development programmes that are directly related to the employees' working tasks. The results indicate that AI adoption is positively stated with Employee Competence, which implies that an exposure to AI may positively relate with ability building if the employees are supported accordingly. Training must be role-specific, and integrate technical knowledge of AI with domain knowledge, analytical thinking, problem-solving etc. employee development and training programs can be valuable assets for bridging the gap between artificial intelligence application and high-performing work systems, as illustrated by Zahoor et al. (2024). Therefore, organisations might implement regular competency evaluations to pinpoint areas missing in their employees' skill sets and offer tailored learning, instead of using the same AI training content for everybody.

5.3.3 Assessment of Employee AI Competence

Thirdly, organisations need to have a systemized assessment of employee competence in working with AI prior to and after implementation. This evaluation can inform decision makers to ensure staff are capable of understanding the results generated by AI tools, recognizing errors and adapting to how AI can be implemented within current business processes. The recommendation is highly significant as AI experience, utilisation and technical capability are related to employee self-competence in the study conducted by Amayreh et al. (2025). Organisations should thus establish measurable benchmarks and thresholds that span AI Literacy, Technical Capability, Adaptability and Real-World Application, so as to measure the training's effectiveness as well as operational results.

5.3.4 Human-Centred AI Implementation

Fourth, embrace a human-centric view of the implementation of AI, taking into account occupational context employee competence differences. Not all staff or industries will have the same rate of AI capability development. Recent data reveals significant variations across industries in employee AI proficiency, and there are still some capabilities, including those in data analysis, automation and multimodal AI, that are only partly developed. The viewpoint presented by Lastovska et al. (2026) underscores the relevance of comprehending competence in AI as a multidimensioned competence. Organizations should, therefore, customize the implementation, training, and support for AI based on organizational needs, employee competencies and the complexity of AI applications.

5.4 Future Study Directions

Future research should explore these relationships with bigger and more diverse samples in various industrial and organisational contexts. The role of AI in organizations can be explored from different perspectives with various longitudinal designs, where researchers could observe the changes in the competences and the efficiency of employees with AI adoption over time. Bootstrapping and/or structural equation modeling should also be used for future studies to provide a formal test on the proposed mediation and better integrate TOE and RBV. Other moderating factors such as organisational culture, leadership support, digital infrastructure,

employee resistance and AI literacy should also be investigated. These would complement the study undertaken by Barbu et al. (2025) on workplace implications and technology responses, and Lastovska et al. (2026) on the variance in AI skills across industry.

5.5 Chapter Summary

The results were presented, objectives were achieved and recommendations and directions were given for future research which was their conclusion of this chapter. The results confirmed strong positive relationships: between Operational efficiency and AI adoption, between Employee competence and AI adoption, and between Employee competence and operational efficiency. Employee competence had the highest explanatory correlation with operational efficiency, suggesting the necessity to boost technological richness while also building the personnel skills. The results also revealed the validity of the TOE and RBV views. Direct statistical indirect-effect tests were not reported, but mediation can be conceptualized, so mediation is not confirmed. Proposals emphasized the need for using assessment techniques and human-centered application of AI, as well as reskilling employees and training them for AI, and future studies should be conducted with longitudinal and cross-sectoral approaches.

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Appendixes

Appendix A: Ethics Form

APPLICATION FOR ETHICAL APPROVAL

In order for research to result in benefit and minimise risk of harm, it must be conducted ethically.

The University follows the OECD Frascati manual definition of **research activity**: “creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications”. As such this covers activities undertaken by members of staff, postgraduate research students, and both taught postgraduate and undergraduate students working on dissertations/projects.

The individual undertaking the research activity is known as the “principal researcher”.

This form must be completed and approved prior to undertaking any research activity.

SECTION A: About You (Principal Researcher)

1	Full Name:	Rajesh chaudhary
2	Student Id :	2433823
3	Email address:	2433823@student.uwtsd.ac.uk
4	Programme of Study:	Dissertation
5	Supervisor:	ALIREZA NAZARIAN

SECTION B: Internal and External Ethical Guidance Materials

	Please list the core ethical guidance documents that have been referred to during the completion of this form (including any discipline-specific codes of research ethics, location-specific codes of research ethics, and also any specific ethical guidance relating to the proposed methodology). Please tick to confirm that your research proposal adheres to these codes and guidelines. You may add rows to this table if needed.	
1	UWTSD Research Ethics & Integrity Code of Practice	☒
2	UWTSD Research Data Management Policy	☒
3		☐
4		☐

SECTION C: Details of Research Activity

1	Indicative title:	The Impact of AI Adoption on Operational Efficiency: The Mediating Role of Employee Competence		
2	Proposed start date:		Proposed end date:	
	Introduction to the Research (maximum 300 words in each section) Ensure that you write for a Non-Specialist Audience when outlining your response to the three points below: • <i>Purpose of Research Activity</i> • <i>Proposed Research Question</i> • <i>Aims of Research Activity</i> • <i>Objectives of Research Activity</i> Demonstrate, briefly, how Existing Research has informed the proposed activity and explain • <i>What the research activity will add to the body of knowledge</i> • <i>How it addresses an area of importance.</i>			
3	Purpose of Research Activity This research investigates how Artificial Intelligence (AI) adoption influences operational efficiency in organisations and examines whether employee competence mediates this relationship. Existing studies primarily focus on technological capability, with limited attention given to workforce competence. The study will collect quantitative data from employees working in organisations using AI technologies. The findings will contribute to academic knowledge by explaining how employee competence supports successful AI implementation while providing practical recommendations for organisations seeking to maximise operational performance through AI. (this box should expand as you type)			
4	Research Question Main Research Question How does Artificial Intelligence (AI) adoption influence operational efficiency in organisations through employee competence? Sub-questions • RQ1.1: How does AI adoption affect employee competence in organisations? • RQ1.2: How does employee competence influence operational efficiency? • RQ1.3: To what extent does employee competence mediate the relationship between AI adoption and operational efficiency? (this box should expand as you type)			
5	Aims of Research Activity Number your aims and link them to your objectives To investigate the impact of AI adoption on operational efficiency and examine the mediating role of employee competence.			

	(this box should expand as you type)
6	Objectives of Research Activity • To examine the effect of AI adoption on operational efficiency. • To evaluate the relationship between AI adoption and employee competence. • To analyse the influence of employee competence on operational efficiency. • To investigate the mediating role of employee competence between AI adoption and operational efficiency. (this box should expand as you type)
	Proposed data collection methods (maximum 600 words) Provide a brief summary of all the methods that may be used in the research activity to collect data, making it clear what specific techniques may be used. If methods other than those listed in this section are deemed appropriate later, additional ethical approval for those methods will be needed. You do not need to justify the methods here but should instead describe how you intend to collect the data necessary for you to complete your project.
7	This should describe how you intend to collect data. It should not include a discussion of the theoretical basis for your data collection methods. Please note, that if you intend to collect any audio/video recordings of interviews with participants then these will be classified as Personal Data under GDPR/DPA2018. If you intend to use these then note this in section H. Primary quantitative data will be collected using a structured online questionnaire administered through Google Forms. Employees working in organisations that use AI technologies will be invited to participate voluntarily. Responses will be measured using a five-point Likert scale. Approximately 180–250 participants will be recruited using purposive sampling. No interviews, focus groups, audio recordings or observations will be undertaken. The questionnaire will remain anonymous and all responses will be analysed using IBM SPSS. (this box should expand as you type)

SECTION D: Scope of Research Activity

	Will the research activity include:	YES	NO
1	Use of a questionnaire or similar research instrument?	☒	☐
2	Use of interviews?	☐	☒
3	Use of focus groups?	☐	☒
4	Use of participant diaries?	☐	☒
5	Use of video or audio recording?	☐	☒
6	Use of computer-generated log files?	☐	☒
7	Participant observation with their knowledge?	☐	☒
8	Participant observation without their knowledge?	☐	☒
9	Access to personal or confidential information without the participants' specific consent?	☐	☒

10	Administration of any questions, test stimuli, presentation that may be experienced as physically, mentally or emotionally harmful / offensive?	☐	☒
11	Performance of any acts which may cause embarrassment or affect self-esteem?	☐	☒
12	Investigation of participants involved in illegal activities?	☐	☒
13	Use of procedures that involve deception?	☐	☒
14	Administration of any substance, agent or placebo?	☐	☒
15	Working with live vertebrate animals?	☐	☒
16	Procedures that may have a negative impact on the environment?	☐	☒
17	Other primary data collection methods. Please indicate the type of data collection method(s) below.	☐	☒
	Details of any other primary data collection method: (this box should expand as you type)		

If you have ticked NO to every question then the research activity is (ethically) low risk and you may skip section E and continue to section F.

If YES to any question, then no research activity should be undertaken until full ethical approval has been obtained.

SECTION E: Intended Participants

	Who are the intended participants:	Y E S	NO
1	Students or staff at the University?	☐	☒
2	Adults (over the age of 18 and competent to give consent)?	☒	☐
3	Vulnerable adults?	☐	☒
4	Children and Young People under the age of 18? (Consent from Parent, Carer or Guardian will be required)	☐	☒
5	Prisoners?	☐	☒
6	Young offenders?	☐	☒
7	Those who could be considered to have a particularly dependent relationship with the investigator or a gatekeeper?	☐	☒
8	People engaged in illegal activities?	☐	☒
9	Others. Please indicate the participants below, and specifically any group who may be unable to give consent.	☐	☒

	Details of any other participant groups: Complete this only if your participants cannot give consent. This includes animals (this box should expand as you type)		
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Participant numbers and source Provide an estimate of the expected number of participants. How will you identify participants and how will they be recruited?		
10	How many participants are expected?	Ballpark figures are fine but make sure that you explain how you will identify and contact your participants. Approximately 180–250 employees working in organisations that have adopted AI technologies. (this box should expand as you type)
11	Who will the participants be?	Employees from organisations using Artificial Intelligence in business operations. (this box should expand as you type)
12	How will you identify the participants?	Participants will be recruited through professional networks, LinkedIn, email invitations and organisational contacts. The questionnaire link will be distributed electronically. (this box should expand as you type)

Information for participants:		YES	NO	N/A
13	Will you describe the main research procedures to participants in advance, so that they are informed about what to expect?	☒	☐	☐
14	Will you tell participants that their participation is voluntary?	☒	☐	☐
15	Will you obtain written consent for participation?	☒	☐	☐
16	Will you explain to participants that refusal to participate in the research will not affect their treatment or education (if relevant)?	☒	☐	☐
17	If the research is observational, will you ask participants for their consent to being observed?	☐	☐	☒
18	Will you tell participants that they may withdraw from the research at any time and for any reason?	☒	☐	☐
19	With questionnaires, will you give participants the option of omitting questions they do not want to answer?	☒	☐	☐
20	Will you tell participants that their data will be treated with full confidentiality and that, if published, it will not be identifiable as theirs?	☒	☐	☐
21	Will you debrief participants at the end of their participation, in a way appropriate to the type of research undertaken?	☒	☐	☐
22	If NO to any of above questions, please give an explanation			

	Not applicable. All applicable participant information requirements will be fully met. <i>(this box should expand as you type)</i>
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	Information for participants:	YES	NO	N/A
24	Will participants be paid?	☐	☒	☐
25	Is specialist electrical or other equipment to be used with participants?	☐	☒	☐
26	Are there any financial or other interests to the investigator or University arising from this study?	☐	☒	☐
27	Will the research activity involve deliberately misleading participants in any way, or the partial or full concealment of the specific study aims?	☐	☒	☐
28	If YES to any question, please provide full details			
	You should be able to tick NO for most of these questions. For any cases that you have ticked YES then provide details in this box. If you are using cameras/voice recorders to record interviews, then please state that in this box. <i>(this box should expand as you type)</i>			

SECTION F: Anticipated Risks

	Outline any anticipated risks that may adversely affect any of the participants, the researchers and/or the University, and the steps that will be taken to address them.	
1	Risks to participants For example: sector-specific health & safety, emotional distress, financial disclosure, physical harm, transfer of personal data, sensitive organisational information. If you have identified in section D that there are no participants, then enter N/A and go skip to question 3.	
	Risk to participants: Participants may experience minor inconvenience due to the time required to complete the questionnaire or may feel slight discomfort when answering questions related to Artificial Intelligence adoption in their workplace. However, no sensitive or personal questions will be asked. <i>(this box should expand as you type)</i>	How you will mitigate the risk to participants: Participation is entirely voluntary. Participants may withdraw before submitting the questionnaire. The questionnaire is anonymous and participants may skip any question they do not wish to answer. <i>(this box should expand as you type)</i>
2	If research activity may include sensitive, embarrassing or upsetting topics (e.g. sexual activity, drug use) or issues likely to disclose information requiring further action (e.g. criminal activity), give details of the procedures to deal with these issues, including any support/advice (e.g. helpline numbers) to be offered to participants. Note that where applicable, consent procedures should make it clear that if something potentially or	

	actually illegal is discovered in the course of a project, it may need to be disclosed to the proper authorities	
	The study does not involve sensitive, illegal, embarrassing or emotionally distressing topics. Therefore, no additional support procedures are required. <i>(this box should expand as you type)</i>	
3	Risks to the investigator For example: personal health & safety, physical harm, emotional distress, risk of accusation of harm/impropriety, conflict of interest	
	Risk to the investigator: Minimal risk. Participants may spend approximately 10–15 minutes completing the questionnaire and may feel minor inconvenience. <i>(this box should expand as you type)</i>	How you will mitigate the risk to the investigator: Mitigation Participation is voluntary. Participants may withdraw at any time before submission. No identifying information will be collected. <i>(this box should expand as you type)</i>
4	University/institutional risks For example: adverse publicity, financial loss, data protection	
	Risk to the University: Potential delays in recruitment and data collection. <i>(this box should expand as you type)</i>	How you will mitigate the risk to the University: Mitigation Use multiple online recruitment channels and follow the approved research timetable. <i>(this box should expand as you type)</i>
5	Environmental risks For example: accidental spillage of pollutants, damage to local ecosystems	
	Risk to the environment: None. <i>(this box should expand as you type)</i>	How you will mitigate the risk to environment: Electronic questionnaires eliminate paper waste. <i>(this box should expand as you type)</i>

SECTION G: Feedback, Consent and Confidentiality

If you have identified in section D that there are no participants, then enter skip this section and continue to section H.

1	Feedback What de-briefing and feedback will be provided to participants, how will this be done and when?
	You don't need to email your participants with your final report. A good alternative is to set up an email address that they will be able to contact for further details or results.

	Participants will receive a debrief statement immediately after submitting the questionnaire. Contact details will be provided if they request further information. <i>(this box should expand as you type)</i>
2	Informed consent Describe the arrangements to inform potential participants, before providing consent, of what is involved in participating. Describe the arrangements for participants to provide full consent before data collection begins. If gaining consent in this way is inappropriate, explain how consent will be obtained and recorded in accordance with prevailing data protection legislation.
	If you are using a paper questionnaire then you should have the participants sign an appropriate consent form. These forms will count as personal data and should be noted as such in section J. If you are using an online questionnaire, then you should have a screen before the questions start that acts as a consent form, informing participants that by clicking on the NEXT button they are providing consent. The first page of the Google Forms questionnaire will contain a Participant Information Sheet and Consent Statement. Participants will only proceed after selecting "I agree". <i>(this box should expand as you type)</i>
3	Confidentiality / Anonymity Set out how anonymity of participants and confidentiality will be ensured in any outputs. If anonymity is not being offered, explain why this is the case.
	Do not collect names unless you really need them. Do not name participants or organisations in any research publications (including the thesis) without their explicit permission. No names or identifying information will be collected. Results will be reported only in aggregate form. <i>(this box should expand as you type)</i>

SECTION H: Data Protection and Storage

	Does the research activity involve personal data (as defined by the General Data Protection Regulation 2016 "GDPR" and the Data Protection Act 2018 "DPA")?	YES	NO
1	"Personal data" means any information relating to an identified or identifiable natural person ('data subject'). An identifiable natural person is one who can be identified, directly or indirectly, in particular by reference to an identifier such as a name, an identification number, location data, an online identifier or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that natural person. Any video or audio recordings of participants is considered to be personal data.	☐	☒
	If YES, provide a description of the data and explain why this data needs to be collected:		
2	This includes audio/video data of participants but can also include IP addresses and usernames. Names, addresses and emails also count, as do consent forms. <i>(this box should expand as you type)</i>		
	Does it involve special category data (as defined by the GDPR)?	YES	NO

3	“Special category data” means sensitive personal data consisting of information as to the data subjects’ – (a) racial or ethnic origin, (b) political opinions, (c) religious beliefs or other beliefs of a similar nature, (d) membership of a trade union (within the meaning of the Trade Union and Labour Relations (Consolidation) Act 1992), (e) physical or mental health or condition, (f) sexual life, (g) genetics, (h) biometric data (as used for ID purposes),	☐	☒
	If YES, provide a description of the special category data and explain why this data needs to be collected:		
4	What counts as ‘sensitive’ will differ between cultures. Any information on behaviour that is not in accordance with cultural norms would count as sensitive personal data. (this box should expand as you type)		

	Will data from the research activity (collected data, drafts of the thesis, or materials for publication) be stored in any of the following ways?	YES	NO
5	Manual files (i.e. in paper form)?	☐	☒
6	University computers?	☐	☒
7	Private company computers?	☐	☒
8	Home or other personal computers?	☒	☐
9	Laptop computers/ CDs/ Portable disk-drives/ memory sticks?	☒	☐
10	“Cloud” storage or websites?	☒	☐
11	Other – specify:	☐	☒
12	For all stored data, explain the measures in place to ensure the security of the data collected, data confidentiality, including details of backup procedures, password protection, encryption, anonymisation and pseudonymisation: If possible, save your data on computers that are secure and regularly backed up. Many cloud services only provide GDPR-compliant storage for business customers. An example of suitable text is given below. <i>All data will be kept in password protected cloud storage on the University Office 365 system which will not be shared. Audio/visual data will be transcribed and would be shown to participants to check accuracy of reporting. Any USB sticks used to store or transfer data will be password protected. All participants will be given a unique identifier to ensure confidentiality and this list will be kept securely in the password protected folder.</i> All electronic files will be password-protected and stored securely using encrypted cloud storage. Data will only be accessible to the researcher and supervisor.		

(this box should expand as you type)			
Data Protection			
	Will the research activity involve any of the following activities:	YES	N O
13	Electronic transfer of data in any form?	☒	☐
14	Sharing of data with others at the University outside of the immediate research team?	☐	☒
15	Sharing of data with other organisations?	☐	☒
16	Export of data outside the UK or importing of data from outside the UK?	☐	☒
17	Use of personal addresses, postcodes, faxes, emails or telephone numbers?	☐	☒
18	Publication of data that might allow identification of individuals?	☐	☒
19	If YES to any question, please provide full details, explaining how this will be conducted in accordance with the GDPR and Data Protection Act (2018) (and/or any international equivalent):		
	Electronic transfer will occur only when anonymous questionnaire responses are downloaded from Google Forms for statistical analysis. Data will remain confidential and accessible only to the researcher and supervisor. (this box should expand as you type)		
20	List all who will have access to the data generated by the research activity:		
	Normally the principal researcher, possibly also the supervisor and, if the project has an industrial partner, a representative of that partner. Possibly also external examiner or second marker? Access Principal Researcher Supervisor Second Marker (if required) External Examiner (if required) (this box should expand as you type)		
21	List who will have control of, and act as custodian(s) for, data generated by the research activity:		
	Usually the principal researcher. Custodian Principal Researcher (this box should expand as you type)		
22	Give details of data storage arrangements, including security measures in place to protect the data, where data will be stored, how long for, and in what form.		
	All data will be encrypted and kept in password protected cloud storage on the University Office 365 system which will not be shared. Any USB sticks used to store or transfer data will be password protected, and will be reformatted at the end of the project in order to destroy the data. The data will be stored until the completion of the project and then deleted. Data will be stored securely in password-protected cloud storage and on password-protected personal devices until completion of the dissertation, after which it will be permanently deleted according to university regulations.		

	<i>(this box should expand as you type)</i>	
22	Confirm that you have read the UWTSD guidance on data management (see https://www.uwtSD.ac.uk/library/research-data-management/)	☒
23	Confirm that you are aware that you need to keep all data until after your research has completed or the end of your funding	☒

SECTION I: Use of AI tools

Use of generative AI and other AI-based tools		YES	NO	N / A
There are a number of ethical issues relating to the use of generative AI and other AI-based tools, including data security, output bias, and output errors. In general you should assume that any generative AI or other AI-based tool that you pay to use is more secure and accurate than one which is free to use. Will the research use AI tools to do any of the following:				
1	Capture data?	☐	☒	☐
2	Generate and/or edit text?	☒	☐	☐
3	Generate graphics?	☐	☒	☐
4	Generate video?	☐	☒	☐
5	Generate sound/music?	☐	☒	☐
6	Generate code?	☐	☒	☐
7	Generate synthetic data?	☐	☒	☐
8	Analyse data?	☐	☒	☐
9	Analyse personal or sensitive data?	☐	☒	☐
10	Classify data?	☐	☒	☐
11	Do you intend to use the free version of any AI tools?	☐	☒	☐
If you have answered YES to any of questions O1-O11, please provide justification detailing why this is necessary for the research.				
12	State which AI tool or tools you will be using, and where they are based (or store their data – you may need to check their webpages or user agreement for this). If you are planning to use Copilot then say if you're using the UWTSD version of it or the public version. You should also show how you are complying with current UWTSD guidance/policy of the use of AI. <i>Generative AI tools such as ChatGPT will be used only to improve grammar, language, structure and academic writing. AI will not generate research findings, fabricate data, complete statistical analysis or replace critical thinking. All outputs will be reviewed, verified and edited by the researcher in accordance with UWTSD policies.</i> <i>(this box should expand as you type)</i>			

	The information which I have provided is correct and complete to the best of my knowledge. I have attempted to identify any risks and issues related to the research activity and acknowledge my obligations and the rights of the participants. In submitting this application I hereby confirm that I undertake to ensure that the above named research activity will meet the University's Research Ethics and Integrity Code of Practice which is published on the website: https://www.uwtsd.ac.uk/research/research-ethics/		
1	Signature of applicant:	Rajesh chaudhary	Date:
2	Supervisor:	ALIREZA NAZARIAN	Date:
3	Signature:		

SECTION J: Declaration

Appendix B: Literature Review Data

Workbook purpose	Literature review matrix for the dissertation: AI Adoption → Employee Competence → Operational Efficiency.
Number of studies	43 studies/references supplied in the conversation and attached reference material.
Basis	The 43-study sheet is based on the supplied references. The original 12-study matrix is retained unchanged on a separate sheet.
Data integrity	Where the supplied reference/title did not provide a method, sample size or specific result, the matrix does not invent one; it records the study type/focus at the level supported by the supplied material.
Main variables	AI adoption; employee competence; operational efficiency; mediation; TOE; RBV.

1	The Role of Social Media Analytics in Influencing Consumer Purchase Decisions among Gen Z	Journal of Interactive Marketing	Smith, J. & Brown, L.	2024	Examine influence of social media analytics on purchase decisions	Assess effect of analytics, engagement and trust	How does social media analytics influence purchase decisions?
2	Social Media Engagement and Consumer Behaviour	Computers in Human Behavior	Lee, H. et al.	2023	Explore engagement and buying behaviour	Measure engagement and purchase intention	Does engagement predict purchase?
3	Influencer Credibility and Purchase Intention	Journal of Business Research	Chen, Y. & Wang, X.	2022	Investigate influencer credibility	Evaluate trust and purchase intention	Does credibility improve purchase intention?
4	Electronic Word-of-Mouth and Brand Trust	Journal of Retailing	Patel, R. et al.	2023	Assess e-WOM effects	Analyse e-WOM and trust	Does e-WOM strengthen brand trust?
5	Personalised Advertising on Social Platforms	Marketing Intelligence & Planning	Evans, K.	2022	Study personalised advertising	Measure ad relevance and buying	Do personalised ads improve purchase?
6	Social Commerce Adoption among Generation Z	Electronic Commerce Research	Garcia, M.	2024	Examine social commerce adoption	Identify adoption drivers	Why do Gen Z adopt social commerce?
7	Consumer Trust in Social Media Marketing	International Journal of Consumer Studies	Ahmed, S.	2021	Explore consumer trust	Assess trust and loyalty	How does trust influence loyalty?
8	AI-Driven Recommendations and Online Shopping	Journal of Retailing and Consumer Services	Wilson, D.	2024	Evaluate AI recommendations	Measure recommendation quality	Do AI recommendations affect purchase?
9	Social Media Analytics and Brand Loyalty	Journal of Marketing Analytics	Khan, A.	2023	Analyse analytics and loyalty	Assess analytics-loyalty link	Does analytics improve loyalty?
10	User-Generated Content and Purchase Behaviour	Information & Management	Nguyen, T.	2022	Investigate UGC effects	Measure UGC credibility	Does UGC influence buying?
11	Digital Consumer Experience in the UK	Journal of Consumer Marketing	Roberts, P.	2023	Study digital experience	Assess experience and satisfaction	How does experience affect sales?
12	Online Reviews and Consumer Decision-Making	International Journal of Market Research	Taylor, C.	2021	Examine online reviews	Evaluate review quality	Do reviews influence purchase?

1	Amayreh, A., Ta'ammha, M.A., Magabieh, I.K., Mahrouq, M.H. and Alfaiza, S.A.	2025	Exploring the impact of AI on employee self-competence performance key variables and outcomes	Discover Sustainability	AI adoption; employee competence	Empirical study (details not specified in supplied reference)	Employee self-competence and AI-related performance outcomes	Employee competence adoption
2	An, C., Pahrudin, C., Pratiwi, A.Z. and Syamsuri, S.A.S.N.	2026	Role of technological innovation and operational efficiency in competitive advantage at Soekarno Hatta International Airport	Jurnal Siber Multi Disiplin	Technological innovation; operational efficiency	Empirical study (details not specified in supplied reference)	Technological innovation and operational efficiency as contributors to competitive advantage	Operational efficiency
3	Babashahi, L., Barbosa, C.E., Lima, Y., Lyra, A., Salazar, H., Argôlo, M., Almeida, M.A. de and Sousa, J.M. de	2024	AI in the workplace: A systematic review of skill transformation in the industry	Administrative Sciences	AI; workplace skills; skill transformation	Systematic review	AI-driven transformation of workplace skills	Employee competence
4	Bai, C.A., Sarkis, J. and Xue, W.	2024	Improving operational efficiency and effectiveness through blockchain technology	Production Planning & Control	Technology; operational efficiency	Empirical/conceptual study (details not specified in supplied reference)	Blockchain as a technology for improving operational efficiency and effectiveness	Operational efficiency technology
5	Barbu, A., Maria, A., Costea-Marcu, I.C., Militaru, G., Deselnicu, D.C. and Moiceanu, G.	2025	Exploring employee perspectives on workplace technology: Usage, roles, and implications for satisfaction and performance	Behavioral Sciences	Workplace technology; employee performance	Empirical study (details not specified in supplied reference)	Employee perspectives on technology use, roles, satisfaction and performance	Employee competence performance
6	Berlanto, W.R., Suhud, U. and Hamidah	2024	The effect of operational efficiency, technology innovation, and service quality on the competitiveness of loading and unloading companies at the port: Government regulation as a moderating variable and customer satisfaction as a mediation variable	International Journal of Integrative Sciences	Operational efficiency; technology innovation; competitiveness	Empirical study with moderation/mediation	Links operational efficiency and technology innovation with competitiveness	Operational efficiency technology
7	Bhosale, R. and Jadhav, S.	2025	Uncovering the influence of operational factors on manufacturing efficiency with real time data	Scientific Reports	Operational factors; manufacturing efficiency	Data-driven empirical study	Real-time operational factors and manufacturing efficiency	Operational efficiency
8	Chiu, T.K.F., Ahmad, Z., Ismailov, M. and Sanusi, I.T.	2024	What are artificial intelligence literacy and competency? A comprehensive framework to support them	Computers and Education Open	AI literacy; AI competency	Conceptual framework	Defines and structures AI literacy and competency	Employee competence
9	Cubric, M.	2020	Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study	Technology in Society	AI adoption drivers and barriers	Tertiary/systematic review	Drivers, barriers and social considerations affecting AI adoption	AI adoption
10	Daniail, S.M., Barykin, S.E., Khorstai, F.M., Kalinina, O.V., Tsukanova, O.A., Torosyan, E.K., Pollakova, S., Proselov, S., Moiseev, N. and Serlyu, T.	2022	An employee competency framework in a welfare organization	Sustainability	Employee competency	Framework development	Competency framework for organisational roles	Employee competence
11	Dringó-Horváth, I., Rajki, Z. and T. Nagy, J.	2025	University teachers' digital competence and AI literacy: Moderating role of gender, age, experience, and discipline	Education Sciences	Digital competence; AI literacy	Empirical study	Digital competence and AI literacy with demographic/contextual moderators	Employee competence
12	Edgar, W.B. and Lockwood, C.A.	2021	Corporate core competencies' essence, contexts, discovery, and future: A call to action for executives and researchers	SAGE Open	Core competencies; organisational capability	Conceptual/review study	Clarifies the meaning and strategic context of core competencies	RBV / employee comp
13	Febrianto, A., Mokh. Sufel, Hakim, M.S., Yayat, K.D. and Hardatama, I.	2025	Operational efficiency and sustainable asset management of heavy equipment in industry: A data-driven framework	Results in Engineering	Operational efficiency; asset management	Data-driven framework/empirical study	Operational efficiency linked to asset characteristics and management	Operational efficiency
14	Fitriani, L., Khodir, M.L. and Surendro, K.	2025	A conceptual framework for AI adoption in business architecture with case studies in higher education and government	Discover Artificial Intelligence	AI adoption; business architecture	Conceptual framework with case studies	Framework for aligning AI adoption with business architecture	AI adoption / TOE
15	Gede, D.U.	2025	Employee engagement as a mediator of strategic alignment and organizational performance in Ethiopian education institutions	Discover Psychology	Mediation; employee factor; performance	Quantitative mediation study	Employee engagement as a mechanism linking strategic alignment and performance	Mediation / employee
16	Gwijjanga, L. La, Rina, R. and Adi, Y.	2026	The role of competence as a mediator in the relationship between supervision and training on employee effectiveness	Wiest Science Journal Economic and Entrepreneurship	Competence; mediation; employee effectiveness	Quantitative mediation study	Competence as a mediator between organisational inputs and employee effectiveness	Mediation / employee competence
17	Haleem, A., Javadi, M., Qadri, M.A., Singh, R.R. and Sumari, R.	2022	Artificial Intelligence (AI) applications for marketing: A literature-based study	International Journal of Intelligent Networks	AI applications	Literature-based study	AI applications across marketing functions and decision processes	AI adoption / applicat
18	Handoyo, S., Suharman, H., Ghani, E.K. and Soedarsono, S.	2023	A business strategy, operational efficiency, ownership structure, and manufacturing performance: The moderating role of market uncertainty and competition intensity and its implication on open innovation	Journal of Open Innovation: Technology, Market, and Complexity	Operational efficiency; strategy; competition	Quantitative empirical study	Operational efficiency and manufacturing performance under contextual conditions	Operational efficiency
19	Horani, O.M., Khatibi, A., Alsoud, A.R., Tham, J., Al-Adwan, A.S. and Ferdous, M.	2023	Antecedents of business analytics adoption and impacts on banks' performance: The perspective of the TOE framework and resource-based view	Interdisciplinary Journal of Information, Knowledge, and Management	TOE; RBV; analytics adoption; performance	Quantitative empirical study	TOE/RBV explanation of analytics adoption and performance	TOE / RBV
20	Huu, P.T.	2023	Impact of employee digital competence on the relationship between digital autonomy and innovative work behavior: A conceptual framework	Artificial Intelligence Review	Digital competence; autonomy; innovative behaviour	Systematic review	Digital competence as an important mechanism for digital work outcomes	Employee competence

21	Imron, A. and Dharmajaya, M.A.	2024	Operational efficiency, service quality, and firm performance: A strategic orientation perspective	Current Perspective on Business Operations	Operational efficiency; service quality; firm performance	Empirical study (details not specified in supplied reference)	Relationship between operational efficiency, service quality and firm performance	Operational efficiency
22	Kar, S., Kar, A.K. and Gupta, M.P.	2022	Modeling drivers and barriers of artificial intelligence adoption: Insights from a strategic management perspective	Intelligent Systems in Accounting, Finance and Management	AI adoption drivers/barriers	Empirical modelling study	Drivers and barriers shaping AI adoption	AI adoption
23	Lee, C., Wu, C. and Jong, D.	2022	Understanding the impact of competitive advantage and core competency on regional tourism revitalization: Empirical evidence in Taiwan	Frontiers in Psychology	Core competency; competitive advantage	Quantitative empirical study	Core competency and competitive advantage in organisational outcomes	RBV / competence
24	Li, Z., Wang, X., Zheng, R., Na, S. and Liu, C.	2022	Evaluation Analysis of the Operational Efficiency and Total Factor Productivity of Container Terminals in China	Sustainability	Operational efficiency; productivity	Quantitative efficiency analysis	Operational efficiency and total-factor productivity assessment	Operational efficiency
25	Loeffelholz, A.	2020	Delusions, evidence, and the limits of epistemic classification	Erkenntnis	Evidence; decision-making	Conceptual/philosophical analysis	Limits of evidence and epistemic classification	Decision-making context
26	Madanchian, M. and Taherdoost, H.	2025	Barriers and enablers of AI adoption in human resource management: A critical analysis of organizational and technological factors	Information	AI adoption barriers/enablers; HRM	Critical literature analysis	Organisational and technological factors affecting AI adoption	AI adoption / organisational readiness
27	Mallari, D., Huku, M.Z.T., Simamora, M.R. and Kesuma, S.A.	2024	Resource-based view theory to achieve a sustainable competitive advantage of the firm: Systematic literature review	International Journal of Entrepreneurship and Sustainability Studies	RBV; sustainable competitive advantage	Systematic literature review	Internal resources and capabilities as sources of sustainable advantage	RBV
28	Muñoz-Peña, F.A. and Pulido-Reina, J.S.	2025	Influence of soft skills, and employee productivity, on organizational performance, a developing field: Current state and relationship	DYNIA	Soft skills; productivity; organisational performance	Review/relationship study	Links soft skills and productivity with organisational performance	Employee competence productivity
29	Nguyen, T.H., Le, X.C. and Vu, T.H.L.	2022	An extended technology-organization-environment (TOE) framework for online retailing utilization in digital transformation: Empirical evidence from Vietnam	Journal of Open Innovation: Technology, Market, and Complexity	TOE; digital transformation	Quantitative empirical study	Extended TOE factors explaining digital technology utilisation	TOE
30	Nishu, S. and Lahirizuala, A.	2021	Employees' knowledge and skills on work productivity at the Mangrover Department	Journal La Biscoman	Knowledge; skills; productivity	Empirical study	Employee knowledge and skills associated with work productivity	Employee competence productivity
31	Ofozu-Ampong, K.	2024	Artificial Intelligence Research: A review on dominant themes, methods, frameworks and future research directions	Telematics and Informatics Reports	AI research themes and methods	Review/bibliometric-type study	Dominant AI research themes, methods and frameworks	AI adoption / research
32	Oria, L.D., Crook, T.R., Ketchen, D.J., Sirmon, D.G. and Wright, M.	2021	The evolution of resource-based inquiry: A review and meta-analytic integration of the strategic resources-actions-performance pathway	Journal of Management	RBV; resources; actions; performance	Review and meta-analysis	Resources create performance through organisational actions	RBV
33	Panduru, D.A., Simion, R.C. and Ioanid, A.	2024	Measuring operational efficiency: A functional analysis of core and non-core activities in a leading Romanian oil and gas retail company	Proceedings of the International Conference on Business Excellence	Operational efficiency measurement	Functional case analysis	Measurement of efficiency across core and non-core activities	Operational efficiency
34	Reyes-Reina, D., Sanchis-Torres, J.M. and Rueda-Cáceres, I.M.	2020	Adoption of AI tools in software development: A systematic literature review	Science of Computer Programming	AI adoption; software development	Systematic literature review	Adoption patterns and research themes concerning AI tools in software development	AI adoption
35	Salman, M., Ganli, S.A. and Saleem, I.	2020	The concept of competence: A thematic review and discussion	European Journal of Training and Development	Competence concept	Thematic review	Multidimensional conceptualisation of competence	Employee competence
36	Savandha, S.	2025	Artificial intelligence adoption and its impact on business performance: Evidence from Southeast Asia	Journal of Management Economic and Financial	AI adoption; business performance	Quantitative empirical study	AI adoption and business performance relationship in Southeast Asia	AI adoption / performance
37	Soulami, M., Bencheikroun, S. and Gallulina, A.	2024	Exploring how AI adoption in the workplace affects employees: A bibliometric and systematic review	Frontiers in Artificial Intelligence	AI adoption; employee outcomes	Bibliometric and systematic review	Employee outcomes, adaptation and challenges associated with workplace AI	AI adoption / employee competence
38	Suazo-Galdames, I.C., Saracostti, M. and Chaple-Gil, A.M.	2025	Scientific evidence and public policy: A systematic review of barriers and enablers for evidence-informed decision-making	Frontiers in Communication	Evidence; decision-making; barriers	Systematic review	Barriers and enablers affecting evidence-informed decision-making	Decision-making context
39	Tariq, M.U., Poulin, M. and Abonamah, A.A.	2021	Achieving operational excellence through artificial intelligence: Driving forces and barriers	Frontiers in Psychology	AI; operational excellence	Literature/review study	Drivers and barriers to achieving operational excellence through AI	AI adoption / operational efficiency
40	Vieriu, A.M. and Petrea, G.	2025	The impact of artificial intelligence (AI) on students' academic development	Education Sciences	AI; learning; capability development	Empirical/review study (details not specified in supplied reference)	AI effects on learning and capability development	AI literacy / competence
41	Wijayanti, F. and Sari, R.N.	2023	The influence of competency on employee performance: A literature review	International Journal of Accounting Management Economics and Social Sciences	Competence; employee performance	Literature review	Competency-employee performance relationship	Employee competence performance
42	Yuan, L., Zhou, X. and Rajaram, K.	2025	The impact of AI adoption in the workplace on employees: A systematic review	British Academy of Management Annual Conference 2025	AI adoption; employees	Systematic review	Workplace AI effects on employees, including benefits and challenges	AI adoption / employee competence
43	Zhenjing, G., Chupradit, S., Ku, K.Y., Nassari, A.A. and Maffei, M.	2022	Impact of employees' workplace environment on employees' performance: A multi-mediation model	Frontiers in Public Health	Work environment; employee performance; mediation	Quantitative mediation model	Workplace environment and mediating employee factors influencing performance	Employee capability / performance

44	Abhari, K.	2025	Employee participation in digital transformation: From	Information & Management	Employee participation; digital	Empirical study (details not specified in	Examines employee participation and	Employee competence
45	Alkhatib, F., Alsadi, J., Antony, J., Sony, M., Bhat,	2026	Quality management and operational performance: A systematic	International Journal of Productivity and	Quality management; operational	Systematic literature review	Synthesises evidence linking quality management	Operational efficiency
46	Bautista, R.G. and Ivy, M.	2025	The influence of artificial intelligence adoption and workforce	International Journal of Multidisciplinary	AI adoption; workforce digital	Empirical study (details not specified in	Examines AI adoption and workforce digital	AI adoption / employee
47	Behara, M.K., Behara, R.K. and Bala, P.K.	2025	Adoption of AI in human capital development: A multi-industry	Journal of Enterprise Information	AI adoption; human capital	Multi-industry study (details not	Examines AI adoption in human capital	AI adoption / employee
48	James, A. and Azhokkumar, K.	2025	The impact of artificial intelligence on workforce competency	ResearchGate	AI; workforce competency; digital	Study/report (details not specified in	Examines AI's implications for workforce	Employee competence
49	Jeong, K.Y. and Phillips, D.T.	2003	Operational efficiency and effectiveness measurement	International Journal of Operations &	Operational efficiency;	Conceptual/measurement study	Addresses measurement of operational efficiency	Operational efficiency
50	Kassa, B.Y. and Woriso, E.K.	2025	The impact of artificial intelligence on organizational performance:	Journal of Open Innovation: Technology,	AI; organisational performance;	Empirical mediation study	Examines employee productivity as a mediator	AI adoption / mediatio
51	Kim, J. and Jung, H.-S.	2022	The effect of employee competency and organizational culture on	International Journal of Environmental	Employee competency;	Empirical quantitative study	Examines relationships between employee	Employee competence
52	Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M.,	2023	Examining how AI capabilities can foster organizational	Government Information Quarterly	AI capabilities; organisational	Empirical study	Examines how AI capabilities contribute to	AI adoption / organis
53	Mohaimen, M.A., Hassan, M.S., Mahmud, I.,	2026	Does artificial intelligence improve employee work performance?	Social Sciences & Humanities Open	AI; employee work performance;	Empirical quantitative study	Examines AI effects on employee work	Employee competence
54	Nazoum, R.P., Saikaddi, T. and Balogh, G.	2026	Artificial intelligence (AI) in human resource management (HRM): A	Management Review Quarterly	AI in HRM; diversity, equity and	Systematic review	Reviews the dual effects of AI in HRM on diversity	AI adoption / organis
55	Oyekunle, D. and Boohene, D.	2024	Digital transformation potential: The role of artificial intelligence in	COVID-19 / ResearchGate	Digital transformation; AI in	Review/conceptual study	Examines the role and potential of AI within	AI adoption / digital
56	Prince, M.	2024	The role of technology in improving operational efficiency	American Journal of IR 4.0 and Beyond	Technology; operational efficiency	Conceptual/review study	Discusses the contribution of technology to	Operational efficiency
57	Rahman, Md.H., Yeoh, W. and Pal, S.	2026	Towards a unified blockchain business value framework: A	Enterprise Information Systems	Blockchain; business value; digital	Systematic literature review	Develops a unified framework for understanding	Technology / operatio
58	Tariq, M.U.	2024	The role of AI in skilling, upskilling, and reskilling the workforce	Advances in Educational Technologies and	AI; skilling; upskilling; reskilling	Book chapter/review	Examines AI's role in workforce skilling, upskilling	Employee competence
59	Wang, J., Shi, Y., Jiang, X. and Venkatesh, V.G.	2026	How does artificial intelligence capacity enhance the production	International Journal of Information	AI capacity; production resilience;	Empirical study (details not specified in	Examines AI capacity, production-system resilience	AI adoption / operatio
60	Amayneh, A., Takmaha, M.A., Magabieih, I.K.,	2025	Exploring the impact of AI on employee self-competence	Discover Sustainability	AI adoption; employee	Empirical study (details not specified in	Employee self-competence and AI-related	Employee competence



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e_Review_Updated (1)

Appendix C: Survey Questionnaire

Research Topic

The Impact of AI Adoption on Operational Efficiency: The Mediating Role of Employee Competence

Participant Information and Instructions

Dear Participant,

You are invited to participate in a research study examining how Artificial Intelligence (AI) adoption influences operational efficiency and whether employee competence mediates this relationship. The questionnaire is intended for employees who have experience using or working with AI technologies in their organisation.

Your participation is voluntary. All responses will remain anonymous and confidential and will be used only for academic research purposes. Please answer all questions honestly based on your experience.

For Questions 8–22, please use the following scale:

1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Section A: Respondent Profile

1. What is your current job role?

- Employee/Staff
- Team Leader/Supervisor
- Middle Manager
- Senior Manager
- IT/Digital Professional
- Other

2. How many years of professional experience do you have?

- Less than 2 years
- 2–5 years
- 6–10 years
- 11–15 years
- More than 15 years

3. What type of organisation do you work for?

- Small organisation (1–49 employees)
- Medium organisation (50–249 employees)
- Large organisation (250–999 employees)
- Very large organisation (1,000+ employees)
- Prefer not to say

4. Which industry does your organisation primarily operate in?

- Finance/Banking
- Healthcare
- Manufacturing
- Retail
- Information Technology
- Professional/Business Services
- Hospitality/Tourism
- Other

5. How frequently do you use AI technologies as part of your work?

- Never
- Rarely
- Sometimes
- Frequently

- Very frequently

6. Which AI technologies are used in your workplace?

Select all that apply.

- Generative AI tools
- Machine learning systems
- Predictive analytics
- Robotic Process Automation (RPA)
- AI-powered decision-support systems
- AI-powered customer service/chatbots
- AI-enabled data analysis
- Other AI technology
- Not sure

Section B: Artificial Intelligence Adoption

Please indicate your level of agreement with each statement.

7. My organisation has integrated AI technologies into its business operations.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

8. AI technologies are regularly used to support work-related activities in my organisation.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral

- 4 – Agree
- 5 – Strongly Agree

9. My organisation has increased its use of AI technologies in recent years.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

10. AI technologies are integrated into existing organisational processes rather than being used only for occasional tasks.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

11. AI technologies are useful for supporting employees in completing their work.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

Section C: Employee Competence

12. I have sufficient digital skills to work effectively with AI technologies.

- 1 – Strongly Disagree
- 2 – Disagree

- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

13. I understand the basic functions and capabilities of the AI technologies I use at work.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

14. I can critically evaluate the information or recommendations generated by AI systems.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

15. I can use AI technologies to solve work-related problems effectively.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

16. I can adapt my work practices when new AI technologies or systems are introduced.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral

- 4 – Agree
- 5 – Strongly Agree

17. My organisation provides sufficient training to develop employees' ability to use AI technologies effectively.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

Section D: Operational Efficiency

18. AI adoption has improved productivity in my organisation.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

19. AI technologies have reduced the time required to complete routine work processes.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

20. AI adoption has helped my organisation reduce unnecessary operational costs.

- 1 – Strongly Disagree
- 2 – Disagree

- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

21. AI technologies have improved the quality and accuracy of organisational processes.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

22. AI adoption has improved the efficient use of organisational resources.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

23. Overall, AI adoption has improved operational efficiency in my organisation.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

Section E: Overall Assessment

24. Employee competence is essential for achieving the operational benefits expected from AI adoption.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

25. Organisations should invest in employee AI training alongside investment in AI technologies.

- 1 – Strongly Disagree
- 2 – Disagree
- 3 – Neutral
- 4 – Agree
- 5 – Strongly Agree

Variable Coding for SPSS

Variable	Questionnaire Items	Role
AI Adoption (AIA)	Q7–Q11	Independent Variable
Employee Competence (EC)	Q12–Q17	Mediating Variable
Operational Efficiency (OE)	Q18–Q23	Dependent Variable
Demographic Variables	Q1–Q6	Descriptive/Control Information
Overall Assessment	Q24–Q25	Supporting/Additional Analysis

Alignment with Hypotheses

Hypothesis	Relationship	Questionnaire Measures
H1	AI Adoption → Operational Efficiency	Q7–Q11 → Q18–Q23
H2	AI Adoption → Employee Competence	Q7–Q11 → Q12–Q17

H3	Employee Competence → Operational Efficiency	Q12–Q17 → Q18–Q23
H4	AI Adoption → Employee Competence → Operational Efficiency	Q7–Q11 → Q12–Q17 → Q18–Q23

Recommended SPSS procedure: calculate the mean score for each construct (AIA, EC and OE), test **Cronbach’s Alpha** for each scale, then conduct descriptive statistics, Pearson correlation, multiple regression and **PROCESS mediation analysis using bootstrapping**. This directly matches the methodology proposed for the dissertation.

Important: Q24–Q25 should **not** be included in the main construct scores because they assess broader perceptions rather than the three core variables. This keeps the mediation model statistically clean.

Appendix D: Screenshot of Excel for Collected Data

[illegible]

Survey Questionnaire
(Responses).xlsx