

**FACTORS AFFECTING THE ADOPTION OF ARTIFICIAL  
INTELLIGENCE IN AUDITING IN VIETNAM**

Research dissertation presented in partial fulfilment of the requirements  
for the degree of  
**MSc in Accounting and Financial Management**

Griffith College Dublin

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**4 September 2024**

## Candidate Declaration

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I certify that the dissertation entitled: **FACTORS AFFECTING THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN AUDITING IN VIETNAM**

submitted for the degree of: **MSc in Accounting and Financial Management** is the result of my own work and that where reference is made to the work of others, due acknowledgment is given.

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## ABSTRACT

The advent of artificial intelligence (AI) has presented more opportunities for audit firms to improve their productivity and audit quality. Currently, all big 4 audit firms have implemented their AI-powered audit systems, however the acceptance and use of AI technologies in auditing are still limited, especially in Vietnam. Furthermore, few studies have explored the predictors of AI adoption in auditing in Vietnam. To address this research gap, this study proposes a conceptual research model developed by incorporating individual-level predictors (derived from the UTAUT model and status quo bias theory) and firm-level predictors (derived from the TOE framework) of technology acceptance and use. The factors affecting auditors' intention to adopt AI include technological compatibility, training, competitive pressure, performance expectancy, effort expectancy, switching costs, colleague opinion, and facilitating conditions.

An online survey was conducted at audit firms based in Vietnam, including Big 4, non-Big, and local firms. 150 valid responses were collected and used to test all hypotheses. Results of the PLS-SEM analysis show that competitive pressure, performance expectancy, effort expectancy, colleague opinion, and facilitating conditions positively influence auditors' AI adoption intention. On the other hand, switching costs are found to discourage AI adoption intention. It is also confirmed that technological compatibility and training both have positive effects on performance expectancy and effort expectancy. The data also supports the indirect positive effects of technological compatibility and training on AI adoption intention, which are mediated by performance expectancy and effort expectancy.

Key words: artificial intelligence (AI), adoption intention, auditing

## LIST OF ABBREVIATIONS

AI	Artificial intelligence
BI	Behavioural intention
CAAT	Computer assisted audit technique
CO	Colleague opinion
CP	Competitive pressure
EE	Effort expectancy
FC	Facilitating conditions
ICT	Information and Communications Technology
IS	Information system
PE	Performance expectancy
PEU	Perceived ease of use
PLS	Partial least square
PU	Perceived usefulness
SC	Switching costs
SEM	Structural equation modelling
TC	Technological compatibility
TR	Training

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## CHAPTER 1. INTRODUCTION

### 1.1. *Background of the study*

Artificial intelligence (AI) is an emerging technology that has been gradually integrated into auditing practices. However, auditors have yet to take advantage of this tool fully. According to Dennis (2024), AI can significantly improve audit quality because it enables auditors to perform analysis on full datasets. AI also facilitates journal entry testing at an early stage of the audit to identify high-risk areas. Despite the benefits of AI in audit, AI adoption has not become prevalent among audit firms because of the lack of training and technological infrastructure, high implementation costs, and distrust of AI's usefulness. (Dennis, 2024). So far, AI can offer human support, repetitive task automation, and context awareness and learning to support accounting and auditing tasks (Kokina and Davenport, 2017). According to Baldwin et al. (2006), AI applications can be used in auditing tasks such as analytical review procedures, classification, materiality assessment, risk assessment, and going concern assumption assessment (Baldwin *et al.*, 2006).

According to KPMG Ireland (2024), AI has significantly affected companies' operations, including their systems, processes, controls, and governance over financial reporting. On a global scale, audit firms have also enjoyed improved analytical capabilities and insights offered by AI. Up to 64% of the surveyed companies require auditors to assess their use of AI in financial reporting and give assurance over their AI controls (KPMG Ireland, 2024). Therefore, it is urgent and essential for audit firms to adopt AI to meet this new market demand.

Overall, AI adoption appears to be more common among large firms. Big 4 accounting firms reported that they were planning to adopt AI in audit planning, risk assessment, testing, analytical procedures, and preparing work papers to save time, improve accuracy, and provide better client service (Munoko *et al.*, 2020). All Big 4 audit firms have developed their own AI-powered audit tools. For example, KPMG has adopted KPMG Clara, which is a cloud-based audit platform allowing the firm to apply various checks on each transition to detect anomalies more effectively (KPMG, 2023). In contrast, small and medium-sized audit firms are reluctant to adopt AI because of inadequate training and infrastructure, high costs, and perceived difficulties in using (Dennis and Jenkins, 2024). According to ICAEW (2023),

although small audit firms have yet to set up fully automated processes, they can still use AI for risk assessment, planning, and sampling (ICAEW, 2023).

Currently, researchers have yet to explore predictors of AI adoption. According to Hasan (2021), previous studies on AI have only examined its conceptualisation and potential effects. Research on AI implementation has only been conducted in several industries and mostly in developed countries (Hasan, 2021). Therefore, little is known about AI adoption in the field of auditing and its predictors.

## **1.2. Problem statement**

Audit firms' adoption of AI is still at an elementary level. According to Gotthardt et al. (2020), companies that have matured in adopting AI only account for 5%. This indicates that companies are far from reaping all the benefits of this new technology. Considering the fast pace of technological advances, companies should quickly gain expertise in this field (Gotthardt *et al.*, 2020). As companies are adopting AI-powered accounting systems, audit firms need to integrate AI into their audit procedures to maintain their competitive advantage and audit quality. Dennis and Jenkins (2024) found that auditors' resistance to change is the primary obstacle to successful AI implementation. Overall, auditors reported to have inadequate training to use the system. Additionally, auditors view AI as costly and difficult to use (Dennis and Jenkins, 2024).

According to PwC (2023), 64% of executives in Vietnam have no plans to invest in artificial intelligence in the next three years (PwC, 2023). This indicates that the adoption level in Vietnam is still low. In the audit field, so far, only the Big 4 audit firms can integrate AI into their audit procedures. Local audit firms appear to lag behind in adopting this new technology because of their limited financial resource and technological readiness. Furthermore, there is a lack of empirical research on the adoption of AI in Vietnam (Tran and Hoang, 2021). According to Albawwat and Frijat (2021), previous studies have mixed results on auditors' perceptions of applying artificial intelligence in audit engagements. While audit firms have been investing more in AI applications, it is unclear how auditors would accept this technological change (Albawwat and Frijat, 2021). Therefore, factors affecting auditors' adoption of AI have not been clearly understood.

### **1.3. Research question and objectives**

Considering the research problem, this paper will answer the following question: **What are the predictors of auditors' intention to adopt AI in Vietnam?**

To answer this research question, the following objectives will be accomplished in this study:

RO1. To construct a critical examination of literature concerning factors affecting auditors' adoption of AI in auditing in Vietnam.

RO2. To critically examine the relationship between technological compatibility, training, performance expectancy, effort expectancy, switching costs, colleague opinion, facilitating conditions, competitive pressure, and behavioural intention to use AI using structural equation modelling analysis.

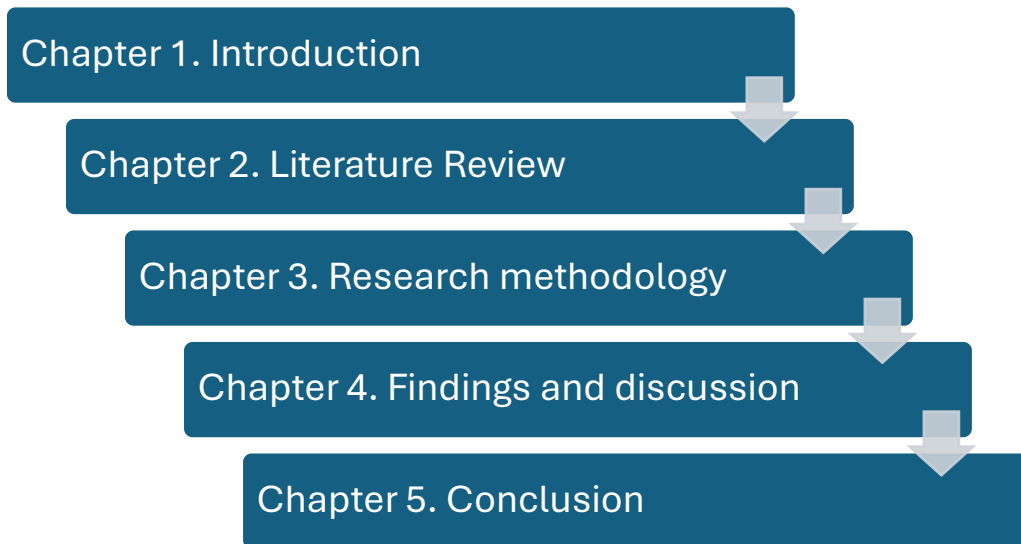
RO3. To interpret the analysis results and identify predictors of auditors' adoption of AI in auditing in Vietnam.

### **1.4. Research Significance**

This study will explore predictors of auditors' intention to adopt AI in auditing in Vietnam. For researchers, this study will contribute to the growing body of literature in technology acceptance and use. Regarding the literature gap in research on AI adoption intention, this research will provide more empirical evidence on predictors of auditors' AI adoption intention in Vietnam. With this knowledge, audit firms in Vietnam can implement AI technologies more effectively to improve their productivity and audit quality. Auditors are the end-users of AI applications, thus it is important to encourage their acceptance and use of the technology to ensure successful implementation. Even if the use AI applications is mandatory, auditors can still resist the change by mis-using or under-using the technology. Hence, by understanding the factors encouraging and discouraging auditors' intention to use AI, audit firms can manage the transition to AI-powered audit systems more smoothly, thus securing their competitive advantage.

### **1.5. Structure of the study**

This research paper consists of five chapters as outlined in the below figure.



*Figure 1. Structure of the study*

Chapter 1 will introduce the research topic by providing the research background, problem statement, research questions and objectives, research significance, and the study's structure.

Chapter 2 is a literature review comprising conceptual literature and empirical and contextual literature.

Chapter 3 will provide the research model built from the literature review. The development of research hypotheses is also discussed. Additionally, this chapter will give an overview of the research methodology, including research strategy, data collection, data analysis method, and ethical considerations.

Chapter 4 will provide findings of the quantitative analysis. This includes a descriptive analysis, reliability and validity test, and path analysis using the Smart PLS 3.0 software to test the hypotheses. A critical discussion of the findings will also be included in this chapter.

Chapter 5 will provide recommendations for audit firms to promote AI adoption. Research limitations, contributions, and suggestions for future research will be discussed.

## CHAPTER 2. LITERATURE REVIEW

### 2.1. Introduction

This chapter consists of three main parts: conceptual literature, empirical literature, and research gap. Technology acceptance models and the status quo bias theory will be critically discussed to construct the conceptual framework. Previous empirical studies on factors affecting AI adoption will also be examined to obtain an overview of the research landscape in this domain. These findings will be used to identify the research gap, which would be addressed in this study.

### 2.2. Conceptual literature

According to Joshi (2005), upon the implementation of a new information system (IS), users can either accept or resist it depending on their assessment of changes coming from the system (Joshi, 2005). It should be noted that user acceptance does not suggest the absence of user resistance. If the new IS implementation is compulsory, users may still resist the change through underutilisation (Nah *et al.*, 2004). Hence, this part will critically examine various existing technology acceptance theories and models alongside the status quo bias theory (which explains user resistance) to build a conceptual framework for this study.

#### 2.2.1. Technology acceptance theories and models

##### 2.2.1.1. Theory of Planned Behaviour (TPB)

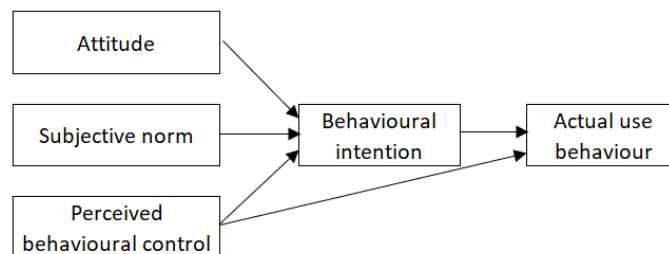


Figure 2. Ajzen's (1991) TPB model

Ajzen (1991) theorised that people will have the behavioural intention to perform a task when: (1) they deem the behaviour positive (attitude), (2) they think others encourage the behaviour (subjective norm), and (3) they believe that there are facilitating conditions supporting their performance (Ajzen, 1991). In other words, this theory proposes that an

individual's acceptance of technology is determined by *behavioural beliefs* about the behaviour's potential results and assessment of such results, *normative beliefs* about others' expectations and the inclination to meet those expectations, and *control beliefs* about the factors affecting behaviour performance (Ajzen, 2002).

A large body of literature have confirmed the strong correlation between behavioural intention and actual use behaviour, which aligns with the TPB model. This has created a strong foundation for later studies, models, and theories on technology acceptance to rely on. Planned behavioural control (control beliefs) has also been found to consistently lead to behaviour (McEachan *et al.*, 2011). However, the model only focuses on rational reasoning and fails to include unconscious influences on behaviour (Sheeran *et al.*, 2013) as well as the emotional aspect of decision-making (Conner *et al.*, 2013).

### 2.2.1.2. Technology Acceptance Model (TAM)

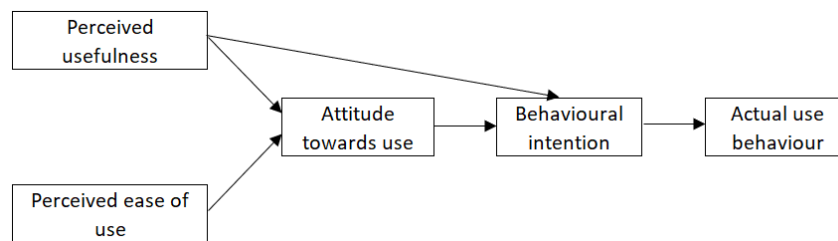


Figure 3. TAM model (Davis, 1989).

Among an array of models of acceptance and usage of technology by users, Davis' (1989) TAM model is the most widely adopted one. This model is considered to have effectively contributed to Ajzen's (1991) theory of planned behaviour by specifying two determinants of users' attitude towards use (Aljarrah *et al.*, 2016). The model proposes that how an individual perceives a technology's usefulness and ease of use predicts his/ her attitude towards using the technology, which determines the intention to use that technology and actual use behaviour. According to Liu *et al.* (2015), the TAM model has been widely adopted in information systems research to investigate barriers to companies' implementation of new information systems (Liu *et al.*, 2015). However, Davis' (1989) TAM model excludes subjective norms and perceived behavioural control. Therefore, the TPB model is considered more comprehensive.

### 2.2.1.3. Unified Theory of Acceptance and Use of Technology (UTAUT)

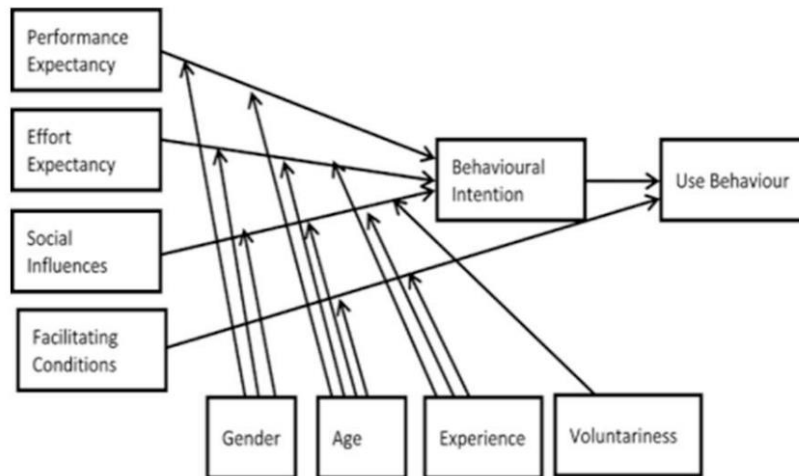


Figure 4. Venkatesh et al.'s (2003) UTAUT model.

The UTAUT model developed by Venkatesh et al. (2003) offers a more comprehensive framework, incorporating the TPB and TAM models. The UTAUT model identifies four predictors of users' intention to use new technology: performance expectancy, effort expectancy, social influences, and facilitating conditions. Performance expectancy and effort expectancy correspond to the TAM model's perceived usefulness (PU) and perceived ease of use (PEU) constructs respectively. Social influences align with the TPB model's subjective norms while facilitating conditions correspond to its planned behaviour control construct. Therefore, the UTAUT model can be viewed as a comprehensive framework integrating the constructs of previous models.

According to Venkatesh (2022), the UTAUT model has been employed to investigate the full spectrum of technology adoption from pre- to post-adoption on an individual level. Performance expectancy is defined as an individual's level of belief in a technology's ability to improve their job performance. Effort expectancy refers to an individual's perception of how easy it is to utilise a technology. Social influence refers to an individual's perception of others' encouragement of technology adoption. Facilitating conditions are defined as an individual's perception of the availability of organisational and technical infrastructure to support the adoption (Venkatesh, 2022).

#### 2.2.1.4. *TOE framework*

The TOE framework developed by Tornatzky and Fleischer (1990) outlines three aspects of the organisational context that shape how a company adopts a new technology: technological context, organisational context, and environmental context. Technological context includes both internal technological capabilities and external technologies available to a company. Organisational context is measurable by organisational scope, size, and structure. Lastly, environmental context refers to the environment in which business operations are conducted (e.g. industry, competitors, and regulations) (Tornatzky *et al.*, 1990). According to Oliveira and Martins (2011), the TOE framework has a solid theoretical foundation. There are many empirical studies on the information system innovation domain supporting this framework. TOE has been widely adopted to investigate predictors of firm-level technology adoption (Oliveira and Martins, 2011).

#### 2.2.1.5. *A critical assessment of technology acceptance theories and models*

Many researchers argue that technology acceptance models such as TPB, TAM, and UTAUT are unsuitable for examining technology acceptance predictors in an organisational context because company rules and policies dictate employees' attitudes and intentions to utilise new technology (Ajibade, 2018). However, this argument is flawed because employees can still resist the technology through underutilisation and/ or misuse despite the company's pressure. Furthermore, the success of new technology's implementation is greatly determined by employees – the technology users. Therefore, it is still important to examine technology acceptance predictors on an individual level, which is supported by the TAM and UTAUT models.

According to Rejali *et al.* (2023), the TAM and UTAUT models only examine the technology's capabilities as predictors of user acceptance while the TPB model focuses more on the cognitive and psychological factors of the technology (Rejali *et al.*, 2023). Radhakrishnan and Chattopadhyay (2020) argue that the TOE framework and UTAUT model are the dominant theories in AI adoption research. However, the TOE framework is commonly utilised on an organisational adoption level while the UTAUT model is utilised on an individual adoption level (Radhakrishnan and Chattopadhyay, 2020).

### **2.2.2. User resistance: status quo bias theory**

User resistance in IS research is defined as an adverse reaction (Hirschheim and Newman, 1988) or users' opposition to changes coming from a new IS implementation (Markus, 1983). According to Ali (2016), in any new IT implementation, user resistance is a leading concern. Therefore, it is important for companies to understand user resistance to carry out the implementation process successfully and benefit from it (Ali *et al.*, 2016).

Samuelson and Zeckhauser (1988) developed the status quo bias theory to explain user resistance. The theory proposes three constructs: rational decision-making, cognitive misperceptions, and psychological commitment predicting people's preference for maintaining their current situation. First, rational decision-making is the process of assessing net benefits before making a change. Transition costs and uncertainty costs are also weighted in this process. Transition costs arise from adapting to the new situation while uncertainty costs come from perceived risks associated with the change. Second, cognitive misperception of loss aversion, which also leads to status quo bias refers to users' mistaken belief of weighting losses more than gains of an equivalent size (Samuelson and Zeckhauser, 1988). Third, psychological commitment comprises sunk cost, social norms, and efforts to feel in control. Sunk costs arise when a change makes previous commitments redundant. Social norms (e.g. colleague opinions) refer to the norms about the change that can influence an individual's status quo bias. Efforts to feel in control refer to an individual's desires to deciding their own situation (Kim and Kankanhalli, 2009).

Table 1. Comparison between status quo bias theory and UTAUT (Author, 2024)

Status quo bias theory's constructs	Compared with UTAUT
Rational decision-making	The UTAUT model does not include perceived costs.
Cognitive misperception of loss aversion	
Psychological commitment	<p>Sunk costs are not covered in the UTAUT model.</p> <p>Social norms correspond with UTAUT's social influence construct (and also TPB's subjective norm) (Kim and Kankanhalli, 2009).</p> <p>Control corresponds with UTAUT's facilitating conditions construct (and also TPB's perceived behavioural control) (Kim and Kankanhalli, 2009).</p>

As aforementioned (in section 2.2.1.5), this study will integrate the two dominant theories in technology acceptance research: UTAUT and TOE to develop a more comprehensive research model. The status quo bias theory is relevant to this study because user resistance can still happen in the presence of acceptance and companies' implementation decision. Evidently, the status quo bias theory is applicable on an individual level, thus its constructs are compatible with UTAUT's. *Table 1* comparing the two theories shows that the UTAUT model excludes costs associated with adapting to a new situation.

According to Kim and Kankanhalli (2009, p.573), switching costs are "*the perceived utility a user would enjoy in switching from the status quo to the new IS*". They can positively affect user resistance. In other words, the higher the switching costs are, the more likely it will be for an individual to stay in their current status or position (Kim and Kankanhalli, 2009). This suggests that switching costs would discourage people from adopting new technology. Consequently, the conceptual framework of this study will include switching costs as a predictor of auditors' intention to use AI.

### 2.2.3. Conceptual framework

#### Justifications for the conceptual framework

Firm-level predictors of technology acceptance can significantly influence employees' adoption intention because the implementation process can be forced upon them. However, the implementation success is greatly determined by individual-level predictors of employees' technology acceptance and use. This is because employees are the end users and they can resist change (Strebel, 2009). However, examining individual-level predictors alone is inadequate as employees' intention to adopt AI can be influenced by external firm-level factors. Therefore, this study's conceptual framework will employ both the UTAUT model and the TOE framework to gain a comprehensive understanding of AI adoption predictors.

Among the individual-level technology acceptance theories and models, the UTAUT model proposed by Venkatesh et al. (2003) offers the most comprehensive framework, encompassing all constructs proposed by previous models. Therefore, this study will primarily rely on UTAUT to develop the conceptual framework. The TOE framework will also be integrated into the research model because it has been widely adopted in technology adoption studies and supported by empirical results. Many researchers also support the use of this framework to examine the predictors of AI adoption because it has been successfully applied in different socioenvironmental contexts with a focus on technological issues (Yang et al., 2015; Chatterjee et al., 2021).

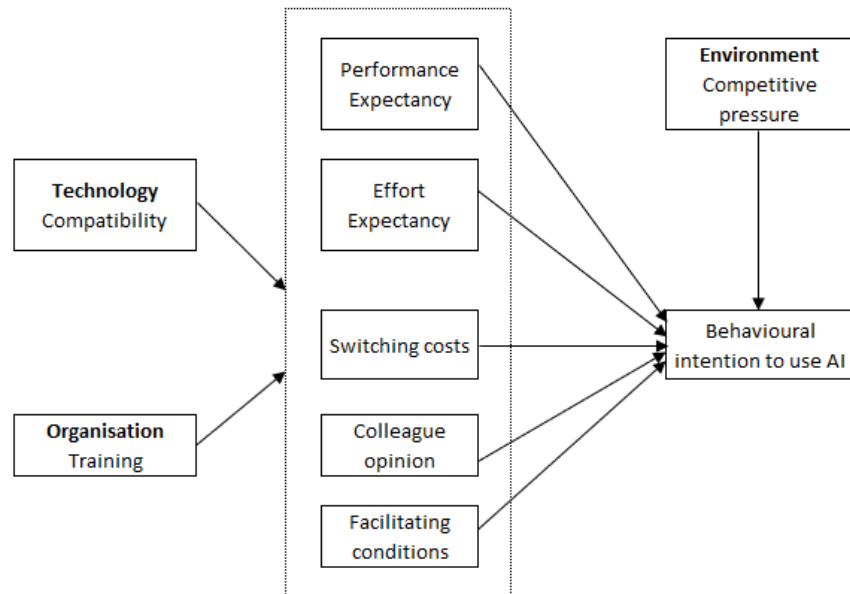


Figure 5. Conceptual framework (Author, 2024)

*Figure 5* illustrates this study's conceptual framework, which integrates the UTAUT model, TOE framework, and the status quo bias theory. Switching costs are adapted from the status quo bias theory and added to the conceptual framework because the original UTAUT model has not examined costs associated with changing to a new system. Additionally, this study's conceptual framework adds compatibility, training, and competitive pressure as the three new constructs derived from the TOE framework to investigate how firm-level factors affect individual-level factors of AI adoption.

## Definition of constructs

Table 2. Definition of constructs (Author, 2024)

Constructs	Definition
Performance expectancy	Performance expectancy is the degree to which an individual perceives a technology's ability to help him/ her improve his/ her job performance (Venkatesh <i>et al.</i> , 2003).
Effort expectancy	Effort expectancy is the degree to which an individual perceives a technology's ease of use (Venkatesh <i>et al.</i> , 2003).
Switching costs	Switching costs refer to the adverse effects arising from switching. They comprise transition costs, uncertainty costs, and sunk costs (Kim and Kankanhalli, 2009).
Colleague opinion	Colleague opinion is adapted from UTAUT's Social Influence construct (renamed for more relevance). This refers to an individual's perceptions of colleagues' encouragement to use the technology (Venkatesh <i>et al.</i> , 2003).
Facilitating conditions	Facilitating conditions are "The degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system" (Venkatesh <i>et al.</i> , 2003; p.453).
Compatibility	Compatibility refers to the degree to which a technology is perceived as consistent with an organisation's/ individual's values, operations, and experiences (Peng <i>et al.</i> , 2012).
Training	Training the degree to which a company offers guidance to its employees in utilising a technology in terms of quality and quantity (Schillewaert <i>et al.</i> , 2005).
Competitive pressure	Competitive pressure is a company's perceived level of pressure coming from competitors in the industry (Zhu and Kraemer, 2005).
Behavioural intention	Behavioural intention is the immediate antecedent to behaviour; "a function of salient information or beliefs about the likelihood that performing a particular behaviour will lead to a specific outcome" (Madden <i>et al.</i> , 1992; p.3).

### **2.3. The role of artificial intelligence technology in auditing**

Duan et al. (2019, p.63) define AI as “the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks” (Duan *et al.*, 2019). Many researchers agree that AI can significantly improve auditors’ work by automating risk assessments, 100% population testing, enhancing judgements on audits, reducing human errors and bias, supporting continuous auditing, and monitoring data patterns. Consequently, Big 4 audit firms have been developing and implementing different AI tools to become more competitive (Seethamraju and Hecimovic, 2023).

According to Issa et al. (2016), public accounting firms have been increasing their investments in deep learning. Each Big 4 accounting firm has successfully developed their own AI-powered audit system to make the audit process “smarter, more insightful, and more efficient”. For example, PwC possesses AI tools such as DeNovo to assess the disruptive potential and future use of financial technologies and GL.ai, which is an anomaly detector for general ledger (Issa *et al.*, 2016). KPMG has implemented Clara, which is an AI-powered audit platform using data analytics and machine learning to examine information and compare it with assumptions to identify risks (Seethamraju and Hecimovic, 2023).

Currently, both Big 4 and non-Big audit firms have been extensively utilised AI in auditing to improve audit quality and productivity. It is reported that audit firms are under the pressure of employing state-of-the-art technologies like AI from clients. Anomaly detection and fraud prevention are found to be the main functions of AI in audit. More specifically, machine learning is applied in conducting pattern analysis, matching orders with invoices, mapping receivables with cash receipts, assessing financial risks, preventing money laundering, analysing big data for benchmarking. Interestingly, audit engagements of clients in sectors with many small repeat transactions such as retail benefit from this technology the most (Fedyk *et al.*, 2022).

There are a large body of literature advocating the use of AI in auditing and affirming its benefits in the field. However, most of the studies on AI were conducted in developed countries whose technological capabilities are much more advanced than developing countries such as Vietnam. In fact, only 6% of Vietnamese companies are investing in AI and automation, which is in stark contrast to the US where over a quarter of the companies are adopting AI (Nguyen *et al.*, 2022). Upon investigating digital transformation in Vietnam,

Nguyen et al. (2024) found that local Vietnamese audit firms are lagging behind in adopting new technologies compared to global Big 4 and non-Big firms. Nonetheless, the researchers advocate the use of AI in auditing in Vietnam, affirming that auditors can still benefit from the technology regardless of firm size. Interestingly, while the technology cannot completely replace auditors, it will create new roles for auditors such as consulting and analysing data for decision-making (Nguyen *et al.*, 2024).

## **2.4. Factors affecting auditors' adoption of AI**

### **2.4.1. Technological compatibility**

A large body of literature confirm that technological compatibility is an important factor affecting companies' adoption decisions of new technologies (Baig *et al.*, 2019). Not only should the technology support business needs, but it should also be compatible with the existing IT infrastructure. Technological compatibility is considered one of the most important antecedents in predicting adoption of technological innovations (Sun *et al.*, 2018). This argument is supported by Verma and Bhattacharyya's (2017) research, which reveals that technological compatibility is the primary reason causing non-adoption of big data analytics among Indian companies (Verma and Bhattacharyya, 2017). Given that India and Vietnam are both emerging economies, their findings may suggest that compatibility is also a significant predictor of AI adoption in Vietnam.

An empirical study on determinants of AI adoption in Vietnam conducted by Nguyen et al. (2022) reveals that technological compatibility encourages companies to adopt AI. The higher the level of compatibility is, the greater the adoption success will be. This is because AI, particularly machine learning needs a lot of data. If the AI applications are compatible with existing IT infrastructure, the installation process will be less costly and time-consuming. Consequently, this would encourage companies to adopt AI more (Nguyen *et al.*, 2022).

### **2.4.2. Training**

According to Cubric (2020), training is crucial for promoting AI adoption in the business and management context. Training can help employees cooperate with robots more effectively by eradicating the misconception of robots being competitors instead of helpers (Cubric, 2020). Similarly, Lee et al. (2022) agree that education and training are the keys to successful AI implementation. Currently, there is a shortage of the supply for technical

workers with AI capabilities. Furthermore, such workers are sought after by large companies at a high premium. As a result, smaller companies are lagging behind in AI adoption and commercialisation. The primary solution to this is to train existing staff on AI knowledge and skills (Lee *et al.*, 2022).

An empirical study conducted by Gangwar *et al.* (2015) confirms that training encourages adoption intention of cloud computing through improving users' perceptions of the technology's usefulness and ease of use. Training helps employees understand the functional and technical aspects of new technologies and gain first-hand information and experience (Gangwar *et al.*, 2015).

### **2.4.3. Competitive pressure**

Many researchers agree that competitive pressure encourages companies to utilise technological innovation. According to Vu *et al.* (2022), the level of competition in the assurance services market positively correlates with the potential of adopting AI. In other words, when the competitive pressure is high, audit firms are more likely to employ AI technologies in their auditing practices. Due to globalisation and Vietnam's participation in free trade agreements, the domestic market is expected to become more competitive. With such increasing levels of competition in the domestic market, local audit firms may be more encouraged to adopt the technology to improve their competitive advantage (Vu *et al.*, 2022).

However, in the same country of study, Nguyen *et al.* (2022) rejected the impacts of competitive pressure on companies' intention to adopt digital transformation in the retail sector (Nguyen *et al.*, 2022). Similarly, Maroufkhani *et al.* (2022) also found that competitive pressure did not affect small and medium-sized enterprises' intention to adopt big data analytics (Maroufkhani *et al.*, 2022). This suggests that the impacts of competitive pressure on companies' adoption intention of new technologies may vary depending on market characteristics, the technology itself, and company size. Additionally, the sample size can also affect findings of these studies. Hence, it is important to examine the effects of competitive pressure on auditors' adoption intention of AI in Vietnam.

#### **2.4.4. Performance expectancy**

In an empirical study conducted by Anh et al. (2024), the modified TAM model was employed to investigate the impact of technology readiness on AI adoption in accounting and auditing in Vietnam. Their findings show that perceived usefulness positively affects AI adoption (Anh et al., 2024). This suggests that as accountants and auditors acknowledge the benefits of AI in improving their professional performance more, they will be more likely to utilise the technology. Vu et al. (2022) also agree that when managers understand AI applications and their potential contributions to improving audit quality and efficiency, audit firms will be more willing to adopt the technology. However, the application level of AI in auditing in Vietnam is still elementary. Additionally, audit managers have not acknowledged the significance of AI in auditing. Thus most local firms have not invested in AI applications in auditing (Vu et al., 2022).

#### **2.4.5. Effort expectancy**

There are many empirical studies advocating the positive effects of effort expectancy (or in other words, perceived ease of use) on behavioural intention to adopt a new technology. Balakrishnan et al. (2024) found that perceived ease of use improved individuals' attitudes towards AI-powered voice assistants, which ultimately encouraged adoption intention (Balakrishnan et al., 2024). In a study conducted by Pedrosa et al. (2020) on CAATs (Computer Assisted Auditing Tools), it is revealed that effort expectancy is one of the most significant predictors of auditors' intention to adopt CAATs (Pedrosa et al., 2020). In the context of Vietnam, previous empirical studies have also shown that people are more likely to utilise AI if they deem it easy to use. This finding is also consistent in the field of accounting and audit (Anh et al., 2024).

#### **2.4.6. Switching costs**

Prior research has examined the effects of switching costs on adoption intention and confirmed that switching costs discouraged companies and/ or individuals to adopt new technologies. Switching costs are the combination of transition costs, uncertainty costs, and sunk costs (Kim and Kankanhalli, 2009). Upon investigating the effects of switching costs on technology acceptance, Polites and Karahanna (2012) found that rationalisation coming from perceived transition costs and psychological commitment coming from perceived sunk

costs contribute to inertia, which mediates the effects of these variables on the acceptance of new technologies (Polites and Karahanna, 2012). This suggests that switching costs discourage people's intention to adopt new technologies. Balakrishnan et al. (2024) explored predictors of AI-powered voice assistants and found that switching costs have negative impacts on adoption intention (Balakrishnan *et al.*, 2024). Their empirical findings are consistent with Kim and Kankanhalli's (2009) argument. Similarly, Ghazali et al. (2016) argue that AI transition may give a rise to substantial switching costs, which discourage technology acceptance (Ghazali *et al.*, 2016). Although there are theoretical evidence backing the negative effects of switching costs on adoption intention, there is a lack of empirical evidence on this relationship in the context of AI adoption.

#### **2.4.7. Colleague opinion**

Colleague opinion represents the social influence construct in the UTAUT model proposed by Venkatesh et al. (2003). This construct has been utilised to examine technology acceptance and use in organisational settings in many studies (Hausman and Stock, 2003). There is substantial evidence that this factor encourages people's intention to adopt new technologies such as blog usage (Hsu and Lin, 2008), CAATs (Meiryani *et al.*, 2022), and big data analytics (Cabrera-Sánchez and Villarejo-Ramos, 2020). However, empirical evidence on the relationship between colleague opinion and adoption intention is mixed when it comes to accounting and auditing technologies. For example, Meiryani et al. (2022) argue that social influence does not significantly affect the adoption intention of CAATs (Meiryani *et al.*, 2022). However, Jain et al. (2022) found that social influence greatly encouraged the adoption and use of AI-powered tools in India (Jain *et al.*, 2022).

Kulviwat et al. (2009) explain that the effects of social influence on adoption intention will be much stronger when a technological innovation is publicly consumed instead of privately consumed (Kulviwat *et al.*, 2009). Furthermore, this construct is found to be less potent in voluntary context but more significant in mandatory settings (Mahzan and Lymer, 2014). This suggests that when the use of an AI-powered audit system is mandatory, colleague opinion (or social influence) will have a significant impact on auditors' intention to adopt the system.

#### **2.4.8. Facilitating conditions**

Many studies have found that facilitating conditions encourage people's adoption of new technologies. Venkatesh et al. (2003) explain that facilitating conditions comprise IT infrastructure and top management support that help employees adopt the new technologies (Venkatesh *et al.*, 2003). Pedrosa et al.'s (2020) empirical study reveals that facilitating conditions have significant positive impacts on CAATs adoption and use among auditors (Pedrosa *et al.*, 2020). Horani et al. (2023) found that top management support had positive effects on AI adoption on an organisational level. Additionally, existing IT infrastructure was found to be the key to successful AI adoption (Horani *et al.*, 2023). Similarly, Pumplun et al. (2019) agree that business applications, processes, and IT infrastructure should be compatible with AI applications to encourage adoption (Pumplun *et al.*, 2019). A broad array of studies also confirm that top management support can predict AI adoption because it allocates resources for AI adoption and helps employees adapt to the new system more effectively (Chen *et al.*, 2020). Interestingly, prior studies have confirmed the relationship between facilitating conditions and AI adoption, however, few studies have explored this correlation in the context of auditing.

#### **2.5. Research gap**

First of all, prior studies on determinants of AI adoption are conducted on an organisational level rather than on an individual level. Hence, previous studies mostly adopt the TOE framework or an integrated TAM-TOE model (Gangwar *et al.*, 2015; Chatterjee *et al.*, 2021). Prior research has yet to fully explore antecedents of AI adoption on an individual level, thus the UTAUT model and status quo bias theory have not been examined in the context of AI adoption.

Second, adopting artificial intelligence in auditing is relatively new. Hence, only a handful of studies have investigated determinants of AI adopting in auditing. Hasan (2021) argues that current studies on AI have only focused on its conceptualisation and potential impacts. There is a lack of research on AI implementation in specific industries and countries. Furthermore, factors affecting AI implementation have not been investigated at all (Hasan, 2021). Furthermore, depending on the technology and industry, factors identified in previous theoretical models will have different impacts on adoption intention. Therefore, findings of predictors of one particular technology's adoption intention may not be applicable for another

technology's. In short, factors affecting AI adoption intention deserve more attention and examination.

Third, most studies on the adoption of AI were conducted in developed countries with a focus on Big 4 audit firms (Nguyen *et al.*, 2022; Mihai and Dutescu, 2024). Little is known about the determinants of AI adoption in the audit sector in Vietnam. Given that Vietnam is an emerging economy whose business culture and national culture are vastly different from that of Western (and/ or developed) countries, it is reasonable to assume that Vietnamese auditors would respond differently to utilising AI in auditing. Hence, findings of previous studies may not be applicable in Vietnam. Furthermore, previous studies may lack generalisability due to their focus on Big 4 firms, which are much larger and more complex than local firms.

## **2.6. Summary**

To summarise, this chapter has examined long-standing theories and models of technology acceptance and user resistance to produce the conceptual framework. This study's research model is developed by integrating the TOE framework into the UTAUT model. This modified model examines both firm-level and individual-level factors affecting AI adoption, thus successfully compensating for the flaws of each standalone model. Furthermore, switching costs derived from the status quo bias theory are added to the research model.

Regarding the empirical and contextual literature, it is found that AI plays a vital role in improving auditors' productivity and audit quality. The literature review identifies three main gaps that will be addressed in this research. First, previous studies have not examined factors affecting AI adoption on an individual level. There is also a lack of a comprehensive research model encompassing both firm-level and individual-level determinants. Second, researchers have not explored predictors of AI adoption in the context of auditing. Lastly, only a handful of studies have examined AI adoption in developing countries such as Vietnam with an inclusive focus on all audit firms regardless of size.

## **CHAPTER 3. RESEARCH METHODOLOGY**

### **3.1. Introduction**

This chapter provides the research design for this study including the research paradigm, method, and model. The hypotheses, which detail how the predictors affect auditors' AI adoption intention are developed based on the conceptual framework developed in the previous chapter. An online survey will be conducted to collect the data for hypotheses testing. The sampling method, questionnaire design, and ethical issues are also discussed in this chapter.

### **3.2. Research design**

#### **3.2.1. Research paradigm**

This research employs the positivism paradigm. According to Park et al. (2020), positivism takes a hypothetico-deductive approach to test hypotheses, typically using the quantitative method (however this may not always be the case). This paradigm involves establishing functional relationships between variables that cause the examined phenomena (independent variables) and the outcomes or impacts (dependent variables). This research paradigm relies on ontology, epistemology, axiology (Park *et al.*, 2020). The positivism paradigm relies on deductive reasoning in which the conclusion's validity depends on the accuracy of its premises (Petherick and Turvey, 2023).

This research paradigm is suitable for this study because it will help identify and test the relationship between antecedents of auditors' AI adoption (independent variables) and AI adoption intention (dependent variable). Factors affecting auditors' intention to adopt AI in Vietnam represent an objective reality that is measurable and examinable. Thus, to answer this study's research questions, hypotheses testing must be conducted. This is supported by the positivism paradigm.

#### **3.2.2. Research method**

This study adopts the quantitative method. This method works under the positivism paradigm, which enables the examination of cause-and-effect relationships and hypothesis testing (Maksimović and Evtimov, 2023). This method is the most effective in studying large groups of people and generalising findings from the study sample to the broader population.

The flow of a quantitative study commences with identifying the research question, then determining the population and sample, identifying the variables and their measurement scales, selecting analysis tools, and interpreting the results (Swanson and Holton, 2005).

The aim of this study is to identify factors affecting auditors' intention to adopt AI in auditing. This will be done by testing hypotheses on the relationship between the hypothesized predictors and AI adoption intention. Therefore, the quantitative method is the best fit for this research. Thanks to this method, findings of this study can be generalised to the larger population of auditors in Vietnam or in similar cultures and business settings. Additionally, this study's findings may be also applicable for other similar emerging technologies.

### 3.2.3. Research model and hypotheses

Based on the conceptual framework developed from the literature review, the research model is constructed as below.

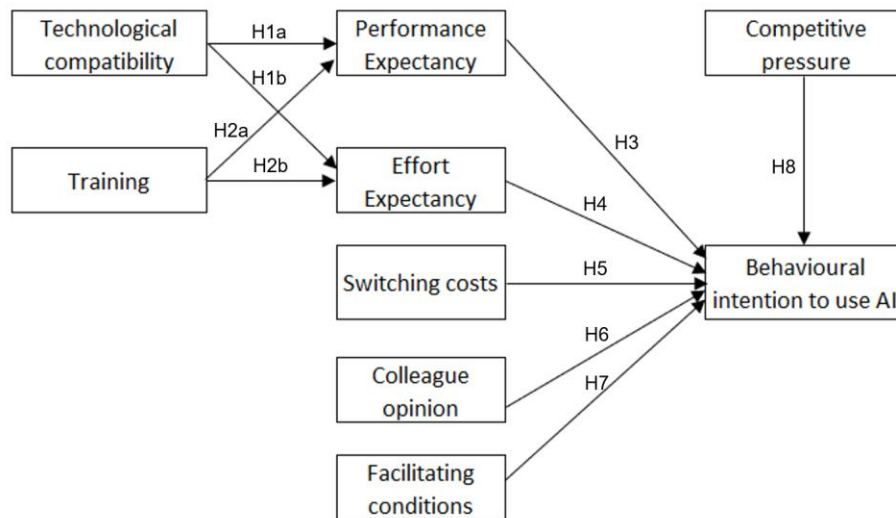


Figure 6. Research model (Author, 2024)

According to Lin and Chen (2012), technological innovations should be compatible with company policy, IT infrastructure, and business needs to ensure successful implementation and use (Lin and Chen, 2012). Calisir et al. (2009) explain compatibility as a technology's perceived level of consistency with users' existing values, experiences, and requirements (Calisir et al., 2009). Successful adoption of an innovation greatly depends on how the

technology aligns with the company's current strategy. Thus, it is deduced that greater compatibility leads to faster adoption rates (Hubert *et al.*, 2018).

A large body of literature support the connection between compatibility and performance expectancy and effort expectancy. Studies on technology acceptance have also shown that compatibility has significant effects of perceived usefulness and perceived ease of use (Chen and Tan, 2004; Peng *et al.*, 2012). This suggests that if AI applications are compatible with the current IT infrastructure, audit firms will be able to leverage the technology more easily. This will encourage AI adoption because auditors can understand and use the system more effectively. Hence, the following hypotheses are proposed.

*H1a: Technological compatibility has a positive effect on performance expectancy.*

*H1b: Technological compatibility has a positive effect on effort expectancy.*

According to Gangwar *et al.* (2015), training is important in ensuring successful implementation of a new technology. Their study examined antecedents of adoption intention of cloud computing and found that training positively influenced employees' perceived usefulness and perceived ease of use (Gangwar *et al.*, 2015). Karahanna and Straub (1999) also agree that training and support for end-users are important facilitating conditions to encourage technology use. This is because training improves employees' self-efficacy and outcome expectations, which encourage system use. When employees have more experience with the technology, they will acknowledge the system's ease of use more. Similarly, training can raise employees' awareness of the IT and thereby perceived usefulness of the technology in performing tasks (Karahanna and Straub, 1999). Hence, the following hypotheses are put forward.

*H2a: Training has a positive effect on performance expectancy.*

*H2b: Training has a positive effect on effort expectancy.*

Extensive research shows that performance expectancy is a significant predictor of adoption intention. This applies for a vast number of technologies that are applicable in accounting and auditing such as big data (Soon *et al.*, 2016) and CAATs (Mahzan and Lymer, 2014). Jain *et al.* (2022) found that performance expectancy positively affected social development organisations' intention to adopt AI-powered tools in India (Jain *et al.*, 2022). Similarly,

Chatterjee et al. (2021) agree that performance expectancy is linked to using AI-powered systems to enhance performance (Chatterjee *et al.*, 2021). Therefore, the following hypothesis is formulated as below.

*H3: Performance expectancy has a positive effect on behavioural intention to use AI.*

The relationship between effort expectancy (or perceived ease of use) and technology adoption intention is also supported by many empirical studies (Martins *et al.*, 2014). Gangwar et al. (2015) found that perceived ease of use has a significant positive impact on cloud computing adoption. In other words, the easier it is for employees to use the system, the more likely it will be for them to adopt cloud computing (Gangwar *et al.*, 2015). Similarly, Balakrishnan et al. (2024) found that perceived ease of use improved users' attitudes towards AI-powered voice assistants, which ultimately encouraged their adoption intention (Balakrishnan *et al.*, 2024). Although there is a lack of empirical evidence supporting the relationship between effort expectancy and AI adoption intention in auditing, it is reasonable to extend the argument to AI-powered auditing tools. This is because of the well-established theoretical foundation of the correlation between effort expectancy and technology adoption intention in general. Hence, the following hypothesis is proposed.

*H4: Effort expectancy has a positive effect on behavioural intention to use AI.*

A large body of literature have confirmed that switching costs influence people's rational decision-making and psychological commitment. More specifically, the higher the switching costs are, the more likely that individuals will opt to stay in the current position or status (Kim and Kankanhalli, 2009; Polites and Karahanna, 2012). Mikalef et al. (2021) identify switching costs as an economic inertia that inhibits big data analytics adoption. When the costs of investment are considered high and above perceived benefits or value, companies are more reluctant to adopt such technologies (Mikalef *et al.*, 2021). This suggests that switching costs may directly discourage users' intention to accept a new technology such as AI. Therefore, the following hypothesis is proposed.

*H5: Switching costs have a negative effect on behavioural intention to use AI.*

Venkatesh et al. (2003) argue that users' perceptions of an innovation are influenced by their social environment (Venkatesh *et al.*, 2003). In this study, the social environment consists of co-workers and management whose opinions will affect users' adoption intention.

Previous studies show that this factor can affect adoption intention in both mandatory and voluntary settings. Employees may be pressured to adopt a new technology because of the fear of missing out, especially when their co-workers are using the technology (Jain *et al.*, 2022). Therefore, the following hypothesis is put forward.

*H6: Colleague opinion has a positive effect on behavioural intention to use AI.*

Regarding AI adoption and use, Venkatesh (2022) argues that facilitating conditions can encourage employees' intention to use the system (Venkatesh, 2022). Alshahrani *et al.* (2022) argue that IT infrastructure is a crucial element in facilitating AI adoption. These structural environments include hardware, software, and communications (Alshahrani *et al.*, 2022). Similarly, Horani *et al.* (2023) confirm that top management support encourages employees to accept the new system (Horani *et al.*, 2023). Hence, the following hypothesis is formulated as below.

*H7: Facilitating conditions have a positive effect on behavioural intention to use AI.*

Gangwar *et al.* (2015) found that competitive pressure positively affects cloud computing adoption (Gangwar *et al.*, 2015). When adopting a technology is considered a strategic necessity, competition in the market should encourage companies to adopt that new technology (Ramdani *et al.*, 2009). Considering that AI applications are gradually becoming more prevalent among companies in different industries, it is urgent that audit firms adopt this new technology to enhance their audit quality, gain the first-mover advantages, and outperform their competitors. Therefore, the following hypothesis is proposed.

*H8: Competitive pressure has a positive effect on behavioural intention to use AI.*

### **3.3. Sampling and data collection**

Primary data was collected by carrying out an online survey. More specifically, respondents were contacted via work emails to obtain their informed consent to participate in the research. The survey was uploaded onto Google Forms and sent to the respondents by attaching its link in the email.

The target population of this study is auditors working in Vietnam. According to World Bank (2020), there are 159 audit firms in Vietnam, which are inclusive of the Big 4, non-Big firms,

and local firms (World Bank, 2020). Additionally, most companies and audit firms are scattered in Hanoi and Ho Chi Minh City, which are the two largest cities and economic centres in Vietnam. Therefore, this study will mainly target auditors working in these cities. To ensure the study’s generalisability, the survey invitations were sent to audit firms from all sizes: Big 4, Non-Big, and local firms. The participants were also selected from the audit assistant level and above with at least one year of working at the current firm. This would ensure that the participants have adequate understanding of their firm and the technology to assess implementation impacts.

Due to the time constraint and limited access to auditors in certain firms, this study employs the convenience sampling method. More specifically, up to 230 survey invitations were sent to the audit department of different public accounting firms in Vietnam via emails. These invitations were scattered across firms with different sizes including the Big 4 firms, non-Big firms such as Mazars, BDO, Grant Thornton, RSM, and Nexia, and local firms such as AASC and Ocean Auditing.

### **3.4. Questionnaire design**

An online survey is used to collect the data and test all hypotheses. The questionnaire consists of two main parts: demographic questions and questions about factors affecting auditors’ AI adoption intention.

First, the demographic section serves the purpose of obtaining an overview of the participants’ characteristics regarding gender, age, job title, qualifications, and tenure.

The second part of the questionnaire is constructed using the 5-point Likert scale, which is commonly adopted to evaluate participants’ levels of agreement with each statement. In this study, the respondents will be asked to rate their level of agreement with each statement from the scale of 1- totally disagree to 5- totally agree based on their experience of adopting or approaching AI in auditing. The questionnaire comprises 36 indicators as depicted in the table below.

*Table 3. Measurement scales (Author, 2024)*

<b>Construct</b>	<b>Code</b>	<b>Indicator</b>	<b>Source</b>
------------------	-------------	------------------	---------------

Technological compatibility	TC1	The AI-powered audit system is compatible with my firm's existing technological architecture.	Géczy <i>et al.</i> (2011); Nguyen <i>et al.</i> (2022)
	TC2	Customisation in the AI-powered audit system is easy.	
	TC3	Adopting AI is consistent with our business practices.	
	TC4	It is easy to incorporate AI into our firm.	
Training	TR1	My firm provided me with complete training in using the AI-powered audit system.	Venkatesh and Davis (1996); Amoako-Gyampah and Salam (2004)
	TR2	My level of understanding has been improved after the training program.	
	TR3	The trainers were knowledgeable and supported me in understanding the AI-powered audit system.	
Competitive pressure	CP1	We acknowledge that our competitors are using AI in their audits.	Lin and Lin (2008)
	CP2	We believe that adopting AI will give us a competitive advantage in our industry.	
Performance expectancy	PE1	Using AI in auditing would help me finish my tasks more quickly.	Venkatesh <i>et al.</i> (2003)
	PE2	Using AI in auditing would improve my performance.	
	PE3	Using AI would make auditing easier.	
	PE4	I would find AI useful in my auditing job.	
Effort expectancy	EE1	It is easy for my firm to operate an AI-powered audit system.	Venkatesh <i>et al.</i> (2003); Gangwar <i>et al.</i> (2015)
	EE2	Interacting with the AI-powered audit system would be clear and understandable for me.	
	EE3	It would be easy for me to master the AI-powered audit system.	
	EE4	I would find the AI-powered audit system easy to use.	

Switching costs	SC1	Switching to the AI-powered audit system would take a lot of time and effort.	Fan <i>et al.</i> (2015)
	SC2	There will be a lot of unexpected hassles if we switch to using AI in auditing.	
	SC3	Switching to the AI-powered audit system will waste a lot of effort that I already made in the previous system.	
Colleague opinion	CO1	My co-workers think I should use the AI-powered audit system.	Venkatesh <i>et al.</i> (2003); Moore and Benbasat (1996)
	CO2	My superiors think I should use the AI-powered audit system.	
	CO3	I use AI in auditing because a large proportion of co-workers use it.	
	CO4	The auditors who use AI in my firm are more highly regarded.	
Facilitating conditions	FC1	I can access the resources necessary to learn about the new AI-powered audit system.	Venkatesh <i>et al.</i> (2003); Chauhan and Jaiswal (2016)
	FC2	I have the knowledge necessary to learn how to use AI in auditing.	
	FC3	A specific person (or group) is available to assist me in case of difficulties.	
Behavioural intention	BI1	I think using AI in auditing would be advantageous for our firm.	Chatterjee <i>et al.</i> (2021)
	BI2	I would like to use the AI-powered audit system to its full potential.	
	BI3	I intend to use AI in my work soon.	

### 3.5. *Data analysis method*



Figure 7. *Data analysis process (Author, 2024)*

The flow of data analysis consists of four main steps. First, data screening is conducted before analysing the data to examine raw data, test normality, identify outliers, and ensure that there is no missing data. Second, a demographic analysis is performed to obtain an overview of the participants' portrait regarding gender, age, job title, current firm, and qualifications. Third, a descriptive analysis is performed to describe the characteristics of the data obtained. This will offer the foundation for rationalising the model analysis (Agresti *et al.*, 2021). Lastly, the model analysis comprises two parts: measurement model and path analysis.

To analyse the quantitative primary data, the IBM SPSS Statistics 26 and Smart PLS 3.0 software will be employed in this study. The SPSS software will be utilised for screening the data and conducting the demographic and descriptive analysis. The path analysis will be performed using the Smart PLS 3.0 software.

Regarding the model analysis, the measurement model is assessed by performing reliability and validity tests. Bryman and Bell (2011, p.158) explain that reliability tests are essential for examining the consistency of the responses. Validity tests are recommended for developing instruments and ensuring that measurement scales are appropriate (Bryman and Bell, 2011). The second part- SEM (structural equation modelling) analysis is performed to test relationships between observed and latent variables. This is crucial for testing the

hypotheses of this study. 5,000 bootstraps should be used to calculate the significance of path coefficients (Hair *et al.*, 2012).

### **3.6. Ethical considerations**

An online survey is conducted to collect primary data in this study. This data collection method has a number of ethical issues such as voluntary participation, informed consent, anonymity, confidentiality, and results communication. To address these ethical concerns, this study adopts the following controls and guidelines. First, participants can freely withdraw their responses because the survey is conducted online. At the beginning of the survey, participants will be notified about the research purposes and asked to give consent by filling in the informed consent form. Personal identity information will not be asked to maintain anonymity. The data collected for this research will be used for research purposes only and destroyed after completion. Lastly, the researcher will process the data and communicate the findings in its entirety without any manipulation.

### **3.7. Summary**

To summarise, this research employs the quantitative research method. The research model and hypotheses are developed by integrating the UTAUT model with the TOE framework and status quo bias theory. For hypotheses testing, the study will collect primary data by carrying out an online survey targeting auditors in Vietnam. Survey invitations were sent to auditors from all firm types including Big-4, non-Big, and local firms to enhance the study's generalisability. The Smart PLS 3.0 software will be used to test the measurement model's reliability and validity and perform the structural equation modelling analysis.

## CHAPTER 4. FINDINGS

### 4.1. *Data screening*

In this research, 210 invitations were sent out, however only 150 valid responses were received. There was no missing data because all questions were adequately addressed (Appendix B). This was checked by the SPSS software. Additionally, the data was also examined for response bias and errors. More specifically, the data was scanned for responses in which one answer was selected for all questions. It was found that the data did not contain such an error. In short, the dataset is suitable for the next analysis steps.

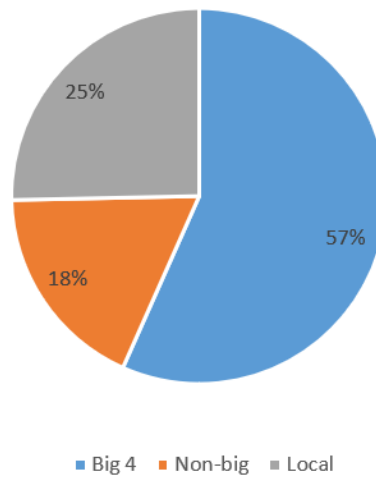
### 4.2. *Demographic and descriptive analyses*

Table 4. Demographics statistics (Author, 2024)

	<b>N</b>	<b>%</b>
<b>Age</b>		
22-30	59	39%
31-40	61	41%
41-50	28	19%
Above 50	2	1%
<b>Gender</b>		
Male	47	31%
Female	98	65%
Other	5	3%
<b>Firm type</b>		
Big 4	85	57%
Non-big	27	18%
Local	38	25%
<b>Tenure</b>		
Less than 3 years	45	30%
3-5 years	52	35%
5-10 years	35	23%
Over 10 years	18	12%
<b>Job title</b>		
Assistant	34	22%

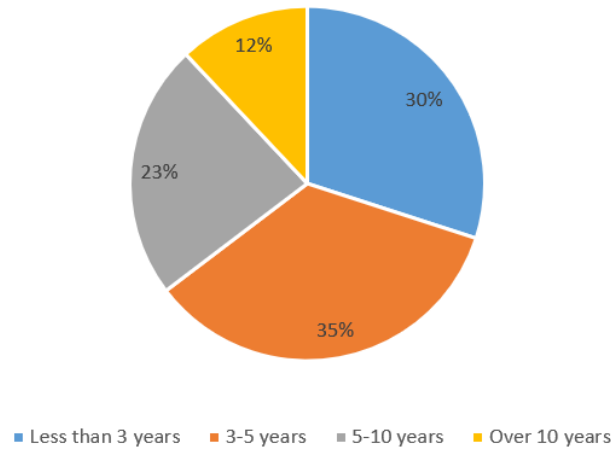
	Senior	61	41%
	Manager	51	34%
	Partner	4	3%
<b>AI Adoption status</b>	Adopted	98	65%
	Not yet adopted	52	35%
	<b>Total</b>	<b>150</b>	<b>100%</b>

Based on the demographics statistics, it is revealed that most of the participants are female (65%).



*Chart 1. Distribution of participants by firm type (Author, 2024)*

Up to 57% of the participants is currently working at Big 4 audit firms. A quarter of the sample comes from local firms. Auditors working at non-Big firms only account for 18% in this study. Senior auditors account for the largest proportion (41%) in this study, followed by audit managers (34%) and audit assistants (22%). This shows that the majority of the respondents are experienced in the field.



*Chart 2. Distribution of participants by tenure (Author, 2024)*

Furthermore, 70% of the participants has committed with their current firm for more than 3 years. This suggests that most participants are long-tenured employees with a good understanding of their firm to judge the suitability and significance of adopting AI at their firm. Interestingly, 65% of the participants reported that their firms were currently using AI in auditing. This shows that the sample size has a good mix of adopters and non-adopters.

The below table summarises findings of the descriptive analysis.

Table 5. Descriptive statistics. Source: Compiled from IBM SPSS 26.

<b>Variables</b>	<b>Code</b>	<b>Indicator</b>	<b>Min</b>	<b>Max</b>	<b>Mean</b>	<b>SD</b>
Technological compatibility	TC1	The AI-powered audit system is compatible with my firm's existing technological architecture.	1	5	3.72	.836
	TC2	Customisation in the AI-powered audit system is easy.	1	5	3.45	.994
	TC3	Adopting AI is consistent with our business practices.	1	5	3.26	.986
	TC4	It is easy to incorporate AI into our firm.	1	5	3.42	.950
Training	TR1	My firm provided me with complete training in using the AI-powered audit system.	1	5	3.83	.923
	TR2	My level of understanding has been improved after the training program.	1	5	3.52	.865
	TR3	The trainers were knowledgeable and supported me in understanding the AI-powered audit system.	1	5	3.57	.886
Competitive pressure	CP1	We acknowledge that our competitors are using AI in their audits.	1	5	4.09	.741
	CP2	We believe that adopting AI will give us a competitive advantage in our industry.	1	5	4.23	.789
Performance expectancy	PE1	Using AI in auditing would help me finish my tasks more quickly.	1	5	3.77	.921
	PE2	Using AI in auditing would improve my performance.	1	5	3.85	.910
	PE3	Using AI would make auditing easier.	1	5	3.83	.886
	PE4	I would find AI useful in my auditing job.	1	5	3.95	.865

Effort expectancy	EE1	It is easy for my firm to operate an AI-powered audit system.	1	5	3.77	.829
	EE2	Interacting with the AI-powered audit system would be clear and understandable for me.	1	5	3.98	.807
	EE3	It would be easy for me to master the AI-powered audit system.	1	5	3.73	.825
	EE4	I would find the AI-powered audit system easy to use.	1	5	3.85	.817
Switching costs	SC1	Switching to the AI-powered audit system would take a lot of time and effort.	1	5	3.13	.892
	SC2	There will be a lot of unexpected hassles if we switch to using AI in auditing.	1	5	3.04	.889
	SC3	Switching to the AI-powered audit system will waste a lot of effort that I already made in the previous system.	1	5	3.08	.879
Colleague opinion	CO1	My co-workers think I should use the AI-powered audit system.	1	5	3.95	.834
	CO2	My superiors think I should use the AI-powered audit system.	1	5	3.92	.840
	CO3	I use AI in auditing because a large proportion of co-workers use it.	1	5	3.56	.855
	CO4	The auditors who use AI in my firm are more highly regarded.	1	5	3.53	.825
Facilitating conditions	FC1	I can access the resources necessary to learn about the new AI-powered audit system.	1	5	3.97	.893
	FC2	I have the knowledge necessary to learn how to use AI in auditing.	1	5	3.67	.855

	FC3	A specific person (or group) is available to assist me in case of difficulties.	1	5	3.73	.904
Behavioural intention	B11	I think using AI in auditing would be advantageous for our firm.	1	5	3.79	.627
	B12	I would like to use the AI-powered audit system to its full potential.	1	5	3.86	.602
	B13	I intend to use AI in my work soon.	1	5	3.84	.656
	Valid N (listwise)	N= 150				

Regarding technological compatibility, the majority of participants (69%) agreed that AI applications were compatible with their firms' existing IT infrastructure. This indicator (TC1) has the highest mean in this construct, indicating a high level of agreement among participants. Overall, participants unanimously supported technological compatibility and training, however, they also demonstrated a higher level of neutrality in these constructs compared to others. This suggests that a large number of participants were uncertain about compatibility and the effectiveness of training programmes.

Competitive pressure has the highest mean values compared to other constructs. Only a handful of participants disagreed with the statements. This shows that the auditors unanimously acknowledge competing firms' use of AI and the technology's role as a competitive advantage. Similarly, high levels of agreement are also observed in performance expectancy and effort expectancy. Most respondents believe that the use of AI is beneficial for their work and learning how to use AI applications should be easy. The majority of participants also reported that their co-workers and superiors advocated the use of AI. This has encouraged them to adopt AI to be regarded more highly. Additionally, most participants acknowledged the availability of facilitating conditions supporting their use of AI. Consequently, high levels of agreement with the use of AI in auditing (behavioural intention) were recorded.

However, it is also noted that switching costs have the lowest mean values. This is because there were more participants disagreeing with the statements. Overall, the participants had mixed opinions about switching costs. Approximately 20% of the participants disagreed with the incurrance of switching costs upon AI adoption while only around 30% advocated the

existence of switching costs. The majority of participants demonstrated neutrality regarding switching costs.

### **4.3. Partial Least Square (PLS) Modelling Results**

#### **4.3.1. Measurement model**

The below table summarises the results of the measurement model's reliability and validity tests. In this section, factor loadings, composite reliability values, and AVE are examined. More specifically, the factor loadings indicate the indicator reliability. They show how much variations in the latent variable is explainable by the observed variables. The composite reliability values are used to test latent variables' reliability. Lastly, the AVE (average value extracted) is used for testing convergent validity. In other words, it shows how much variations in each construct can be explained by the latent variables.

Table 6. Measurement scales of constructs. Source: Compiled from Smart PLS 3.0.

<b>Construct</b>	<b>Label</b>	<b>Factor loading</b>	<b>Composite reliability</b>	<b>AVE</b>
Colleague opinion	CO1	0.777	0.863	0.611
	CO2	0.792		
	CO3	0.797		
	CO4	0.762		
Competitive pressure	CP1	0.936	0.891	0.804
	CP2	0.856		
Effort expectancy	EE1	0.808	0.880	0.647
	EE2	0.760		
	EE3	0.768		
	EE4	0.876		
Facilitating conditions	FC1	0.852	0.867	0.686
	FC2	0.858		
	FC3	0.771		
Performance expectancy	PE1	0.766	0.877	0.642
	PE2	0.784		
	PE3	0.834		
	PE4	0.818		
Switching costs	SC1	0.794	0.865	0.682
	SC2	0.800		
	SC3	0.880		
Technological compatibility	TC1	0.782	0.872	0.631
	TC2	0.751		
	TC3	0.812		
	TC4	0.831		
Training	TR1	0.847	0.866	0.683
	TR2	0.794		
	TR3	0.837		
Behavioural intention	BI1	0.801	0.879	0.708
	BI2	0.835		
	BI3	0.887		

According to Hair et al. (2019), factor loadings that are below 0.4 show that the indicators are not reliable and should be removed from the model. On the other hand, the measurement scale is considered reliable when its factor loading is above 0.7 (Hair *et al.*, 2019). Table 6 shows that all factor loadings exceed 0.7, confirming the reliability of observed variables. Many researchers agree that the composite reliability value should be above 0.7 (Henseler and Sarstedt, 2013; Hair *et al.*, 2019). Table 6 shows that all constructs have composite reliability values exceeding 0.8, meaning that the measurement scales are reliable.

Regarding convergent validity, AVE should be above 0.5. In other words, at least 50% of the variations of the observed variables can be explained by the latent variable (Hair *et al.*, 2019). Table 6 shows that the AVE values of all constructs exceed 0.5. Hence, the measurement scale's convergent validity is ensured.

Table 7. Construct correlations. Source: Compiled from Smart PLS 3.0.

	BI	CO	CP	EE	FC	PE	SC	TC	TR
BI	<b>0.842</b>								
CO	0.453	<b>0.782</b>							
CP	0.459	0.179	<b>0.897</b>						
EE	0.662	0.368	0.281	<b>0.805</b>					
FC	0.416	0.183	0.162	0.329	<b>0.828</b>				
PE	0.674	0.450	0.160	0.664	0.232	<b>0.801</b>			
SC	-0.235	0.043	-0.011	-0.136	-0.329	-0.093	<b>0.826</b>		
TC	0.511	0.419	0.186	0.648	0.228	0.616	-0.059	<b>0.794</b>	
TR	0.478	0.411	0.070	0.627	0.189	0.617	0.036	0.382	<b>0.826</b>

Note: \*The square root of AVE on diagonal

Regarding discriminant validity, according to Fornell and Larcker (1981), the AVE from individual constructs should be higher than the shared variance between constructs (Fornell and Larcker, 1981). Table 7 shows that the square root of AVE of each construct meets this criteria, thus the measurement scales' discriminant validity is ensured. To conclude, the data is suitable for structural equation modelling analysis.

#### 4.3.2. Structural model

Hypothesis testing is conducted by performing a path analysis using PLS SEM. For each hypothesis, the standardised path coefficient is generated using a bootstrap sample of 5,000. Results of the path analysis are summarised in the below table.

Table 8. Summary of the path analysis. Source: Compiled from Smart PLS 3.0

	<b>Hypotheses</b>	<b>Path coefficients</b>	<b>SD</b>	<b>T-stat</b>	<b>P-value</b>	<b>Result</b>
H1a	Technological compatibility → Performance expectancy	0.446	0.058	7.705	0.000	Supported
H1b	Technological compatibility → Effort expectancy	0.446	0.058	8.195	0.000	Supported
H2a	Training → Performance expectancy	0.446	0.089	4.99	0.000	Supported
H2b	Training → Effort expectancy	0.445	0.055	8.114	0.000	Supported
H3	Performance expectancy → Behavioural intention	0.382	0.084	4.523	0.000	Supported
H4	Effort expectancy → Behavioural intention	0.215	0.095	2.254	0.024	Supported
H5	Switching costs → Behavioural intention	-0.125	0.056	2.242	0.025	Supported
H6	Colleague opinion → Behavioural intention	0.129	0.052	2.464	0.014	Supported
H7	Facilitating conditions → Behavioural intention	0.146	0.049	2.955	0.003	Supported
H8	Competitive pressure → Behavioural intention	0.290	0.052	2.464	0.014	Supported

Model fit: SRMR= 0.076

R Square = 0.681

Adjusted R square = 0.688

According to Hu and Bentler (1999), the SRMR (standardised root mean squared residual) should be under 0.08 to ensure the model fit (Hu and Bentler, 1999). In this study, the SRMR value is  $0.076 < 0.08$ , indicating that the model is a good fit for the data. Table 8 shows that the p-values of all hypotheses are below 0.05. Therefore all hypotheses are accepted in this study.

Regarding the strength of impact, performance expectancy has the strongest effect on behavioural intention, followed by competitive pressure, effort expectancy, facilitating conditions, colleague opinion, and switching costs. This is determined by the standardised coefficient's absolute value of each path (hypothesis). It should be noted that switching costs have a negative effect on behavioural intention while other factors (PE, CP, EE, FC, and CO) have positive impacts.

*Table 9. Summary of R square and R square adjusted of dependent variables (BI, EE, and PE). Source: Compiled from Smart PLS 3.0.*

	<b>R Square</b>	<b>R Square Adjusted</b>
BI	0.681	0.668
EE	0.589	0.584
PE	0.550	0.544

Table 9 provides the adjusted R square values of each dependent variable. In this study, it is found that technological compatibility and training can explain 58.4% of the variability of effort expectancy. Similarly, 54.4% of the variability observed in performance expectancy is predicted by technological compatibility and training. Lastly, the examined independent variables (PE, EE, SC, CO, FC, and CP) can explain up to 66.8% of the variability of auditors' behavioural intention to adopt AI.

Table 10. Specific indirect effects (mediation analysis). Source: Compiled from Smart PLS 3.0.

	<b>Standardised coefficients</b>	<b>SD</b>	<b>T-stat</b>	<b>P Values</b>
Technological compatibility → Effort expectancy → Behavioural intention	0.103	0.047	2.172	0.030
Training → Effort expectancy → Behavioural intention	0.096	0.046	2.092	0.037
Technological compatibility → Performance expectancy → Behavioural intention	0.170	0.042	4.067	0.000
Training → Performance expectancy → Behavioural intention	0.171	0.048	3.546	0.000

Table 10 summarises findings of the mediation analysis, which is performed using 5,000 bootstraps. More specifically, it is confirmed that effort expectancy mediates the impacts of technological compatibility and training on behavioural intention. Similarly, performance expectancy is found to mediate the impacts of technological compatibility and training and behavioural intention. Interestingly, the indirect effects of technological compatibility and training on behavioural intention are stronger when mediated by performance expectancy.

The structural model is illustrated in the below figure.

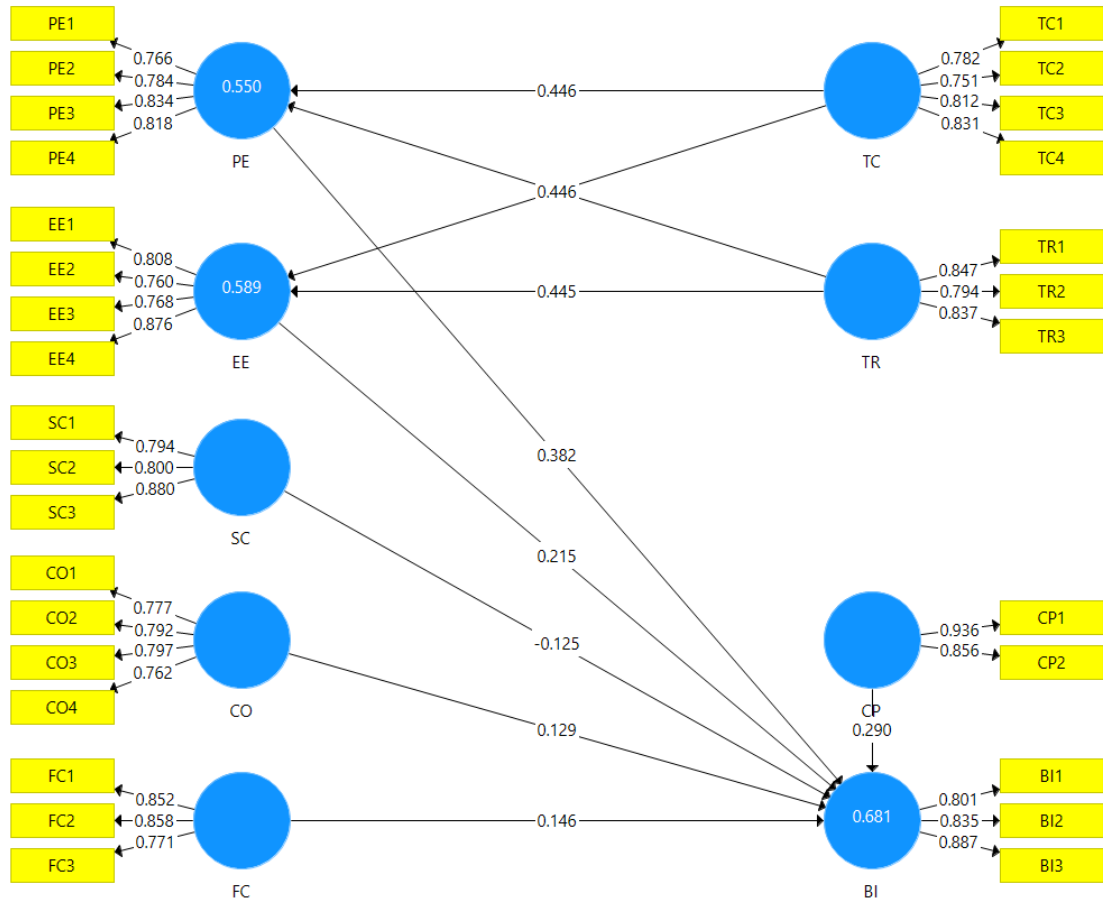


Figure 8. Estimate of structural model. Source: Compiled from Smart PLS 3.0.

#### 4.4. Summary

To summarise, hypotheses testing results show that all hypotheses are accepted. Performance expectancy, competitive pressure, and effort expectancy have the most significant positive impact on auditors' AI adoption intention. It is also found that technological compatibility and training positively influence performance expectancy and effort expectancy. Furthermore, this study also has also found that the indirect effects of technological compatibility and training on behavioural intention are mediated by performance expectancy and effort expectancy. Facilitating conditions are also found to positively influence adoption intention, however the impact is insignificant. Similarly, it is confirmed that colleague opinion has positive effects while switching costs have negative effects on behavioural intention, however, the strength of impact is weak.

## CHAPTER 5.DISCUSSION

### 5.1. *Result of H1: Technological compatibility*

Technological compatibility is found to positively affect performance expectancy and effort expectancy in this study. A large body of literature point out that potential users want to accept and use technologies that are the most suitable for and compatible with their intended use. The expected implementation time and cost will be lower if the AI applications align with current work processes and IT infrastructure (Chen *et al.*, 2021; Hamm and Klesel, 2021).

A study conducted by Gangwar *et al.* (2015) also found that compatibility improved performance expectancy. More importantly, the researchers confirmed that performance expectancy and effort expectancy both could mediate the impacts of technological compatibility on behavioural intention (Gangwar *et al.*, 2015). This supports this study's findings. Nguyen *et al.* (2022) also confirmed that technological compatibility encouraged AI adoption in Vietnam (Nguyen *et al.*, 2022). However, their study only confirmed the direct positive effects of technological compatibility on AI adoption while this study adds the mediating role of performance expectancy and effort expectancy in the relationship between technological compatibility and AI adoption intention.

### 5.2. *Result of H2: Training*

This study found that training had positive effects on performance expectancy and effort expectancy. This concurs with previous studies' findings. Researchers agree that it is essential to develop talent skilled in AI. The lack of training programs on AI will leave employees ill-equipped for AI adoption, thus causing poor appropriation of value and hindering knowledge dissemination in the organisation (Füller *et al.*, 2022; Ångström *et al.*, 2023). Lee *et al.* (2022) argue that training is especially important for small firms to successfully implement AI due to their limited financial resources to acquire high-skilled workers (Lee *et al.*, 2022). According to Karahanna and Straub (1999), the availability of user training and support is found to facilitate system use. By providing one-on-one consultations or a helpline, companies can help employees understand the system better. Hence, training can positively influence perceived usefulness and perceived ease of use (Karahanna and Straub, 1999).

Furthermore, this study confirms that training's positive indirect effects on behavioural intention are mediated by performance expectancy and effort expectancy. Gangwar et al. (2015) also support this finding. Training can help employees become more experienced and knowledgeable in utilising a new technology. Hence, employees will find the technology easier to use and understand its role in their job performance, which ultimately encourage technology adoption (Gangwar *et al.*, 2015).

### **5.3. Result of H3: Performance expectancy**

The findings show that performance expectancy positively influences auditors' intention to adopt AI. This factor is an important positive predictor of technology acceptance in many software acceptance studies. This aligns with previous research's findings (Chatterjee *et al.*, 2021; Ahmad Khan *et al.*, 2024). In the auditing context, Curtis and Payne (2014) found that performance expectancy has significant positive impacts on auditors' AI adoption intention (Curtis and Payne, 2014). A large body of literature in technology acceptance in accounting also support the strong positive relationship between performance expectancy and technology adoption intention (Bedard *et al.*, 2003; Loraas and Wolfe, 2006). Chatterjee et al. (2021) also advocate the positive effects of performance expectancy on AI adoption intention. The researchers explain that when employees acknowledge a technology's benefits in improving their job performance, they will be more motivated to adopt the technology (Chatterjee *et al.*, 2021).

### **5.4. Result of H4: Effort expectancy**

Effort expectancy is found to encourage auditors' intention to adopt AI. This supports the theoretical foundation of the TAM model and UTAUT model developed by Davis (1989) and Venkatesh et al. (2003) respectively. Curtis and Payne (2014) agree that effort expectancy has positive effects on auditors' AI adoption intention. In an audit context, the relationship between effort expectancy and behavioural intention is more complex. Supporting factors such as training, compatibility, and management support can improve effort expectancy, thus encouraging AI adoption (Curtis and Payne, 2014). In another study conducted in Vietnam, Anh et al. (2014) also found that perceived ease of use (effort expectancy) encouraged accountants' and auditors' intention to use AI in their work. When AI applications are considered easy to use, accountants and auditors tend to have more positive attitudes towards the technology (Anh *et al.*, 2024).

### **5.5. Result of H5: Switching costs**

This study asserts that switching costs negatively influence AI adoption intention. This finding aligns with the status quo bias theory. Switching costs, which comprise transition costs, uncertainty costs, and sunk costs increase user resistance to change, thus inhibiting their acceptance and use of a new technology (Kim and Kankanhalli, 2009). The negative effects of switching costs on adoption intention are also supported by earlier studies. Mikalef et al. (2021) confirm that switching costs are an economic inertia discouraging companies from adopting new technologies (Mikalef *et al.*, 2021). Huang and Hsieh (2012) explain that when switching to a new system, users will have to spend more time and mental effort on learning the new system. Additionally, the knowledge and experience in utilising the previous system may become redundant (Huang and Hsieh, 2012). Hence, auditors will be more reluctant to adopt AI when the switching costs are high.

### **5.6. Result of H6: Colleague opinion**

The findings show that colleague opinion positively influences auditors' intention to adopt AI. This further provides empirical evidence for the UTAUT model proposed by Venkatesh et al. (2003). Previous studies have mixed results in the effects of social influence on adoption intention. Interestingly, if adoption is voluntary, social influence or colleague opinion will have little to no effect on adoption intention. This is exemplified by Chau and Hu's (2002) study, which rejects the correlation between colleague opinion and technology adoption intention (Chau and Hu, 2002). On the contrary, if adoption is mandatory, colleague opinion will have a significant impact on adoption intention. Curtis and Payne (2008) found that superiors (managing partners) have significant influence on employees' intention to adopt a new technology (Curtis and Payne, 2008). Similarly, Loraas and Wolfe (2006) found the same positive effects of supervisors on employees' adoption intention (Loraas and Wolfe, 2006).

### **5.7. Result of H7: Facilitating conditions**

Facilitating conditions are found to have positive effects on auditors' intention to adopt AI. This aligns with previous empirical studies on technology acceptance. Previous studies have confirmed that facilitating conditions encourage accountants to adopt CAATs. When technology implementation is deemed necessary, companies will create facilitating conditions to promote adoption by offering training sessions and technical support and

improving the IT infrastructure (Janvrin *et al.*, 2009; Pedrosa *et al.*, 2020). However, Gonzalez *et al.* (2012) add that facilitating conditions' impact on adoption intention is insignificant compared to effort expectancy and social influence (Gonzalez *et al.*, 2012). Curtis and Payne (2008) also confirm that in the presence of other constructs in the UTAUT model, facilitating conditions' impact tends to be insignificant (Curtis and Payne, 2008).

### **5.8. Result of H8: Competitive pressure**

The findings indicate that competitive pressure drives auditors to adopt AI to compete with other audit firms. This is supported by previous studies (Pumplun *et al.*, 2019; Pillai and Sivathanu, 2020). Horani *et al.* (2023) explain that AI adoption can cut costs significantly and help firms outperform their competitors. Hence, companies are more willing to adopt AI to survive in the ever-changing business market (Horani *et al.*, 2023).

However, Chen *et al.* (2021) reject the impacts of competitive pressure on AI adoption in the telecom industry in China. 5G networks and AI technologies go hand in hand. Hence, companies in the telecom industry are driven to adopt AI by their own business development needs and industry demand rather than the market's competitiveness (Chen *et al.*, 2021). Similarly, AISheibani *et al.* (2020) argue that when the barriers to AI adoption are too high, companies will not be influenced by competitive pressure (AISheibani *et al.*, 2020). This suggests that the effects of competitive pressure on companies' AI adoption intention may vary across industries.

## CHAPTER 6. CONCLUSION AND RECOMMENDATIONS

### 6.1. *Conclusions*

This research has proposed a model for testing AI adoption predictors by integrating the UTAUT model with the status quo bias theory and TOE framework. The research model has examined both individual-level and firm-level predictors, thus offering a holistic picture of determinants of AI adoption in auditing in Vietnam. An online survey was conducted to collect the data and 150 valid responses were received. Results of the data analysis have validated the measurement scales and approved all research hypotheses. More specifically, performance expectancy is found to have the strongest positive impact on auditors' intention to adopt AI. This is followed by competitive pressure and effort expectancy. The effects of switching costs, colleague opinion, and facilitating conditions on adoption intention are also confirmed, however, the strength of impact is insignificant. Additionally, switching costs are the only variable with negative effects on adoption intention. Furthermore, it is confirmed that technological compatibility and training positively influence performance expectancy and effort expectancy. More importantly, this study asserts that the indirect effects of technological compatibility and training on adoption intention are mediated by performance expectancy and effort expectancy.

Findings of this study suggest that improving performance expectancy and effort expectancy is the key to promote AI adoption in auditing. When auditors acknowledge the use of AI in enhancing their job performance and how easy it is to utilise the technology, they will be more inclined to adopt AI. Audit firms can promote this by investing in training. AI applications should also be compatible with the current IT infrastructure and audit practices. The strong positive effects of competitive pressure on adoption intention indicate that when competitors adopt AI as a competitive instrument, other audit firms will be pressured to follow suit to maintain their competitive advantage.

The research has also confirmed the effects of switching costs, colleague opinion, and facilitating conditions on AI adoption intention. However, the strength of impact is insignificant compared to PE, EE, and CP. Switching costs' negative effects on adoption intention suggests that auditors will be discouraged to adopt AI if the AI applications are vastly different from their previous system and the switch to AI makes their understanding of the previous system become redundant. On the other hand, auditors will be more motivated to adopt AI applications if their co-workers, supervisors, and managers encourage them to

do so. By acknowledging that their peers are excelling in the work thanks to AI, auditors will be more likely to use the technology. Lastly, auditors need facilitating conditions such as top management support, technical support, and adequate training to feel confident in utilising AI applications.

## **6.2. Recommendations for actions**

Performance expectancy and effort expectancy are the two most significant predictors of AI adoption among auditors, thus it is advisable that audit firms focus on promoting these factors. In other words, auditors will be more willing to adopt AI if they acknowledge the use of technology in enhancing their performance and its ease of use. Audit firms can improve this first by providing a comprehensive training program on AI. According to Gangwar et al. (2015), training improves employees' understanding of the functions and technical aspects of AI and helps them gain experience in utilising the new technology. As employees become more well-equipped and experienced to use AI, it will be easier for them to utilise and understand how the technology will enhance their job performance (Gangwar *et al.*, 2015). Hence, managers should design effective training programmes that adequately address auditors' knowledge and skill gap. Apart from training the staff on AI applications, it is also important to enhance auditors' adaptability. This will help auditors navigate through uncertainties more effectively, embrace new technologies, and adapt to changing roles and responsibilities (Tursunbayeva and Chalutz-Ben Gal, 2024). To enhance the effectiveness of training, facilitating conditions such as top management support and ensuring an acceptable technological competence level before letting auditors work with AI are also important.

This study's findings show that technological compatibility positively influences performance expectancy and effort expectancy, which ultimately encourages AI adoption. Therefore, it is important for audit firms to ensure that the current audit system and IT infrastructure are compatible with AI applications. According to Dubosson et al. (2020), employees are afraid of losing the power, experience, and control gained from their skills and expertise. Switching to a new system and adopting new ways of working can impair their recognition from peers. Hence, the higher the switching costs are, the less likely employees will be to accept the new technology (Dubosson *et al.*, 2020). Consequently, audit firms should ensure that AI applications are seamlessly integrated into current audit procedures instead of replacing existing processes. This will reduce the switching costs and encourage auditors to adopt AI.

### **6.3. Contributions**

From a theoretical perspective, this research has provided more empirical evidence supporting the theoretical foundation of the UTAUT model developed by Venkatesh et al. (2003). This study has confirmed the reliability and validity of the measurement scales of AI adoption and its predictors. The validated research model is an integrated framework of the UTAUT model, status quo bias theory, and TOE framework. Hence, the research has provided a more holistic approach to examine factors affecting technology acceptance and use. Furthermore, the research has also clarified how training and technological compatibility can encourage adoption intention through improving performance expectancy and effort expectancy. In short, this research has enriched the literature in AI technology acceptance.

Regarding practical contributions, this research has shed light on predictors of AI adoption intention in auditing in Vietnam, which have not been investigated by previous studies. More specifically, performance expectancy, competitive pressure, and effort expectancy are found to have significant positive effects on auditors' intention to adopt AI. This suggests that audit firms should focus on these factors to promote AI adoption. Additionally, technological compatibility and training positively influence performance expectancy and effort expectancy. This suggests that audit firms should provide adequate training and invest in the IT infrastructure to help employees adapt to the new AI-powered audit system.

### **6.4. Limitations**

The nature of this study's research methodology and design has inherent limitations. First, the findings may lack generalisability despite being a quantitative study due to its small sample size. Only 150 valid responses were collected, thus the sample size is deemed small. This suggests that the findings should be generalised with caution in other contexts of different technologies and industries. Furthermore, the scope of this study is limited to Vietnam, which is a developing country with a lack of technological readiness. Hence, this study's findings may only be applicable within the country or to other countries of similar conditions. On the other hand, this research limitation has been partially mitigated because the sample is inclusive and representative. More specifically, sample includes auditors from different firm types in Vietnam (Big 4, Non-Big, and local firms) and has a good mix of AI adopters and non-adopters.

Second, only three firm-level factors namely technological compatibility, training, and competitive pressure were examined in this study. Evidently, there are many other predictors within the TOE framework that have not been tested. Hence, this research has only peeked into the effects of firm-level factors affecting AI adoption. Furthermore, the mediating relationship among variables have not been thoroughly investigated in this research. The moderators in the original UTAUT model such as age, gender, experience, and voluntariness of use were also omitted from the research model. Hence, the findings have yet to provide a comprehensive and in-depth understanding of AI adoption predictors.

### **6.5.        *Suggestions for future research***

Future quantitative studies should re-examine the proposed predictors with a larger sample size to ensure generalisability. This study should be extended and replicated to other geographical and economic landscapes to offer wider support. Non-adopters and adopters should also be examined separately to identify motivators as well as inhibitors of technology acceptance, thus offering a bigger picture of AI adoption decisions. Qualitative studies should be conducted to gain an in-depth understanding of how these firm-level and individual-level predictors affect AI adoption. Furthermore, according to Khanfar et al. (2024), AI adoption predictors are interconnected and may interact (Khanfar *et al.*, 2024). Hence, future research should investigate the interconnection between these variables using SEM.

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## APPENDICES

### *Appendix A. Survey instrument – questionnaire*

#### **Section 1. Demographics**

1. How old are you?

22-30                  31-40                  41-50                  Above 50

2. What is your gender?

Male                  Female                  Other

3. Which type of firm are you working for?

Big 4                  Non-big                  Local

4. How long have you worked for this firm?

Less than 3 years    3- 5 years                  5-10 years                  Over 10 years

5. What is your job title?

Intern                  Assistant                  Senior                  Manager                  Partner

6. Has your firm adopted AI in auditing?

Yes                  No

#### **Section 2. Factors affecting AI adoption in auditing**

1. The AI-powered audit system is compatible with my firm's existing technological architecture.

Strongly disagree    Disagree                  Neutral                  Agree                  Strongly agree

2. Customisation in the AI-powered audit system is easy.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

3. Adopting AI is consistent with our business practices.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

4. It is easy to incorporate AI into our firm.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

5. My firm provided me with complete training in using the AI-powered audit system.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

6. My level of understanding has been improved after the training program.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

7. We acknowledge that our competitors are using AI in their audits.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

8. We believe that adopting AI will give us a competitive advantage in our industry.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

9. Using AI in auditing would help me finish my tasks more quickly.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

10. Using AI in auditing would improve my performance.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

11. Using AI would make auditing easier.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

12. I would find AI useful in my auditing job.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

13. It is easy for my firm to operate an AI-powered audit system.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

14. Interacting with the AI-powered audit system would be clear and understandable for me.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

15. It would be easy for me to master the AI-powered audit system.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

16. I would find the AI-powered audit system easy to use.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

17. Switching to the AI-powered audit system would take a lot of time and effort.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

18. There will be a lot of unexpected hassles if we switch to using AI in auditing.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

19. Switching to the AI-powered audit system will waste a lot of effort that I already made in the previous system.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

20. My co-workers think I should use the AI-powered audit system.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

21. My superiors think I should use the AI-powered audit system.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

22. I use AI in auditing because a large proportion of co-workers do it.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

23. The auditors who use AI in my firm are more highly regarded.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

24. I can access the resources necessary to learn about the new AI-powered audit system.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

25. I have the knowledge necessary to learn how to use AI in auditing.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

26. A specific person (or group) is available to assist me in case of difficulties.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

27. I think using AI in auditing would be advantageous for our firm.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

28. I would like to use the AI-powered audit system to its full potential.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

29. I intend to use AI in my work soon.

Strongly disagree      Disagree      Neutral      Agree      Strongly agree

**Appendix B. Missing data checking**

<b>Case Processing Summary</b>						
	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
TC1	150	100.0%	0	0.0%	150	100.0%
TC2	150	100.0%	0	0.0%	150	100.0%
TC3	150	100.0%	0	0.0%	150	100.0%
TC4	150	100.0%	0	0.0%	150	100.0%
TR1	150	100.0%	0	0.0%	150	100.0%
TR2	150	100.0%	0	0.0%	150	100.0%
TR3	150	100.0%	0	0.0%	150	100.0%
CP1	150	100.0%	0	0.0%	150	100.0%
CP2	150	100.0%	0	0.0%	150	100.0%
PE1	150	100.0%	0	0.0%	150	100.0%
PE2	150	100.0%	0	0.0%	150	100.0%
PE3	150	100.0%	0	0.0%	150	100.0%
PE4	150	100.0%	0	0.0%	150	100.0%
EE1	150	100.0%	0	0.0%	150	100.0%
EE2	150	100.0%	0	0.0%	150	100.0%
EE3	150	100.0%	0	0.0%	150	100.0%
EE4	150	100.0%	0	0.0%	150	100.0%
SC1	150	100.0%	0	0.0%	150	100.0%
SC2	150	100.0%	0	0.0%	150	100.0%
SC3	150	100.0%	0	0.0%	150	100.0%
CO1	150	100.0%	0	0.0%	150	100.0%
CO2	150	100.0%	0	0.0%	150	100.0%
CO3	150	100.0%	0	0.0%	150	100.0%
CO4	150	100.0%	0	0.0%	150	100.0%
FC1	150	100.0%	0	0.0%	150	100.0%
FC2	150	100.0%	0	0.0%	150	100.0%
FC3	150	100.0%	0	0.0%	150	100.0%

BI1	150	100.0%	0	0.0%	150	100.0%
BI2	150	100.0%	0	0.0%	150	100.0%
BI3	150	100.0%	0	0.0%	150	100.0%