AI Adoption in Auditing: Risk Perception, Social Influences, and Algorithm Aversion

Thesis Submitted for the Award of
Doctor of Philosophy (PhD)
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November 2025

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A Thesis Submitted to Dublin City University Business School in Partial Fulfilment of the Requirements for the Degree of Doctor of Philosophy

DECLARATION

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of Doctor of Philosophy is entirely my own work, and that I have exercised reasonable care to ensure that the work is original and have conformed to the regulations on the use and declaration of Generative AI, and does not to the best of my knowledge breach any law of copyright, and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work. I hereby certify that no Generative Artificial Intelligence (Gen AI) tools have been used in the creation of the thesis.

Student ID: 22264836

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Date: 01/07/2026

DEDICATION

To my esteemed parents, supportive friends, and distinguished colleagues.

ACKNOWLEDGEMENTS

First and foremost, I wish to convey my deepest gratitude to my supervisors, Dr. Michael Dowling and Dr. Orla Feeney. Your unwavering support, insightful advice, and continuous encouragement have been the foundations of my thesis completion. Your profound expertise in various aspects, particularly in AI applications within accounting and auditing, has significantly shaped my research journey. I feel exceptionally fortunate to have been supervised by you and to have pursued my academic research under your guidance. Your patience and willingness to share your knowledge have been a guiding light throughout this journey.

I would also like to express my profound appreciation to Dr. Sandeep Rao. Your insightful suggestions and constructive feedback have greatly enhanced the precision and quality of my studies. The thoroughness with which you reviewed my work and the thoughtful critiques you provided have significantly contributed to the refinement of my research. Your dedication to academic excellence and your willingness to invest time in guiding me have been deeply appreciated.

I extend my heartfelt thanks to DCU Business School for providing the essential resources and a conducive environment for my academic research. The access to extensive academic databases, the availability of state-of-the-art facilities, and the supportive administrative staff have all played a crucial role in enabling the successful completion of my thesis. I am grateful for the opportunities to attend various seminars and workshops that have broadened my knowledge and skills.

I am deeply grateful to my family and friends for their unwavering support throughout my entire academic journey. To my parents, your faith in me and your continuous encouragement have given me the strength to face any challenges during my studies. Your belief in my potential and your constant reassurance have been my anchor. To my friends, your companionship and encouragement have been a source of great inspiration.

Lastly, I wish to thank all those who have contributed to this research in any capacity. Your help and understanding have played a significant role in my academic journey. This

is just the first step, and with everyone's continued support, I will strive to advance further in my academic endeavours. Every bit of assistance, no matter how small, has been instrumental in shaping this work. I look forward to the future with a heart full of gratitude and a commitment to continue this journey of learning and discovery.

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Note. The variables in the tables are displayed differently across the three studies because each study employs a distinct model-development strategy tailored to its specific research objective, data structure, and theoretical focus. Study 1 identifies functional and operational risk perceptions, Study 2 incorporates social-influence and client-side factors, and Study 3 examines innovation resistance and psychological barriers; therefore, the corresponding measurement blocks, variable names, and model specifications necessarily differ to reflect these conceptual boundaries. Presenting the variables in a study-specific format has two advantages: first, it preserves internal coherence within each model by aligning the displayed variables directly with the constructs being tested; second, it allows the thesis to build a cumulative, multi-layered contribution, with each study extending the prior one rather than repeating identical specifications. This structured differentiation makes the tables easier to interpret, reduces construct contamination across studies, and clearly demonstrates how the analytical framework evolves as new empirical insights are incorporated.

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LIST OF ABBREVIATIONS

AA=Algorithm Aversion
AI=Artificial Intelligence
AJA=AI-augmented joint audits
ANOVA=Analysis of Variance
BTC=Baker Tilly China
CAL=Clients' acceptance level
CICPA= Chinese Institute of Certified Public Accountants
EJA=Experience of Joint Audits
FRP=Functional Risk Perception
HAA=Headquarter's Acceptance of Augmented AI
HTMT=Heterotrait-monotrait Ratio
IRT=Innovation Resistance Theory
NLP=Natural Language Processing
ORP=Operational Risk Perception
PAF=Principal Axis Factoring
PAL=Peers' acceptance level
PCA=Principal Component Analysis
PEOU=Perceived Ease of Use
PLS-SEM=Partial Least Squares Structural Equation Modeling
PU=Perceived Usefulness
RPA=Robotic Process Automation
SRE=Supportiveness of Regulatory and Policy Environment
TAM=Technology Acceptance Model
TRI=Technology Readiness Index
UTAUT=Unified Theory of Acceptance and Use of Technology

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ABSTRACT

The integration of artificial intelligence (AI) in auditing offers significant potential for technological advancements, but its widespread adoption brings with it numerous challenges. My thesis investigates these challenges by examining the use of AI in a variety of auditing contexts across multiple branches of a Chinese accounting firm. This research facilitates the development of a framework for AI implementation in external audits, emphasizing the crucial roles of client attitudes and auditors' risk tolerance. It examines how social factors influence auditors' acceptance of augmented AI systems, specifically in joint audits, revealing that positive client attitudes and supportive regulatory environments significantly enhance AI acceptance. The study goes on to explore auditors' AI algorithm aversion in general audit environments, driven by perceived risks and a preference for conventional methods, through the lenses of innovation resistance theory and the technology readiness index. The results indicate that psychological barriers significantly contribute to algorithm aversion, while functional barriers are less impactful, and clients' technology readiness does not moderate these relationships. These findings provide practical implications for balancing AI innovation with auditors' concerns, offering comprehensive insights into the challenges and factors influencing AI adoption in auditing.

CHAPTER ONE: INTRODUCTION

1.1 Chapter Introduction

Artificial intelligence (AI) is transforming the accounting profession, automating routine bookkeeping, accelerating financial analyses, and enhancing real-time decision support. As these technologies mature, their influence extends from broader accounting functions into the specialised domain of auditing, where machine-learning (ML) and natural-language-processing (NLP) tools now scan entire ledgers, flag anomalous journal entries, and generate continuous risk assessments that once demanded extensive manual effort. Global standard-setters such as the International Auditing and Assurance Standards Board (IAASB) and the Public Company Accounting Oversight Board (PCAOB) increasingly debate how AI reshapes audit quality, signaling the field's shift from experimental prototypes to emerging professional practice.

Against this backdrop, the present chapter defines the thesis's scope, rationale, and scholarly contribution. It first reviews the evolution of AI in accounting and highlights the distinctive challenges and opportunities the technology creates for auditors. It then situates the study within theories of technology acceptance, risk perception, social influence, and algorithm aversion, explaining why these lenses are well suited to unpack variation in AI uptake across external, joint, and general audits. Building on this foundation, the chapter articulates the central research objectives, frames the guiding questions, and sets out the hypotheses that structure subsequent analysis.

To ground the investigation empirically, the chapter concludes with a concise overview of the mixed-method design: survey experiments that quantify adoption patterns and in-person interviews carried out in five branches of Baker Tilly China that enrich interpretation. China's status as an early mover–supported by robust digital infrastructure and proactive governmental policy–provides a fertile context for deriving insights into feasible implementation frameworks, workforce upskilling, and regulation that are relevant to audit practitioners worldwide.

Together, these elements position the remainder of the thesis to explain not only whether auditors adopt AI, but why, under what conditions, and with what implications for audit quality and professional judgement.

1.2 Research Background

AI has become a recognised driver of digital transformation, and its deployment in auditing introduces a set of analytical and practical considerations. From the earliest expert-system prototypes (Copeland, 1989) to contemporary machine-learning (ML) and generative-AI applications (Wei, Wu, and Chu, 2023), the profession has explored AI's capacity for data processing, anomaly detection, and predictive modelling (Brynjolfsson and Mitchell, 2017; Taylor, 2000; Tan and Yeo, 2023; Godsell et al., 2023). These functions can support evidence gathering, promote more consistent judgements, and improve audit quality across external, joint, and broader audit settings–notably, in joint audits multiple firms must coordinate complex procedures and integrate heterogeneous information (Leng and Zhang, 2024; Armenia, Franco, Iandolo, Maielli, and Vito, 2024).

Empirical work reports efficiency gains when AI-enabled tools automate repetitive tasks, facilitate near real-time collaboration, and augment auditors' analyses (Costello, Down, and Mehta, 2020; Nguyen et al., 2019; Munoko et al., 2020; Song, 2021). At the same time, the literature notes a continued reluctance to rely on algorithms, driven by concerns over reliability, transparency, and the potential erosion of professional judgement–issues that may be more pronounced when responsibilities are shared across joint-audit partners (Dietvorst, Simmons, and Massey, 2018; Lanz, Briker, and Gerpott, 2024; Munoko, Brown-Liburd, and Vasarhelyi, 2020; Commerford, Dennis, Joe, and Ulla, 2022). These reservations intersect with broader ethical, data-privacy, and labour-market considerations associated with AI adoption (Stahl, Brooks, Hatzakis, Santiago, and Wright, 2023).

Thus, although AI demonstrably supports audit effectiveness–including in joint settings–it also generates psychological and context-specific implementation challenges.

Systematic evidence on how contextual, psychological, and social factors jointly influence auditors' adoption decisions remains limited across different audit environments. This thesis addresses that gap through three studies that examine the determinants of AI uptake in external audits, joint audits, and a general audit context, thereby contributing to scholarship on technology adoption and audit quality.

1.3 Research Objectives and Questions

AI is reshaping the audit profession, yet its integration remains uneven across different engagement types. Understanding why auditors adopt–or resist–AI-enabled tools is therefore critical for both researchers and practitioners seeking to enhance audit quality and efficiency. This thesis pursues three interconnected objectives that correspond to the principal audit settings analysed throughout the dissertation:

1. ***External audits*** – risk and client context. Identify how auditors' perceptions of engagement-specific risks, together with salient client characteristics, influence their willingness to use AI for external-audit tasks, especially risk-management procedures.
2. ***Joint audits*** – social dynamics. Evaluate the role of social factors–such as peer influence, regulators, and perceived professional norms–in shaping auditors' adoption of AI when two or more firms collaborate on a joint audit.
3. ***General audit practice*** – psychological barriers. Explore the extent to which psychological resistance, with a focus on algorithm aversion, deters auditors from relying on AI systems in routine audit contexts.

To address these objectives, the study poses a set of focused research questions that guide the empirical analyses:

- What specific challenges impede auditors' use of AI for risk-management tasks in external audits?
- How do social interactions and normative pressures affect auditors' acceptance of AI in joint-audit engagements?

- Which factors underlie auditors' aversion to AI algorithms in broader, non-engagement-specific audit settings?

By linking these questions to distinct audit contexts, the thesis develops a detailed understanding of both the facilitators and barriers of AI adoption. The answers obtained advance theoretical perspectives on technology acceptance in professional services and offer practical insights for firms aiming to embed AI responsibly and effectively in audit workflows.

1.4 Theoretical Framework

AI adoption in auditing entails a detailed interaction of acceptance, resistance, and readiness that differs across engagement contexts. To explicate these dynamics and address the study's research objectives and questions, this thesis integrates three complementary theories–Technology Acceptance Model (TAM), Innovation Resistance Theory (IRT), and Technology Readiness Index (TRI)–into a unified analytical framework.

- 1.4.1 **Technology Acceptance Model (TAM)**
  TAM (Davis, 1989) attributes technology use to perceived usefulness and perceived ease of use. In this dissertation, the model is extended to external- and joint-audit settings by incorporating engagement-specific risk perception, client attitudes toward AI, and regulatory influences as additional determinants of auditors' behavioural intentions.
- 1.4.2 **Innovation Resistance Theory (IRT)**
  IRT (Ram & Sheth, 1989) differentiates between functional barriers (e.g. performance, usage, value, risk) and psychological barriers (e.g. tradition, image) that impede technology uptake. Applying IRT elucidates why auditors may resist AI–even when conventional acceptance drivers are favourable–thereby clarifying the sources of algorithm aversion identified in Objective 3.
- 1.4.3 **Technology Readiness Index (TRI)**

TRI (Parasuraman & Colby, 2015) captures optimism, innovativeness, discomfort, and insecurity toward novel technologies. In the present investigation, the index is operationalised at the client level: perceived client readiness moderates the relationship between innovation resistance (IRT) and auditors' algorithm aversion, thereby explaining variation in AI adoption across engagements.

Collectively, TAM elucidates the cognitive antecedents of acceptance, IRT diagnoses the attitudinal and contextual bases of resistance, and TRI introduces a readiness dimension that reshapes the balance between the two. This tripartite framework thus provides a multi-level perspective–encompassing individual cognition, inter-firm relationships, and institutional context–through which auditors' decisions to adopt AI in external, joint, and general audit practice are systematically interpreted.

1.5 Research Hypotheses

Guided by the research questions, three interrelated sets of hypotheses are articulated.

- Study One – External audits. Drawing on the TAM (Davis 1989), auditors' propensity to deploy AI is expected to diminish as perceptions of functional risk and transparency-and-fairness risk intensify. By contrast, client endorsement of AI and demonstrable client technological competence should amplify adoption intentions.
- Study Two – Joint audits. Successful AI-augmented joint engagements hinge on social legitimation. Adoption is hypothesised to rise with (i) client support, reflecting clients' connector role in auditors' networks (Aghazadeh & Hoang 2020; Malsch 2024); (ii) a conducive regulatory–policy environment that signals societal approval (Deore, Gallani, & Krishnan 2023; Munoko et al. 2020); and (iii) affirmative peer norms that confer professional approbation.
- Study Three – General audit context. Integrating IRT (Ram & Sheth 1989) and TRI (Parasuraman & Colby 2015; Blut & Wang 2020) with TAM, five resistance barriers–usage, value, risk, tradition, and image–are posited to heighten

algorithmic aversion. Perceived client technology readiness moderates these relationships: high innovativeness/optimism attenuates, whereas high discomfort/insecurity accentuates, the influence of the IRT barriers.

Collectively, these hypotheses offer a multilevel, theoretically grounded account of auditors’ AI adoption decisions across external, joint, and general audit settings.

1.6 Research Framework

Figure 1 illustrates the overall framework of this thesis, which provides a comprehensive examination of AI implementation in the accounting industry, focusing on both current adoption practices and future potential applications in auditing. Initially, the framework emphasizes how AI enhances accountants' abilities to collect, interpret, and forecast financial information. The potential for AI in auditing is then explored and categorized into three modes: assisted, augmented, and autonomous, as identified in the existing literature. These modes represent varying levels of AI involvement and integration in audit processes.

Based on this foundation, the thesis digs into three specific auditing contexts where AI could be impactful: external audits, joint audits, and general audit contexts. Each context examines different aspects of auditors' interactions with AI, including acceptance in risk management, social factors influencing acceptance in joint audits, and general aversion to AI algorithms. The framework highlights both the areas that have been extensively explored in existing research and those that remain under-explored, identifying the gaps that this thesis aims to address.

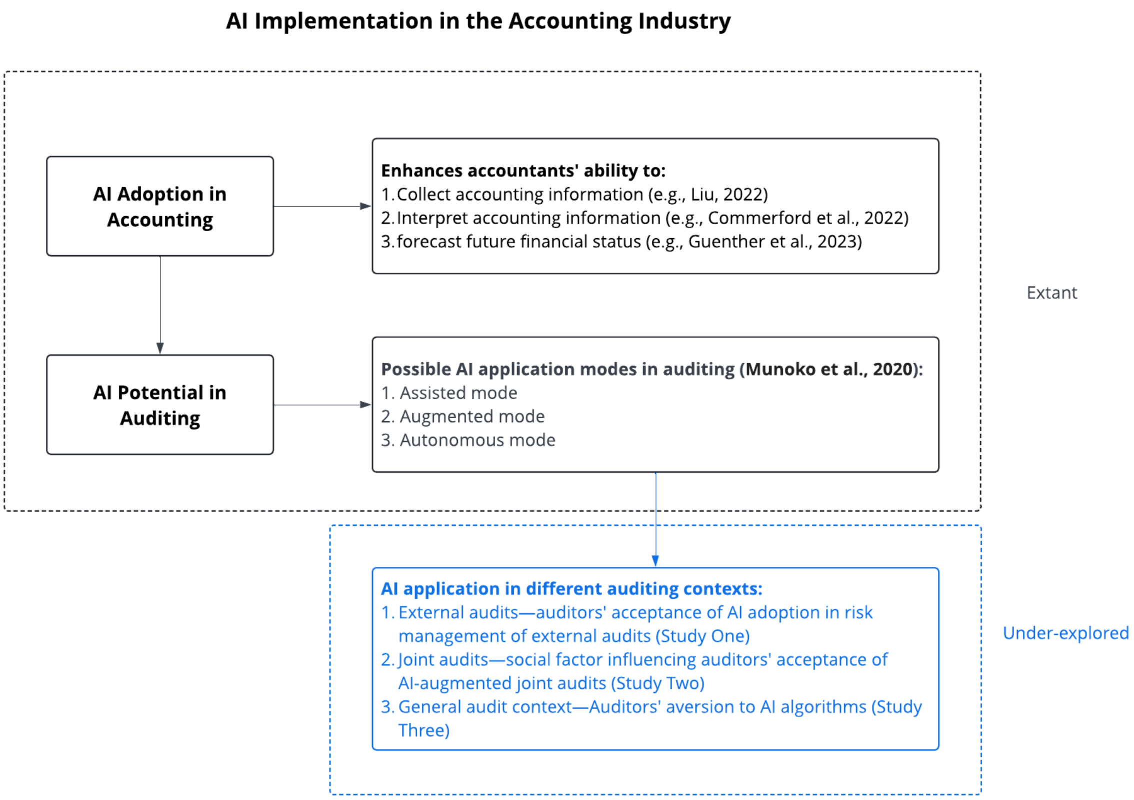


Figure 1. Overall framework

1.7 Research Methodology and Case Context

This thesis adopts a mixed-methods design that integrates survey experiments with follow-up, semi-structured interviews. The survey component captures auditors' behavioural intentions and perceptions under experimentally manipulated scenarios, while the interviews allow for in-depth exploration of the mechanisms underlying those responses. Data were collected from five geographically dispersed branches of Baker Tilly China, ensuring variation in organisational size, client portfolios, and local market conditions.

China offers an analytically rich context for studying AI adoption in auditing. Chinese accounting firms have become early movers in deploying AI, catalysed by an advanced digital infrastructure and national policies that explicitly incentivise AI-driven innovation (Leng & Zhang, 2024; Lennox & Wu, 2022). Baker Tilly China's experience therefore illuminates how audit firms can: (i) structure a feasible AI implementation framework; (ii) cultivate a digitally skilled workforce; and (iii) operate within a regulatory environment that is rapidly converging with international auditing standards. By systematically analysing evidence from this context, the thesis offers insights that can inform audit-firm strategy and regulatory policy worldwide, thus advancing a global understanding of responsible and effective AI integration in assurance services.

1.8 Thesis Structure

The sequence of chapters is designed to progress from conceptual foundations through methodological execution to theoretical and practical synthesis. The thesis is structured as follows:

- **Chapter 2** surveys the evolution of AI applications in auditing – spanning expert systems, ML, and generative AI – and pinpoints unresolved questions surrounding adoption drivers, barriers, and contextual factors that shape auditors’ decisions.
- **Chapter 3** integrates TAM, IRT, and TRI, explicating how their constructs interact in auditing contexts and deriving testable hypotheses for three distinct audit settings (external, joint, and general).
- **Chapter 4** describes the mixed-methods approach, detailing the survey experiment, semi-structured interviews, measurement scales, sampling strategy across five Baker Tilly China branches, and the procedures for data collection and preprocessing.
- **Chapter 5** presents the measurement-model evaluation, structural-model analyses (PLS-SEM), robustness checks, and qualitative insights, linking each finding to the corresponding hypothesis.
- **Chapter 6** interprets the empirical evidence in light of the integrated framework, assesses implications for audit practice (e.g. risk management, joint-audit coordination) and regulation, and contrasts the results with prior studies.
- **Chapter 7** summarises the thesis’s theoretical and practical contributions, acknowledges methodological limitations, and proposes concrete directions for future research on AI integration in assurance services.

These chapters build a coherent narrative that advances understanding of how, why, and under what conditions auditors embrace AI technologies.

1.9 Chapter Summary

This chapter positions the thesis at the intersection of technological innovation and professional judgment in auditing. It traces the evolution of AI – from early rule-based expert systems to today's machine-learning and generative models – to show how AI can streamline evidence collection, sharpen anomaly detection, and strengthen risk assessment. Yet adoption decisions hinge on more than technical capability: auditors remain attuned to ethical safeguards, data privacy, and algorithmic transparency when deciding whether to trust AI outputs.

Viewing AI uptake as a socially and psychologically embedded process, the chapter foregrounds three analytical lenses – risk perception, social influence, and algorithm aversion – that shape auditors' openness to AI across external, joint, and general audit engagements. A mixed-methods design, combining surveys and interviews in five branches of Baker Tilly China, leverages China's digitally advanced audit environment to generate insights with global relevance.

By clarifying the research questions, theoretical scaffolding, and empirical strategy, this chapter lays the groundwork for the thesis's key contributions. The study advances theory by integrating technology-acceptance and innovation-resistance perspectives to explain AI adoption in professional services; it enhances methodology through a multi-context, mixed-methods approach; and it delivers practical guidance for regulators, firms, and educators seeking to balance AI's efficiency gains with the human and institutional factors that ultimately determine its success in the audit profession.

CHAPTER TWO: LITERATURE REVIEW

2.1 Chapter Introduction

AI has evolved from early rule-based expert systems to contemporary deep-learning and natural-language architectures, fundamentally transforming the informational foundations of accounting and auditing (Law and Shen, 2025; Eisikovits, Johnson and Markelevich, 2025). In doing so, AI promises unprecedented speed in evidence gathering, sharper anomaly detection, and more consistent judgement-making (Cheng and Dai, 2025; Leng and Zhang, 2024). Yet technological potential alone does not guarantee professional uptake. As shown in Table 1, adoption unfolds through behavioural mechanisms that reflect auditors' risk perceptions, social interactions, and resistance to algorithmic decision-making (Ram, 2025;). This chapter therefore reviews the state of knowledge on those mechanisms, weaving together technology-focused and behaviourally oriented streams of research.

Guided by the thesis objectives, the review centres on three behavioural constructs. First, it explores perceived functional risk and transparency-and-fairness risk – concepts rooted in TAM – to clarify how auditors evaluate the technical soundness and procedural integrity of AI tools in external audits (Emett, Eulerich, Lipinski, Prien and Wood, 2024). Second, it examines social legitimation factors in joint audits, unpacking how client support, the surrounding regulatory – policy context, and prevailing peer norms collectively define AI's professional acceptability within multi-firm engagements. Third, it analyses five innovation-resistance barriers – usage, value, risk, tradition, and image – drawing on IRT and TRI to illuminate the psychological and contextual hurdles auditors face when encountering algorithmic systems in general audit settings.

By integrating these constructs across individual, client-relational, and institutional levels, the chapter clarifies how AI's technical affordances intersect with human judgement and social influence (Brynjolfsson, Li and Raymond, 2025). The review first surveys AI's functional contributions to accounting and auditing, then analyses the empirical evidence on each behavioural construct, and finally synthesises the gaps that motivate the thesis's hypotheses. In so doing, it lays a conceptual foundation for understanding not only whether AI can transform the audit profession, but under what behavioural conditions that transformation is likely to occur.

Table 1. Summary of the primary literature review

AI adoption	**AI in accounting**	***AI's functions in accounting (e.g. Costello et al., 2020):*** (i) Collecting accounting information (e.g. Liu, 2022) (ii) Interpreting current situations (e.g. Commerford et al., 2022) (iii) Forecasting future financial status (e.g. Guenther et al., 2023)
		AI adoption in the Chinese accounting industry: (i) Development of the Chinese accounting industry (Lennox and Wu, 2022) (ii) AI-related innovation environment (e.g. governmental initiatives: Li, 2018) (iii) Contributions of AI-related studies in Chinese accounting to broader literature (e.g. Lennox and Wu, 2022)
	AI in auditing	***Possible modes of AI adoption in auditing (Munoko et al., 2020):*** (i) *Assisted mode* (Munoko et al., 2020) (ii) *Augmented mode* (Raisch and Krakowski, 2020) (iii) *Autonomous mode* (Moll and Yigitbasioglu, 2019)
		AI in external audits: (i) Risks in external audits: a. Inherent risks (e.g. Dirsmith and Haskins, 1991) b. Control risks (e.g. Seidel, 2017) c. Detection risks (e.g. Luippold et al., 2015) (ii) AI's potential in alleviating the risks in external audits: a. Mitigating inherent risks by, such as, enhancing auditors' ability to identify financial misstatements (Brynjolfsson and Mitchell, 2017) b. Mitigating control risks by, such as, enhancing auditors' ability to review financial plans (e.g. Rahwan et al., 2019) c. Mitigating detection risks by, such as, enhancing auditors' ability to identify unusual patterns within financial data (Munoko et al., 2020)

Table 1. (*Continued*)

		AI in joint audits: (i) The practice of joint audits varies across regions

		a. Relatively common but not uniformly required in the EU (e.g. Kermiche & Piot, 2018) b. Not widely employed in the U.S. (Deng et al., 2014) c. Not mandatory but can be selected in China (per the CICPA documents) (ii) The practice of joint audits is limited by: a. Communication complexity (e.g. Lobo et al., 2017) b. Accountability complexity (e.g. Hoos et al., 2019) (iii) The potential of augmented AI application mode in joint audits: a. Accounting firm level: 1. Data security and integrity (e.g. Janvrin & Wang, 2022) 2. Integration and collaboration (e.g. Bauer et al., 2022) 3. Strategic insights and decision making (e.g. Dierynck et al., 2023) b. Auditor level: 1. Enhanced analytical capabilities (e.g. Luo et al., 2021) 2. Advanced communication tools (e.g. Chukwuani, 2022) 3. Automation and efficiency (e.g. Eulerich et al., 2022)

Table 1. (*Continued*)

		AI algorithm aversion in general audit environments: (i) AI algorithm aversion in other fields: a. In highly regulated fields (e.g. Trocin et al., 2023) b. In fields where human intuition and experience are highly valued (Lavanchy et al., 2023) (ii) AI algorithm aversion in auditing: a. Concerns about the limitations in AI's functions and operations (e.g. dealing with complex financial reports: Estep et al., 2023) b. Concerns about the drawbacks in AI's adaptiveness (e.g. adapting to characteristics of clients at non-Big Four accounting firms: Jemine et al., 2023) c. Concerns over AI's explainability and accountability (e.g. Glikson & Woolley, 2020)
		The importance of auditor attitude in realizing AI's potential in auditing: (i) The importance of auditor attitude in using AI to augment or replace traditional audit methods (e.g. Samiolo et al., 2023). (ii) The importance of auditor attitude in adapting AI to various audit contexts (e.g. Munoko et al., 2020).

This table provides a summary of the primary literature review for my thesis, covering AI applications in accounting, AI's potential across various auditing contexts, the advantages and disadvantages of AI adoption in audits, and the critical role of auditor attitude in integrating AI into the audit process. This review informs the selection of research models in the subsequent chapter.

2.2 Artificial Intelligence (AI)

AI is functionalized as the simulation of human intelligence processes by machines, particularly computer systems (Law and Shen, 2025; Estep, Griffith, and MacKenzie, 2023). These processes comprise learning, reasoning, and self-correction. As an essential evolution of AI concepts, ML refers to an AI subset that enables systems to learn and improve from work experience autonomously. This function is achieved by developing algorithms that can interpret, predict, and respond to data, facilitating a dynamic and responsive AI system. AI technologies, including artificial neural networks and natural language processing, have advanced AI's applicability in complex tasks ranging from multiple sectors (de Kok, 2025; Bochkay, Brown, Leone, and Tucker, 2023).

AI has demonstrated significant potential in advancing accounting and auditing technologies to meet the evolving demands of the market (Costello, Down, and Mehta, 2020) since its initial practical application as an expert system in the accounting field (Copeland, 1989). As a specialized form of technological innovation, AI-enabled programmes equip accounting firms to address complex issues and perform repetitive tasks with greater efficiency (Leng and Zhang, 2024). By mimicking accountants' and auditors' behaviours – especially those related to cognitive activities (Song, 2021) – through machine learning (ML, Nguyen et al., 2019), AI enhances their capacity to handle intricate decisions (Commerford, Dennis, Joe, and Ulla, 2022; Hodge, Mendoza, and Sinha, 2021). For instance, human-like AI, such as generative AI (e.g. ChatGPT), boosts the efficiency of accounting and auditing tasks, thereby contributing to the evolution of these professions (Wei, Wu, and Chu, 2023). Accounting firms are incorporating AI into auditing processes to streamline audit procedures, reduce manual workloads, and improve overall audit quality (Brynjolfsson, Li and Raymond, 2025; Munoko et al., 2020). This technological progress allows auditors to concentrate more on complex judgmental areas, thereby enhancing the value of their work.

However, as AI advances, it also engenders ethical considerations and societal implications, thus requiring users to explore an effective and appropriate approach to its development and deployment (Ram, 2025; Munoko et al., 2020). This exploration includes the assessment of various dimensions, notably AI's inherent drawbacks and users' acceptance of using it. Therefore, research on the adoption of AI in professional contexts is essential for industrial practitioners.

2.3 AI Implementation in Accounting

AI-related technological innovation is vital for accounting firms as it facilitates firm growth in the era of digital transformation (Cordery, Goncharenko, Polzer, McConville, and Belal, 2023; Costello et al., 2020; McDaid, Andon, and Free, 2023). In financial and managerial accounting fields (Eulerich, Sanatizadeh, Vakilzadeh and Wood, 2024; Orthaus, Pelger, and Kuhner, 2023; Ricci, 2022; Robson, Young, and Power, 2017), AI helps accountants analyse accounting information by simulating their cognitive processes (Kuselias et al., 2023; Song, 2021). Thus, practical AI implementations in accounting typically contribute to analyzing financial documents and managing potential risks (Beneish and Vorst, 2022; van der Heijden, 2022).

AI enhances accountants' ability in three steps. See Table 1. First, AI-based technologies enable accountants to collect accounting information that emerges in targeted environments comprehensively and efficiently (Hoff and Bashir, 2015; Liu, 2022; Rahwan et al., 2019). Such information can contain various types, including textual, audio, and video. Thus, AI provides accountants with reliable information foundations when helping organizations make decisions about business lending (Liu, 2022), financial investment (Coleman, Merkley, and Pacelli, 2022), and innovation deployment (Balakrishnan, Huang, and Xuan, 2023; Henri and Wouters, 2020). Second, AI improves accountants' ability to interpret situations logically according to the obtained accounting information, even if the contexts are complex (Eulerich, Sanatizadeh, Vakilzadeh and Wood, 2024; Commerford et al., 2022). During this process, AI also allows accountants to develop effective logical patterns, thereby increasing efficiency and effectiveness when explaining similar situations in the future (Brynjolfsson and Mitchell, 2017). Third, AI enables accountants to forecast organizations' future financial status by analyzing obtained accounting information, thus assessing the reliability of financial statements. Such a function helps accountants avoid risks in the accounting process from multiple aspects, such as predicting effective tax rates (Emett, Eulerich, Lipinski, Prien and Wood, 2024; Guenther et al., 2023), detecting financial misstatements (Brown, Crowley, and Elliott, 2020), and identifying accounting fraud (Bao et al., 2020; Beneish and Vorst, 2022). Although academic interest in AI within accounting has intensified, its implications for auditing procedures remain comparatively underexplored. A rigorous examination is required to determine how the technology influences evidence gathering, judgment consistency, and risk evaluation in contemporary audit practice.

2.4 AI's Potential in Auditing

AI's ability to improve the accounting process implies its potential in auditing activities, considering the relationships between accounting and auditing (Bracci, 2023). The interplay between accounting and auditing is the foundation of financial reporting and corporate governance. Accounting serves as the systematic process of recording, analyzing, and interpreting financial transactions, guiding the preparation of financial statements that reflect organizations' financial positions and performances (Eisikovits, Johnson and Markelevich, 2025; Robson and Ezzamel, 2023). Auditing, in contrast, acts as an important oversight mechanism, providing an independent examination of these financial statements to ensure their accuracy and reliability (Emett, Kaplan, Mauldin, and Pickerd, 2023). Based on the principles of transparency and accountability, while accounting lays the groundwork for financial reporting, auditing examines the authenticity and compliance of these reports with established standards and regulatory frameworks. The integration of accounting and auditing becomes increasingly critical in mitigating financial misstatements and fraud. Based on AI's enhancement in accounting, such interplay between accounting and auditing also suggests AI's potential contribution to auditing activities.

AI's potential in auditing is diverse, offering distinct advantages to various practices. For instance, in external audits, AI's ability to learn about financial situations allow auditors to find feasible solutions to financial issues, thus reducing inherent risk (Cheng and Dai, 2025; Brynjolfsson and Mitchell, 2017; Taylor, 2000). AI can also help auditors anticipate the outcomes of client firms' financial plans (Tan & Yeo, 2023) before they conduct any actual investment (Godsell et al., 2023). This function helps auditors test the reasonability of client firms' financial plans, thereby lowering control risks in external audits (Glikson and Woolley, 2020; Seidel, 2017). Furthermore, AI enables auditors to avoid detection risks when evaluating clients' financial statements (Smith, 2023) by providing them with more elaborate financial information foundations (Glikson and Woolley, 2020; Luippold, Kida, Piercey, and Smith, 2015). The incorporation of AI is also significant in audit teamwork or cooperative auditing scenarios, such as joint audits, where AI can enhance data analysis, improve error detection, and facilitate collaboration among auditors. In joint audits, AI, particularly in its augmented application mode (Munoko et al., 2020), has the potential to overcome the limitations of joint audits. Specifically, augmented AI is a concept that includes specific forms of AI that can enhance human auditors' activities (Munoko et al., 2020). In the context of joint audits, augmented AI systems can be integrated into workflows and decision-making processes, enhancing communications between auditors and clients and among auditors themselves, thereby elevating the quality of joint audits.

AI encompasses a spectrum of approaches, from rule-based expert systems to fully autonomous agents, but four principal forms are most prominent in auditing contexts. ML refers to algorithms that enable systems to identify patterns in historical data and iteratively improve their performance without explicit reprogrammeming. Building on ML, DL employs multi-layered artificial neural networks to model complex, non-linear relationships, making it especially powerful for tasks like anomaly detection in large financial datasets. Generative AI, a recent evolution of DL, uses architectures such as transformers to produce novel content–text, code, or even synthetic data–based on learned representations (e.g. ChatGPT for drafting audit reports). Finally, automated AI systems integrate ML or DL models into end-to-end workflows, orchestrating data ingestion, analysis, and routine decision-making with minimal human intervention (e.g. bots that automatically flag transaction exceptions).

In the thesis's fieldwork, I consider that auditors generally viewed AI as an advanced form of analytics that could automate repetitive, rule-based procedures but still required human oversight for judgment-intensive tasks. They perceived it less as an autonomous decision-maker and more as a tool to augment their efficiency and focus on complex, value-added audit judgments.

Prior conceptual analysis of AI adoption in auditing based on Big Four accounting firms has shown three possible modes of AI integration (Munoko et al., 2020). The first is the *assisted mode* (Munoko et al., 2020). This mode in auditing primarily functions as a support tool that enhances human auditors' capabilities without replacing their judgment. The mode leverages AI to automate routine tasks including data collection and preliminary analysis, enabling auditors to allocate more time to complex audit processes. For instance, AI-powered document review tools can rapidly analyse large volumes of transaction records, identifying errors that warrant further examination. This assistance increases the audit's efficiency by accelerating time-consuming tasks and enhances its effectiveness by improving the accuracy and thoroughness of the data analysis. Assisted mode represents a collaborative approach between human auditors and AI technology, where the primary decision-making responsibility remains with the human professionals.

The second is the *augmented mode* (Raisch and Krakowski, 2020). Augmented mode takes the concept of assistance a step further by supporting and enhancing auditors' decision-making capabilities. Namely, human auditors and AI are co-decision-makers in this mode (Munoko et al., 2020). The mode integrates more sophisticated AI technologies to give auditors deeper insights into financial data and predict potential issues. Augmented mode can help auditors identify complex trends within the data that might be tough to detect through manual analysis alone. By presenting auditors with predictive analytics and risk assessment tools, augmented mode enables them to make more informed decisions. This mode still relies on auditors to interpret and act on the insights provided, ensuring that human judgment remains central to the audit process.

The third is the *autonomous mode* (Moll and Yigitbasioglu, 2019), designed to conduct various audit tasks with minimal human intervention. The mode embodies the most advanced AI capabilities, capable of executing entire audit processes, from data collection and analysis to generating audit reports (Munoko et al., 2020). Autonomous mode is developed upon complex algorithms that can adapt and learn from audit outcomes, continuously improving AI performance over time. While the potential for autonomous AI in auditing is vast, offering the promise of unprecedented efficiency and accuracy, it also raises significant ethical considerations regarding oversight and accountability. The deployment of autonomous AI in auditing entails strict standards and frameworks to ensure that AI programmes operate within ethical and professional requirements, maintaining the integrity of the audit process. Building on the transformative potential of AI in auditing, the forthcoming sections analyse its specific applications across three contexts: external audits, joint audits, and the broader general audit practice.

2.5 AI in External Audits

The three modes of AI applications suggest AI's capability of contributing to specific auditing activities, especially risk management of external audits. See Table 1. Audit risk management is an essential audit-planning process that assesses the potential risks in audits, thus influencing the overall conduct of audits significantly (Smith, 2023; Taylor, 2000). Potential risks in external audits have been featured in various types, including inherent (Dirsmith and Haskins, 1991; Taylor, 2000), control (Christensen, Lei, Shu, & Thomas, 2023; Seidel, 2017), and detection risks (Luippold et al., 2015). Auditors balance the levels of these risks based on audit standards, obtaining appropriate audit results (Guénin-Paracini, Malsch, and Paillé, 2014; Salterio, Hoang, and Luo, 2021).

Inherent risks refer to the risks caused by mistakes or neglect in financial statements because of factors other than client firms' failures of internal controls (Dirsmith and Haskins, 1991). During external audits, inherent risks typically appear when financial transaction records are complex, or under contexts that entail superior ability of financial assessment (Ashton, 1991; Taylor, 2000). Control-risk assessment is the process of examining the effectiveness of client firms' pre-designed internal controls regarding the prevention and detection of material misstatements (Christensen, Schmardebeck, and Seidel, 2022; Seidel, 2017) in their financial statements. Inappropriate external auditing processes result in client firms' vulnerability in their policies or procedures (Seidel, 2017), risking insufficient controls of financial misstatements (Christensen et al., 2023). Detection risks in external audits are associated with auditor' ability to identify material misstatements in financial reports (Luippold et al, 2015; Aghazadeh and Joe, 2022). Such capability is affected by auditors' knowledge of professions (Goldman, Harris, and Omer, 2022) and client firm managers' behaviours (Luippold et al, 2015). From the client side, for example, managers could divert auditors (Luippold et al, 2015), either with good intentions or not, away from financial accounts (Bay, 2018) with high risks toward lower ones. This activity could affect auditors' detection of financial overstatements. This type of judgment error may increase detection risks in external audits.

AI can be leveraged in external audits by alleviating these risks. In terms of inherent risks, AI can assist auditors in analyzing massive financial and operational data to identify patterns and anomalies (e.g. financial misstatements) related to clients' businesses and industries (Brynjolfsson and Mitchell, 2017; Cohen, Krishnamoorthy, and Wright, 2017; Taylor, 2000). AI algorithms can predict inherent risks associated with economic fluctuations or industry-specific challenges according to the learning of historical data. Such functions allow auditors to understand clients' risk profiles more comprehensively, thereby controlling inherent risk levels. Moreover, AI can enhance control risk evaluation by simulating financial processes, notably transactions, using robotic process automation (RPA: Eulerich et al., 2022) and continuously monitoring organizations' internal controls to detect and address control failures timely. Auditors can also use AI-enabled technologies, notably natural language processing (de Kok, 2025; NLP: Gepp, Linnenluecke, O'Neill, and Smith, 2018), to review the documents about financial plans for deficiencies and inconsistencies (Rahwan et al., 2019; Seidel, 2017). In addition, AI can mitigate detection risks by optimizing sample selection, identifying unusual patterns within financial data using anomaly detection, and automating audit procedures through AI-enabled applications, all of which enhance auditors' ability to detect material misstatements during external audits. Nevertheless, auditors must possess professional judgment and maintain compliance with audit standards while integrating AI into their audit procedures (Munoko et al., 2020).

Given AI's potential in auditing, especially in external audits, AI technologies are spreading fast in auditing areas (Bracci, 2023; Centobelli, Cerchione, Del Vecchio, Oropallo, and Secundo, 2022). Notwithstanding, prior studies have identified several factors impeding AI's popularization in auditing. Notably, in complex financial reporting, managers' uncertainty about AI's usefulness affects their willingness to integrate AI-based information, provided by auditors, into their reporting decisions (Ram, 2025; Estep et al., 2023). Moreover, in non-Big Four accounting firms, the quality of AI-enabled audit services is doubted due to AI's constraints in adapting to heterogeneous client features, hindering AI's wide application (Jemine, Puyou, and Bouvet, 2023; Knechel, Thomas, and Driskill, 2020). These studies highlight the importance of investigating the obstacles to deploying AI in specific auditing contexts, particularly in the risk management of external audits.

A summary of AI-enabled capabilities mapped to each external-audit risk type:

- **Inherent Risk**

  1. AI-powered anomaly mining: machine-learning models sift huge transaction and operational datasets to flag unusual patterns or misstatements.
  2. AI-driven risk forecasting: predictive algorithms learn from historical macro-economic and industry data to anticipate client-specific shocks that raise inherent risk.

- **Control Risk**

  3. AI-based robotic-process-automation (RPA): simulates end-to-end transaction flows to expose weak or missing internal controls in real time.
  4. AI continuous-monitoring agents: stream real-time control-effectiveness metrics, alerting auditors the moment a control fails.
  5. AI natural-language-processing (NLP): reads policies, manuals, and process

narratives to detect gaps, inconsistencies, or outdated control descriptions.

- **Detection Risk**

1. AI anomaly-detection engines: score every ledger entry, guiding auditors to high-risk items and optimizing sample selection.
2. AI-augmented substantive procedures: automate ratio analysis, pattern matching, and other tests so auditors can expand coverage without extra hours.
3. AI outlier-surfacing dashboards: highlight unusual journal entries or trends that merit deeper human investigation, improving judgment accuracy.

2.6 AI in Joint Audits

Joint audits refer to the practice where multiple independent accounting firms are appointed to conduct the audit of an entity, working collaboratively to provide assurance on the entity's financial statements (Guo et al., 2017). This approach is based on the principle of enhancing audit quality and reliability by incorporating diverse perspectives, thereby mitigating the risk of oversight or bias that might occur with a single accounting firm. Joint audits are particularly required in complex audit environments, where the scale, nature, or geographical dispersion of the audited entity's operations need a multifaceted audit ability that a single firm may not fully possess (Guo et al., 2017).

The practice of joint audits varies in prevalence and regulatory support across different regions. See Table 1. These audits can be used in situations where the entity being audited is complex, large-scale, or geographically dispersed, although their necessity is debated. In some regions, such as France, joint audits are mandatory for publicly listed companies (Francis, Richard, & Vanstraelen, 2009; Kermiche & Piot, 2018), while in others, like the United States, they are rare and not required by law (Deng, Lu, Simunic, & Ye, 2014). In China, joint audits are encouraged for entities with international operations or those considered highly complex, including those listed on the stock exchange[1]. While joint audits may offer benefits, they are not always necessary for every entity and can be

[1] For details on joint audits in China, refer to the documents issued by the Chinese Institute of Certified Public Accountants (CICPA), such as the "Notice of the Ministry of Finance on Issuing Several Provisions on Improving and Strengthening the Management of Auditing of Annual Accounting Statements of Enterprises" (Articles 12 and 29), dated June 28th, 2004. https://www.cicpa.org.cn/ztzl1/zthf/Legal_norms/bmgz/200804/t20080428_43986.html

challenging to implement effectively. Overall, the adoption of joint audits reflects regional regulatory features and market dynamics, with significant variation observed across these major economies.

The practice of joint audits is limited by two significant challenges. Ineffective communication, delays, and inefficiencies are common challenges (Ittonen & Trønnes, 2015; Lobo, Paugam, Zhang, & Casta, 2017), as well as issues with accountability when multiple firms are involved (Hoos et al., 2019). Furthermore, joint audits introduce challenges of coordination between auditors and clients, which can affect audit effectiveness (Nekhili et al., 2022; Lobo et al., 2017). When different firms, including a Big Four and a non-Big Four firm, are involved, this complexity can increase due to differences in internal methodologies, priorities, and corporate cultures (Keune, Mayhew, & Schmidt, 2016; Khurana, Lundstrom, & Raman, 2021; Lobo et al., 2017). These disparities can lead to misunderstandings in audit approaches and findings, complicating the integration of final audit results. Additionally, effective client-to-auditor communication is crucial in joint audits (Nekhili et al., 2022). Each auditor must maintain clear and consistent channels of communication with the client to gather necessary information efficiently and to minimize the risk of conflicting requests and extra costs (André, Broye, Pong, & Schatt, 2016). This requires a high level of synchronicity and transparency between the auditors to present a unified report to the client, which can be difficult to achieve and manage, especially in larger or more complex joint audit environments. These communication needs also underscore the importance of selecting the appropriate team composition in teamwork audits (Nekhili, Javed, & Chtioui, 2018; Nekhili et al., 2022).

The second issue is that joint audits can introduce complexities in accountability that may obscure the clarity of responsibility (Hoos et al., 2019). When multiple firms are involved, it can become challenging to identify accountability for specific audit decisions or findings. This diffusion of responsibility can lead to situations where errors or misjudgments cannot be promptly identified and addressed, as each firm may assume the other is responsible for overseeing a particular aspect of the audit (Hoos et al., 2019).

Furthermore, in the event of an audit failure or discovery of misstatements, it can be difficult to establish liability, potentially leading to legal disputes or damage to professional reputations. In some environments, regulatory frameworks may lack specific guidelines on handling all possible situations in joint audits, which can further complicate accountability issues (Hoos et al., 2019). This lack of clear accountability measures can make clients and accounting firms hesitant to engage in joint audit arrangements, despite the potential benefits of enhancing audit quality by integrating multiple expertise and resources.

AI, particularly its augmented application mode. See Table 1. demonstrates the potential to mitigate the limitations of joint audits. Augmented AI refers to systems designed to enhance human capabilities by incorporating specific forms of AI technologies into the human activities, rather than replacing humans entirely (Brynjolfsson, Li and Raymond, 2025; Munoko et al., 2020). This approach combines the strengths of AI technologies with human judgment, creativity, and expertise. The goal of augmented AI is to improve the accuracy, efficiency, and productivity of human tasks without fully automating them, thus allowing for human oversight where necessary. By leveraging AI as a supportive tool, augmented AI fosters a collaborative interaction where machines handle computationally intensive tasks, enabling humans to focus on more complex and professional activities (Brynjolfsson et al., 2025; Munoko et al., 2020). This collaboration mode ensures that the AI systems are used ethically, as humans can intervene in and guide AI decisions, effectively creating an augmented intelligence that could potentially lead to more responsible use of AI technologies.

The necessity of augmented AI in joint audits stems from the inherent challenges associated with communications (cf. Munoko et al., 2020). Augmented AI has the potential to address the communication issue by offering advanced analytical capabilities, enhancing data security, and strengthening connections both among auditors and between clients and auditors in joint audits. Specifically, the application of augmented AI in joint audits unfolds across several dimensions. For instance, first, augmented AI technologies (e.g. AI-involved RPA: Eulerich et al., 2022) can enhance human auditors' ability to identify patterns, anomalies, and trends by processing vast quantities of data efficiently (Asif, Searcy, & Castka, 2023; Chen, Cho, Dou, & Lev, 2022). This capability is valuable because it improves communications in joint settings where efficient information sharing is essential. Second, specific forms of augmented AI, including AI-enhanced virtual reality (Chukwuani, 2022), can simulate the on-site audit experience, providing virtual walkthroughs of business operations. This technology can create the sensory and contextual aspects of on-site audits, facilitating a more tangible understanding of the business environment and a tighter connection with clients (Emett, Eulerich, Lipinski, Prien and Wood; 2024; Brazel, Agoglia, & Hatfield, 2004; Francis, Golshan, & Hallman, 2022). Third, technologies related to augmented AI (e.g. anomaly detection systems: Luo et al., 2021) can monitor data in real-time, efficiently detecting and mitigating potential security breaches (Burke, Hoitash, & Hoitash, 2020; Janvrin & Wang, 2022). This function ensures the integrity and confidentiality of the communications in joint audits, ensuring secure collaboration even when participants are remote (Bauer, Humphreys, & Trotman, 2022; Dierynck, Kadous, & Peters, 2023). Fourth, deploying certain AI types, notably generative AI, in an augmented mode, can improve communications by providing services notably language translation, sentiment analysis, and summarization of conversations and documents (Ardekani et al., 2024; Wei et al., 2023). This ability ensures clear and effective communication across auditors, ensuring the quality of communication during the joint audit process. Figure 2 illustrates practical examples of how AI-augmented systems contribute to joint audits at both individual and firm levels.

Accounting firm level

a. Data Security and Integrity (*Burke, Hoitash, & Hoitash, 2020; Janvrin & Wang, 2022; Munoko et al., 2020*)

AI-based Cybersecurity Systems:

Task Example: Continuous monitoring of audit data exchanges for potential security breaches or unauthorized access.
Benefits: Ensures the confidentiality and integrity of sensitive audit information, protecting both the firm and the client.

b. Integration and Collaboration (*Bauer et al., 2022; Dierynck et al., 2023*)

AI-enhanced Collaborative Platforms:

Task Example: Using a shared, AI-monitored data platform where auditors can upload and access audit evidence and working papers.
Benefits: Facilitates effective data sharing and real-time updates, reducing delays and enhancing coordination among audit teams.

Shared Data Repositories with AI Monitoring:

Task Example: Real-time AI analysis of shared audit data to identify inconsistencies or areas needing further review.
Benefits: Ensures data accuracy and integrity, improving the overall quality of the joint audit.

c. Strategic Insights and Decision Making (*Dierynck et al., 2023; Munoko et al., 2020*)

AI-driven Analytics:

Task Example: Predictive analytics to forecast potential risk areas in the client's financial statements based on historical data and industry trends.
Benefits: Helps auditors focus on high-risk areas, improving the efficiency and effectiveness of the joint audit.

Continuous Improvement Systems:

Task Example: AI analyzes past joint audit processes and outcomes to suggest improvements and best practices for future audits.
Benefits: Enhances audit methodologies and ensures continuous improvement in joint audit practices.

Auditor level

a. Enhanced Analytical Capabilities

Anomaly Detection Systems (Luo et al., 2021):

Task Example: During the audit of financial statements, auditors use AI to scan transactional data for unusual patterns, such as large transactions occurring at irregular times.
Benefits: Quickly identifies potential fraud or errors, allowing auditors to focus on investigating significant issues.

Generative AI (Ardekani et al., 2024; Wei et al., 2023):

Task Example: AI generates preliminary audit reports and summaries based on analyzed data.
Benefits: Saves time on report writing, ensures consistency in documentation, and allows auditors to validate AI-generated content rather than creating it from scratch.

b. Advanced Communication Tools

AI-enhanced Virtual Reality (Chukwuani, 2022):

Task Example: Auditors from different firms collaborate in a virtual meeting room to discuss audit findings and plan the next steps.
Benefits: Real-time, immersive collaboration that enhances understanding and decision-making without the need for physical travel.

AI-driven Communication Platforms (Munoko et al., 2020):

Task Example: Automated summarization of client communications and audit documentation for quick reference during audit meetings.
Benefits: Reduces time spent on reviewing communications and ensures that all team members are informed of key points and updates.

c. Automation and Efficiency

Robotic Process Automation (Eulerich et al., 2022):

Task Example: Automating the extraction and reconciliation of financial data from client systems to the accounting firm's systems.
Benefits: Increases accuracy and efficiency, freeing auditors to perform higher-level analytical tasks.

Figure 2. Multi-level contributions of augmented AI to joint audits

However, integrating augmented AI into joint audits presents unique accountability challenges, primarily stemming from the diffusion of responsibility and the interpretation of AI-generated insights (Munoko et al., 2020). In a joint audit scenario, multiple auditors collaborate, and the introduction of augmented AI could obscure the lines regarding responsibility for audit decisions and outcomes (Dwivedi et al., 2023; Munoko et al., 2020). Specifically, when augmented AI is used to analyse large volumes of data and make complex recommendations, determining which auditor is responsible for specific parts of the audit can become complicated. Each auditor might rely on the AI's analysis, potentially leading to a situation where critical judgments made by the augmented AI systems are less thoroughly examined by human auditors (Methnani, Chiou, Dignum, & Theodorou, 2024; Munoko et al., 2020). This reliance increases the risk that auditors may accept AI-generated audit conclusions without adequate independent verification. Moreover, the interpretation of data and recommendations provided by augmented AI can vary between different auditors. This variation could lead to inconsistencies in audit findings or conclusions if each auditor applies different interpretative approaches to the AI's output. Consequently, when discrepancies arise, it may be challenging to clarify accountability, as each auditor could attribute the responsibility for any errors or oversight to the other or to the augmented AI system (Munoko et al., 2020). The accountability issue could worsen with the deployment of certain technologies in augmented AI systems, where the algorithms are not fully transparent or explainable (Dwivedi et al., 2023). Auditors may struggle to fully validate and justify the recommendations made by augmented AI, raising potential concerns about the joint audits conducted by human-AI teams (Methnani et al., 2024). Thus, while augmented AI can enhance auditors' communications, it increases accountability challenges in joint audits.

2.7 AI Aversion in Auditing

Despite the potential of AI in various auditing practices, auditors may still be reluctant to adopt AI algorithms. AI algorithms are computational processes that leverage programmes to perform tasks traditionally requiring human intelligence (Hanisch, Goldsby, Fabian, & Oehmichen, 2023; Murphy & Feeney, 2023). These tasks range from simple pattern recognition to complex decision-making and problem-solving (Ram, 2025; Broekhuizen, Dekker, de Faria, Firk, Nguyen, & Sofka, 2023). AI algorithms can be rule-based systems that follow explicitly programmemed instructions, or they can be machine learning models that learn patterns from data. Features of AI algorithms include their ability to process vast amounts of data at high speeds, learn from new data to improve over time, and make predictions or decisions without human intervention. Advanced AI algorithms, particularly those based on deep learning, can handle unstructured data including images, text, and audio, enabling applications in diverse professional fields (de Kok, 2025; Mahlendorf, Martin, & Smith, 2023).

AI algorithm aversion is a phenomenon where individuals prefer human judgment over AI, even when the AI can perform better (Castelo, Bos, & Lehmann, 2019; Liu, Tang, Xia, Zhang, Zhu, & Meng, 2023; Reich, Kaju, & Maglio, 2023; Turel & Kalhan, 2023). This aversion stems from a lack of trust in the AI's capabilities, discomfort with technology, or fear of losing control. Psychological factors such as the desire for human accountability and empathy play a significant role. When AI makes errors, people tend to be less forgiving compared to when humans err, often due to the perception that machines should be flawless (Dietvorst et al., 2015). Additionally, there is a fear of the unknown and the potential consequences of AI errors, which can lead to resistance in adopting AI-driven solutions. This aversion can impede the integration of AI technologies in various domains, despite their potential benefits.

The manifestation of algorithm aversion varies across industries and professional contexts due to varying degrees of trust, familiarity, and perceived impact on decision-making (Lavin et al., 2022). In highly regulated industries notably healthcare (Trocin, Mikalef, Papamitsiou, & Conboy, 2023) and finance (Aziz, Dowling, Hammami, & Piepenbrink, 2022), there is significant aversion due to the critical nature of decisions and potential risks to human life or large sums of money. Professionals in these fields can prefer human judgment, fearing that AI might make errors that could have severe consequences. Even in fields that are tech-driven and innovation-centric, there is a cautious approach to completely releasing control to AI, particularly for creative or strategic decisions where human intuition and experience are highly valued (Lavanchy, Reichert, Narayanan, & Savani, 2023). Across all industries, the common thread in AI algorithm aversion lies in the balance between the perceived reliability of AI and the value placed on human expertise. Building trust in AI through transparency, explainability, and demonstrated efficacy is crucial for mitigating aversion and fostering a collaborative human-AI relationship (Munoko et al., 2020).

Algorithm aversion in auditing refers to the skepticism that auditors exhibit toward relying on AI algorithms for the audit process, despite evidence that these algorithms can match or surpass human performance in detecting anomalies or misstatements in financial data (Coleman, Merkley, & Pacelli, 2022; Commerford et al., 2022; Libby & Witz, 2024). Auditors may be concerned that using AI could lead to unexplainable errors or overlook contextual insights (e.g. social contexts: Mahmud, Islam, Ahmed, & Smolander, 2022) that a human auditor might catch. Moreover, there is a concern about the accountability of decisions made by AI, as it complicates attributing responsibility for mistakes, which is crucial in an auditing context (e.g. in audit teams: Bucaro, Wilks, & Yust, 2023) where accuracy and accountability are paramount. As a result, even when AI algorithms provide high accuracy and efficiency, their adoption in auditing is hindered by these barriers, along with a preference for the traditional, more interpretable methods where the decision-making process is more transparent and familiar to the auditing professionals.

Auditors' algorithm aversion differs from similar phenomena in other fields due to the unique nature and high stakes of the auditing profession. In auditing, errors or oversights can lead to severe consequences, including significant financial losses, legal liabilities, and reputational damage (Libby & Witz, 2020). Auditors are traditionally trained to rely on their professional judgment, refined through experience and adherence to established standards and practices. The introduction of AI algorithms challenges this paradigm, as auditors may be skeptical of the algorithm's ability to handle the complex, context-specific, and detailed decisions often required in auditing. This skepticism is further compounded by concerns over explainability and accountability, as auditors may struggle to understand and trust the decision-making processes of AI, especially when these processes are perceived as uninterpretable (Glikson & Woolley, 2020; Munoko et al., 2020). In contrast, algorithm aversion in other fields often stems from a general mistrust of automation (Ashraf, 2024) and fear of job displacement or loss of personal touch. While these concerns are valid, the context-specific nature of auditing amplifies the impact of algorithm aversion.

2.8 Auditor Attitude in AI adoption

The benefits and challenges of incorporating AI in auditing highlight the need to understand how factors influence auditors' attitudes toward this integration. The acceptance of AI by auditors is crucial for realizing the potential of AI in audits, as it directly influences the extent to which AI technologies can be effectively utilized to enhance audit quality and efficiency (cf. Chatterjee et al., 2021). The integration of AI into auditing processes requires a significant shift in traditional audit methodologies, involving the adoption of new tools and techniques that can process vast amounts of data faster and with greater accuracy than human auditors alone (Samiolo et al., 2023). However, the potential of these AI-driven tools can only be fully realized if auditors are willing to trust AI-generated insights for decision-making. This trust is essential for encouraging auditors to actively use tools related to AI in their work, which in turn fosters an environment where continuous improvement and innovation in audit processes can take place. Therefore, I conducted three studies to investigate auditors' attitudes toward AI in three distinct audit contexts: external, joint, and general audit environments.

In external audits, I explore the factors impeding AI's widespread implementation. Although prior research has shown conceptual frameworks for using AI in auditing, notably AI's ethical application in audits (Munoko et al., 2020), the determinants of auditors' acceptance of AI, particularly those that emerge in external audits, remain unclear. I used TAM (Davis, 1989) as the foundational model and proposed the factors affecting auditors' attitudes toward AI, examining the barriers to AI implementation in risk management of external audits.

In joint audits, I consider that the external implementation contexts of augmented AI may vary across different audit practices, affecting auditors' acceptance of the pros and cons of its integration into certain audit processes. When auditors accept the benefits and drawbacks of augmented AI within specific contexts, it helps ensure that its implementation in various audit modes aligns with professional standards and regulatory requirements, thus preserving the integrity and credibility of the audit process (cf. Munoko et al., 2020). Additionally, this acceptance fosters collaboration among auditors from different firms by standardizing procedures and establishing a shared understanding of how augmented AI can be utilized to meet audit objectives. Therefore, auditors' acceptance of augmented AI is crucial for its successful adoption, driving the evolution of audit practices towards more effective, efficient, and high-quality audits in specific settings. I introduced the TAM model to explore this acceptance in the context of joint audits.

In general audit contexts, I investigate auditors' aversion to AI algorithms using a refined IRT-TRI model. Understanding this aversion is crucial for the successful integration of AI in auditing, as it can inform the development of AI systems that are more transparent, explainable, and aligned with auditors' professional values and workflows (Munoko et al., 2020). Addressing auditors' concerns directly through education, demonstration of AI's reliability, and inclusion of auditors in the AI development process can enhance acceptance and effective use of AI tools. This is important for improving audit quality and efficiency, ensuring that the adoption of AI in auditing supports the trust and integrity that are foundational to the profession (Omrani, Rivieccio, Fiore, Schiavone, & Agreda, 2022).

2.9 Chapter Conclusion

AI is reshaping the informational and procedural foundations of accounting and auditing. Contemporary tools, ranging from machine-learning classifiers to large-language models, can automate repetitive tasks, interrogate vast data sets, and surface patterns that sharpen auditors’ judgements and enhance risk management. Yet the review also establishes that technological capability alone does not guarantee professional uptake: persistent concerns over transparency, accountability, and ethical use constrain adoption and, in many cases, reinforce auditors’ instinctive reluctance to rely on algorithmic outputs.

Critically, the extant literature privileges technical performance metrics and firm-level cost efficiencies while leaving auditors’ behavioural responses almost ancillary. Empirical evidence on how engagement-specific risk perceptions, peer and regulatory pressures, and algorithm aversion jointly shape acceptance is both fragmented and context-bound. Studies seldom disaggregate external audits, joint audits, and routine audit work, and they offer limited theorisation of cross-context differences. This gap makes it hard to identify when AI will be trusted, resisted, or used strategically, thereby hindering the development of clear guidance for practitioners and regulators.

The thesis positions itself within this gap. By integrating insights from the TAM, IRT, and TRI, it builds a multi-level framework that links auditors’ risk appraisals, social influences, and psychological barriers to concrete adoption intentions across three audit settings. In doing so, the dissertation enriches behavioural accounting theory and delivers practice-relevant evidence on how AI systems can be tailored, and their implementation strategies calibrated, to secure auditors’ confidence and, ultimately, improve audit quality.

The next chapter develops the theoretical foundations for this contribution: it revisits the original TAM and its extensions for external and joint audits, introduces refined IRT- and TRI-based models for general audit settings, and derives the hypotheses that guide the empirical analyses to follow.

CHAPTER THREE: THEORETICAL MODELS AND FRAMEWORKS

3.1 Chapter Introduction

Building on the gaps identified in the preceding literature review, this chapter positions the thesis's central contribution: the systematic integration of behavioural-science theories into the study of AI adoption in auditing. By adapting and combining the Technology Acceptance Model (TAM), Innovation Resistance Theory (IRT), and the Technology Readiness Index (TRI), the chapter offers a unified analytical lens that captures both the enablers and inhibitors of auditors' engagement with AI tools.

The discussion begins with TAM, originally formulated by Davis (1989) and subsequently extended through TAM2 and TAM3, to explain how perceived usefulness and ease of use drive technology acceptance. While TAM's parsimony has secured its status as a foundational model across information-systems research, its explanatory power in auditing remains limited unless domain-specific factors are incorporated. Accordingly, the model is refined here to include external variables salient to audit practice, notably engagement-specific risk perceptions and social-influence cues originating from clients, peers, and regulators.

To capture auditors' potential reluctance toward AI, the chapter augments TAM with IRT, which foregrounds functional and psychological barriers that impede uptake, and with TRI, which gauges individual and organisational preparedness to deploy novel technologies. This triadic framework enables a more complete behavioural explanation than any single model can offer, recognising that adoption decisions in auditing are shaped simultaneously by perceived benefits, perceived risks, and readiness conditions.

On this theoretical foundation, a series of hypotheses is developed to guide the empirical analyses that follow, targeting auditors' intentions to apply AI across external, joint, and routine audit contexts. A synopsis of the core studies informing these model adaptations is provided in Table 2. By embedding behavioural theories within the auditing domain, the chapter clarifies the cognitive and contextual mechanisms underlying AI acceptance and advances the broader discourse on technology diffusion in professional services.

Table 2. Overview of the primary literature on models and frameworks

Technology Acceptance Model (TAM)	**TAM's ability to assess user acceptance of technological adoption**	***TAM and its variants:*** (i) Original TAM (Davis, 1989) (ii) TAM2 (Venkatesh & Davis, 2000) (iii) TAM3 (Venkatesh & Bala, 2008) (iv) UTAUT (Venkatesh et al., 2003) (v) UTAUT2 (Venkatesh et al., 2012) (vi) Extended TAM for specific technologies: a. E-shopping technology (Ha & Stoel, 2009) b. New power-generation technology (Lu et al., 2023)
	TAM's ability to assess user acceptance of AI adoption	***Improved TAM for specific contexts:*** (i) For specific industries: a. Manufacturing industry (Chatterjee et al., 2021) b. Architectural industry (Lin & Xu, 2022) (ii) For specific disciplines: a. Supply chain management (Hasija & Esper, 2022)
IRT-TRI framework	**Innovation Resistance Theory (IRT: Ram & Sheth, 1989)**	***The relevance of IRT to AI adoption in auditing:*** (i) Usage barriers (e.g. Coleman et al., 2022) (ii) Value barriers (e.g. Commerford et al., 2022) (iii) Risk barriers (e.g. Munoko et al., 2020) (iv) Tradition barriers (e.g. Dierynck et al., 2023) (v) Image barriers (e.g. Coleman et al., 2022)
	Technology Readiness Index (TRI: Parasuraman & Colby, 2015)	***The relevance of TRI to AI adoption in auditing:*** (i) Motivating factors (e.g. Lanz et al., 2024) (ii) Inhibiting factors (e.g. Blut & Wang, 2020)

This table presents the key literature reviewed during the development of the theoretical models and frameworks for my thesis. Based on this review, and considering the research gaps identified in the previous chapter regarding AI adoption in auditing, I formulated the hypotheses outlined in this chapter.

3.2 Technology Acceptance Model (TAM)

3.2.1 Original TAM

TAM (Davis, 1989) is a seminal framework in information systems that explains how users accept and use a novel technology. Built upon the theory of reasoned action, TAM (shown in Figure 3) posits that the acceptance of technology is determined by two primary perceptions: perceived usefulness (PU) and perceived ease of use (PEOU). PU is the degree to which a person believes using a specific technology would improve their working performance. This concept emphasizes the importance of users' belief in the practical advantages gained from the technology. PEOU refers to the level to which a person believes that effort needs to be paid when using a specific technology, highlighting the role of user-friendliness in technological adoption. TAM suggests that these perceptions shape the users' attitudes towards using the technology, influencing their behavioural intention to use it. External variables, including technological features and adoption context, are theorized to affect PU and PEOU. The model has been widely applied and empirically tested across diverse information systems, evidencing its robustness and adaptability (Legris, Ingham, and Collerette, 2003).
Particularly, TAM is effective for investigating users' attitudes toward AI adoption in various professions (Budhwar et al., 2023; Glikson & Woolley, 2020; Hunkenschroer & Luetge, 2022).

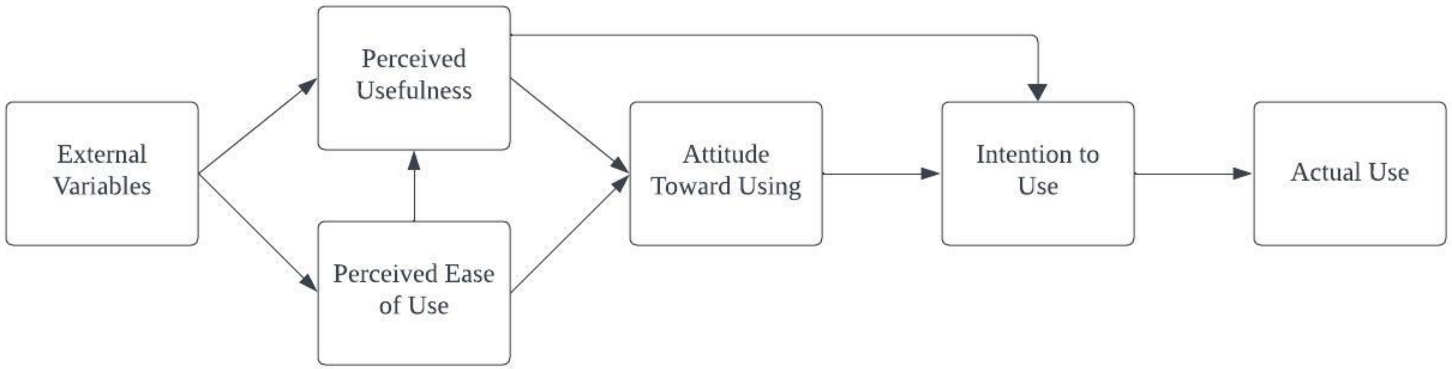


Figure 3. Davis's (1989) TAM

TAM provides an effective analytical framework for evaluating auditors' readiness and willingness to integrate AI technologies into audit processes for two key reasons (cf. Glikson & Woolley, 2020; Hunkenschroer & Luetge, 2022). First, TAM facilitates the understanding of auditors' attitudes toward AI by focusing on its PU and PEOU (Davis, 1989). Second, TAM can be adapted to incorporate external factors, including social influences (Legris et al., 2003), to assess auditors' acceptance of the advantages and disadvantages of AI within different audit contexts. More specifically, by evaluating auditors' perceptions of the usefulness and ease of use of AI in conducting different types of audits, TAM can help to identify key factors that influence auditors' acceptance levels (Legris et al., 2003). For instance, if AI tools can significantly streamline financial data analysis, reduce statement errors, and improve audit quality, they are perceived as useful. Similarly, if these tools are user-friendly and can be effectively integrated into the existing procedures of audits, their perceived ease of use is high. Through evaluations based on TAM's constructs, insights into how auditors perceive the adoption of AI in auditing can be collected, facilitating strategies to enhance adoption rates and overcome resistance.

In the manufacturing industry, TAM was combined with the technology-organization-environment framework to learn the process of AI implementation (Chatterjee, Rana, Dwivedi, and Baabdullah, 2021). In the architectural industry, TAM was extended to include the AI's features and usage context developed for architectural designs (Lin and Xu, 2022). Research on specific disciplines, such as supply chain management (Hasija and Esper, 2022), added social influence on the original TAM to emphasize the importance of AI's trustworthiness during its adoption.

Nevertheless, TAM has its limitations, particularly its failure to consider social influences that might affect technology acceptance (Legris et al., 2003). While TAM focuses on the cognitive processes underlying technology adoption, it overlooks how elements including social norms, peer influence, and the broader cultural and organizational context can impact individuals' attitudes and intentions. Social factors play a critical role in investigating users' acceptance of innovative technologies due to their significant influence on individual behaviours and attitudes (Chatterjee et al., 2021). Notably, social norms (Deore et al., 2023), which represent the shared expectations and rules within a community or society, deeply affect individuals' willingness to adopt new technologies, as these norms identify what is considered acceptable or desirable. Similarly, peer influence (Griffith et al., 2020), the impact that people within an individual's social networks have on their behaviour, can significantly drive or hinder technology adoption. Individuals may look to their peers for cues on how to behave and what to adopt. Acceptance may become more likely if technology is seen as popular or endorsed by others. Furthermore, the broader cultural and organizational context shapes the environment in which these technologies are introduced, affecting their perceived utility and compatibility with existing values and practices (Robson & Ezzamel, 2023). Cultures that highly value innovations are more likely to accept new technologies, while organizational contexts that support learning and exploring can facilitate their acceptance. These social factors jointly create a complex ecosystem that technology acceptance models should consider when learning how users adopt innovative technologies.

3.2.2 TAM2 and TAM3

TAM oversimplifies the technology adoption process and is limited in its capacity to assess contextual complexity and diversity derived from the differences in organizations and technologies (Legris et al., 2003). Therefore, TAM has also undergone several evolutions, with notable extensions including TAM2 (Venkatesh and Davis, 2000) and TAM3 (Venkatesh and Bala, 2008) under the usage context of computer-related technologies. TAM2 extends the original model by introducing social influence and cognitive instrumental processes (Venkatesh and Davis, 2000). These additions integrate factors, including subjective norms and job relevance, affecting users' technology decisions into the model. Thus, TAM2 more comprehensively explains the perceived usefulness and user acceptance of technologies in organizational contexts. In contrast, TAM3 focuses on PEOU to extend the original model (Venkatesh and Bala, 2008). TAM3 incorporates users' experience with systems and system features, including computer self-efficacy and perceived enjoyment, as additional variables, offering a more holistic view of how managers' interventions can lead to more effective technological deployment.

Advances from TAM to TAM3 represent an increasing complexity and refinement in learning users' acceptance of technological adoption. While the original TAM provides a foundational understanding focused on PU and PEOU, TAM2 and TAM3 introduce variables that acknowledge the role of differences across individuals and systems, expanding the scope to include a broader range of technology-usage contexts. TAM2 and TAM3 are particularly relevant in the context where user acceptance is essential for enacting successful technological innovations.

Despite TAM2 and TAM3 mitigating some of the original model's drawbacks, their complexity can reduce the models' feasibility and effectiveness in some practical situations. Given this reason, prior research has introduced different variables into the original TAM per various contextual requirements of technology usage (King and He, 2006). For instance, shopping quality, enjoyment, and consumer trust were integrated into TAM to assess the consumer acceptance of e-shopping (Ha and Stoel, 2009). Lu et al.'s study (2023) on promoting new power-generation technology considers the perceived risks, PU, and PEOU as three dimensions affecting the acceptance of the technology to revise and expand the traditional TAM. These improved TAMs provide more practical and flexible patterns for analyzing the technology adoption process in different contexts.

Due to the widespread use of TAM in analyzing various technology deployments, prior research has also improved and used TAM to explore the implementation of AI technologies in different areas. The original TAM is more suitable for studying AI adoption in professional environments with the addition of extra factors because of its simplicity and foundational nature. The two main determinants of TAM are straightforward and essential when introducing complex technologies, including AI. These core factors provide a clear framework to understand users' initial acceptance and attitudes toward AI in specific contexts. By starting with TAM's basic structure, researchers can integrate additional relevant factors specific to AI adoption without the complexities introduced by TAM2 or TAM3. Although TAM2 and TAM3 offer extended variables, they are more suited for environments where technology is already established and user behaviours are more complex. For emerging fields, notably AI adoption in external audits, the foundational simplicity of the original TAM allows for more flexible and targeted modifications, ensuring a robust and tailored approach to understanding AI adoption.

3.2.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

The limitations of TAM have also led to the development of several other extended models, notably the Unified Theory of Acceptance and Use of Technology (UTAUT: Venkatesh, Morris, Davis, & Davis, 2003) and its extension, UTAUT2 (Venkatesh, Thong, & Xu, 2012). UTAUT extends TAM by introducing key constructs notably performance expectancy, effort expectancy, social influence, and facilitating conditions, and considers moderators like gender, age, experience, and voluntariness of use, to provide a more comprehensive understanding of technology adoption. Applying UTAUT to the study of users' acceptance of technological innovations allows for a broader examination of influences, including those social and environmental factors absent in the original TAM framework (Venkatesh et al., 2003).

Despite the comprehensive nature of UTAUT and its variants, these extended models are debated by their own drawbacks (e.g. Tamilmani, Rana, Wamba, & Dwivedi, 2021). For instance, the UTAUT model introduces a significant number of variables and interactions, which can make its application and interpretation challenging. This complexity may lower the practicality and feasibility of the model in specific contexts, as it needs data collection from a wide range of factors and analyzing the interactions among them (Venkatesh et al., 2003). Moreover, the model's broad scope (Venkatesh et al., 2003) can weaken the focus on individual elements, making it difficult to identify the most critical factors influencing technology adoption in certain scenarios, such as in joint audits. UTAUT and similar models offer valuable insights into the multifaceted nature of technology acceptance, providing a richer, albeit more complex, framework for understanding the adoption of innovative technologies in professional fields (e.g. Norzelan, Mohamed, & Mohamad, 2024).

Nevertheless, the extant literature lacks adequate analysis on improving the TAM to analyse AI implementation in auditing. To address this gap and build on the recommendations of prior research (Legris et al., 2003), I revised and extended the original TAM for various auditing contexts, exploring effective AI implementation in both external and joint audits.

3.3 Study One Modelization

I considered the determinants of auditors' acceptance of using AI in risk management of external audits from three aspects: auditors, clients, and auditing regulators (Aghazadeh and Hoang, 2020; Munoko et al., 2020). Specifically, according to TAM, my model included auditors' PU and PEOU of AI implementation in external audits. Demographic differences among auditors were also considered in the model because they can significantly influence auditors' perceptions of AI adoption by affecting their trust in AI (Kaplan, Kessler, Brill, and Hancock, 2023). On these bases, as shown in Figure 4, I propose that auditors' perceived risks of using AI and their perceptions of client-side situations will be two additional primary dimensions influencing auditors' acceptance of AI. The dimension of audit regulation was omitted in the model because the links between regulators' attitudes toward AI and auditors' willingness to use relevant technologies remain vague in the extant literature. However, considering the role of regulators in ensuring audit quality (Francis, 2004), such links could be potential directions for future research.

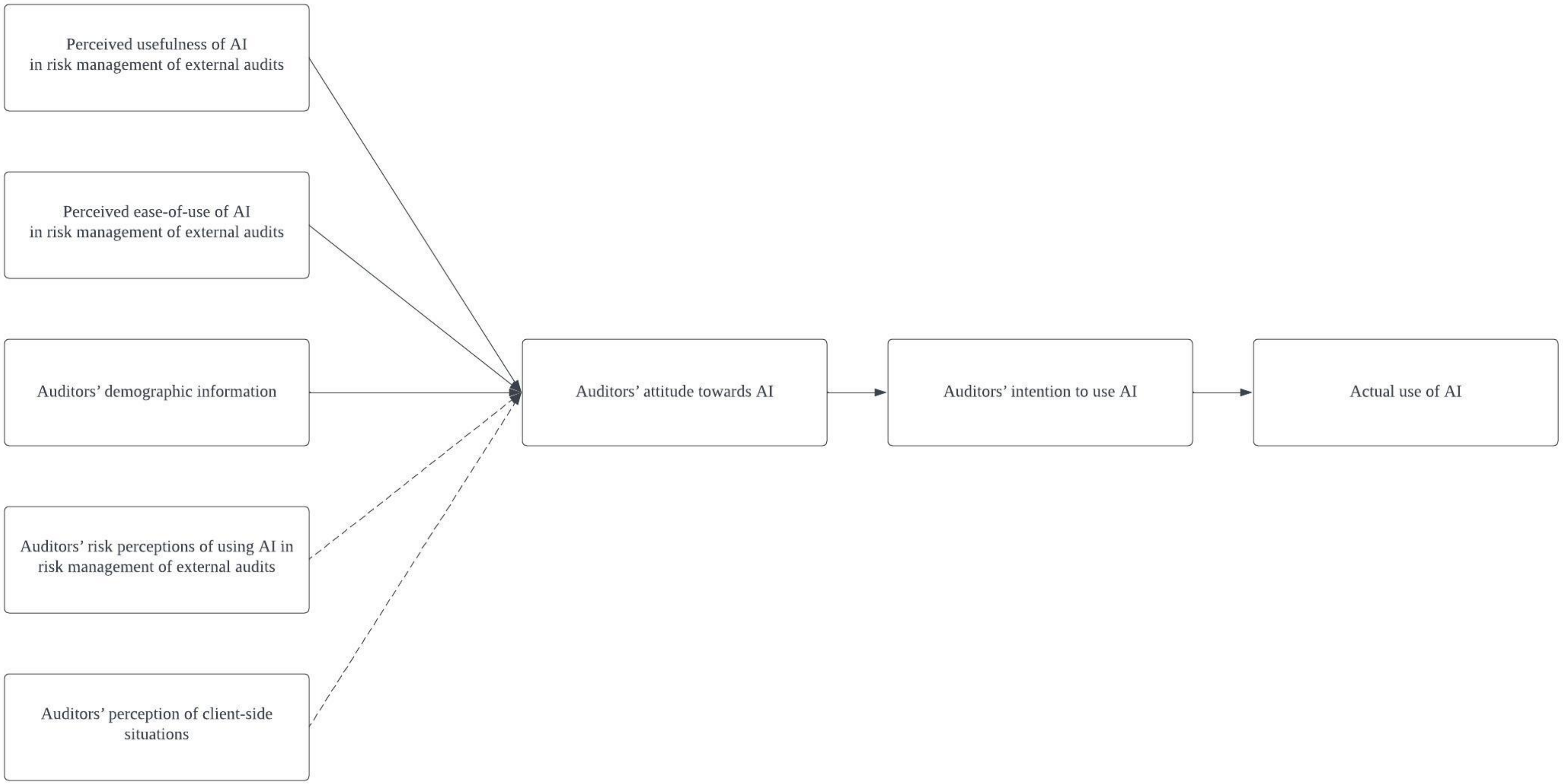


Figure 4. TAM in the context of external audits

My modelization aims to investigate auditors' individual perceptions of firm-level AI adoption. TAM is effective for examining these perceptions within an accounting firm for two primary reasons. First, by applying TAM, I can evaluate how auditors perceive AI's benefits (PU) and the degree to which they believe AI is convenient to use (PEOU). Second, as reviewed in previous sections, TAM can be extended to adapt to specific contexts. I incorporated additional factors into the original TAM to fit the context of external audits. This extended TAM aligns more closely with practical situations, allowing my study to help accounting firms identify potential barriers to AI adoption and facilitate training and support measures to improve auditor acceptance. I will elaborate on my propositions in the following sections.

3.3.1 Risk perceptions of using AI

I first consider the risk perception theory in technological innovation (He, Jacob, Vashishtha, and Venkatachalam, 2022). Risk perceptions allow auditors to create views on the drawbacks of new technologies without actual financial investment, thus helping accounting firms avoid financial loss in enacting innovation (Biais & Weber, 2009; Godsell et al., 2023; Lerner, 2006; Millo and MacKenzie, 2009). I argue that auditors' risk perceptions of using AI in external audits are developed upon their interpretation and prediction of the outcomes regarding applying AI to practical tasks. Such perceptions affect auditors' acceptance of AI from the micro level. Thus, I focus on two types of perceived risks to explore their impacts on AI implementation in external audits.

First, I propose that perceived functional risks of using AI affect auditors' acceptance of it in external audits. Such perception usually derives from individual concerns about AI's reliability in terms of simulating complex human behaviours. Notably, AI shows limitations in interpreting situations under social context (Henschel et al., 2020; Li, Lin, and Lu, 2023). Namely, AI technologies lack social intelligence (Henschel et al., 2020) when dealing with practical issues. Even when some advanced AI meets this functional requirement through deep ML (Nguyen et al., 2019), managers will be likely to be anxious about AI's transparency (Sanders et al., 2014) and fairness (Thurman et al., 2019). Auditors may mentally refuse to build trust in AI when they fail to identify AI's algorithmic mechanisms when using AI in external audits. One of the primary reasons is that external audits need to objectively verify client firms' financial statements to ensure that the statements have provided accurate and fair views of firms' financial status according to audit standards (Christensen et al., 2023; Desai, Roberts, & Srivastava, 2010). Black boxes in AI programmes may provide rhetorical outcomes per designers' specific intentions, resulting in auditors' doubts about AI's fairness (Glikson and Woolley, 2020). AI programmes with higher intelligence entail more transparency to prove their reliability in auditing. For these reasons, auditors' recognition of AI's functional limitations shapes their risk perception of using AI in risk management of external audits. Such perception may hinder auditors from building trust in AI. Thus, I propose that:

H1.1a. Auditors' functional risk perception reduces their acceptance of using AI in risk management of external audits.

According to the original TAM, auditors' perceived usefulness could arguably encompass their functional risk perceptions. However, I believe that they should be considered independently due to their differing focuses and implications. Functional risk perception involves auditors' concerns about the potential threats and vulnerabilities associated with using AI in auditing. These risks are primarily about the dependability of incorporating AI into auditing processes. In contrast, the perceived usefulness of AI relates to auditors' beliefs about the practical benefits that AI can bring to their work. This can include expectations of overall better performance in auditing tasks. Perceived usefulness is about the advantages and added value that AI can provide in making the auditing process more effective and productive. By separating these two perceptions, I can more effectively assess the impact of each area on auditors' acceptance of AI. The data analysis in the later section also demonstrates the lack of correlation between these two elements.

Second, I posit that auditors' operational risk perception of AI influences their acceptance of using relevant technologies. Specifically, auditors' concerns about potential ethical and security consequences (Hunt, Curtis, and Rixom, 2022) caused by human errors, such as operations violating audit standards (Christensen et al., 2023), lead to their operational risk perception of using AI. Prior studies have suggested several reasons for these operational issues (Rana, Chatterjee, Dwivedi, and Akter, 2022). From the managerial perspective, firms' ability to develop feasible frameworks for enacting AI-related financial innovation determines the probability of the mis-operation of AI programmes, which is termed AI governance (Rana et al., 2022). Firms lacking this ability will mislead their staff to use AI without standards. As one of the negative results, staff may ignore necessary inputs of AI programmes based on their subjective considerations, thus obtaining outputs with ethical problems (Hunt et al., 2022; Rana et al., 2022). From the technological view, staff's knowledge levels of AI are a primary factor that affects their operations on AI programmes. AI users need a proper understanding of relevant technologies to ensure AI's performance (Rana et al., 2022). Staffs' low AI-related training levels reduce their ability to operate AI ethically and safely (Rana et al., 2022) or even are likely to decline their willingness to use AI technologies (Paschen, Wilson, and Ferreira, 2020). Therefore, I suggest that auditors' perception of anthropogenic risks may influence their attitudes toward using AI. That is:

> *H1.1b. Auditors' perception of operational risks impedes their acceptance of using AI in risk management of external audits.*

3.3.2 Client-side situations

I then consider the consumer preference theory in deploying innovative technologies (Jeong, Ko, and Taylor, 2023). Since external audits aim to provide their clients with objective verification of the authenticity and fairness of clients' financial statements (Dezoort, Houston, and Peters, 2001), accounting firms' abilities to manage their relationship with clients is essential for external audit services (Aghazadeh and Hoang, 2020; Kadous et al., 2003; McCracken et al., 2008).

As one of the most important criteria, accounting firms assess their audit service qualities by their clients' satisfaction ratings on relevant services (Behn, Carcello, Hermanson, and Hermanson, 1999; Hoang et al., 2019). Auditors perceive pressure to obey audit standards and satisfy their clients simultaneously (Aghazadeh and Hoang, 2020). However, there is a debate about whether clients' satisfaction is vital for auditors (Aghazadeh and Hoang, 2020). From a positive perspective, the pressure from clients can improve audit quality (Aghazadeh and Hoang, 2020; Krishnan, Singer, and Zhang, 2023). Auditors, who are conscious of clients' opinions, are more likely to build positive relationships with clients (Christensen et al., 2023; McCracken et al, 2008), thus enhancing clients' collaboration in auditing. On the negative side, auditors could develop biased judgments in evaluating clients' financial reports (Cohen et al., 2017) to obtain higher satisfaction ratings from clients (Aghazadeh and Hoang, 2020). Auditors show greater willingness to tolerate clients' aggressive accounting that overstates their financial performance when clients explicitly put pressure on accepting the statements (Backof, Bamber, and Carpenter, 2016; Desai, Hogan, and Wilkins, 2006; Koch and Salterio, 2017).

Therefore, based on the auditor-client relationship in external audits, I propose the impacts of auditors' perceived client-side situations on their acceptance of AI from two aspects. First, in order to ensure audit quality, auditors' perception of their clients' technological ability to accept AI services may affect their trust in AI. Auditors will need clients to collaborate during the AI-enabled external audits. For instance, clients may be asked to provide financial documents in specific formats (Brynjolfsson and Mitchell, 2017) to support AI's functions. Clients' technological limitations in such ability may decline audit quality. Moreover, clients may also need to be capable of interpreting the outcomes of AI-enabled audit outcomes. To achieve high satisfaction ratings, auditors typically prefer audit methods clients can understand (Kadous et al., 2003). Thus, I consider that:

H1.2a. Auditors' perception of clients' higher technological level raises their acceptance of using AI in risk management of external audits.

Second, even when clients possess requisite technology levels, their willingness to accept AI-involved audit services will be essential for auditors. I thus argue that clients' attitudes toward using AI may affect auditors' willingness to introduce AI in their services. To satisfy clients, auditors are less likely to use AI in external audits when their clients refuse to accept it. That is:

> *H1.2b. Auditors' perception of their clients' greater willingness to accept AI-related services enhances their acceptance of using AI in risk management of external audits.*

I consider this modelization effective in two key aspects. First, the adoption of AI in external audits diverges from other emerging technologies due to heightened risk perceptions and the complex nature of AI integration. Traditional technological upgrades typically improve efficiency without fundamentally altering audit processes. In contrast, AI introduces complex algorithms and data analytics that can transform audit methodologies. This transformation may lead auditors to perceive AI adoption as risky due to concerns over reliability, ethical implications, and regulatory compliance. Auditors must also carefully assess clients' situations related to the utilization of AI to ensure it aligns with audit standards and ethical guidelines.

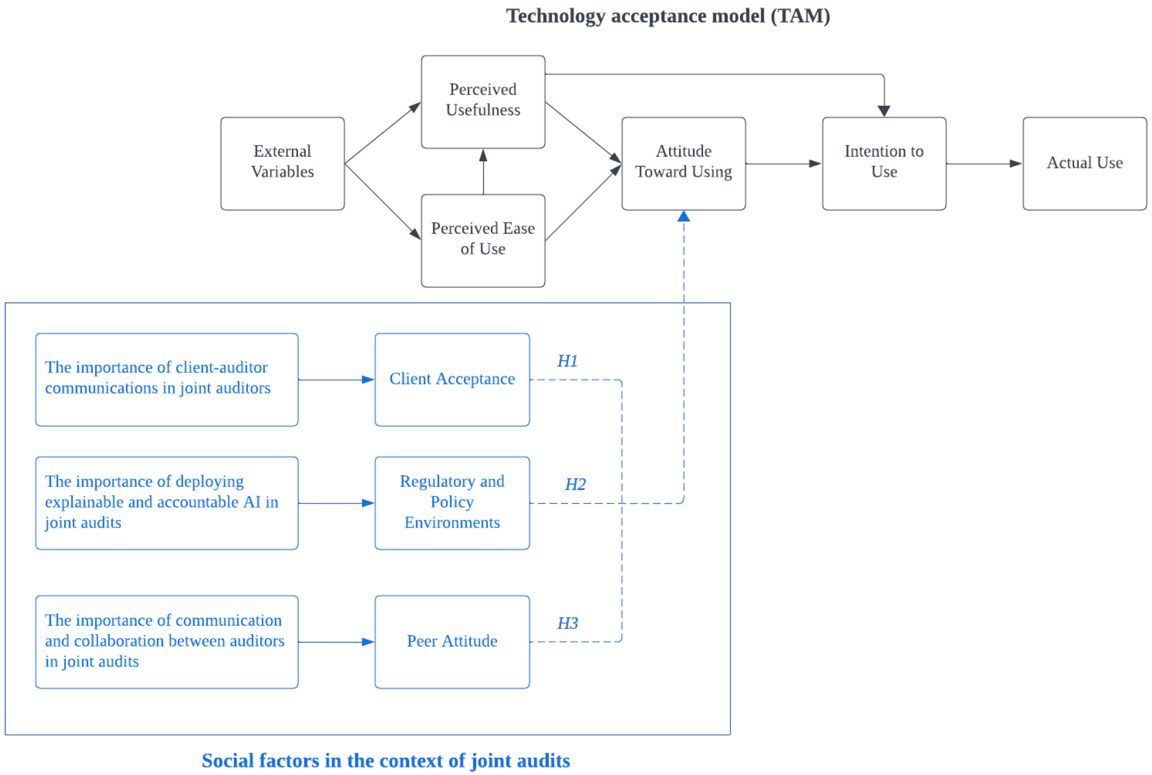
Second, my selection of factors aligns with prior research suggestions. For instance, Afsay, Tahriri, and Rezaee (2023) recommend considering several factors when investigating AI adoption in auditing. Beyond PU and PEOU, *influential people's opinions*, *facilitating conditions*, *cost-benefit of AI technology*, *AI's compatibility*, *firm size and readiness*, *top management support*, *clients' technological levels*, *competitive pressure*, and *support from professional accounting bodies* are essential for user acceptance of information technology (Afsay et al., 2023). I examined *influential people's opinions*, *facilitating conditions*, and *clients' technological levels* by assessing client-side situations of using AI in risk management of external audits. Additionally, I evaluated the *cost-benefit of AI technology*, *AI's compatibility*, and *firm readiness* by considering auditors' functional and operational risk perceptions of AI. Details on my focus on non-Big Four accounting firms (*firm size*) and my initial assessment of AI adoption in auditing through interviews with senior managers (*top management support*) are elaborated in later sections. Although these two factors were not directly included in my model, I investigated them and demonstrated their importance in my study. Competitive pressure and professional accounting bodies' support levels were omitted because AI adoption in risk management for external audits is at the early stage; future studies could investigate their impacts.

3.4 Study Two Modelization

Considering social factors is essential for investigating auditors' acceptance of augmented AI in joint audits because these factors significantly influence auditor behaviour in the joint audit process. Social dynamics, notably the influence of social networks within the auditing community (Nurunnabi, Donker, & Jermakowicz, 2020; Pittman, Wang, & Wu, 2022), are central to understanding how auditors interact with and perceive AI technologies. These dynamics can either facilitate or hinder the acceptance of AI, as auditors look to their peers and the broader professional community for cues on how to navigate new technologies (Griffith et al., 2020). For auditors, who operate in environments that highly value trust, reliability, and professional judgment, the social acceptance of AI technologies is crucial. If AI adoption aligns with the professional culture and ethical standards expected in auditing, it's more likely to be embraced (Munoko et al., 2020; Robson & Ezzamel, 2023). Moreover, understanding social dynamics can help in identifying potential resistance toward AI, thereby enabling the development of strategies to facilitate its integration into joint audits. This understanding helps to develop AI systems that meet technological and regulatory requirements and are perceived as valuable and trustworthy tools among auditors. Therefore, in the following sections, I focus on three essential social factors in the context of joint audits to assess auditors' acceptance of augmented AI, thus proposing my hypotheses.

3.4.1 Client attitude

As shown in Figure 5, Based on TAM, I first consider that client attitudes significantly impact auditors' acceptance of AI-augmented joint audits. In joint audits, multiple auditing firms work together, and clients act as vital connectors between them, shaping communication, trust, and the overall direction of the audit. In this audit context, clients play a more complex role in facilitating the adoption of augmented AI by bridging multiple auditors' perspectives. Clients are instrumental in enhancing the information exchange across the different audit teams, fostering collaboration, and promoting trust (Aghazadeh & Hoang, 2020). Communications with clients contribute to shaping the joint audit's direction and focus by sharing business insights, raising concerns, and providing feedback (Malsch, 2024). Cilents' active engagement encourages a more targeted and effective joint audit approach, ensuring that the audit process aligns with their specific needs and expectations. Therefore, client acceptance plays a critical role in the auditors' acceptance of augmented AI in joint audits, serving as a social factor that can significantly influence the integration and utilization of relevant technologies.



Note. Cells in black are the elements of the original TAM, and those in blue are my proposed social factors.
Figure 5. Extended TAM by social factors in the context of joint audits

The client's role in providing positive reinforcement and support for augmented AI in joint audits is critical, making the acceptance of new technologies, notably AI, a critical element in its adoption. When clients express strong support for AI tools, it boosts auditors' confidence in adopting such technology. This support can improve audit efficiency, accuracy, and reduce human errors (Krishnan, Singer, & Zhang, 2023). Moreover, client acceptance of augmented AI can lead to increased investment and resources toward relevant technologies, fostering a more innovative environment. This environment, in turn, can improve audit efficiency and accuracy, reduce human errors, and allow auditors to focus on more complex aspects of the joint audit process. Thus, client acceptance is essential for facilitating AI-augmented joint audits and underpins the broader adoption and integration of AI technologies within the auditing profession.

Clients may value AI's potential for process acceleration and operational benefits (Munoko et al., 2020), but concerns about audit quality, data privacy, and security can still pose significant barriers to AI acceptance (Cahan, Che, Knechel, & Svanström, 2022; Cohen, Gaynor, Krishnamoorthy, & Wright, 2022; Knechel & Williams, 2023). The integration of AI technology into audit procedures is embraced when it accelerates processes, provides deep insights, and significantly enhances operational value, thus offering a competitive edge. AI's ability improves the joint audit process, making it more efficient and insightful. This transformation appeals to clients who recognize the potential for improved decision-making and operational efficiency. However, acceptance diminishes if AI is perceived solely as a cost-cutting tool. Concerns arise over potential compromises in audit quality and ethical issues related to data privacy and security. These concerns can overshadow the technological benefits, leading to apprehension about negative impacts.

The level of client acceptance of AI-augmented joint audits may vary significantly across different industries, influenced by various factors including the industry's regulatory environment, the complexity of business operations, and the corporate culture towards technology adoption (Cahan, Che, Knechel, & Svanström, 2022; Cohen, Gaynor, Krishnamoorthy, & Wright, 2022; Knechel, & Williams, 2023). Industries with a more technology-related outlook may be more receptive to the adoption of augmented AI in auditing processes, recognizing its potential to enhance efficiency and accuracy. In contrast, industries that are more traditional or regulated may exhibit greater resistance due to concerns about data security, privacy, or the potential loss of human oversight. This disparity in acceptance can pose challenges for auditors (Cahan et al., 2022; Knechel, & Williams, 2023), as they must navigate these differences and enact their approach to the adoption of augmented AI to align with the expectations and comfort levels of their clients in each industry. Understanding and addressing these industry-specific concerns are crucial for auditors to gain client trust and facilitate the broader acceptance of augmented AI in joint audit processes.

In this context, client attitudes toward AI adoption are not guaranteed to lead to a smooth or straightforward increase in auditor acceptance. Auditors' willingness to embrace AI-augmented joint audits depends on the alignment between client support and professional standards. When client support is genuinely aligned with quality benchmarks and takes into account the complexities of AI adoption, it fosters a collaborative environment where technology integration is smoother and more effective. In contrast, if auditors perceive that client support is superficial or driven by operational convenience without regard for audit quality, their skepticism can hinder the widespread adoption of AI tools in joint audits.Thus, despite the potential for dissonance in client-auditor perspectives, I propose the following hypothesis:

H2.1. Auditors demonstrate a greater willingness to implement AI-augmented joint audits when clients exhibit a higher level of acceptance for such technology.

3.4.2 Regulatory and policy environments

Second, regulatory and policy environments are crucial in shaping auditors' acceptance of augmented AI, as they provide the legal and ethical frameworks within which auditors operate. These frameworks reflect broader social norms, legal mandates, and ethical expectations that ensure technology adoption aligns with values including transparency, accountability, and fairness in the auditing process. In joint audits, where multiple auditing firms collaborate, the influence of regulatory and policy environments is magnified due to the need for consistent compliance across different organizations working together.

In joint audits, auditors must adhere to both national and international regulations, which may differ depending on the jurisdictions of the various audit firms involved. This adds a layer of complexity in how auditors perceive and adopt AI. Regulatory clarity is especially critical in these situations because it provides clear guidance on how AI technologies can be used within an ethical and legally compliant framework. When the regulatory environment is well-defined, it helps auditors understand both the potential benefits and risks of augmented AI, ensuring that the technology is used in a way that upholds audit quality and complies with legal standards (Samiolo et al., 2023; Kaur, Uslu, Rittichier, & Durresi, 2022). In this context, having clear regulations that apply to multiple firms can foster a more collaborative and aligned approach to adopting AI, reducing uncertainties and increasing auditors' willingness to embrace new technologies (Eulerich et al., 2022).

However, regulatory and policy environments can also introduce challenges that are more pronounced in joint audits than in single audits. While clear, supportive regulations build trust and reduce uncertainties (Munoko et al., 2020), overly restrictive or ambiguous regulations may act as a barrier to AI adoption. In joint audits, the need to satisfy multiple regulatory standards across different firms can raise compliance hurdles, making it more difficult for auditors to adopt AI without fear of violating regulations or facing penalties. This complexity can lead to delays in AI adoption, as auditors may be more cautious about integrating AI if they perceive the regulatory framework to be restrictive or not fully aligned with technological advancements.

Furthermore, in joint audits, regulatory tensions can arise when regulations lag behind the rapid pace of technological change. Auditors may become wary of adopting AI if they believe that current regulations do not adequately address the risks or benefits of these technologies. If auditors view regulations as burdensome or as a barrier to innovation, their reluctance to adopt augmented AI could increase. For instance, if auditors fear that using AI could expose them to legal risks or result in non-compliance with evolving standards, they may hesitate to integrate AI into their audit processes.

In contrast, a supportive regulatory environment can foster a climate where auditors feel empowered to explore AI within a controlled and ethically sound context. Supportive policies help reduce the perceived risks and provide auditors with the guidance they need to integrate AI technologies without fear of non-compliance or ethical breaches. This is particularly crucial in joint audits, where auditors from multiple firms need to ensure consistency in their approach to AI adoption while respecting each firm's regulatory requirements.

Overall, while regulatory uncertainty or rigid frameworks may impede AI acceptance, a supportive regulatory and policy environment can significantly increase auditors' readiness to embrace augmented AI in joint audits. In such an environment, auditors are more likely to feel confident in adopting AI, knowing that they are operating within legal and ethical boundaries. Therefore, I propose the following hypothesis:

> *H2.2. Auditors' readiness to embrace augmented AI in joint audits increases in regulatory and policy environments that are more supportive.*

3.4.3 Peer attitude

Third, I consider that peer attitude plays a critical role in influencing auditors' acceptance of augmented AI, particularly because it reflects the collective perceptions, norms, and behaviours of auditors. In joint audits, where multiple auditing firms collaborate, the role of peer attitudes becomes even more significant due to the social dynamics and the greater complexity of coordination across different teams. Communication among peers and their shared experiences with technology can shape the broader cultural and professional norms surrounding AI adoption in joint audits. These dynamics differ notably from single audits, where the influence of peers may be more limited to a single auditing firm.

In joint audits, the influence of peer attitudes is amplified because auditors are exposed to diverse perspectives and opinions across firms, which can either support or hinder the acceptance of augmented AI. Auditors are strongly influenced by their social environment, and normative expectations within their peer groups can significantly shape their willingness to adopt new technologies like AI (Beck et al., 2024; Bianchi, 2018). This collective influence leads to the formation of shared attitudes and values about AI-augmented audits, creating a culture that either supports or resists technological innovation.

The importance of peer attitudes in AI adoption is multifaceted in joint audits. First, trust and mutual understanding among auditors–especially across different firms–can make auditors more receptive to their peers' views. The exchange of knowledge and experiences between auditors from different teams facilitates a deeper understanding of AI's benefits and challenges (Griffith et al., 2020). In joint audits, this exchange is particularly valuable as auditors can compare and learn from the experiences of others within a collaborative framework. Second, positive peer attitudes can provide validation, building confidence among auditors. When peers express confidence in the benefits of AI, it reduces uncertainties and encourages more openness to adopting new technologies (Eulerich, Masli, Pickerd, & Wood, 2023; Griffith et al., 2020). Third, in joint audits, social learning is a crucial factor. Auditors can observe and emulate successful AI adoption practices from their peers, leading to enhanced collective efficiency in the auditing process (Li, Sun, & Ettredge, 2017). As auditors see their peers successfully integrating AI into audits, they are more likely to follow suit, further spreading the acceptance of AI within the profession. In addition, positive peer attitudes help establish shared standards and protocols in joint audits. This ensures that AI-augmented audits maintain consistency, reliability, and the integrity of the audit process, regardless of the number of auditing firms involved.

However, not all auditors are equally influenced by peer attitudes. Some auditors may prioritize individual judgment and rely on personal risk assessments rather than conforming to the collective attitudes of their peers. They might adhere to organizational norms or personal beliefs that do not fully align with industry trends (Beck et al., 2024; Bianchi, 2018). For these auditors, skepticism toward new technologies, or concerns about the risks and benefits, may outweigh the influence of peer attitudes. In such cases, their acceptance of AI could be limited by internal factors, including firm policies, personal professional experience, or individual risk assessments (Commerford, Dennis, Joe, & Ulla, 2022). A case in point is the Public Company Accounting Oversight Board (PCAOB), based in the United States, and its guidance on the use of AI in auditing, which underscores the importance of maintaining professional skepticism when applying AI-assisted tools. The PCAOB cautions that while AI can improve audit efficiency and effectiveness, auditors should carefully evaluate the reliability and limitations of AI systems. Some auditors may feel that the integration of AI into their practice requires additional scrutiny to ensure compliance with regulatory standards, and this caution may stem from personal or organizational resistance to change, further hindering AI adoption.

Despite these potential differences, positive peer attitudes generally have a significant impact on auditors' willingness to adopt AI-augmented joint audits. As more auditors within the joint audit environment perceive AI as valuable, resistance to AI adoption – often based on concerns about reliability and technology risks – decreases. The growing acceptance of AI among peers helps to shift the profession toward embracing new technologies, thereby making AI adoption an industry-wide movement. This shift is particularly beneficial in joint audits, where cooperation across firms is critical. A shared understanding and acceptance of AI can lead to better communication and collaboration, allowing AI to help meet evolving demands for effectiveness, efficiency, and accountability in audits.

In summary, peer attitudes in joint audits play a crucial role in shaping auditors' willingness to adopt AI technologies. The influence of peers is amplified in joint audits due to the increased interaction and collaboration between auditors from different firms. Positive peer attitudes create a supportive environment that fosters the adoption of augmented AI, improving the quality and efficiency of joint audits. On this basis, I propose the following hypothesis:

> *H2.3. A higher acceptance of AI-augmented joint audits among peers enhances auditors' willingness to adopt such technology.*

3.5 Study Three Modelization

I employed an additional model to explore AI adoption in general audit contexts. Given the significance of understanding algorithm aversion among auditors for developing effective AI systems in auditing, as shown in Figure 6, I combine innovation resistance theory and the technology readiness index to investigate the antecedents of aversion to algorithmic audit decisions among auditors. In the following sections, I will first review the development of my model based on existing theories and models, and then propose my hypotheses.

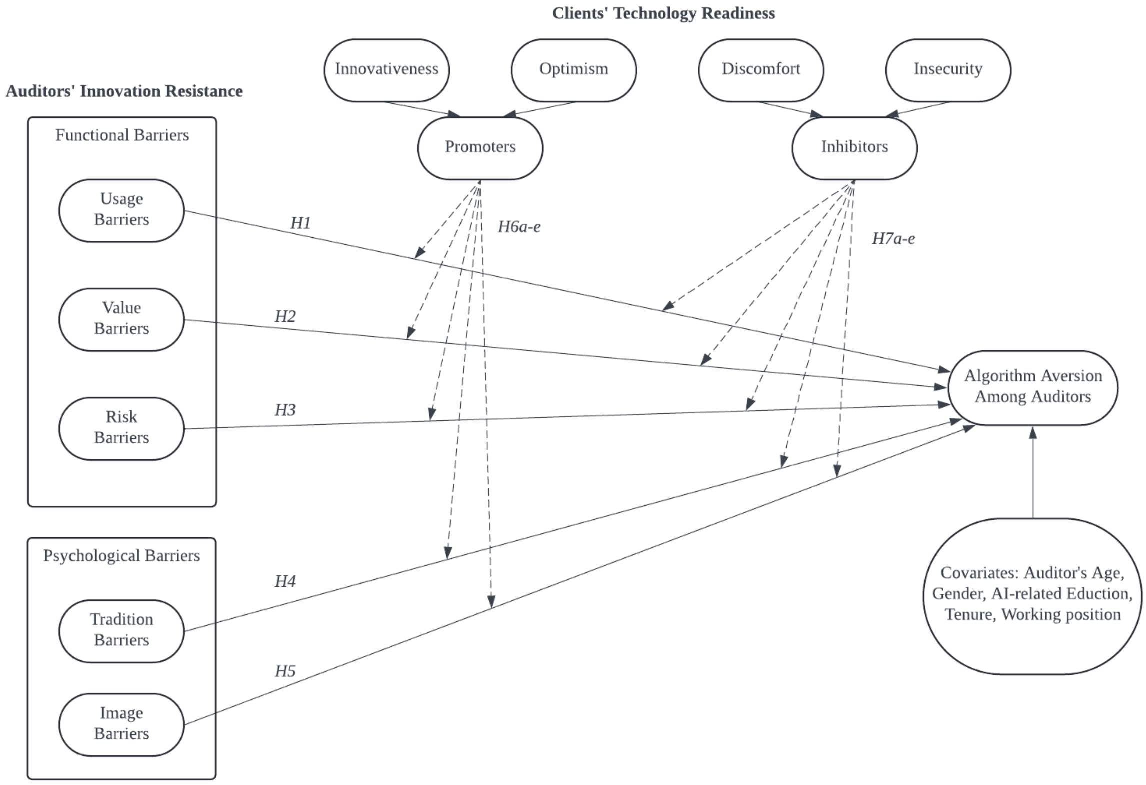


Figure 6. The antecedents of auditors' algorithm aversion

3.5.1 Innovation Resistance Theory (IRT)

IRT is a framework for understanding why individuals resist deploying innovations in the professions despite their potential benefits (Ram & Sheth, 1989). This theory posits that resistance can be primarily attributed to two primary types of barriers: functional and psychological (Claudy, Garcia, & O'Driscoll, 2015; Park, Werder, Cao, & Ramesh, 2022; Querci, Monsurrò, & Peverini, 2024). Functional barriers arise from perceived issues related to the innovation's utility, such as increased operational complexity, a lack of perceived usefulness, or potential deployment risks. Psychological barriers, on the other hand, stem from personal preferences or emotional responses, including fear of change, reliance on tradition, or negative past experiences with similar technologies. IRT emphasizes that resistance to innovation is a natural reaction of users and an essential part of the adoption process of innovative technologies. It suggests that these barriers must be addressed proactively for an innovation to be effectively implemented.

I believe that IRT is particularly useful in explaining auditors' aversion to AI algorithms because it directly addresses the psychological and practical factors that lead auditors to resist adopting new technologies. In the context of auditing, where accuracy and compliance are essential for practical processes, IRT can help comprehensively explain auditors' multifaceted reluctance to fully embrace AI technologies. I argue that the barriers identified by the IRT–namely usage, value, risk, tradition, and image–substantially influence auditors' aversion to algorithms.

3.5.2 Usage barriers

Auditors may resist AI because of perceived complexities in using AI technologies in their existing workflows. Auditing processes typically require attention to detail and deep contextual understanding, areas where auditors may consider AI cannot match the capabilities of human auditors (Coleman et al., 2022; Commerford et al., 2022). Concerns about continuous learning and training to effectively integrate AI tools can deter auditors from adopting these technologies. Moreover, usage barriers to AI may become more apparent if AI tools are challenging to integrate with existing audit systems or require substantial changes in daily operations. This resistance often comes from the worry that more time will need to be spent managing technology rather than leveraging it for efficiency gains. I thus propose that:

> ***H1.*** *Usage barriers lead to algorithm aversion among auditors.*

3.5.3 Value barriers

The value barrier arises when auditors perceive minor added benefits from AI technologies compared to traditional audit methods. Although AI promises enhanced efficiency, improved accuracy, and the ability to analyse large datasets quickly, auditors may doubt these advantages if they fail to see immediate and clear improvements over existing practices (Coleman et al., 2022; Commerford et al., 2022; Munoko et al., 2020). The accountable judgments required in the auditing process, including assessing the quality of financial disclosures, might still seem beyond AI's capability. Furthermore, when the initial cost of AI implementation is high and the return on investment is unclear or unpredictable in some organizational contexts, auditors may question the economic value of adopting such technologies, reinforcing their aversion. Thus:

H2. *Value barriers lead to algorithm aversion among auditors.*

3.5.4 Risk barriers

Auditing errors are associated with significant legal and reputational risks. Auditors may fear that relying on AI could lead to new types of errors or oversight, particularly when audit decision-making processes driven by AI algorithms lack transparency or explainability (Munoko et al., 2020). The potential for AI to miss detailed or contextual factors that a human auditor would catch can be a significant deterrent. Additionally, data security concerns, especially with confidential financial information, heighten resistance. If AI is perceived to increase the likelihood of breaches or data mishandling, the risk barrier will influence auditors' algorithm aversion. Namely:

H3. *Risk barriers lead to algorithm aversion among auditors.*

3.5.5 Tradition barriers

Auditing traditions are shaped by standardized practices (Commerford et al., 2022; Dierynck, Kadous, & Peters, 2023). These traditions are crucial because they include the auditing methods that are habitual and unanimously accepted across industries. They also encompass professional skepticism – that is, critical thinking – which forms the mental foundation of the auditing profession. Auditors are trained to critically evaluate information, a mindset that may foster skepticism towards AI's capability to effectively perform audit tasks. The transition from human to machine-driven audit decisions could be perceived as a departure from the rigor and personal accountability that characterize traditional auditing. Therefore, any technological shift that appears to undermine these foundational aspects can be met with considerable resistance. I posit that:

H4. *Tradition barriers result in algorithm aversion among auditors.*

3.5.6 Image barriers

Image barriers refer to how adopting AI might affect the perceived professionalism and identity of auditors (Coleman et al., 2022; Commerford et al., 2022; Munoko et al., 2020). There is a social identity in the analytical capability and judgment that auditors bring to their work, which might be perceived as being diminished or replaced by using AI. Concerns about being viewed as less skilled or reliant on AI technology can deter auditors from embracing AI, fearing that it might devalue their expertise in the eyes of clients or colleagues. This barrier is closely linked to the professional identity of auditors under social contexts, who may see AI tools as undermining their role rather than augmenting it. Therefore, I consider that:

H5. *Image barriers result in algorithm aversion among auditors.*

Based on these, I further consider the relationships between auditors and clients in the context of auditing (Aghazadeh & Hoang, 2020; Dodgson, Agoglia, Bennett, & Cohen, 2020; Peecher, Ricci, & Zhou, 2024), thus introducing the moderating impacts of clients' technology readiness on auditors' perceived barriers and algorithm aversion. This moderating influence stems from the fact that the relationship between auditors and their clients is foundational to the auditing process, whether in internal or external contexts (Commerford, Mullis, & Stefaniak, 2023), and significantly affects the effectiveness and credibility of the audit.

Internal auditors typically view various departments within their own organization as their clients (Kotb, Elbardan, & Halabi, 2020). They are employed by the organization itself and their primary role is to provide independent and objective evaluations of the company's operations, specifically aiming to improve operational efficiency, manage risk, and ensure compliance with laws and regulations. The auditor-client relationship in internal audits facilitates open communications and trust to encourage departments to act on recommendations suggested by the auditing outcomes.

External auditors serve an independent role from the organization they audit, typically being hired by stakeholders including shareholders or regulators. In external auditing, auditors are expected to provide an unbiased opinion on the truth and fairness of an organization's financial statements. The auditor-client relationship in this context is crucial for maintaining the integrity of financial reporting and investor confidence (Aghazadeh, Brown, Guichard, & Hoang, 2022). The auditors must maintain both a professional distance to ensure objective judgments and a cooperative relationship to ensure they receive all necessary information and cooperation from the clients.

In both cases, the strength and quality of the auditor-client relationship can determine the audit's success. A positive relationship helps ensure that auditors can conduct thorough and effective assessments without interference, and that the clients are more likely to accept and act on the audit findings and recommendations. Conversely, negative relationships can lead to resistance to collaboration, withholding of information, and even disputes over findings. Such consequences can compromise the effectiveness of the audit and, by extension, the transparency and accountability of the audit process. Thus, whether interacting with internal departments or external entities, auditors must manage their relationships with clients to sustain the standards of their profession and the objectives of their audit work. I investigated the impacts of such relationships on auditors' algorithm aversion by introducing clients' technology readiness index into my model.

3.5.7 Technology Readiness Index (TRI)

TRI is developed to measure users' propensity to embrace novel technologies to achieve goals at professional work (Parasuraman & Colby, 2015). It assesses an individual's readiness across four dimensions: optimism, innovativeness, discomfort, and insecurity (Blut & Wang, 2020; Lanz et al., 2024; Ma, Yang, Wang, & Song, 2022). Optimism and innovativeness represent the positive motivators that encourage technological innovation. Optimism refers to the belief that technology can offer increased control, flexibility, and efficiency in professional tasks, whereas innovativeness relates to a user's tendency to be a technology pioneer and thought leader. On the other hand, discomfort and insecurity serve as inhibitors. The discomfort stems from a perceived lack of control over technology, while insecurity involves doubts about the technology's reliability in terms of, including, protecting personal information. The TRI is used in various sectors to help understand how ready the users are to accept and use new technologies. By examining these dimensions, organizations can tailor their technology implementation strategies to address specific barriers and motivators, effectively facilitating the acceptance and integration of technologies. This strategic approach can significantly enhance technological adoption.

Previous research has investigated managers' aversion to AI algorithms in financial institutions by integrating TRI into IRT, focusing on the relationship between managers' perceived barriers and their aversion to algorithms, while also considering their readiness levels as moderating factors (Mahmud et al., 2023). It has highlighted the importance of understanding algorithm aversion across different industries and the necessity of tailoring research methods to specific contexts. Building on this foundation, I modified the model using IRT to explore the latent factors contributing to auditors' aversion to algorithms and incorporated clients' TRI levels as moderators in these relationships. I argue that these moderating effects manifest in two aspects: motivators and inhibitors.

3.5.8 Motivating factors

From the perspective of motivators (Lanz et al., 2024; Parasuraman & Colby, 2015), clients' innovativeness and optimism can play a critical role in mitigating auditors' aversion to AI algorithms by shaping the perceived risk and potential benefits associated with AI adoption in auditing practices. Innovative and optimistic clients are more likely to embrace advanced technologies, including AI, viewing them as opportunities rather than threats. This positivity and forward-thinking attitude can encourage auditors to reassess their perceived barriers, such as concerns about the complexity, accountability, or ethical implications of AI. When clients are enthusiastic about the potential of AI to enhance audit quality and efficiency, they can provide practical support and resources that help mitigate these barriers. For instance, they can be early adopters of new technologies themselves and may possess a more robust infrastructure that supports AI implementation. This can reduce logistical and technological barriers for auditors, providing them with firsthand exposure to successful AI integration and its benefits.

Moreover, optimistic clients contribute by fostering a positive outlook towards the adoption of innovative technologies, thereby highlighting the potential enhancements AI can bring to accuracy, efficiency, and analytical capabilities in auditing tasks. Such optimism can counterbalance auditors' fears and skepticism by aligning their expectations with positive outcomes and reducing the perceived risk associated with AI adoption. Therefore, in an environment where clients are innovative and optimistic, auditors may feel more encouraged and supported to overcome their initial barriers, leading to a decrease in their aversion to AI algorithms. This positive influence helps auditors transition from apprehension to a more accepting towards leveraging AI in their professions, aligning technology integration with audit objectives and client expectations. Thus:

> ***H6a-e.*** *The motivating factors of clients' technology readiness, including innovativeness and optimism, weaken the impacts of auditors' perceived usage, value, risk, tradition, and image barriers on their aversion to algorithms.*

3.5.9 Inhibiting factors

From the perspective of inhibitors (Blut & Wang, 2020; Parasuraman & Colby, 2015), clients' discomfort and insecurity can significantly amplify the relationship between auditors' perceived barriers to AI adoption and their aversion to AI algorithms because these client emotions introduce a complex layer of risk that auditors must manage, intensifying their existing apprehensions. When clients express discomfort or insecurity about the implementation of AI, auditors may perceive these sentiments as additional barriers to successful adoption, beyond the logistical or ethical concerns they might already have. This perception can make auditors more cautious, as they must also consider client trust and the potential impact on their professional relationships. The necessity to maintain a stable, trusting relationship with clients means that auditors must be particularly sensitive to any factors that could reduce this trust. Therefore, auditors facing client discomfort might be more likely to resist adopting new audit technologies to avoid the risk of unsettling the client further or failing to meet their expectations, which could result in damaging the relationship.

Additionally, auditors might also consider that any failure to integrate AI into their auditing processes effectively could lead to errors or oversights, which would affect the audit quality and potentially increase clients' insecurity. Thus, the pre-existing barriers auditors perceive can become more significant in environments where client discomfort is pronounced, leading to a stronger aversion towards AI algorithms. This dynamic can result in a negative circle where auditors' reluctance to embrace AI further increases clients' doubts, reinforcing the barriers to AI integration and leading to a long-term existence of algorithm aversion among auditors. Thus, managing clients' discomfort and insecurity is crucial in moderating the influence of perceived barriers on auditors' willingness to adopt AI technologies. I thus propose that:

> ***H7a-e.*** *The inhibiting factors of clients' technology readiness, including discomfort and insecurity, strengthen the influences of auditors' perceived usage, value, risk, tradition, and image barriers on their aversion to algorithms.*

3.6 Chapter Conclusion

This chapter develops a tailored technology-acceptance framework and formulates the specific hypotheses tested in subsequent analyses. It begins by refining the original TAM, centered on perceived usefulness and ease of use, for audit contexts, adding constructs for functional and operational risk, client technological readiness, and client acceptance.

Extensions including TAM2, TAM3, and UTAUT were considered but set aside because their additional social and demographic moderators unduly complicate measurement and dilute explanatory focus.

To capture affective and identity-based resistance, the chapter then proposes a hybrid model combining Innovation Resistance Theory (which classifies barriers of usage, value, risk, tradition, and image) with the Technology Readiness Index (which gauges optimism, innovativeness, discomfort, and insecurity). By integrating IRT's barrier taxonomy with TRI's readiness metrics, the model maintains theoretical clarity while enabling nuanced hypotheses about how client readiness moderates resistance to AI tools.

Two boundary conditions temper the framework's reach. First, regulatory oversight and professional standards, though conceptually linked to perceived risk, are omitted from empirical models to preserve tractability and focus on individual-level mechanisms; however, their potential impact on AI adoption remains important and warrants future inclusion. Second, organizational influences (e.g. firm size, inertia, prior AI exposure) are excluded to avoid multilevel complexity in this thesis's single-level design, yet they too may independently shape adoption and should be addressed in later research.

CHAPTER FOUR: RESEARCH METHODOLOGY

4.1 Chapter Introduction

Chapter Four of this thesis presents the research methodology employed to investigate auditors' acceptance of AI within the context of Baker Tilly China (BTC). This chapter outlines the structured approach taken to explore the complexities of auditors' perceptions, attitudes, and acceptance of AI across different branches of BTC. By employing a mixed-methods research design, the study aims to gain a comprehensive understanding of how different factors influence auditors' acceptance of AI technologies in external audits, joint audits, and broader audit practices. The methodology is anchored in three studies that collectively aim to provide qualitative insights, quantitative evidence, and a robust analytical framework to explore AI adoption in a non-Big Four accounting firm in China. The chosen methods ensure the reliability and validity of the findings, aligning with the overall research objectives and contributing significantly to the literature on AI integration in auditing.

4.2 Research Overview

The research methodology chapter is structured around three distinct but interconnected studies. The first study employs a mixed-methods approach, beginning with qualitative in-depth interviews followed by a quantitative survey experiment, to explore auditors' perceptions and acceptance of AI in external audits. The second study adopts a quantitative approach through a survey experiment designed to assess auditors' acceptance of AI-augmented joint audits, emphasizing the impact of social and environmental factors. The third study uses a quantitative survey-based approach to explore auditors' aversion to AI algorithms, examining barriers to adoption and the psychological factors influencing their resistance. Each study is designed to address specific research questions while collectively contributing to a comprehensive understanding of AI adoption in auditing. The combined insights from these studies provide a detailed perspective on the factors driving or hindering AI acceptance among auditors in a non-Big Four firm in China.

4.3 Research Approach

The research approach integrates both qualitative and quantitative methods to explore the multifaceted nature of AI adoption among auditors in BTC. The qualitative component involves semi-structured interviews with senior managers, providing rich, contextual insights into auditors' perceptions and concerns regarding AI implementation in external audits. This approach allows for the exploration of individual experiences and the identification of perceived risks and benefits associated with AI adoption. The quantitative component includes survey experiments and structured questionnaires that quantitatively assess auditors' acceptance levels of AI-augmented joint audits and aversion to AI algorithms. By employing Likert scale questions and regression analysis, the quantitative studies seek to validate the hypotheses derived from the qualitative findings and provide statistical evidence to support the proposed relationships. This mixed-methods approach ensures a comprehensive exploration of the research questions, enhancing the overall robustness and validity of the study.

4.4 Research Design and Strategy

4.4.1 Approach selection

The research employs a sequential exploratory mixed-methods approach, integrating both qualitative and quantitative methods across three interconnected studies to examine auditors’ acceptance of AI technologies at BTC. This approach ensures a comprehensive exploration of the research problem by starting with qualitative insights and building upon them with quantitative validation, providing a robust analytical framework that addresses the research objectives from multiple angles.

The first study adopts a two-stage design, integrating both qualitative and quantitative components to provide a comprehensive understanding of auditors' perceptions and acceptance of AI in external audits. The initial stage involves qualitative data collection through in-depth, semi-structured interviews with senior managers across four BTC branches. These interviews are designed to explore auditors' perceptions, focusing on how their individual risk perceptions and perceived client attitudes influence their acceptance of AI. The choice of a semi-structured format allows for flexibility in probing deeper into participants' responses, enabling the capture of rich, detailed insights into the auditors' experiences and concerns. The qualitative data identifies key themes related to perceived risks, benefits, and functional requirements for AI adoption. This stage provides valuable contextual insights that inform the design of the quantitative phase.

Building on the qualitative findings, the second stage of the first study employs a quantitative survey experiment to test the hypotheses derived from the initial interviews. The survey is designed with seven-point Likert scale questions, which are structured to quantitatively measure the variables identified in the qualitative phase, including perceived usefulness, ease of use, and specific functional and operational risks associated with AI. This experimental approach allows for the examination of auditors' acceptance of AI using a revised Technology Acceptance Model (TAM), offering a structured framework to assess the relationships between the identified factors. The combination of qualitative insights with quantitative validation in this study ensures a thorough exploration of the psychological and perceptual factors that influence AI acceptance, providing a solid empirical foundation for the subsequent studies.

The second study extends the investigation to the broader social and environmental factors affecting auditors' acceptance of AI-augmented joint audits. This study employs a cross-sectional survey design, targeting auditors across four BTC branches to assess how factors such as peer influence, regulatory support, and client acceptance levels impact their acceptance of AI in joint audits. The survey, also designed with seven-point Likert scale questions, allows for the collection of quantitative data that provides a broader perspective on the social dynamics influencing AI adoption. The data are analysed using regression analysis, which helps to identify the key drivers of AI acceptance and quantify their impact. By focusing on social and environmental influences, this study complements the individual-focused findings of the first study, highlighting the role of external factors in shaping auditors' attitudes toward AI.

The first two studies employ ordinal logistic regression (OLR) to analyse auditors' acceptance of AI, measured on seven-point Likert scales, because OLR is specifically tailored to ordered, categorical outcomes and does not require assuming equal distances between scale points. In the first study's quantitative experiment, OLR links predictors including perceived usefulness, perceived ease of use and risk perceptions (identified in the preceding qualitative interviews) to the likelihood of higher acceptance ratings; by estimating log-odds and proportional odds ratios, it quantifies how each incremental change in a predictor shifts the probability of an auditor selecting a stronger agreement category. In the second, cross-sectional survey, OLR similarly relates social and environmental factors, peer influence, regulatory support and client acceptance, to ordinal acceptance scores, accommodating potential clustering at scale extremes and yielding more efficient, unbiased estimates than either linear or multinomial models. Overall, OLR's proportional-odds framework leverages the full ranking information of seven-point items, providing a rigorous yet interpretable test of the revised TAM hypotheses without overstating measurement precision.

Building on the thematically derived insights from the semi-structured interviews, the survey instruments for Studies One and Two were developed from first principles to ensure precise measurement of auditors' perspectives and behaviours. Each construct in Studies One and Two was captured by a single, carefully formulated survey question. Terminology and scenario context for each item were drawn directly from the most salient themes in the semi-structured interviews. Each question was reviewed by senior audit professionals and pretested with practicing auditors to ensure clarity, relevance, and face validity. Responses were recorded on seven-point Likert scales to preserve nuance. Although multi-item scales were not employed, content validity was maximized through this rigorous, practice-grounded development process and supported by pilot testing to confirm that each single-item measure coherently represents its intended construct.

The third study shifts the focus to individual psychological barriers to AI adoption, specifically examining auditors' aversion to AI algorithms. This study utilizes a survey-based path analysis through Partial Least Squares Structural Equation Modeling (PLS-SEM), a method well-suited for exploring complex models with multiple interrelated variables. The survey includes measurement items that assess auditors' algorithm aversion, perceived risks, tradition barriers, and other factors that may inhibit AI adoption. The path analysis allows for a detailed examination of the relationships between these factors, revealing not only the direct effects of perceived barriers but also the indirect effects through interactions among the variables. This in-depth exploration provides a detailed understanding of the individual-level challenges to AI adoption, offering insights that are critical for addressing resistance and promoting more effective integration of AI technologies in auditing practices.

PLS-SEM is particularly well suited to operationalize the core tenets of Innovation Resistance Theory (IRI) and the Technology Readiness Index (TRI) because it conceptualizes constructs including functional resistance, value resistance, tradition barriers, optimism, innovativeness, discomfort, and insecurity as latent variables that manifest indirectly through multiple survey items. Unlike covariance-based techniques, PLS-SEM maximizes explained variance in endogenous constructs without imposing strict normality assumptions – an advantage when modeling the typically skewed, perception-driven responses characteristic of IRI/TRI scales. Moreover, PLS-SEM readily accommodates non-linear and threshold effects, central to both theories, by incorporating latent-variable interactions or product indicators, thereby capturing situations in which a marginal increase in perceived complexity or insecurity precipitates a sudden surge in resistance. The two-stage approach of estimating measurement and structural models in PLS-SEM parallels the IRI/TRI framework's dual emphasis on (a) rigorously validating that each block of items reliably and validly reflects its intended psychological disposition and (b) elucidating how these dispositions interrelate to influence adoption behaviour. Finally, PLS-SEM provides composite reliability, average variance extracted, and cross-loading diagnostics, tools that mirror IRT's item-level scrutiny, ensuring that each perception-based variable is measured with precision before mapping its effects on other readiness or resistance constructs.

By integrating all three studies within a unified theoretical framework, the research design offers a comprehensive, multi-dimensional examination of AI adoption among auditors at BTC. In Study One, auditors' assessments of AI's practical benefits, ease of integration, functional risks and responses to varied client scenarios are elicited through semi-structured interviews in external audits and then quantified via a targeted survey. Study Two reconceptualizes those assessments for the joint-audit context, focusing on AI's collaborative capabilities, procedural fit, risk implications and client expectations, and situates them alongside social drivers including peer attitudes, regulatory encouragement and overall client readiness. Study Three embeds the risk and usability concerns identified in the first two studies within a path-analysis model of resistance, evaluating how algorithm aversion, adherence to traditional audit protocols and discomfort with opaque decision rules influence acceptance both directly and indirectly. Throughout, perceived risk functions as a central latent factor, explored qualitatively, measured quantitatively in each audit setting and assessed as a mediator of resistance, while judgments of AI's utility and social influences are traced from narrative themes through survey constructs into a structural equation model. This integrated approach strengthens the validity and reliability of the findings and delivers actionable insights for firms, policymakers and technology developers seeking to navigate the challenges of AI integration in auditing.

4.4.2 Context selection

This research is conducted within the Chinese Accounting Industry for a number of reasons. China plays a significant role in the global economy and its ever-evolving business landscape (Lennox & Wu, 2022). The vast and diverse Chinese market, is becoming increasingly integrated with global financial systems, meaning that trends and practices within Chinese accounting firms offer valuable insights into broader global patterns. These firms navigate both local and international accounting standards and practices, providing a unique perspective on the interplay between regional and global accounting processes (Lennox & Wu, 2022).

Moreover, China is aligning its accounting standards with international norms, particularly for publicly traded firms (Li, Liu, and Wang, 2021). This convergence with international standards indicates the country-level commitment to global accounting practices and facilitates cross-border investments and financial reporting. It also demonstrates the potential contribution of studies on technological innovation in the Chinese accounting industry to the broader accounting literature (Lennox and Wu, 2022).

The study of AI adoption in Chinese accounting firms contributes significantly to the global accounting industry (Leng & Zhang, 2024). The rapid modernization and increasing complexity of the Chinese accounting industry underscore the necessity for AI integration to enhance efficiency and accuracy. The Chinese government is pivotal in driving technological adoption across various sectors, including accounting and auditing (Leng and Zhang, 2024; Zhu, Spence, and Ezzamel, 2021). Government initiatives notably "Made-in-China 2025" and "Industry 4.0" have actively encouraged the integration of new technology into the operation of core industries (Li, 2018), thus providing the environment for AI-related innovation in the accounting industry. Consequently, China stands at the forefront of technological innovation, particularly in AI development and implementation (Leng & Zhang, 2024). However, although the rapid expansion of China's economy and capital markets has created a high demand for accounting and auditing services (Lennox and Wu, 2022), AI adoption in accounting firms, particularly in non-Big Four firms (Cahan, Hay, and Li, 2021), remains in the early stage.

Therefore, understanding the barriers to AI implementation in Chinese accounting firms, particularly in specific audit practices notably risk management of external audits, is crucial for the widespread adoption of AI in the accounting industry, especially among non-Big Four accounting firms. For the first study, prior research has demonstrated the feasibility of understanding individual-level impacts on audits by focusing on Chinese accounting firms (Gul, Wu, and Yang, 2013). Since the study aims to explore the micro-level determinants of auditors' acceptance of AI in external audits based on TAM, selecting a sample from the Chinese accounting industry aligns with the research requirements.

The progress of AI innovation in China is also evident in social interactions, highlighting the cultural significance in China. The acceptance of AI in joint audits is influenced by these social dynamics. As Chinese auditors navigate these evolving dynamics, their experiences highlight the critical interplay between technological innovation and social factors. By examining such experiences of Chinese auditors, this study highlights how the integration of AI in joint audits can lead to improved audit quality and efficiency, providing a model for other countries to follow. While opting for joint audits in China is voluntary, it is encouraged for entities engaged in international or complex business activities. Investigating AI-augmented joint audits in China offers a significant case study for those interested in exploring the effectiveness of joint audits and the approaches that can enhance this effectiveness. I provide valuable insights into the Chinese accounting landscape and offer broader implications for the global adoption of AI in accounting practices, demonstrating how technological and social factors can drive progress in this field. The experiences of Chinese accounting firms with AI can guide firms worldwide in navigating their digital transformation trajectories.

Furthermore, the Chinese accounting industry provides a unique and effective context for understanding the antecedents of auditors' aversion to AI algorithms due to its rapid modernization and digital transformation, driven by the government's emphasis on technology and innovation (Lennox & Wu, 2022; Yang & Huang, 2022; Zhu, Spence, & Ezzamel, 2021). This dynamic environment allows me to observe how auditors respond to the introduction of AI technologies. Chinese auditors operate in a fast-paced business landscape, which may heighten their concerns and resistance towards AI adoption. By studying these reactions, I can gain insights into the specific factors contributing to auditors' resistance to innovation, notably perceived threats to job security, lack of understanding or trust in AI algorithms, and concerns over ethical implications and data security.

Moreover, the diversity in technological adoption and readiness among Chinese clients provides a rich foundation for exploring how varying levels of technology readiness impact auditors' resistance to AI (Leng & Zhang, 2024). Clients in China range from highly advanced technology firms to traditional, less technologically equipped businesses. This variation enables a comprehensive analysis of how clients' technology readiness moderates auditors' aversion to AI. For example, auditors working with technologically advanced clients might experience less resistance due to better support and understanding from the client side. In contrast, those dealing with less tech-ready clients might face higher resistance due to increased pressure to ensure the accuracy and reliability of AI systems. Understanding these dynamics in China can offer valuable insights into the broader implications for global accounting practices, providing lessons on managing AI integration in diverse regulatory and technological landscapes.

Therefore, the insights gained from studying the Chinese accounting industry can be beneficial for accounting firms in other countries. China's rapid adoption of AI in various sectors, including accounting, offers a preview of potential challenges and opportunities that firms in other regions might encounter as they implement similar technologies (Lennox & Wu, 2022). By analyzing the Chinese experience, accounting firms worldwide can develop strategies to address auditors' innovation resistance effectively.

Sampling bias arises from the exclusive reliance on auditors from one Chinese accounting firm with multiple branches, since firm-specific practices, technological infrastructures and client portfolios may systematically diverge from those of other accounting firms; despite this potential bias, the sample remains representative of the chosen case by encompassing auditors across diverse regional offices, engagement types and demographic profiles. Instrument reliability and construct validity are rigorously assessed to prevent measurement error. The single-firm, in-depth case study design affords theoretical generalisability by uncovering underlying mechanisms, including perceived threats to professional autonomy, algorithmic trust and client technology readiness, that can inform hypotheses in other contexts; however, statistical generalisability is constrained, as specific effect sizes and contextual interactions observed within this firm may not extend to organizations with different governance structures, market positions or regulatory environments.

4.5 Ethical Considerations

Ethical considerations are paramount throughout this research to ensure the integrity and confidentiality of the data collected. All participants were provided with detailed information about the study's purpose, procedures, and their rights, including the right to withdraw at any time without penalty. Informed consent was obtained from all participants before their involvement in interviews or surveys. The data collected were anonymized to protect participants' identities, and all recordings and transcripts were securely stored with restricted access to authorized personnel only. Moreover, ethical approval was sought and obtained from the relevant institutional review board (see Appendix B), adhering to guidelines on research involving human subjects. The study also takes into account the sensitivity of working with proprietary information from BTC, ensuring that no confidential business data is disclosed. These ethical practices are critical to maintaining the trust of participants and the credibility of the research findings.

4.6 Sample Selection

All three studies were conducted within Baker Tilly China (BTC), a non-Big Four accounting firm ranked among China's top ten (105 firms were included in the list) by the Chinese Institute of Certified Public Accountants in September 2023 for its 2022 performance. BTC was chosen because its auditors possess deep, practice-based expertise in external audit engagements and routinely apply both Chinese and international auditing standards. As one of the leading mid-tier firms with branches in every major provincial capital, BTC provides a representative setting for examining AI adoption in China's accounting industry.

For the first two studies, I focused on four BTC branches–Kunming, Chengdu, Wuhan, and Zhengzhou[2] –all classified as new first-tier cities by China Business Network on May 30, 2023. These emerging urban centers combine rapid economic growth, strong innovation ecosystems, and rising living standards, making them ideal for exploring auditors' risk perceptions (Study 1) and social-influence factors on augmented-AI use in joint audits (Study 2). To broaden the scope for Study 3, I added the Beijing branch–China's capital and a fully mature first-tier audit market–ensuring a geographically diverse sample that spans both highly developed and fast-evolving contexts.

By sampling multiple branches within the same firm rather than across different firms, I minimized variability stemming from distinct organizational cultures, training programmes, audit methodologies, and IT infrastructures. This approach holds the institutional environment constant and allows individual auditors' perceptions, attitudes, and experiences to emerge as the principal sources of analytic variation.

Across all studies, participants were professional auditors with at least six months of tenure at BTC; interns and those with shorter tenure were excluded. For Studies 1 and 2, auditors needed at least theoretical familiarity with AI applications via internal trainings or previous engagements. For Study 3, respondents were required to have direct, hands-on experience integrating AI tools into their audit tasks. In every case, participants were proficient in both Chinese and international auditing standards, supporting comparability across diverse engagement types.

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[2] Kunming, Chengdu, Wuhan, and Zhengzhou were classified as new first-tier cities according to China Business Network (CBN) on 30th May 2023. 15 out of 660 cities were recognized in this tier. The tier was recognized for a city's potential to rival traditional first-tier cities (Beijing, Shanghai, Guangzhou, and Shenzhen) in terms of living standards, business innovation, and economic opportunities. This research focused on the BTC branches in these cities as they provide research values for exploring AI adoption in auditing in the context of emerging and rapidly growing financial markets, which bears significant practical implications of promoting AI.

Data collection proceeded in a tiered, mixed-methods design. Study 1 began with in-field, semi-structured interviews of senior managers from the four new first-tier branches to identify perceived functional requirements and operational risks of AI in external-audit risk management. Building on those insights, I conducted an online survey experiment among branch auditors–using seven-point Likert items based on a revised Technology Acceptance Model–to quantify perceived usefulness, ease of use, risk perceptions, and client-attitude effects. Study 2 then surveyed the same auditors on social-influence constructs (client acceptance, regulatory support, peer attitudes) affecting willingness to deploy AI-augmented processes in joint audits. Finally, Study 3 employed a cross-sectional survey of auditors from all five branches to assess innovation resistance and aversion to AI algorithms, incorporating clients' technology-readiness as a potential moderator to capture both the depth and breadth of auditors' psychological barriers to AI adoption. Although participants may overlap across the three studies in this thesis, each study carefully selects individuals based on their audit experience and professional knowledge.

4.7 Study One

4.7.1 Stage One: Understanding auditors' ideas about AI adoption

4.7.1.1 Data collection

The first-stage study commenced with a pre-test in which two senior partners at BTC evaluated the draft interview questions, offering feedback solely on wording clarity and without affecting the study's substantive objectives. Their recommendations were then incorporated to enhance the questions' precision and comprehensiveness. Following the pre-test, I invited 21 senior managers of BTC to complete my formal interviews. These managers belonged to different departments, including government affairs consultation, financial auditing, and engineering auditing. The departments were referred to as project groups, with 12 to 20 employees, two or three vice managers, and one senior manager. The employees were aged an average of 28 years and had six years of industrial tenure on average. The managers were aged an average of 37 years and had 16 years of industrial tenure on average. The participants comprised ten males and 11 females with a bachelor's or master's degree in accounting or technology. Their specializations included auditing, taxation, business administration, and software engineering. Each interviewee was working full-time. The basic information of these managers is shown in Table 3.

Table 3. Information on senior managers from the Stage-One study

Participant No.	Gender	Tenure	Department	Position
1	M	11	Government affairs consultation	Manager
2	F	2	Government affairs consultation	Consultant manager
3	M	20	Financial auditing	Manager/Department director
4	M	10	Government affairs consultation	IT consultant manager
5	F	13	General	Director
6	F	26	Financial auditing	Department director
7	F	7	Financial auditing	Project director
8	F	8	Engineering auditing	Department director
9	F	9	Financial auditing 3rd	Department director
10	M	15	Engineering auditing	Manager
11	M	9	Financial auditing 2nd	Department director
12	F	2	Management consultation	Consultant manager
13	F	3	Engineering auditing	Assistant auditor
14	F	10	Engineering auditing	Project manager
15	M	12	Financial auditing	Manager
16	M	20	General	Director
17	M	21	General	Director
18	F	7	Financial auditing	Manager
19	F	4	Financial auditing	Manager
20	M	22	General	Director
21	M	20	General	Vice director

This table displays the details of the 21 senior BTC managers interviewed in Stage One of my study, including their genders, industrial tenures, affiliated departments, and job positions.

The participants were chosen according to three criteria (Lipparini, Lorenzoni, and Ferriani, 2014). First, interviewees were required to have a long tenure in the firms, to ensure that they had enough working experience to answer the given questions. Second, interviewees needed to be employed in firms' core positions and had to be directly involved in major operational decisions. Finally, interviewees needed specialization in various domains and should have worked at different levels within the firms, i.e., interviewees were expected to functionally contribute to different aspects that promote their firms' development. During the interviews, the participants were asked to answer several questions after reading an adequate introduction that explained the research theme and context.

4.7.1.2 Qualitative analysis design

The interview process was designed to be adaptive, with questions evolving based on participants' responses. While all questions centered on the practical applications of AI in external audits, they were tailored to each participant to capture a diverse range of perspectives from audit managers on AI-based technologies. Interviews were audio-recorded and transcribed immediately after each session using Trint, a digital transcription tool that utilizes speech-to-text technology for efficient conversion of spoken language into text. This approach facilitated a rapid and accurate transcription process, enhancing the accessibility and analysis of qualitative data. To ensure the reliability and precision of the transcriptions, three reviewers independently verified the outputs. The final dataset comprised 34 interviews, totaling 1,121 minutes of audio and 273,710 words of textual data, which were subsequently subjected to semantic analysis[2]. The interview guide used for this study is presented in Appendix Table A.1.

[2] The interviews were conducted in August 2019. After evaluating the interview outcomes and necessary preparation, I started the subsequent study in May 2021.

4.7.2 Stage Two: Exploring obstacles to auditors' acceptance of AI adoption

4.7.2.1 Data collection

According to the results of the first stage, I subsequently designed a survey with seven-point Likert scale questions (Haesebrouck, van den Abbeele, and Williamson, 2021). I conducted a pre-test before sending this questionnaire out. Two senior accountants with over 35 years of industrial tenure were invited to participate in this test to work through all the questions and provide detailed feedback. This process helped me improve the validity of my questions. After making necessary modifications, I sent the questionnaire to all 459 auditors of the target branches and received 159 effective responses (59 males and 100 females, averaging 28 years old, five years of industrial tenure). Primary survey designs are shown in Appendix Table A.2.

4.7.2.2 Regression analysis design

Such a questionnaire allowed me to measure the variables in my revised TAM. Specifically, auditors were asked to rate their acceptance of using AI considering the AI implementation in the context of risk management in external audits ($ACPTL_{AU}$). Auditors' PU and PEOU of using AI in external audits were measured and labeled as PU_{EA} and $PEOU_{EA}$. Demographic differences among auditors were calculated from three dimensions: genders ($Gender$, recorded as 0 for female and 1 for male), ages (Age), and tenure lengths ($TenL$). I measured auditors' functional and operational risk perceptions of deploying AI according to their specific perceived types of risks, as identified in the first stage. These risks were marked as FRP_{type} and ORP_{type}, respectively. Moreover, auditors were asked to rate their clients' technological levels ($TechL$), and acceptance levels of receiving AI services ($ACPTL_{CL}$) per their prior collaboration experience with clients in external audits.

I introduced $ACPTL_{AU}$ as the dependent variable, FRP_{type}, ORP_{type}, $TechL$, and $ACPTL_{CL}$ as the independent variables, and PU_{EA}, $PEOU_{EA}$, $Gender$, Age, and $TenL$ as covariates into my regression models. The descriptive statistics of these variables is shown in Table 4.

The histogram of $ACPTL_{AU}$ is displayed in Figure 7.

Table 4. Descriptive statistics

	N	MIN	MAX	Mean	SD
PU_{EA}	159	2.000	7.000	4.559	0.945
$PEOU_{EA}$	159	2.000	7.000	4.257	0.975
$Gender$	159	0.000	1.000	0.371	0.484
Age	159	18.000	57.000	28.761	5.964
$TenL$	159	1.000	36.000	5.025	5.830
FRP_{BI}	159	2.000	6.000	4.006	0.822
FRP_{TI}	159	2.000	7.000	3.779	0.904
ORP_{EI}	159	2.000	6.000	3.930	0.812
ORP_{SI}	159	2.000	6.000	4.157	0.807
$TechL$	159	1.000	6.000	4.000	0.720
$ACPTL_{CL}$	159	1.000	6.000	3.578	0.829
$ACPTL_{AU}$	159	1.000	6.000	4.031	0.630

This table presents the descriptive statistics for my variables of interest, detailing the number of observations (N), minimum (MIN) and maximum (MAX) values, mean, and standard deviation (SD) for each. PU_{EA} and $PEOU_{EA}$ stand for auditors' perceived usefulness and ease of use of AI adoption in risk management of external audits; $TenL$ represents auditors' tenure lengths; FRP_{BI} and FRP_{TI} are budget and technological issues in functional risk perceptions; ORP_{EI} and ORP_{SI} are ethical and security issues in operational risk perceptions; $TechL$ and $ACPTL_{CL}$ are clients' technological and acceptance levels of receiving AI services. $ACPTL_{AU}$ represents auditors' acceptance levels of using AI in risk management of external audits.

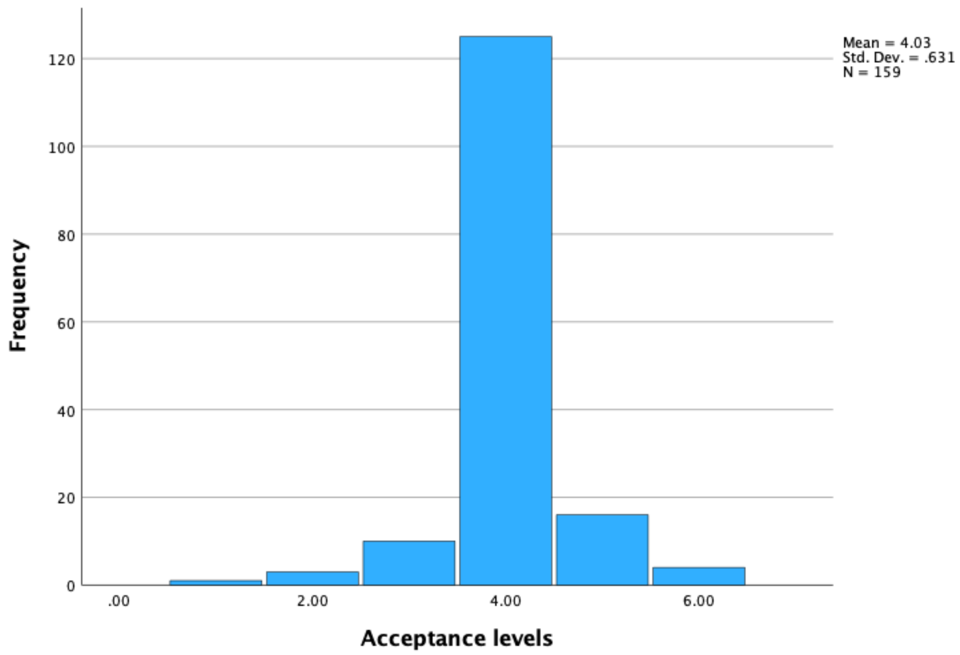

Figure 7. Histogram of auditors' acceptance levels of using AI

I first used the Pearson correlation to test the linear relationship between each pair of factors and then leveraged the ordinal logistic regression (King and Clarkson, 2015) to examine my proposed links, that is:

$$logit[P(ACPTL_{AU} \leq i \mid FRP_{type}, ORP_{type}, TechL, ACPTL_{CL}, PU_{EA}, PEOU_{EA}, Gender, Age, TenL)] \\ = \beta_{0i} + \beta_1 FRP_n + \beta_2 ORP_n + \beta_3 TechL + \beta_4 ACPTL_{CL} + \beta_5 PU_{EA} + \beta_6 PEOU_{EA} \\ + \beta_7 Gender + \beta_8 Age + \beta_9 TenL$$

Where $ACPTL_{AU}$ is the ordinal outcome with categories i, $P(ACPTL_{AU} \leq i)$ is the cumulative probability of $ACPTL_{AU}$ less than or equal to the category $j = 1, 2, \ldots, (i-1)$:

$$P_i = P(ACPTL_{AU} \leq i \mid FRP_{type}, ORP_{type}, TechL, ACPTL_{CL}, PU_{EA}, PEOU_{EA}, Gender, Age, TenL) \\ - P(ACPTL_{AU} \\ \leq i - 1 \mid FRP_{type}, ORP_{type}, TechL, ACPTL_{CL}, PU_{EA}, PEOU_{EA}, Gender, Age, TenL)$$

$$= \frac{1}{1 + \exp[-(\beta_{0i} + \beta_1 FRP_n + \beta_2 ORP_n + \beta_3 TechL + \beta_4 ACPTL_{CL} + \beta_5 PU_{EA} + \beta_6 PEOU_{EA} + \beta_7 Gender + \beta_8 Ag}$$

$$- \frac{1}{1 + \exp[-(\beta_{0i-1} + \beta_1 FRP_n + \beta_2 ORP_n + \beta_3 TechL + \beta_4 ACPTL_{CL} + \beta_5 PU_{EA} + \beta_6 PEOU_{EA} + \beta_7 Gender + \beta_8}$$

4.8 Study Two

4.8.1 Data Collection

Consistent with prior research, we employed seven Likert-scale questions to measure the variables associated with our proposed relationships (for a relevant example in accounting research, see Haesebrouck, Van den Abbeele, & Williamson, 2021). Primary question designs are shown in Appendix Table A.1. We reached out all 459 auditors from the four branches of BTC with experience in joint audits. The auditors were invited to participate via email and were provided with questionnaires. A total of 161 valid responses were received, resulting in a 35% response rate. The sample included 102 females, with an average age of 29 years and an average of approximately five years of experience in joint audits, suggesting that the participants were generally senior auditors.

The survey was conducted in June 2021, with approval obtained from BTC. For two reasons, we consider this survey effective for understanding auditors' acceptance of using augmented AI in joint audits. First, it coincided with the pandemic-driven (Bauer et al., 2022) shift to remote joint audits, which heightened communication challenges and led auditors to adopt AI (Munoko et al., 2020) to maintain audit quality. This period provided valuable insights into their concerns, perceived benefits, and practical challenges with AI-augmented audits. Second, the increasing interest in AI during this time enhanced auditors' familiarity with AI's capabilities and limitations, crucial for assessing their readiness to integrate AI into their workflows (Munoko et al., 2020).

This process allowed me to measure auditors' acceptance level of AI-augmented joint audits (AJA), perceived usefulness (PU) and ease of use ($PEOU$) of augmented AI in joint audits, perceived clients' acceptance level of such technology (CAL), supportiveness of regulatory and policy environments (SRE), and peers' acceptance level (PAL). Using single-item Likert scales to measure key constructs, such as PU and PEOU, can be justified by practical considerations, including brevity and the need to minimize respondent fatigue–an especially important factor in organizational settings like BTC. Single-item measures streamline survey administration, reduce response burden, and can enhance response rates while still providing a useful snapshot of each construct. Although multi-item scales offer greater depth by capturing different dimensions of a construct, the trade-off between comprehensiveness and efficiency makes single-item measures a viable alternative. Given these advantages, we consider the potential limitation of missing subtle details acceptable in exchange for a more practical and less intrusive data collection process for busy professionals.

As previously reviewed, clients' attitudes towards new technologies can vary across industries (Knechel & Williams, 2023). I identified 20 industries in China and collected data on auditors' perceptions of client acceptance of augmented AI within each industry. These industries were classified according to Document *GB/T 4754–2017: Industrial Classification for National Economic Activities*, issued by the National Bureau of Statistics of China. Table 5 presents comparisons of client acceptance among industries, with the F test revealing significant variations across sectors (p<0.01). The scatter plot in Figure 8 illustrates that Industry 7 (*information transmission, software, and consulting technology services*) exhibited the highest acceptance of augmented AI in joint audit services, while Industry 1 (*agriculture, forestry, animal husbandry, and fishery*) showed the lowest. The higher acceptance in Industry 7 may stem from its digital nature and familiarity with technological innovations, where professionals are more inclined to trust and value the efficiencies and analytical improvements augmented AI offers. Conversely, the lower acceptance in Industry 1 can be attributed to its dependence on physical operations and conventional methods. This sector may lack the technological infrastructure and digital literacy to fully appreciate or integrate augmented AI into its joint audit processes, leading to lower acceptance rates. These findings underscore the validity and necessity of measuring client acceptance across industries. I thus use the average acceptance across sectors (CAL_{avg}) to represent each auditor's perceived overall attitude of clients toward AI-augmented joint audits.

Although each individual auditor may not possess in-depth expertise across all 20 industries, asking them to assess client attitudes in this broader context yields valuable insights into general patterns and concerns surrounding AI-augmented joint audits. By exposing participants to various industries, the study encourages them to draw on fundamental audit principles and professional judgment, rather than narrow, industry-specific knowledge. This broad approach helps identify whether and how attitudes about AI-augmented joint audits hold consistently across different sectors, lending greater generalizability and robustness to the findings. It also mitigates the risk of overfocusing on a few well-known industries and allows this study to evaluate potential variations in acceptance and perceived risks that may otherwise go unnoticed if confined to a narrower scope.

Table 5. Comparisons of client attitude toward AI-augmented joint audits across industries

		Acceptance level				
No.	**Industry name**	**Min**	**Max**	**Mean**	**SD**	***F* test**
1	Agriculture, forestry, animal husbandry, and fishery	1.000	7.000	3.670	1.268	11.224*** [1.379e-33]
2	Mining	1.000	7.000	3.869	1.351	
3	Manufacturing	2.000	7.000	4.409	1.153	
4	Electricity, heat, gas, and water production and supply	2.000	7.000	4.459	1.129	
5	Construction	1.000	7.000	4.006	1.242	
6	Transportation, warehousing, and postal services	2.000	7.000	4.614	1.172	
7	Information transmission, software, and consulting technology services	3.000	7.000	5.118	1.158	
8	Wholesale and retail trade	2.000	7.000	4.304	1.230	
9	Accommodation and catering	2.000	7.000	4.366	1.253	
10	Finance	2.000	7.000	4.813	1.235	
11	Real estate	1.000	7.000	4.372	1.155	
12	Rental and business services	2.000	7.000	4.428	1.154	
13	Scientific research and technical services	1.000	7.000	4.683	1.329	
14	Water conservancy, environment, and public facilities management	2.000	7.000	4.354	1.164	
15	Residential services, repairs, and other services	1.000	7.000	4.055	1.285	
16	Education	1.000	7.000	4.316	1.221	
17	Health and social work	2.000	7.000	4.254	1.163	
18	Culture, sports, and entertainment	1.000	7.000	4.254	1.184	
19	Public administration, social security, and social organizations	2.000	7.000	4.273	1.106	
20	International organizations	1.000	7.000	4.304	1.172	

This table shows the variance in clients' attitudes toward employing augmented AI for joint audits across various industries, as determined by an F test that evaluated the significance of these differences among industries. Survey participants were asked to rate their perceived attitude of clients from each industry, resulting in 161 observations for each industry. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively; *p*-value is reported in square brackets. The p-values reported in this table and in subsequent sections of the study are all two-tailed.

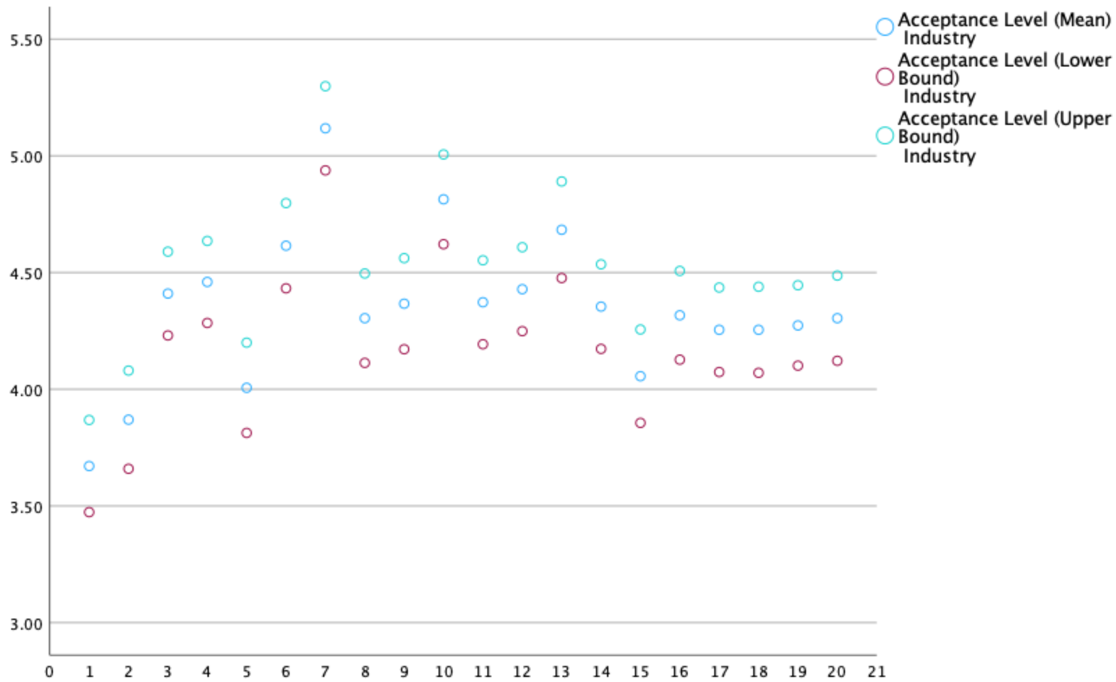

Figure 8. Scatter plot of client attitude toward AI-augmented joint audits across industries

I introduced two additional factors as covariates influencing auditors' acceptance of augmented AI. The first is the auditors' experience of joint audits (EJA). Auditors' experience (Baugh, Hallman, & Kachelmeier, 2022) with joint audits over the years shapes their acceptance of augmented AI primarily through their adaptation to technological advancements and collaborative methodologies. Auditors who have navigated the complexities of joint audits, which involve coordinating efforts between multiple audit firms, become more open to innovations that can improve these processes. The experience associated with evolving audit technologies and practices enhances their willingness to appreciate the efficiencies and analytical ability AI can bring, making them more receptive to integrating augmented AI into their joint audit work. I measured such experience by year.

The second is the headquarter's acceptance of augmented AI (HAA). I consider that in the context of BTC, the perception of headquarter's acceptance of augmented AI significantly influences branch auditors' willingness to adopt AI-augmented joint audits (cf. Contreras, Ghosh, & Kong, 2021). Headquarters' endorsement of AI technologies demonstrates a commitment to leveraging innovative solutions to enhance audit effectiveness and efficiency. This top-down encouragement signals to branch auditors, underscoring the strategic importance and benefits of AI integration in auditing practices. Therefore, auditors at BTC branches, guided by the headquarters' positive stance, are more likely to trust and adopt AI in their audit processes.

4.8.2 Regression Analysis Design

Based on my extended TAM, I considered AJA as the dependent variable (histogram is shown in Figure 9), CAL_{avg}, SRE, and PAL as the independent variables, and PU, $PEOU$, EJA, and HAA as the covariates. The descriptive statistics of these variables are displayed in Table 6.

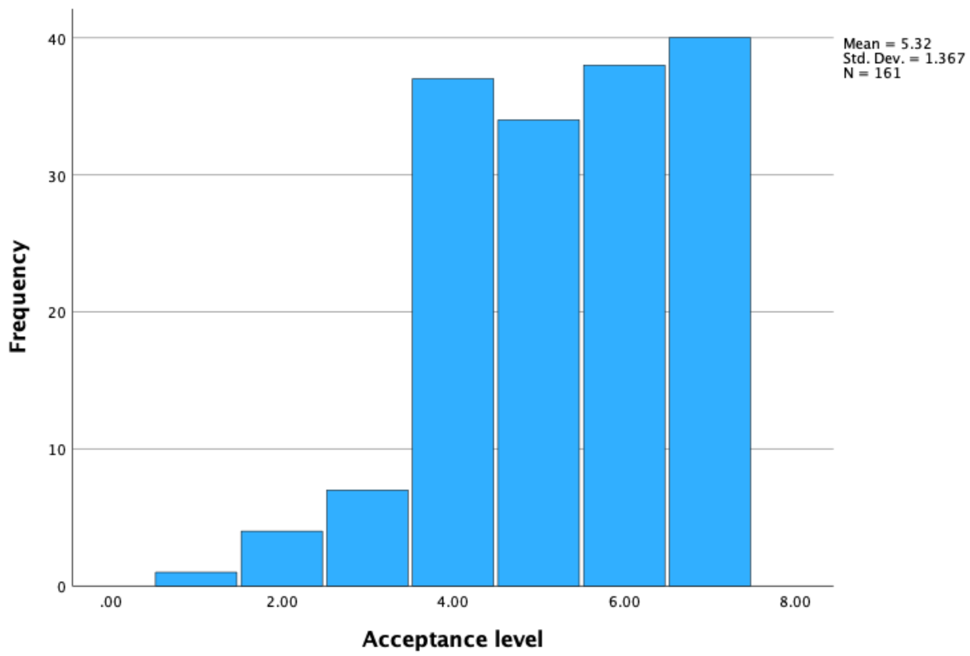

Figure 9. Histogram of auditors' acceptance of AI-augmented joint audits

Table 6. Descriptive statistics of concerned variables

	Min	Max	Mean	SD
Acceptance level of AI-augmented joint audits	1.000	7.000	5.316	1.366
PU	1.000	6.000	4.024	0.631
PEOU	1.000	7.000	4.242	1.004
Experience of joint audits (years)	1.000	36.000	5.049	5.825
Perceived headquarter's acceptance level	1.000	7.000	4.869	1.019
Perceived client's acceptance level (average)	2.250	7.000	4.346	0.867
Perceived supportiveness of regulatory and policy environments	2.000	7.000	4.441	0.967
Perceived peer's acceptance level	1.000	7.000	4.590	1.109

This table shows the descriptive statistics for my factors of interest. PU and PEOU represent auditors' perceived usefulness and perceived ease of use of AI-augmented joint audits. The number of observations is 161.

I first used the Spearman correlation (Smeulders, Dekker, & Van den Abbeele, 2023) to assess the monotonic relationship between each pair of variables. Spearman correlation is appropriate for ordinal data, such as data from Likert scale questions, because it measures the strength and direction of association between ranked variables without assuming a linear relationship.

I then used the ordinal logistic regression (Haesebrouck et al., 2021) to examine the proposed relationships. Ordinal logistic regression is effective for ordinal data because it specifically handles situations where the responses have a natural order. Unlike standard logistic regression, which is commonly used for binary outcomes, ordinal logistic regression can manage multiple categories that follow a ranked order. This makes it ideal for analyzing survey data where responses fall into ordered categories, providing more accurate and meaningful insights. I conducted the examination by:

$$\log\left(\frac{P(AJA \leq j)}{1 - P(AJA \leq j)}\right) = \alpha_j - \left(\beta_1 CAL_{avg} + \beta_2 SRE + \beta_3 PAL + \beta_4 PU + \beta_5 PEOU + \beta_6 EJA + \beta_7 HAA\right)$$

Where $P(ALV \leq j)$ is the probability that AJA falls in category that is less than or equal to j, and α_j is the threshold for category j.

4.9 Study Three

4.9.1 Data Collection

167 selected auditors participated in the study by completing online surveys sent via email, featuring questions formatted on a Likert scale. The study was conducted from July to September 2021. Consistent with prior research (Mahmud et al., 2023), I applied Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the hypothesized relationships. PLS-SEM is effective for small sample sizes and surveys with Likert scale questions. It focuses on maximizing the explained variance of dependent constructs, enhancing the robustness of complex models even with limited data. My sample size meets the requirements of the model (cf. Mahmud et al., 2023).

I first identified the measurement items for each latent variable under study, referred to as constructs in PLS-SEM. Table 7 presents these measurement items for each construct, including auditors' algorithm aversion (AA), perceived usage (UB), value (VB), risk (RB), tradition (TB), and image barriers (IB), as well as the perceived motivating (Mot) and inhibiting (Inh) factors of clients' technology readiness. Additionally, the table indicates the existing literature sources from which these items were selected.

Table 7. Measurement in the context of auditing

Construct	Item	Loading
Algorithm aversion (AA) (Coleman et al., 2022; Commerford et al., 2022)	AA1 – RC: I accept AI-related innovations in the accounting industry.	0.772
	AA2 – RC: I am satisfied with the level of AI adoption within my firm.	0.842
	AA3: I think human capabilities are more important than AI for completing audit tasks.	0.833
Usage barrier (UB) (Coleman et al., 2022; Commerford et al., 2022)	UB1: The application of AI requires specialized skills that are challenging to acquire.	0.914
	UB2: The integration of AI into other auditing technological systems will be challenging.	0.920
	UB3: The flexible adaptation of AI to the auditing process will be challenging.	0.903
Value barrier (VB) (Coleman et al., 2022; Commerford et al., 2022; Munoko et al., 2020)	VB1: The investment potential of AI is limited in the context of auditing.	0.814
	VB2: The sustainable value of AI adoption in auditing is limited. (*Dropped*)	0.365
	VB3 – RC: AI can enhance audit services for clients.	0.922
	VB4 – RC: Adopting AI can help accounting firms outperform competitors in the auditing market. (*Dropped*)	0.086
Risk barrier (RB) (Munoko et al., 2020)	RB1: Adopting AI carries the risk of violating auditing standards.	0.876
	RB2: AI's ability to perform auditing tasks involves uncertainties.	0.821
	RB3: Adopting AI in auditing processes carries the risk of operational errors. (*Dropped*)	0.444

Table 7 (*Continued*)

Tradition barrier (TB) (Commerford et al., 2022; Dierynck et al., 2023)	TB1 – RC: I accept the changes in conventional audit processes resulting from AI adoption.	0.828
	TB2: I find it difficult to ensure audit quality when integrating AI into my audit routines.	0.839
	TB3: I am satisfied with the traditional methods I use for conducting auditing processes.	0.791
	TB4: I have greater trust in audit decisions made by human auditors using traditional methods compared to those made by AI systems.	0.807
Image barrier (IB) (Coleman et al., 2022; Commerford et al., 2022; Munoko et al., 2020)	IB1: I have a negative image of the impact of adopting AI on the accuracy of audit outcomes. (*Dropped*)	0.272
	IB2: I have a negative image of the impact of adopting AI on the efficiency of auditing. (*Dropped*)	0.104
	IB3 – RC: I have an image that policy will support AI-related innovation in auditing practices.	0.875
	IB4 – RC: I have an image that the auditing market will demand AI-related innovation.	0.910
Motivator (Mot) (Lanz et al., 2024; Parasuraman & Colby, 2015)	Mot1 – Innovativeness: My clients have a high level of expertise in deploying technological innovations.	0.752
	Mot2 – Innovativeness: My clients are willing to accept innovative audit technologies.	0.702
	Mot3 – Optimism: My clients trust the benefits of deploying new technologies in their audit services.	0.742
	Mot4 – Optimism: My clients believe that the introduction of new audit technologies will not affect auditing continuity during their long-term cooperation with my firm.	0.734

Table 7 (*Continued*)

Inhibitor (Inh) (Blut & Wang, 2020; Parasuraman & Colby, 2015)	Inh1 – Discomfort: My clients lack confidence in my operations when I employ new audit technologies. (*Dropped*)	0.154
	Inh2 – Discomfort: My clients are reluctant to collaborate when new audit technologies are introduced.	0.925
	Inh3 – Insecurity: My clients are concerned about information security when novel audit technologies are introduced. (*Dropped*)	0.338
	Inh4 – Insecurity: My clients are concerned about compliance security when novel audit technologies are introduced.	0.931

This table outlines the measurement designs of constructs used in Partial Least Squares Structural Equation Modeling (PLS-SEM), including auditors' algorithm aversion, auditors' perceived usage, value, risk, tradition, and image barriers, as well as the motivators and inhibitors of clients' technology readiness. The items for each construct were selected based on my literature review, with corresponding references provided in the table. RC denotes reverse-coded items. The loading of items refers to the correlation between observed variables (indicators) and their corresponding latent constructs, indicating the degree to which each item represents the intended underlying construct. High loadings (above 0.700) suggest that the items are strong indicators of the latent construct, and therefore, these items were retained. Items with loadings below 0.700 were excluded.

The three measurement items of AA assess auditors' aversion to AI algorithms by exploring various dimensions of their attitudes and perceptions. The first item assesses the general acceptance of AI innovations, which directly reflects their openness or resistance to integrating new technology. The second item measures satisfaction with AI adoption, indicating whether auditors feel positively or negatively about the current level of AI integration in their firm. The third item captures the perceived importance of human capabilities versus AI, revealing any underlying preference for human-based traditional methods over technological advancements.

The measurement items of UB examine auditors' perceived usage barriers of AI algorithms by addressing key challenges they may face. The first item highlights the need for specialized skills, indicating whether auditors feel adequately prepared or overwhelmed by the skillset required for AI application. The second item focuses on the integration of AI with existing auditing technologies, revealing concerns about compatibility and the complexity of incorporating AI into current systems. The third item examines the flexibility of AI adaptation to the auditing process, capturing any apprehensions about AI's ability to fit into established workflows.

The items of VB evaluate auditors' perceived value barriers to AI adoption by addressing both potential benefits and limitations. The first item assesses perceptions of AI's investment potential in auditing, revealing whether auditors see AI as a worthwhile financial commitment. The second item measures beliefs about the long-term value AI can provide, indicating concerns about its sustainability and impact. The third item evaluates whether auditors recognize AI's ability to enhance audit services for clients, reflecting their views on practical improvements. The fourth item captures the competitive advantage AI might offer, highlighting whether auditors believe AI can help firms outperform rivals.

RB's items capture auditors' perceived risk barriers to adopting AI algorithms by addressing critical concerns specific to their profession. The first item highlights the risk of violating established auditing standards, which underscores the importance of regulatory compliance and professional integrity. The second item focuses on the inherent uncertainties in AI's ability to perform auditing tasks, reflecting skepticism about the technology's reliability and accuracy. The third item pertains to the risk of operational errors, emphasizing practical concerns about the potential for AI to introduce mistakes into the auditing process.

The measurement items of TB effectively identify auditors' perceived tradition barriers to AI adoption by addressing their attachment to and confidence in conventional auditing methods. The first item assesses their openness to change, directly reflecting their willingness to embrace new AI-driven processes. The second item captures concerns about maintaining audit quality, highlighting skepticism about AI's efficacy compared to traditional methods. The third item indicates satisfaction with established practices, revealing a preference for familiar, time-tested approaches. The fourth item measures trust in human decision-making over AI, emphasizing deep-rooted confidence in traditional human judgment.

The four items of IB capture auditors' perceived image barriers to adopting AI algorithms by addressing their perceptions of AI's impact on key aspects of auditing. The first item assesses their views on AI's impact on audit accuracy, reflecting concerns about the precision and reliability of AI-enhanced audits. The second item evaluates perceptions of AI's effect on auditing efficiency, highlighting consideration about potential improvements in speed and resource utilization. The third item explores the perceived level of policy support for AI innovation, indicating beliefs about regulatory and institutional backing. The fourth item measures perceptions of market demand for AI-driven innovations, revealing expectations about industry trends and client preferences.

The measurement items of Mot assess auditors' perceptions of clients' technology readiness by focusing on innovativeness and optimism. For innovativeness, the items assess clients' expertise in deploying technological innovations and their willingness to accept innovative audit technologies, which are crucial indicators of how open and capable clients are in adopting new methods. For optimism, the items evaluate clients' trust in the benefits of new technologies and their confidence that such innovations will not disrupt ongoing auditing processes, reflecting a positive outlook towards technological advancements and their integration into long-term practices.

The items of Inh estimate auditors' perceived inhibiting factors by addressing the two primary dimensions of clients' technology readiness: discomfort and insecurity. The discomfort items highlight clients' lack of confidence and reluctance to collaborate, which are critical indicators of resistance and unease toward new technologies, reflecting a fear of the unknown or mistrust in the auditor's capabilities. The insecurity items focus on concerns about information and compliance security, which are central to clients' apprehensions about the potential risks and vulnerabilities introduced by novel audit technologies.

The survey questionnaire was subsequently designed based on the identified measurement items, incorporating a seven-point Likert scale for each item to evaluate auditors' opinions (1=strongly disagree; 7=strongly agree). I tested for common method bias in my survey results to assess the validity of the outcomes. Testing for common method bias in Likert-scale questionnaires is crucial to ensure the validity of the research findings. Common method bias occurs when variations in responses are attributable to the measurement method rather than the constructs the measures represent, potentially leading to misleading conclusions. Addressing this bias helps in obtaining more accurate and reliable data, enhancing the credibility of the study's results. I performed Harman's single-factor test (Harman, 1976) using both Principal Component Analysis (PCA) and Principal Axis Factoring (PAF) to evaluate the presence of common method bias in my data. The results showed that a single factor explained 0.222 of the variance in PCA and 0.199 in PAF. Since these values are below 0.500, it suggests that common method bias is low in the dataset.

As shown in Table 7, I retained items with loadings above 0.700 for further analysis and discarded those with loadings below 0.700. In PLS-SEM, item loadings above 0.700 are necessary to ensure that the indicators strongly correlate with their respective constructs, indicating high reliability and validity. Loadings above this threshold demonstrate that a substantial portion of the variance in the indicator is explained by the construct, which is crucial for the accuracy and robustness of the model.

4.9.2 Path Analysis Design

I focused on the retained items and introduced auditors’ demographic characteristics (cf. Pethig & Kroenung, 2023) as covariates into the model, including age, gender (coded as 0 for female and 1 for male), AI-related education level, tenure, and working position (coded as 1 for administrative positions and 0 for regular employees). I consider that auditors’ demographic information is essential when studying their aversion to AI algorithms because these factors can significantly influence their perceptions and acceptance of AI technology. Descriptive statistics for these variables are displayed in Table 8. Based on this foundation, I tested the model’s reliability and validity and then conducted the path analysis.

Table 8. Descriptive statistics

	Mean	Median	Min	Max	SD	Kurtosis	Skewness
Age	29.192	28.000	18.000	57.000	6.174	4.331	1.859
Gender	0.395	0.000	0.000	1.000	0.489	-1.835	0.433
AI-related education level	4.335	4.000	2.000	7.000	1.119	0.335	0.471
Tenure	5.533	3.000	0.000	36.000	6.189	6.280	2.327
Working position	0.186	0.000	0.000	1.000	0.389	0.671	1.632
AA1	5.407	6.000	2.000	7.000	1.332	-0.661	-0.428
AA2	4.617	4.000	2.000	7.000	0.965	0.549	0.310
AA3	4.132	4.000	1.000	7.000	1.081	1.484	0.452
UB1	2.868	2.000	1.000	7.000	1.311	-0.169	0.825
UB2	2.743	2.000	1.000	7.000	1.299	0.210	0.919
UB3	2.533	2.000	1.000	7.000	1.348	0.195	0.958
VB1	4.180	4.000	1.000	7.000	0.931	3.263	0.398
VB3	4.096	4.000	1.000	7.000	0.711	5.132	0.262
RB1	4.371	4.000	2.000	7.000	1.226	-0.265	0.164
RB2	4.425	4.000	2.000	7.000	1.245	-0.452	0.107
TB1	4.395	4.000	1.000	7.000	1.142	-0.072	-0.019
TB2	4.737	5.000	1.000	7.000	1.359	-0.453	-0.248
TB3	4.299	4.000	2.000	7.000	1.124	-0.046	0.357
TB4	4.329	4.000	1.000	7.000	1.191	-0.040	0.304
IB3	4.455	4.000	2.000	7.000	0.965	0.464	0.310
IB4	4.449	4.000	1.000	7.000	1.042	1.061	-0.088
Mot1	4.467	4.000	2.000	7.000	1.147	-0.127	0.190
Mot2	4.240	4.000	1.000	7.000	0.986	1.016	0.523
Mot3	4.503	4.000	2.000	7.000	1.137	-0.346	0.276

Table 8 (*Continued*)

Mot4	4.922	5.000	1.000	7.000	1.027	0.736	-0.077
Inh2	4.503	4.000	1.000	7.000	1.072	0.320	0.154
Inh4	4.497	4.000	1.000	7.000	1.008	0.927	0.114

This table presents the descriptive statistics of auditors' demographic features, including age, gender, AI-related education level, tenure, and working position, along with items for each construct. AA1, AA2, and AA3 represent the acceptance of AI-related innovations in the accounting industry, satisfaction with AI adoption within firms, and opinions about AI capabilities. UB1, UB2, and UB3 denote perceptions of the skills required by AI applications, the integration of AI into other auditing technologies, and the flexibility of AI adoption. VB1 and VB3 indicate opinions about the investment potential of AI and the enhancement of AI in audit services for clients. RB1 and RB2 cover risk perceptions of AI potentially violating auditing standards and uncertainties about AI's abilities. TB1, TB2, TB3, and TB4 relate to the perception of acceptance of changes brought by AI, the impacts of AI on audit routines, satisfaction with traditional audit methods, and trust in AI-generated audit decisions. IB3 and IB4 address feelings about policy support and auditing market demand for AI-related innovation. Mot1, Mot2, Mot3, and Mot4 assess clients' expertise in using new technologies, acceptance of new audit technologies, trust in the benefits of using new audit technologies, and feelings about audit consistency when using new technologies. Inh2 and Inh4 represent clients' reluctance to use new audit technologies and concerns about compliance security when introducing new technologies. Observations=167; Min=Minimum; Max=Maximum; SD=Standard Deviation.

4.10 Integration

The integration of the three studies within this research methodology chapter provides a cohesive and comprehensive exploration of auditors' acceptance of AI technologies at BTC. Each study, while distinct in its focus and approach, is strategically connected to build upon the insights and findings of the others, creating a layered understanding of the factors influencing AI adoption. This integrative approach ensures that the research addresses the complexity of AI acceptance by linking individual, social, and organizational dimensions in a unified framework.

The first study serves as the foundation by integrating both qualitative and quantitative methods to explore auditors' perceptions and acceptance of AI in external audits. The qualitative stage, consisting of in-depth interviews with senior managers, uncovers the key perceived risks, benefits, and requirements for AI adoption. These insights provide a rich contextual understanding of the individual and organizational factors that shape auditors' attitudes toward AI, notably concerns about clients' situations, the reliability of AI tools, and the perceived impact on audit quality. Building on these findings, the quantitative survey experiment further refines and tests the identified factors using a structured framework, offering empirical evidence to support the qualitative insights. This dual-method approach validates the initial findings and extends them by providing a more detailed and statistically robust analysis of the factors influencing AI acceptance among auditors.

The second study builds upon the foundations laid by the first study by shifting the focus to the broader social and environmental factors that impact auditors' acceptance of AI-augmented joint audits. By employing a cross-sectional survey design, this study quantitatively examines how external influences, notably peer acceptance, regulatory environment, and client attitudes, affect auditors' willingness to adopt AI in joint audit contexts. The findings of this study complement the individual-focused results of the first study by highlighting the role of social dynamics and organizational context in shaping AI acceptance. This connection between the studies is crucial, as it demonstrates that AI adoption is not solely driven by individual perceptions but is also significantly influenced by the broader social and environmental landscape in which auditors operate.

The third study looks deeper into individual psychological barriers, specifically focusing on auditors’ aversion to AI algorithms. Using a survey-based path analysis with PLS-SEM, this study identifies and quantifies the specific barriers that contribute to auditors’ resistance to AI, notably perceived risks, tradition barriers, and image concerns. This focused examination of algorithm aversion provides a detailed understanding of the psychological processes that underpin auditors' attitudes toward AI, offering insights into the personal and perceptual challenges that may hinder AI adoption. The integration of these findings with the earlier studies is particularly valuable, as it reveals the complex interplay between individual psychological factors and the broader organizational and social influences identified in the first and second studies. These studies collectively offer a holistic view of AI adoption in auditing.

For the sample selection across the three studies, the female-dominated composition does not indicate sampling bias but accurately reflects the gender structure of China’s auditing workforce. According to the Chinese Institute of Certified Public Accountants, women represent more than half of practicing auditors nationwide, with even higher proportions in non-Big Four and mid-tier firms. Internal demographic information from the participating Baker Tilly China branches likewise confirms that women constituted the majority of staff-level and senior-level auditors in Kunming, Chengdu, Wuhan, Zhengzhou, and Beijing during the data-collection period, typically ranging from 55% to 70%. Because the studies deliberately sampled only experienced auditors with at least six months of tenure, the gender distribution in the dataset closely matches the actual population structure of these branches. Accordingly, the predominance of female respondents is not a sampling artefact but an accurate reflection of auditor demographics within comparable mid-tier Chinese firms, ensuring that the findings are not biased by gender imbalance.

4.11 Chapter Conclusion

Chapter Four has outlined the research methodology employed in this thesis to explore auditors' acceptance of AI within BTC. Through a mixed-methods approach, combining qualitative and quantitative research, this chapter has provided a detailed examination of the study's design, strategy, and execution across three interconnected studies. Each study was crafted to address distinct aspects of AI adoption among auditors, ranging from qualitative insights into individual perceptions and organizational influences to quantitative evaluations of acceptance levels and psychological barriers. The chosen methodology aligns with the research objectives and enhances the validity and reliability of the findings, offering a comprehensive understanding of the factors driving or hindering AI adoption in a non-Big Four accounting firm in China.

The first study used in-depth interviews to gather qualitative data on auditors' initial perceptions and acceptance of AI, revealing key insights into their perceived risks, benefits, and requirements for AI integration in external audits. This foundational qualitative data informed the second study, which employed survey experiments to quantitatively assess auditors' acceptance of AI-augmented joint audits, emphasizing the role of social and environmental factors notably peer influence, regulatory support, and client acceptance. The third study further explored individual barriers to AI adoption, specifically focusing on auditors' aversion to AI algorithms. By using survey-based path analysis, this study identified critical psychological and perceptual factors that contribute to resistance, notably perceived risks, tradition barriers, and image concerns.

The integration of these studies provides a holistic perspective on AI adoption, linking social influences and individual psychological factors. This comprehensive approach allows for a detailed understanding of how these elements interact to shape auditors' acceptance of AI technologies. These method designs directly lead to the empirical results presented in the next chapter, offering quantitative and qualitative evidence that underpins the analysis of AI adoption in BTC. The findings contribute to the academic literature on AI adoption in auditing, offering practical implications for accounting firms, policymakers, and technology developers seeking to enhance AI integration in professional services. Ultimately, this chapter underscores the importance of a multi-faceted research approach in capturing the complexities of technological adoption in the accounting industry, setting the stage for the subsequent analysis and discussion of results in the following chapters.

Each of the three empirical studies directly addresses one of the core research questions and corresponding audit contexts articulated in Chapter 1. Study One's in-depth interviews examine auditors' engagement-specific risk perceptions and salient client characteristics in external audits, thereby shedding light on the particular challenges that impede the use of AI for risk-management tasks. Study Two's survey experiments isolate the influence of social interactions – peer recommendations, regulatory encouragement, and prevailing professional norms – on auditors' willingness to deploy AI in joint-audit settings, thus mapping onto the question of how normative pressures shape adoption when multiple firms collaborate. Finally, Study Three's path-analytic survey probes the psychological underpinnings of algorithm aversion in routine audit practice, identifying the perceptual and emotional barriers that deter auditors from integrating AI across broader, non-engagement-specific tasks. Together, these three studies form a coherent framework that aligns each methodological approach with its respective research question, ensuring that the thesis delivers targeted insights into the facilitators and obstacles of AI adoption in diverse audit environments.

CHAPTER FIVE: RESULTS

5.1 Chapter Introduction

This chapter presents the results of three empirical studies that collectively address the overarching research question: How can AI be systematically adopted within auditing? Each study offers a distinct yet interconnected perspective, elucidating auditors' evaluative judgments, collaborative processes, and enduring cognitive orientations toward AI integration.

The three studies offer a cohesive exploration of AI adoption in auditing, tracing a continuum from initial evaluation to sustained integration. First, auditors' evaluative judgments in external audits are examined through semi-structured interviews and regression analysis, defining perceived usefulness as the conviction that AI enhances precision and efficiency while also assessing risk perceptions concerning budgetary and technological uncertainties. Results indicate that confidence in clients' technical readiness amplifies perceived benefits and attenuates risks, laying the groundwork for initial AI engagement. Building upon these insights, the second study investigates implementation within joint audit contexts, where perceived usefulness is reconceptualized to emphasize inter-firm communication and task synchronization and perceived ease of use addresses the integration of shared AI platforms. Additionally, social influence from clients, corporate headquarters, and regulatory bodies, and the institutional trust they engender, emerges as a critical catalyst for collaborative AI deployment. Finally, the third study addresses the long-term cognitive orientations that determine sustained AI utilization, grounding its analysis in Innovation Resistance Theory and the Technology Readiness Index. By operationalizing algorithm aversion via a multi-item scale that captures professional image concerns, tradition barriers, and reliability issues, and defining trust cognitively as belief in AI's predictive accuracy, it demonstrates that cognitive trust in conjunction with client readiness mitigates resistance. Together, these studies delineate a research trajectory that links evaluative judgment and risk assessment with organizational coordination and enduring cognitive dispositions, yielding an integrated framework for guiding AI adoption in audit practice.

A final consideration concerns measurement rigor across the studies. In the first two investigations, constructs including perceived usefulness, perceived ease of use, and social influence are context-specific and unidimensional, rendering single-item measures both parsimonious and valid (Stephan, Rauch, & Hatak, 2023; Wanous, Reichers, & Hudy, 1997; Zettna et al., 2025). External and joint audit scenarios involve narrowly defined evaluative judgments, such as the extent to which AI improves precision or facilitates inter-firm coordination, where respondent burden and scale reliability concerns are minimal. Conversely, AI aversion in the broader audit context encompasses multifaceted cognitive and affective dimensions, including professional image threats, adherence to tradition, and system reliability perceptions. Capturing these detailed attitudes necessitates a multi-item instrument to ensure content validity, internal consistency, and the capacity to distinguish among distinct resistance facets.

Collectively, these studies form a cohesive research trajectory: the first study delineates the evaluative criteria and risk assessments informing initial AI consideration; the second elucidates organizational dynamics and institutional endorsements facilitating multi-firm implementation; and the third identifies cognitive trust mechanisms essential for maintaining AI integration. The resulting framework offers practitioners and policymakers an empirically grounded guide for orchestrating AI adoption that harmonizes technological innovation with the profession's epistemic and ethical imperatives.

5.2 Study One Results

5.2.1 Stage One Outcomes

My interviews with BTC audit managers allow me to identify two critical routes of AI adoption in external audits: (1) adoptions on the client side, and (2) adoptions in accounting firms. Under this context, I further identify auditors' perceived risks of using

AI in complex external audit work, particularly risk management. Details are elaborated in the following sections.

5.2.1.1Auditors' ideas about client-side AI adoption

According to my interviews with BTC audit managers, AI adoption in the external audit process must begin on the client side. Client-side technological collaboration emerges as a foundation for accounting firms aiming to enhance audit quality and efficiency (Aghazadeh and Hoang, 2020). Client-side AI adoption enables appropriate integration of tools and platforms between clients and auditors, facilitating effective communications. Such a collaborative approach also suggests the importance of clients' technological and willingness levels in AI adoption. As mentioned by interview participants:

> *I think that if we really want to apply AI technologies in the accounting field, accounting work must be used before auditing work, because a large amount of accounting work is repetitive work and is relatively easy to be replaced. If that AI can help accountants find risk points, it can help them make financial statements, and if their financial statements are of higher quality, it will also benefit our audit work.* **[*Manager 8*]**

> *In fact, I think the most critical point of whether a firm uses AI technology depends on the degree of intelligence of the audited company. If the intelligence level of the audited company is not high, or if they still maintain the most primitive bookkeeping method, then we cannot use AI technology when we provide audit or consulting services. Therefore, I think that first of all, our clients need to use the system with AI technology, and then our accounting firm can further promote the use of AI technology in the audit process.* **[*Manager 4*]**

AI applications on the client side primarily aim to help accountants deal with daily tasks, such as check scanning, general ledger creation, and account division, reducing their workloads. Such a process allows AI to help accountants compile financial materials into well-organized financial statements. These financial statements are essential for improving the efficacy of external audits (Emett et al., 2023). They serve as information foundations, facilitating auditors in efficiently navigating through the financial data, thereby streamlining the audit process. The well-organized structure of statements enables auditors to effectively assess the accuracy, completeness, and compliance of financial records with applicable accounting standards. This organization enhances the auditors' ability to detect errors, assess risks, and make appropriate judgments, thereby significantly improving the reliability of the external audit outcomes:

> *I personally think that the application of AI technology is more suitable for accounting personnel in companies than for auditors in accounting firms, because the work of accountants is mainly the kind of work that is highly repetitive and not too complicated, and their work is relatively replaceable. For example, some existing technologies can be used in accounting work, for example: check scanning, this technology can help accountants reduce a lot of workloads.* **[*Manager 7*]**

> *The most important part of the audit work is the auditor's final judgment, and the accounting work is actually not complicated. For many companies, their accounting work is to do the general ledger, divide the accounts, and then summarize the information and compile it into financial statements. AI can help with these accounting works.* **[*Manager 1*]**

> *I think from the perspective of future development, AI technology can help accountants handle daily business. Accounting work is mainly to prepare financial statements. Many of the materials needed to prepare financial statements are repetitive tasks. Isn't that AI technology used in other fields to deal with this repetitive work? Therefore, I think that if AI technology can be introduced into the accounting field, it can assist accountants in making financial statements.* **[*Manager 13*]**

Client-side AI adoption requires AI to possess the capability of continuous learning (Brynjolfsson and Mitchell, 2017). This dynamic learning capability enables AI systems to adapt to new accounting standards, regulatory changes, and evolving financial practices in real time. Such adaptability ensures that AI adoptions remain relevant and effective and enhances their ability to provide predictive insights, automate complex processes, and improve decision-making accuracy:

> *I have some understanding of AI, it is to rely on ML to improve, right? If it is applied to accounting work, I think it should be similar, that is, a database can be built within the company, and then, the data of each financial statement is in the database, and artificial intelligence can learn this way. After a long time, this technology should also improve, I think so.* **[*Manager 15*]**

Moreover, client-side AI adoption follows the *assisted mode* (Munoko et al., 2020). The mode leverages AI to automate accounting routine processes, analyse large datasets, and identify patterns or anomalies, while human oversight ensures the appropriateness of final decision-making, ethical considerations, and compliance with regulatory standards:

I personally do not reject the implementation of AI in the accounting and auditing fields. I don't think there is any pressure. After all, I don't think AI can completely replace humans. Because after all, AI is just a machine, and its final work needs to be reviewed by people in the end, especially the delicate work like accounting and auditing. **[*Manager 3*]**

5.2.1.2 Auditors' ideas about AI adoption in accounting firms

Based on the interviews with audit managers, I identify that auditors mainly require AI to assist them in repetitive audit work. For instance, auditors need AI to help them classify and organize clients' vouchers in external audits. By automating the task of voucher classification and organization, AI enables auditors to allocate more time to analytical and judgment-based activities, thereby enhancing the overall quality and thoroughness of the audit. Furthermore, AI-driven classification potentially fosters a more structured and accessible audit trail, facilitating a smoother audit process:

Personally, I especially hope that AI can be promoted in auditing, because the workload of auditing is really too large. We often have an auditing team to work overtime to check accounts. Many vouchers can only be checked randomly, and it is impossible to comprehensively check. Look, a company's three-year or five-year vouchers are very scary. If AI can assist in the classification, then our auditors will have time to look at more evidence and their financial statements later, and the final report will be more detailed. **[*Manager 9*]**

In my understanding, AI technology is to do simple and repetitive tasks. I think that if this kind of technology is really going to be introduced into the audit work in the future, then it will do some basic work, mainly to assist the audit work. For example, classify the information that the auditor needs to verify into categories, so that it is convenient for the auditor to check. Because the amount of audit work is very large, if AI technology can help auditors record the inspections that have been completed, it can reduce the workload of auditing. **[*Manager 17*]**

Similar to client-side AI adoption, auditors require AI to be equipped with continuous learning ability when deploying related technologies in their firms. Such ability enables AI to adapt to the evolving audit landscape, thus allowing AI to refine its algorithms based on new data, regulatory changes, and emerging audit methodologies, thereby maintaining its relevance and efficacy (Brynjolfsson and Mitchell, 2017). AI's continuous learning ability enhances the precision of audit tasks notably risk assessment and anomaly detection:

> *Although I don't know what other people think, but I think it is feasible to introduce AI into the risk management of external audit work, we just need to help them learn and improve. Every time we audit, or the historical database, we can help our financial robot to improve. If there is any problem in the learning process, we will help AI correct the mistakes, so that AI can learn continuously and repeatedly.* **[*Manager 9*]**

> *In the case of AI, it has already been promoted in other fields, but it is only in the accounting and auditing fields that we have started to get involved in the past few years. In fact, it can be understood as adding a system to assist auditors. We need to train it continuously so that it can help identify risk points in the process of continuous learning, thereby helping auditing be more accurate.* **[*Manager 4*]**

AI adoption in accounting firms also follows the assisted mode, where human auditors can collaborate with AI (Munoko et al., 2020). This approach leverages AI's computational power to handle data-intensive and repetitive tasks, while human auditors apply their judgment, experience, and contextual understanding. This mode enhances audits' effectiveness, enabling a more comprehensive interpretation of findings and ensuring compliance with regulatory and ethical standards. Deploying such a mode in external audits increases audits' efficiency and accuracy. It mitigates the risk of over-reliance on technology, ensuring the audit process remains robust, comprehensive, and aligned with audit standards:

> *Speaking of AI's application in the future auditing process, there are some expectations. First of all, it must reduce the burden on our auditors on simple and repetitive tasks. But to be honest, I feel that this has an invisible effect on the quality of auditors. The requirements and professional ability requirements are higher, because I think that AI has helped to process some basic information, and auditors need to verify the processing results further, because AI is a machine, and it cannot be guaranteed that it will not make mistakes. The result after the auditor's verification is the final thing. In addition, the most important thing in auditing is people. Machines can't replace auditors' judgment on audit results, and the final working paper still needs human participation.* **[*Manager 16*]**

> *If AI, or what we call ML, is to be added to the auditing work, then humans must still dominate. No matter what the machine does, humans must check it last, especially when it comes to auditing. Auditing is the kind of work that many small I think machines can only assist in detail work, and auditors must be the final check.* **[*Manager 11*]**

5.2.1.3 Auditors' risk perception of AI adoption in complex audit work

Based on these auditors' ideas about AI adoption in external audits, I further elicited two types of functional risks and two operational risks that auditors are concerned with the most when promoting AI in complex audit work, especially risk management. Regarding functional risk perception (FRP), I identify budget (FRP_{BI}) and technological (FRP_{TI}) issues. Auditors' concerns about the potential functional issues of AI adoption are related to their perception of AI's functional limitations, as I reviewed above, and the investment toward deploying AI and maintaining its functional performance. The initial investment in AI technologies, including the procurement of software, hardware, and the necessary staff training, can be substantial. Moreover, the ongoing costs related to updating and maintaining AI systems add to the financial burden. These expenditures pose a risk of overshooting budgets, especially for medium and small accounting firms with limited resources (cf. Lennox and Wu, 2022). It is crucial to weigh these costs against the potential long-term efficiencies and improvements in audit quality that AI can bring:

> *The promotion of AI in accounting is still in its infancy. The research cost is too high for small and medium-sized accounting firms. So, it is not easy to give them the positive motivation to implement AI.* **[$\boldsymbol{FRP_{BI}}$, *Manager 11*]**

> *Actually, the operation and maintenance of AI-related systems in later periods also carry a lot of overhead.* **[$\boldsymbol{FRP_{BI}}$, *Manager 4*]**

> *For larger accounting firms, they can provide a sufficient budget to develop AI technology. They are not very concerned about R&D cost, whether the technical level can meet their requirements are truly they concentrate on. But will not be the same for other accounting firms.* **[$\boldsymbol{FRP_{BI}}$, *Manager 5*]**

> *If our personnel make adjustments, the AI should record them and then automatically recognize changes, but it is hard to achieve this function at the current stage.* **[$\boldsymbol{FRP_{TI}}$, *Manager 8*]**

> *Although repeated learning and multiple error corrections followed by feedback sharing each time help the robot improve continuously, this process takes a long time.* **[$\boldsymbol{FRP_{TI}}$, *Manager 4*]**

Regarding the operational risk perception (ORP), I identify ethical (ORP_{EI}) and security (ORP_{SI}) issues. AI adoption in external audits introduces both ethical and security risks that require careful consideration. Ethically, the deployment of AI raises questions about bias and accountability when replacing human judgment in sensitive decision-making. Ensuring AI algorithms are transparent and fair is critical to maintaining trust in audit outcomes (cf. Munoko et al., 2020). Security risks are equally important, as AI processes vast amounts of confidential financial data, making them targets for cyber threats. Protecting this data against breaches is paramount to guarantee confidentiality and integrity. Balancing these risks with the benefits of AI entails robust ethical guidelines and strict security measures to safeguard the audit process:

> *AI is trained by neural networks or deep learning. The training processes rely on programmes written by humans. If the training rules are not transparent and fair, the decisions made by AI will have a relatively large deviation.* **[$\boldsymbol{ORP_{EI}}$, *Manager* 4]**

> *If computers are developed to replace humans, there will be significant ethical problems in audit fields.* **[$\boldsymbol{ORP_{EI}}$, *Manager 2*]**

> *When we audit confidential companies, we cannot use our computers, nor can we use our accounting software. Moreover, their accounts are not information-led, and they still use the original manual accounts. Therefore, we need to input all basic information provided by the company before proceeding with the subsequent audit process.* **[$\boldsymbol{ORP_{SI}}$, *Manager 1*]**

> *The usage of AI has always relied on the network and other media, so network security issues, notably data leakage, are our first consideration. After all, accounting firms belong to the service industry, and it is vital to protect customer privacy.* **[$\boldsymbol{ORP_{SI}}$, *Manager* 6]**

> *When there are emergencies in the computer system, the integrity of the data cannot be guaranteed if relying on AI programmes.* **[$\boldsymbol{ORP_{SI}}$, *Manager* 10]**

The findings in the first stage contribute to exploring the effective mode of AI implementation in the external audit process. My identified AI-system designs for accounting firms and clients show the practical pattern of integrating AI into accounting and audit works. Audit managers of non-Big Four accounting firms prefer the assisted AI application mode over the augmented and automatic in external audits. Specifically, auditors' perception of AI's increasingly significant usefulness facilitates their willingness to incorporate AI into their decision-making. Nevertheless, audit managers are less likely to build trust in fully automatic AI programmes or AI-generated final decisions, especially when conducting complex financial reports, due to AI's potential drawbacks in external auditing activities. Therefore, audit managers prefer to select assisted AI over other technologies. The *assisted AI mode* (Munoko et al., 2020), where artificial intelligence works with human auditors, significantly contributes to the risk management of external audits by enhancing the detection, assessment, and mitigation of various audit risks. In this mode, AI-driven automation of routine audit tasks reduces the likelihood of human error, while final audit decisions remain by human auditors. The mode helps auditors process vast datasets efficiently, identifying patterns, anomalies, and trends indicative of potential risks. This capability enables auditors to identify areas of higher risk with greater accuracy, ensuring that audit efforts are focused where they are most needed. The integration of the assisted AI mode into external audits offers a comprehensive approach to risk management.

Stage One also helps me to identify auditors' risk perception of using AI in risk management of external audits. I introduced such perception into the regression models in Stage Two to explore their linear relationship with auditors' acceptance of using AI.

5.2.2 Stage Two Outcomes

The correlation matrix in Table 9 shows the linear relationship between each pair of my concerned elements. The results indicate that auditors' perceived usefulness of AI, age, and tenure affect their acceptance of AI separately and significantly. Moreover, the correlation between auditors' perceived usefulness of AI and their functional risk perceptions is not significant. This finding supports my earlier argument that these two elements should be evaluated independently. I then used four regression models to further examine the proposed links.

Table 9. Pearson correlation matrix

	1	2	3	4	5	6	7	8	9	10	11
1. PU_{EA}											
2. $PEOU_{EA}$	0.213***										
	[0.007]										
3. $Gender$	0.041	-0.043									
	[0.607]	[0.590]									
4. Age	0.122	0.014	0.289***								
	[0.127]	[0.862]	[<0.001]								
5. $TenL$	0.148	0.044	0.230***	0.823***							
	[0.063]	[0.578]	[0.004]	[<0.001]							
6. FRP_{BI}	0.061	0.053	-0.133	0.089	0.165**						
	[0.448]	[0.506]	[0.095]	[0.263]	[0.038]						
7. FRP_{TI}	-0.010	0.115	-0.145	0.012	0.020	0.333***					
	[0.896]	[0.149]	[0.069]	[0.876]	[0.800]	[<0.001]					
8. ORP_{EI}	0.059	0.023	-0.176**	0.112	0.105	0.531***	0.272***				
	[0.460]	[0.777]	[0.027]	[0.162]	[0.189]	[<0.001]	[<0.001]				
9. ORP_{SI}	0.199**	0.149	-0.101	0.093	0.121	0.494***	0.403***	0.460***			
	[0.012]	[0.061]	[0.203]	[0.242]	[0.127]	[<0.001]	[<0.001]	[<0.001]			
10. $TechL$	0.019	-0.054	-0.073	0.077	0.080	-0.096	0.097	-0.011	0.807		
	[0.816]	[0.499]	[0.364]	[0.337]	[0.317]	[0.228]	[0.223]	[0.892]	[0.275]		
11. $ACPTL_{CL}$	0.125	-0.092	0.014	0.078	0.047	-0.005	-0.040	-0.147	-0.203**	0.138	
	[0.116]	[0.251]	[0.865]	[0.328]	[0.559]	[0.947]	[0.616]	[0.065]	[0.010]	[0.084]	
12. $ACPTL_{AU}$	0.268***	0.038	0.107	0.259***	0.272***	0.158**	0.068	0.041	0.127	0.223***	0.304***
	[<0.001]	[0.633]	[0.181]	[<0.001]	[<0.001]	[0.046]	[0.397]	[0.605]	[0.111]	[0.005]	[<0.001]

This table shows the Pearson correlation of each pair of my concerned factors. PU_{EA} and $PEOU_{EA}$ represent auditors' perceived usefulness and ease of use of AI adoption in risk management of external audits; $TenL$ stands for auditors' tenure lengths; FRP_{BI} and FRP_{TI} are budget and technological issues in perceptions of functional risks; ORP_{EI} and ORP_{SI} are ethical and security issues in perceptions of operational risk; $TechL$ and $ACPTL_{CL}$ are clients' technological and acceptance levels of receiving AI services. $ACPTL_{AU}$ represents auditors' acceptance levels of using AI in risk management of external audits. Observations N=159. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively; *p*-value is reported in square brackets.

As shown in Table 10, I first tested the joint impacts of covariates on auditors' acceptance of using AI in Model 1. The result shows that auditors' perception of AI's usefulness significantly (at the 0.01 significance level) associated with their acceptance. Auditors are more willing to use AI when they feel that AI can contribute more to their auditing work. Auditors' demographic features, including their genders, ages, and tenure lengths, and perceived AI's ease of use are less relevant to their acceptance of AI. These covariates were also introduced into the later regression models.

Table 10. Ordinal logistic regression results of auditors' acceptance of using AI

	Model 1	**Model 2**	**Model 3**	**Model 4**
PU_{EA}	0.707^{***}	0.735^{***}	0.574^{**}	0.581^{**}
	(0.215)	(0.222)	(0.223)	(0.235)
	[0.001]	[<0.001]	[0.010]	[0.013]
$PEOU_{EA}$	0.084	0.062	0.154	0.127
	(0.198)	(0.200)	(0.205)	(0.210)
	[0.673]	[0.755]	[0.453]	[0.547]
$Gender$	0.180	0.228	0.325	0.420
	(0.421)	(0.435)	(0.433)	(0.451)
	[0.670]	[0.601]	[0.453]	[0.352]
Age	0.029	0.040	0.004	0.016
	(0.060)	(0.061)	(0.062)	(0.063)
	[0.635]	[0.510]	[0.951]	[0.798]
$TenL$	0.062	0.048	0.080	0.061
	(0.059)	(0.060)	(0.060)	(0.062)
	[0.294]	[0.425]	[0.182]	[0.325]
FRP_{BI}		0.405		0.406
		(0.294)		(0.320)
		[0.169]		[0.204]
FRP_{TI}		0.146		0.047
		(0.237)		(0.241)
		[0.537]		[0.845]
ORP_{EI}		-0.266		-0.184
		(0.294)		(0.296)
		[0.365]		[0.535]
ORP_{SI}		-0.115		0.058
		(0.311)		(0.321)
		[0.712]		[0.857]

Table 10. (*continued*)

$TechL$			0.586^{**}	0.633^{**}
			(0.266)	(0.277)
			[0.028]	[0.022]
$ACPTL_{CL}$			0.885^{***}	0.872^{***}
			(0.249)	(0.263)
			[<0.001]	[<0.001]
Chi-square	21.954^{***}	24.451^{***}	38.386^{***}	40.676^{***}
	[<0.001]	[0.004]	[<0.001]	[<0.001]

Observations	159	159	159	159

This table shows the primary relations of my study regarding auditors' risk perception and client-side situations, and auditors' acceptance of using AI in risk management of external audits. The dependent variable is the auditors' acceptance level of AI adoption. PU_{EA} and $PEOU_{EA}$ are auditors' perceived usefulness and ease of use of AI adoption in risk management of external audits; $TenL$ represents auditors' tenure lengths; FRP_{BI} and FRP_{TI} stand for budget and technological issues related to functional risk perceptions; ORP_{EI} and ORP_{SI} are ethical and security issues associated with operational risk perceptions; $TechL$ and $ACPTL_{CL}$ are clients' technological and acceptance levels of receiving AI services. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively; standard errors are in parentheses, and *p*-values are reported in square brackets.

Model 2 investigated the influence of the four types of auditors' perceived risks on their acceptance of AI. The regression results imply that auditors' risk perception of AI implementation cannot significantly determine their willingness to deploy relevant technologies in risk management of external audits. Such findings allow me to reject my first group of hypotheses.

I then tested the associations between auditors' acceptance of AI and their perceptions of client-side situations in Model 3. The results show that clients' technological ability to accept AI-related services and their willingness to use AI significantly affect auditors' acceptance of AI (at the 0.05 and 0.01 significance levels, respectively). Auditors are more likely to use AI when their clients possess requisite technology levels and positive attitudes toward AI. Furthermore, clients' willingness to use AI exhibits greater impacts on auditors' acceptance than clients' technology levels do, demonstrating the importance of subjective factors in AI adoption. These results offer empirical evidence for H2a and H2b. These results show that auditors demonstrate a greater willingness to use AI in external audits when their clients are willing and capable of accepting AI-related audit services. Model 4 incorporates all independent variables to check the regression results obtained from the first three models.

Given the correlations observed among several risk dimensions and auditors' acceptance of AI in Table 9—particularly the associations involving budget-related functional risk and ethical operational risk—the null findings for the risk variables in the main models may raise concerns about multicollinearity suppressing their individual effects. To rigorously rule out this possibility, I conducted a series of robustness tests in which each perceived risk dimension was entered into the ordinal logistic regression model separately while retaining all core controls (PU, PEOU, gender, age, and tenure). The results consistently indicate that none of the four risk categories exerts a statistically meaningful influence on auditors' acceptance of AI. Security-related operational risk yields a coefficient that is essentially zero (β = 0.022, p = 0.930), and ethical operational risk similarly shows no substantive association (β = –0.072, p = 0.781). Technological functional risk exhibits a small positive relationship but remains far from significance (β = 0.160, p = 0.476), and budget-related functional risk—although somewhat stronger—still fails to achieve statistical relevance (β = 0.275, p = 0.270). These single-predictor estimations demonstrate that the lack of significance observed in the full model is not an artifact of shared variance among the risk variables but rather reflects a robust empirical pattern: auditors' acceptance of AI in external-audit risk management appears largely insensitive to their perceptions of functional or operational risks when considered independently of other adoption-related beliefs.

I further validate my original logistic regression results using Analysis of Variance (ANOVA). As shown in Table 11, ANOVA reveals significant differences between group means, particularly regarding clients' technological levels and willingness to use AI. This cross-validation enhances the overall evidence of my model's predictive power.

Table 11. Analysis of Variance (ANOVA) of Relevant Factors

Variable	**Comparison**	**Mean Square**	***F*-value**	***P*-value**
PU_{EA}	Between Groups	3.105	3.780	0.003^{***}
	Within Groups	0.821		
$PEOU_{EA}$	Between Groups	2.686	3.000	0.013^{**}
	Within Groups	0.895		
$Gender$	Between Groups	0.179	0.756	0.583
	Within Groups	0.237		
Age	Between Groups	151.405	4.763	$<.001^{***}$
	Within Groups	31.79		

$TenL$	Between Groups	183.349	6.297	<.001***
	Within Groups	29.119		
FRP_{BI}	Between Groups	1.413	2.163	0.061*
	Within Groups	0.653		
FRP_{TI}	Between Groups	1.536	1.932	0.092*
	Within Groups	0.795		
ORP_{EI}	Between Groups	1.653	2.636	0.026**
	Within Groups	0.627		
ORP_{SI}	Between Groups	1.134	1.781	0.120
	Within Groups	0.637		
$TechL$	Between Groups	2.177	4.683	<.001***
	Within Groups	0.465		
$ACPTL_{CL}$	Between Groups	2.718	4.370	<.001***
	Within Groups	0.622		

Table 11. *(continued)*

This table shows the one-way ANOVA of relevant factors. The categorical variable is the auditors' acceptance of using AI in risk management of external audits. PU_{EA} and $PEOU_{EA}$ are auditors' perceived usefulness and ease of use of AI adoption in risk management of external audits; $TenL$ represents auditors' tenure lengths; FRP_{BI} and FRP_{TI} are budget and technological issues related to functional risk perceptions; ORP_{EI} and ORP_{SI} are ethical and security issues associated with operational risk perceptions; $TechL$ and $ACPTL_{CL}$ are clients' technological and acceptance levels of receiving AI services. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

In summary, auditors' perceptions of client-side situations show more statistically significant influences on their acceptance of AI adoption in risk management of external audits than their risk perceptions of using AI. The results partly support my arguments.

5.3 Study Two Results

Building on the interviews with managers in Study One, these same discussions help me establish the context for Study Two.

> *In the scenario where the client's systems were already AI-enabled, I could see how we'd seamlessly plug in and get value. But with no client infrastructure, it's too much work to set up on our own.* ***[Client Attitude, Manager 1]***

Auditors view existing client AI platforms as a prerequisite: high client readiness allows them to focus on analytic enhancements rather than foundational IT deployment.

> *If the regulator issues clear guidelines on AI use, what's allowed, what documentation we need, then I'd be much more willing to try it. Ambiguity makes me hold back."* ***[Regulatory and Policy Environments, Manager 3]***

Clear policy frameworks resolve compliance concerns and give auditors the confidence to integrate AI into judgment-intensive tasks.

> *When I know my peers in another branch are already getting good results with AI tools, I feel more confident asking for it here. It's like a stamp of approval.* ***[Peer Attitude, Manager 1]***

Endorsement from respected colleagues serves as social proof that lowers uncertainty and normalizes assisted AI use.

These insights – drawn from the same manager interviews in Study One – lead me to conduct the subsequent quantitative analysis, testing the relative influence of client readiness, regulation, and peer endorsement on auditors' willingness to adopt AI.

Table 12 shows the Spearman correlation results. All factors are associated with auditor acceptance at the 0.01 significance level, except the impact of the experience of joint audits is significant at the 0.1 level. The relationships between the dependent and other variables suggest that my selected factors influencing auditors' acceptance of AI are reasonable (Smeulders et al., 2023).

Table 12. Spearman correlation matrix

		1	2	3	4	5	6	7
1.	Acceptance level of AI-augmented joint audits							
2.	PU	0.319*** [3.703e-5]						
3.	PEOU	0.209*** [0.007]	0.104 [0.188]					
4.	Experience of joint audits	0.155* [0.050]	0.091 [0.250]	-0.050 [0.526]				
5.	Perceived headquarter's acceptance level	0.426*** [1.756e-8]	0.276*** [3.993e-4]	0.022 [0.784]	-0.018 [0.823]			
6.	Perceived client's acceptance level (average)	0.327*** [2.326e-5]	0.231*** [0.003]	0.064 [0.423]	-0.035 [0.662]	0.297*** [1.315e-4]		
7.	Perceived supportiveness of regulatory and policy environments	0.310*** [6.325e-5]	0.212*** [0.007]	0.127 [0.109]	0.129 [0.103]	0.230*** [0.003]	0.194** [0.013]	
8.	Perceived peer's acceptance level	0.279*** [3.380e-4]	0.253*** [0.001]	0.229*** [0.003]	0.112 [0.157]	0.294*** [1.526e-4]	0.151* [0.056]	0.584*** [4.187e-16]

This table presents the outcomes of examining the monotonic relationships between each pair of factors, utilizing two-tailed tests. The coefficients reported are based on Spearman's rank correlation. PU and PEOU represent auditors' perceived usefulness and perceived ease of use of AI-augmented joint audits. Observations=161. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively; *p*-value is reported in square brackets.

Table 13 displays the regression results. Model 1 shows that PU and PEOU significantly affected auditor acceptance ($p<0.01$), demonstrating that the utilization of TAM is appropriate (Davis, 1989). This result also suggests that in joint audits, PU and PEOU significantly impacted auditor acceptance of using augmented AI due to the unique demands of coordinating tasks and sharing information. Augmented AI's ability to enhance job performance (PU) by, notably automating data analysis and improving decision-making accuracy becomes even more critical in this context, where collaboration and communication efficiency are essential. Furthermore, PEOU ensures that auditors can quickly adapt to and integrate augmented AI tools into their workflows, overcoming potential barriers in joint audits. Such impact on productivity and collaboration in a joint setting fosters a positive attitude toward the adoption of augmented AI among auditors.

Table 13. Ordinal logistic regression analysis of auditor attitude

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
PU	0.897***	0.425*	0.334	0.326	0.354	0.230	0.229
	(0.239)	(0.258)	(0.263)	(0.261)	(0.263)	(0.266)	(0.268)
	[1.746e-4]	[0.099]	[0.203]	[0.211]	[0.178]	[0.385]	[0.392]
PEOU	0.526***	0.570***	0.571***	0.555***	0.537***	0.552***	0.551***
	(0.149)	(0.154)	(0.157)	(0.155)	(0.156)	(0.158)	(0.161)
	[0.412e-4]	[2.043e-4]	[2.878e-4]	[3.397e-4]	[5.700e-4]	[4.973e-4]	[6.134e-4]
Experience of joint audits		0.065**	0.071**	0.063**	0.061**	0.070**	0.069**
		(0.035)	(0.033)	(0.032)	(0.031)	(0.033)	(0.034)
		[0.035]	[0.029]	[0.045]	[0.047]	[0.037]	[0.038]
Perceived headquarter’s acceptance level		0.755***	0.634***	0.700***	0.695***	0.587***	0.586***
		(0.161)	(0.164)	(0.163)	(0.165)	(0.165)	(0.169)
		[2.904e-6]	[1.064e-4]	[1.736e-5]	[2.597e-5]	[3.798e-4]	[5.189e-4]
Perceived client’s acceptance level			0.687***			0.675***	0.675***
(average)			(0.193)			(0.194)	(0.194)
			[3.720e-4]			[4.891e-4]	[4.964e-4]
Perceived supportiveness of regulatory				0.402**		0.382**	0.380*
and policy environments				(0.163)		(0.165)	(0.196)
				[0.013]		[0.020]	[0.053]
Perceived peer’s acceptance level					0.202		0.005
					(0.148)		(0.179)
					[0.172]		[0.978]

Table 13. (*continued*)

Chi-square	25.672***	50.357***	63.183***	56.586***	52.133***	68.785***	68.786***
	[2.663e-6]	[3.040e-10]	[2.667e-12]	[6.154e-11]	[5.066e-10]	[7.254e-13]	[2.598e-12]
Observations	161	161	161	161	161	161	161

This table presents the regression findings on my primary focus: the impact of social factors on auditors' acceptance of AI-augmented joint audits, with the dependent variable being the levels of acceptance among auditors. PU and PEOU represent auditors' perceived usefulness and perceived ease of use of AI-augmented joint audits. Model 1 is the original TAM model. Model 2 introduces two covariates. Model 3 adds my first primary independent variable: clients' acceptance level of AI-augmented joint audits as perceived by auditors. Model 4 introduces the second independent variable: perceived supportiveness of regulatory and policy environments. Model 5 adds the third independent variable: perceived peers' acceptance level. Model 6 includes the two independent variables with significant influences on auditors' acceptance. Model 7 incorporates all three independent variables for comparison with the other models. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively; standard errors are in parentheses, and *p*-values are reported in square brackets.

Model 2 examined the relationships between covariates and auditor acceptance. The experience of joint audits ($p<0.05$) and perceived headquarter's acceptance level ($p<0.01$) positively and significantly influenced auditors' acceptance of AI-augmented joint audits. This outcome implies that the experience of joint audits and the acceptance level of headquarters can be essential for auditors' acceptance of AI-augmented joint audits because they can establish a foundation of trust and familiarity with collaborative and AI-enhanced auditing processes. Experienced auditors, potentially having witnessed the benefits of AI-enhanced collaboration, are more likely to appreciate augmented AI's efficiency, accuracy, and potential for improving audit quality. Furthermore, when headquarters demonstrate a high level of acceptance, it signals organizational support and commitment to innovation (Contreras et al., 2021), encouraging auditors to adopt and integrate AI-powered tools into their auditing practices confidently. Thus, I introduced these covariates into all subsequent models.

In model 3, I tested how auditors' perceived client acceptance level determines their acceptance of AI-augmented joint audits. The result implies that client attitude positively influenced auditor acceptance (p=3.720e-4, significant at the 0.01 level). I consider that higher client acceptance levels act as a significant social factor in auditors' increased openness to AI-augmented joint audits for two reasons. Primarily, when clients support technological advancements in audit processes, auditors feel a greater sense of assurance and legitimacy in adopting such innovations (Aghazadeh & Hoang, 2020). This acceptance signals to auditors that clients value efficiency, accuracy, and the potential for enhanced insights into their financial statements that augmented AI can provide, thereby aligning with clients' evolving expectations. Based on the understanding that clients are on board with AI-augmented methodologies, auditors are likely to anticipate a more effective collaboration during joint audits, reducing concerns over potential conflicts regarding the AI-involved joint audit findings. Secondly, client acceptance can reflect a broader industry trend towards digitization and AI-related technological integration, providing auditors with a convincing reason to align with these shifts to maintain relevance in their joint audit services. It serves as social proof, reinforcing the notion that AI-augmented joint audits are an accepted practice. This acceptance leads auditors to invest in acquiring the necessary skills and knowledge to utilize augmented AI in their work effectively. Thus, H1 was supported.

Model 4 shows the impact of auditors' perceived supportiveness of regulatory and policy environments. Supportiveness positively affected auditor acceptance at the 0.05 significance level (p=0.013). This result implies that higher supportiveness of regulatory and policy environments strengthens auditors' acceptance of using augmented AI in joint audits by creating frameworks that recognize the potential of such technologies to enhance audit quality and efficiency. These frameworks can provide clear guidelines on using augmented AI in joint audits, reducing resistance to technological adoption (Eulerich et al., 2022). Supportive regulations and policies foster an ecosystem where auditors feel more confident to adopt innovative auditing methods. When regulatory bodies demonstrate openness to technological advancements, they signal to auditors that incorporating augmented AI into their joint audit practices aligns with industry standards. Supportive policies potentially offer resources for training and development, making the transition to AI-augmented joint audits smoother for auditors. Such support can be particularly important in the auditing profession. Therefore, a supportive regulatory and policy environment plays a crucial social role in reducing barriers to the adoption of augmented AI. By providing auditors with the necessary confidence, guidelines, and incentives for AI-related innovations, this environment leads to a higher acceptance rate among auditors for AI-augmented joint audits. H2 was supported.

Model 5 tested the links between auditors' perceptions of peers' attitudes toward augmented AI and their acceptance of such innovation in joint audits. The result suggests that peers' attitudes did not significantly determine auditor acceptance ($p>0.1$). I consider there could be two reasons. First, auditors' perceptions of their own situations may play a more important role in shaping their attitudes toward augmented AI. Auditors' personal experience, proficiency with technology, and perception of AI's reliability and usefulness in enhancing audit quality significantly influence their acceptance. These individual assessments can diverge from the collective opinion of peers, making personal feeling a more decisive factor than peer influence. Second, each firm may have different technological abilities, strategic priorities toward innovation, and client bases. These factors can affect the firm's approach to adopting AI in audits, thereby influencing an auditor's acceptance based on the alignment of AI capabilities with the firm's goals and the practical benefits observed in their working environment. Consequently, peers' acceptance seemed less relative than other social factors. This result allowed me to reject H3.

In Model 6, I incorporated client acceptance and the supportiveness of regulatory and policy environments. The positive and significant effects of these two social factors on auditors' acceptance of AI-augmented joint audits provide additional support for our first two hypotheses. Model 7 included all factors, with the results reinforcing the relatively weak relevance of peer attitudes and highlighting the higher priority of client attitudes for auditors–this even outweighs the influence of regulatory and policy environments. This aligns with previous research emphasizing the importance of client attitudes in technology selection within auditing (Aghazadeh & Hoang, 2020). Overall, the significant effects of the two social factors continue to support our first two hypotheses. The combination of client acceptance and regulatory and policy support creates a positive environment that boosts auditors' confidence in adopting AI augmentation, resulting in higher acceptance rates.

Building on these foundations, I carried out two further tests. Initially, to explore the possibility that client acceptance's effects on auditors' openness to augmented AI might vary by industry, I looked into this relationship segmented by industry. The correlation analysis results for industry-specific client acceptance and auditors' attitudes, along with the inclusion of four covariates, are displayed in Table 14. It presents the monotonic relationships through Spearman correlation analysis. The findings highlight inter-industry differences. For example, in traditional sectors, including Industry 1 (*agriculture, forestry, animal husbandry, and fishery*), the acceptance by clients had no significant influence on auditor attitudes. The willingness of auditors to embrace augmented AI in joint audits might be more influenced by other factors including the regulatory and policy landscape, reflecting the complexities tied to adopting cutting-edge technologies in these industries.

In contrast, for sectors including Industries 10 (*finance*) and 11 (*real estate*), auditors' attitudes towards augmented AI were more heavily affected by clients. The subsequent regression analysis by industry, as shown in Table 15, provides extra evidence for the variances among sectors. Although these findings do not alter my overall conclusion that a generally positive client attitude towards augmented AI across various industries boosts auditors' receptiveness to it, they underscore the importance of my industry-specific analysis and suggest that the successful implementation of AI in audits must account for differences between industries.

Table 14. Spearman correlation analysis by industry

No	Industry	Auditor attitude	PU	PEOU	Experience of joint audits	Headquarter acceptance
1	Agriculture, forestry, animal husbandry, and fishery	0.040 [0.615]	0.128 [0.106]	0.004 [0.957]	-0.106 [0.183]	0.069 [0.388]
2	Mining	0.116 [0.142]	0.131* [0.098]	0.048 [0.545]	-0.096 [0.225]	0.136* [0.085]
3	Manufacturing	0.346*** [7.069e-6]	0.204*** [0.009]	0.021 [0.793]	0.073 [0.355]	0.263*** [7.393e-4]
4	Electricity, heat, gas, and water production and supply	0.363*** [2.243e-6]	0.163** [0.039]	0.028 [0.724]	0.090 [0.258]	0.262*** [7.827e-4]
5	Construction	0.163** [0.039]	0.087 [0.274]	0.053 [0.508]	-0.084 [0.290]	0.109 [0.169]
6	Transportation, warehousing, and postal services	0.331*** [1.846e-5]	0.174** [0.028]	0.114 [0.149]	-0.067 [0.401]	0.238*** [0.002]
7	Information transmission, software, and consulting technology services	0.329*** [2.071e-5]	0.165** [0.036]	-0.026 [0.743]	0.092 [0.244]	0.294*** [1.575e-4]
8	Wholesale and retail trade	0.306*** [8.072e-5]	0.211*** [0.007]	0.016 [0.840]	0.090 [0.256]	0.187** [0.018]
9	Accommodation and catering	0.241*** [0.002]	0.132* [0.094]	0.002 [0.984]	-0.112 [0.156]	0.269*** [5.701e-4]
10	Finance	0.390*** [3.252e-7]	0.255*** [0.001]	0.063 [0.426]	0.074 [0.350]	0.323*** [2.857e-5]
11	Real estate	0.245*** [0.002]	0.126 [0.113]	0.115 [0.146]	0.018 [0.818]	0.190** [0.016]

Table 14. (*continued*)

12	Rental and business services	0.289*** [1.958e-4]	0.153* [0.052]	0.032 [0.690]	0.042 [0.593]	0.253*** [0.001]
13	Scientific research and technical services	0.285*** [2.520e-4]	0.196** [0.013]	0.085 [0.282]	0.027 [0.730]	0.233*** [0.003]
14	Water conservancy, environment, and public facilities management	0.303*** [9.471e-5]	0.301*** [1.063e-4]	0.077 [0.334]	-0.020 [0.806]	0.269*** [5.505e-4]
15	Residential services, repairs, and other services	0.181** [0.022]	0.199** [0.012]	0.051 [0.519]	-0.085 [0.284]	0.181** [0.022]
16	Education	0.292*** [1.699e-4]	0.297*** [1.279e-4]	0.050 [0.529]	0.056 [0.479]	0.246*** [0.002]
17	Health and social work	0.147* [0.063]	0.207*** [0.008]	0.041 [0.607]	-0.026 [0.747]	0.169** [0.032]
18	Culture, sports, and entertainment	0.177** [0.024]	0.153* [0.052]	-0.011 [0.893]	-0.068 [0.392]	0.200** [0.011]
19	Public administration, social security, and social organizations	0.206*** [0.009]	0.164** [0.037]	0.019 [0.815]	-0.019 [0.812]	0.301*** [1.028e-4]
20	International organizations	0.259*** [9.094e-4]	0.252*** [0.001]	0.145* [0.066]	-0.085 [0.284]	0.264*** [7.155e-4]

This table displays the results from investigating the monotonic relationships between industry-specific client acceptance levels and various factors. These factors include auditors' acceptance of AI-augmented joint audits, PU, PEOU, auditors' joint audit experience, and auditors' perception of the acceptance level at the headquarters. PU and PEOU represent auditors' perceived usefulness and perceived ease of use of AI-augmented joint audits. The analysis utilized two-tailed tests, with the reported coefficients derived from Spearman's rank correlation. Survey participants were asked to rate their perceived attitude of clients from each industry, resulting in 161 observations for each industry. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively; *p*-value is reported in square brackets.

Table 15. Ordinal logistic regression analysis of the impact of client acceptance on auditor attitude by industry

No	Industry	Without covariates	Chi-square1	With covariates	Chi-square2
1	Agriculture, forestry, animal husbandry, and fishery	0.124 (0.111) [0.266]	1.210 [0.271]	0.074 (0.119) [0.535]	50.733*** [9.808e-10]
2	Mining	0.214** (0.105) [0.042]	4.180** [0.041]	0.173 (0.111) [0.119]	52.805*** [3.687e-10]
3	Manufacturing	0.605*** (0.132) [4.462e-6]	21.232*** [4.069e-6]	0.538*** (0.139) [1.075e-4]	65.521*** [8.738e-13]
4	Electricity, heat, gas, and water production and supply	0.621*** (0.135) [3.999e-6]	22.652*** [1.941e-6]	0.537*** (0.141) [5.043e-5]	67.871*** [2.840e-13]
5	Construction	0.254** (0.115) [0.027]	4.904** [0.027]	0.247** (0.121) [0.042]	54.531*** [1.630e-10]
6	Transportation, warehousing, and postal services	0.617*** (0.130) [1.957e-6]	22.033*** [2.680e-6]	0.474*** (0.134) [4.160e-4]	62.218*** [4.226e-12]
7	Information transmission, software, and consulting technology services	0.581*** (0.130) [7.307e-6]	19.741*** [8.868e-6]	0.438*** (0.136) [0.001]	60.326*** [1.040e-11]
8	Wholesale and retail trade	0.533*** (0.122) [1.319e-5]	18.990*** [1.313e-5]	0.416*** (0.128) [0.001]	61.110*** [7.166e-12]

Table 15. (*continued*)

9	Accommodation and catering	0.380*** (0.116) [0.001]	10.596*** [0.001]	0.266** (0.124) [0.033]	54.935*** [1.346e-10]
10	Finance	0.638*** (0.124) [2.891e-7]	26.371*** [2.817e-7]	0.500*** (0.132) [1.476e-4]	64.670*** [1.312e-12]
11	Real estate	0.439*** (0.127) [5.309e-4]	11.868*** [5.710e-4]	0.302** (0.132) [0.022]	55.314*** [1.125e-10]
12	Rental and business services	0.540*** (0.129) [2.964e-5]	16.830*** [4.087e-5]	0.355*** (0.135) [0.009]	56.814*** [5.523e-11]
13	Scientific research and technical services	0.414*** (0.111) [1.811e-4]	13.117*** [2.926e-4]	0.300*** (0.115) [0.009]	56.718*** [5.782e-11]
14	Water conservancy, environment, and public facilities management	0.584*** (0.130) [6.879e-6]	19.190*** [1.183e-5]	0.418*** (0.139) [0.003]	59.139*** [1.830e-11]
15	Residential services, repairs, and other services	0.279** (0.112) [0.012]	6.156** [0.013]	0.190 (0.118) [0.107]	52.944*** [3.453e-10]
16	Education	0.453*** (0.121) [1.752e-4]	14.168*** [1.671e-4]	0.319** (0.130) [0.014]	56.342*** [6.908e-11]
17	Health and social work	0.298** (0.123) [0.016]	5.475** [0.019]	0.152 (0.133) [0.254]	51.598*** [6.521e-10]

Table 15. (*continued*)

18	Culture, sports, and entertainment	0.340*** (0.122) [0.005]	7.255*** [0.007]	0.251* (0.131) [0.055]	53.872*** [2.226e-10]
19	Public administration, social security, and social organizations	0.443*** (0.132) [8.236e-4]	10.744*** [0.001]	0.226 (0.143) [0.115]	52.699*** [3.878e-10]
20	International organizations	0.517*** (0.128) [4.959e-5]	15.978*** [6.408e-5]	0.369*** (0.140) [0.008]	57.010*** [5.033e-11]

This table presents the regression findings on the effect of industry-specific client attitudes on auditors' acceptance of AI-augmented joint audits. The dependent variable in this analysis is the level of auditors' acceptance of AI-augmented joint audits, with covariates including PU, PEOU, auditors' experience with joint audits, and auditors' perceptions of acceptance levels at headquarters. PU and PEOU represent auditors' perceived usefulness and perceived ease of use of AI-augmented joint audits. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively; standard errors are in parentheses, and *p*-values are reported in square brackets. Participants evaluated clients' attitudes in each industry, each participant rated every industry, yielding 161 observations per industry.

Subsequently, I dug into the impact of peer acceptance on auditors' attitudes towards AI-augmented joint audits, examining this by branch. In line with my earlier investigations, I started with testing the correlations between various factors. Table 16 details the Spearman correlation analysis, respectively. These analyses suggest that in the Kunming and Chengdu branches, there was a notable association between the attitudes of peers and the auditors' acceptance of augmented AI, a connection that appeared less significant in the Wuhan and Zhengzhou branches. Further analysis presented in Table 17 through regression examines this relationship in depth. The findings illustrate that the influence of peers' acceptance of AI-augmented joint audits on auditors' attitudes towards such a technology exhibits variability across different branches. Specifically, in the Kunming branch, auditors were more evidently influenced by their peers, while in other branches, such influence was markedly lighter. These variations suggest that the impact of peer acceptance on auditors may differ among branches, potentially due to elements including distinctive organizational cultures within the accounting and auditing sectors (Robson & Ezzamel, 2023). It is important for the adoption of AI to take these differences into account. Although these findings validate the appropriateness of my branch-specific approach, they do not challenge my overall conclusion that peer attitudes do not significantly alter auditors' overall acceptance of augmented AI.

Table 16. Spearman correlation analysis by branch

Peer acceptance	Auditor attitude	PU	PEOU	Experience of joint audits	Headquarter acceptance
kunming	0.477*** [0.002]	0.200 [0.228]	0.290* [0.078]	0.044 [0.792]	0.316* [0.054]
Chengdu	0.263** [0.042]	0.336*** [0.009]	0.259** [0.046]	0.273** [0.035]	0.275** [0.034]
Wuhan	0.111 [0.515]	0.319* [0.054]	0.038 [0.824]	0.070 [0.681]	0.235 [0.161]
Zhengzhou	0.106 [0.607]	0.055 [0.789]	0.246 [0.226]	-0.162 [0.429]	0.373* [0.061]

This table presents the outcomes of exploring the monotonic relationships between levels of peer acceptance and several factors in each BTC branch. Factors encompass the auditors' acceptance of AI-augmented joint audits, PU, PEOU, experience in joint audits, and auditors' perceptions of acceptance levels at the headquarters. The study employed two-tailed tests, and the coefficients reported are based on Spearman's rank correlation analysis. PU and PEOU represent auditors' perceived usefulness and perceived ease of use of AI-augmented joint audits. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively; *p*-value is reported in square brackets. Observations: A=38, B=60, C=37, and D=26.

Table 17. Ordinal logistic regression analysis of the effect of peer acceptance on auditor attitude by branch

Branch	**Without covariates**	**Chi-square$_1$**	**With covariates**	**Chi-square$_2$**	**Observations**
Kunming	1.171^{***} (0.343) [6.337e-4]	13.348^{***} [2.586e-4]	1.238^{***} (0.409) [0.002]	18.305^{***} [0.003]	38
Chengdu	0.483^{**} (0.223) [0.030]	4.870^{**} [0.027]	-0.114 (0.269) [0.672]	30.411^{***} [1.223e-5]	60
Wuhan	0.160 (0.264) [0.543]	0.387 [0.534]	-0.242 (0.327) [0.460]	17.212^{***} [0.004]	37
Zhengzhou	0.318 (0.349) [0.362]	0.821 [0.365]	-0.104 (0.401) [0.796]	13.408^{**} [0.020]	26

This table displays the outcomes of a regression analysis examining the impact of peer attitudes toward augmented AI on auditors' willingness to embrace AI-augmented joint audits across each BTC branch. The analysis focuses on auditors' acceptance levels as the dependent variable and incorporates covariates PU, PEOU, auditors' prior experience with joint audits, and their perceptions of acceptance levels at the headquarters. PU and PEOU represent auditors' perceived usefulness and perceived ease of use of AI-augmented joint audits. *, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively; standard errors are in parentheses, and *p*-values are reported in square brackets.

5.4 Study Three Results

Grounded in the manager interviews from Study One, Study Three's qualitative findings reveal the psychological obstacles auditors face when considering AI adoption.

> *When AI starts dictating too many steps of the audit, I feel like I'm just following a script, not exercising my professional judgment.* ***[Perceived Loss of Autonomy, Manager 2]***

Auditors express concern that heavy AI guidance could undermine their sense of control and discretion over audit procedures, leading them to resist deeper integration despite potential efficiency gains.

> *A machine might flag odd transactions, sure, but can it understand the context behind a founder's unique business model? I doubt it****. [Distrust of Algorithmic Judgment, Manager 6]***

Auditors question AI's ability to interpret firm-specific nuances, preferring human judgment for complex assessments.

> *If an AI tool misses a material misstatement, who's to blame? The firm? The vendor? I'm not sure the responsibility lines are clear.* ***[Concerns Over Ethical Accountability, Manager 4]***

Ambiguity around liability for AI-driven decisions undermines trust and reinforces the need for strict human oversight.

> *Even when a client has great AI systems, I still feel hesitant. My own doubts about technology don't just vanish because they're ready.* ***[Limited Impact of Client Readiness, Manager 5]***

Although client infrastructure is viewed positively, it does not alleviate auditors' internal resistance – indicating the need for interventions targeting attitudes directly.

These findings from Study One's manager interviews informed the follow-up quantitative models in Study Three, where I assess how innovation resistance and algorithm aversion predict AI acceptance, and whether client readiness moderates those relationships.

In line with previous studies, I assessed the reliability and validity of my model. Initially, I evaluated Cronbach's alpha, composite reliability ρ_a, composite reliability ρ_c, and average variance extracted (AVE). These metrics are essential for assessing construct reliability as they evaluate the internal consistency and validity of a construct (Fornell & Larcker, 1981). For a construct to be considered highly reliable, Cronbach's alpha, ρ_a, and ρ_c should exceed 0.700, indicating robust internal consistency and reliable measurements. Additionally, AVE should be above 0.500, ensuring that the construct explains more than half of the variance of its indicators, thereby confirming convergent validity. The results presented in Table 18 indicate that my measurements meet these requirements.

Table 18. Construct reliability and validity

	Cronbach's alpha	Composite reliability (ρ_a)	Composite reliability (ρ_c)	AVE
Algorithm aversion	0.749	0.747	0.857	0.666
Usage barrier	0.900	0.910	0.937	0.832
Value barrier	0.727	0.832	0.875	0.778
Risk barrier	0.832	0.876	0.921	0.854
Tradition barrier	0.836	0.854	0.889	0.667
Image barrier	0.746	0.761	0.887	0.796
Motivator	0.714	0.716	0.823	0.538
Inhibitor	0.861	0.861	0.935	0.878

This table presents the Cronbach's alpha, Composite reliability (ρ_a), Composite reliability (ρ_c), and Average Variance Extracted (AVE), which are essential metrics for assessing the reliability and validity of constructs in Partial Least Squares Structural Equation Modeling (PLS-SEM). Cronbach's alpha measures internal consistency, indicating how well a set of items measures a single latent construct. Composite reliability (ρ_a) is an alternative to Cronbach's alpha, providing a more accurate estimate by considering the loadings of the items. Composite reliability (ρ_c) further refines this by taking into account the actual model structure and weights of the indicators, ensuring a more precise reliability estimation. AVE assesses convergent validity, indicating the average variance explained by the items of a construct.

I then applied the Fornell-Larcker criterion (Fornell & Larcker, 1981) to assess the validity of my model. This criterion is crucial in PLS-SEM as it assesses the discriminant validity, which ensures that constructs in a model are distinct and measure different concepts. According to this criterion, the square root of the AVE of each construct should be higher than the highest correlation between that construct and any other construct in the model. This comparison is important because if a construct shares more variance with its indicators (as indicated by a high AVE) than with other constructs (indicated by lower inter-construct correlations), it confirms that the construct is unique and not excessively similar to others. This distinctiveness is critical for the validity of the model, as it ensures that the constructs represent separate and identifiable variables, thereby providing reliable and interpretable outcomes in the structural analysis. As shown in Table 19, my model meets this criterion.

Table 19. Fornell-Larcker criterion

	1	2	3	4	5	6	7	8
1. Algorithm aversion	**0.816**							
2. Usage barrier	0.202	**0.912**						
3. Value barrier	0.422	0.244	**0.882**					
4. Risk barrier	0.344	0.116	0.256	**0.924**				
5. Tradition barrier	0.445	0.034	0.295	0.566	**0.817**			
6. Image barrier	0.384	0.050	0.307	0.138	0.192	**0.892**		
7. Motivator	0.497	0.052	0.420	0.590	0.566	0.307	**0.734**	
8. Inhibitor	0.326	0.039	0.257	0.154	0.189	0.637	0.325	**0.937**

This table presents the Fornell-Larcker criterion, a method utilized in Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate the discriminant validity of constructs. The criterion involves comparing the square root of the average variance extracted (AVE) for each construct with the correlations between constructs. The values in bold indicate the square roots of the AVEs, while the other values represent the inter-construct correlations.

I also assessed the cross-loadings of items to ensure the discriminant validity on the item level (Bedford, Speklé, & Widener, 2022.). This level of discriminant validity measures how distinct a construct is from other constructs. In PLS-SEM, each item should load highly on its intended latent construct and minimally on others. High cross-loadings indicate significant overlap with other constructs, compromising the model's validity. The standard for cross-loadings typically requires each item's loading on its associated construct to be substantially higher than its loadings on other constructs. My analysis, as illustrated in Table 20, confirmed that my constructs have discriminant validity relative to each other.

Table 20. Item cross-loadings

	AA	UB	VB	RB	TB	IB	Mot	Inh
AA1	**0.771**	0.151	0.305	0.335	0.361	0.281	0.508	0.217
AA2	**0.842**	0.114	0.354	0.256	0.362	0.337	0.380	0.311
AA3	**0.834**	0.230	0.375	0.244	0.364	0.321	0.318	0.271
UB1	0.165	**0.914**	0.210	0.168	0.050	-0.005	0.079	-0.001
UB2	0.177	**0.920**	0.216	0.048	-0.008	0.088	0.044	0.033
UB3	0.206	**0.903**	0.237	0.106	0.050	0.050	0.024	0.067
VB1	0.279	0.153	**0.827**	0.183	0.224	0.296	0.301	0.246
VB3	0.439	0.259	**0.934**	0.257	0.288	0.260	0.422	0.218
RB1	0.355	0.107	0.270	**0.945**	0.483	0.136	0.550	0.146
RB2	0.271	0.108	0.194	**0.903**	0.579	0.117	0.543	0.138
TB1	0.389	0.017	0.221	0.507	**0.828**	0.129	0.453	0.041
TB2	0.432	0.080	0.301	0.404	**0.839**	0.173	0.434	0.195
TB3	0.277	-0.027	0.184	0.598	**0.791**	0.156	0.559	0.197
TB4	0.319	0.019	0.237	0.375	**0.807**	0.170	0.434	0.203
IB3	0.311	0.034	0.295	0.095	0.122	**0.873**	0.228	0.533
IB4	0.369	0.054	0.257	0.147	0.213	**0.911**	0.314	0.600
Mot1	0.353	0.101	0.215	0.610	0.513	0.203	**0.756**	0.213
Mot2	0.344	-0.015	0.374	0.274	0.267	0.200	**0.702**	0.155
Mot3	0.343	0.072	0.196	0.615	0.603	0.228	**0.742**	0.230
Mot4	0.408	0.000	0.428	0.260	0.297	0.263	**0.734**	0.338
Inh2	0.302	0.036	0.191	0.190	0.117	0.572	0.320	**0.935**
Inh4	0.308	0.037	0.289	0.100	0.236	0.621	0.289	**0.938**

This table displays the cross-loadings of items. Bold values represent the loadings of items on their intended latent constructs, while the remaining values indicate loadings on other constructs. AA1, AA2, and AA3 stand for the acceptance of AI-related innovations in the accounting industry, satisfaction with AI adoption within firms, and opinions about AI capabilities. UB1, UB2, and UB3 represent perceptions of the skills required by AI applications, the integration of AI into other auditing technologies, and the flexibility of AI adoption. VB1 and VB3 stand for opinions about the investment potential of AI and the enhancement of AI in audit services for clients. RB1 and RB2 represent risk perceptions of AI potentially violating auditing standards and uncertainties about AI's abilities. TB1, TB2, TB3, and TB4 relate to the perception of acceptance of changes brought by AI, the impacts of AI on audit routines, satisfaction with traditional audit methods, and trust in AI-generated audit decisions. IB3 and IB4 address feelings about policy support and auditing market demand for AI-related innovation. Mot1, Mot2, Mot3, and Mot4 stand for clients' expertise in using new technologies, acceptance of new audit technologies, trust in the benefits of using new audit technologies, and feelings about audit consistency when using new technologies. Inh2 and Inh4 evaluate clients' reluctance to use new audit technologies and concerns about compliance security when introducing new technologies.

In addition, I used the Heterotrait-monotrait Ratio (HTMT: Henseler, Ringle, & Sarstedt, 2015) to address the limitations of the Fornell-Larcker criterion and cross-loadings. HTMT offers a more reliable and stringent measure of discriminant validity. HTMT values should be less than 0.850, as this threshold indicates that constructs are sufficiently distinct from each other. Higher values suggest potential overlap between constructs, implying they may not represent different concepts effectively, leading to biased results and erroneous conclusions. My examination results, displayed in Table 21, indicate that my model is valid.

Table 21. Heterotrait-monotrait ratio (HTMT) matrix

	1	2	3	4	5	6	7
1. Algorithm aversion							
2. Usage barrier	0.244						
3. Value barrier	0.550	0.285					
4. Risk barrier	0.425	0.136	0.314				
5. Tradition barrier	0.546	0.067	0.361	0.699			
6. Image barrier	0.510	0.064	0.429	0.171	0.238		
7. Motivator	0.670	0.103	0.556	0.777	0.751	0.412	
8. Inhibitor	0.407	0.055	0.330	0.183	0.228	0.791	0.407

This table shows the Heterotrait-Monotrait Ratio (HTMT) matrix, a measure used in Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess discriminant validity between constructs. It evaluates the degree to which constructs are distinct by comparing the average correlations of indicators across different constructs (heterotrait) with those within the same construct (monotrait).

Given the reliability and validity of the model, I proceeded with path analysis to examine my proposed links. I first analysed the relationships between auditors' innovation resistance and their aversion to AI algorithms. As shown in Table 22, auditors' AI-related education level is positively related to their algorithm aversion at the 0.01 significance level (p=0.007). Regarding auditors' perceived barriers, psychological barriers, including tradition (p=0.000) and image (p=0.001) barriers, positively and significantly influence their aversion to algorithms at the 0.01 level. Additionally, auditors' perception of higher value barriers significantly increases their aversion at the 0.05 level (p=0.018).

Table 22 Path analysis

Path	Path Coefficient	SE	*P*
Age → Algorithm aversion	-0.025	0.092	0.395
Gender → Algorithm aversion	0.044	0.127	0.363
AI-related education level → Algorithm aversion	0.175	0.07	0.007**
Tenure → Algorithm aversion	0.109	0.118	0.177
Working position → Algorithm aversion	0.229	0.23	0.159
Usage barrier → Algorithm aversion	0.106	0.069	0.063
Value barrier → Algorithm aversion	0.140	0.067	0.018*
Risk barrier → Algorithm aversion	0.067	0.082	0.206
Tradition barrier → Algorithm aversion	0.306	0.08	0.000**
Image barrier → Algorithm aversion	0.219	0.068	0.001**

This table displays the path analysis results exploring the relationship between auditors' resistance to innovation (considering perceived usage, value, risk, tradition, and image barriers) and their aversion to AI algorithms. The model incorporated auditors' ages, genders, levels of AI-related education, tenure, and working positions as covariates. The results are reported as standardized path coefficients, standard errors (SEs), and *P*-values. * and ** indicate statistical significance at the 5 and 1% levels.

Building on this, I incorporated clients' technology readiness levels into the model to examine their impact on the relationships between auditors' innovation resistance and their aversion to algorithms. The path analysis of these moderating effects is shown in Table 23. Auditors' AI-education levels (p=0.002) and perceived tradition barriers (p=0.005) show positive impacts on their aversion at the 0.01 significance level. Their perception of usage (p=0.031) and image (p=0.038) barriers significantly increases their aversion at the 0.05 significance level. However, the impacts of the motivations and inhibitors of clients' technology readiness appear less pronounced.

Table 23 Path analysis considering clients' impacts

Path	Path Coefficient	SE	*P*
Age → Algorithm aversion	-0.028	0.107	0.395
Gender → Algorithm aversion	0.032	0.136	0.407
AI-related education level → Algorithm aversion	0.218	0.074	0.002**
Tenure → Algorithm aversion	0.079	0.130	0.273
Working position → Algorithm aversion	0.309	0.235	0.094
Usage barrier → Algorithm aversion	0.148	0.079	0.031*
Value barrier → Algorithm aversion	0.087	0.079	0.137
Risk barrier → Algorithm aversion	-0.040	0.098	0.342
Tradition barrier → Algorithm aversion	0.253	0.097	0.005**
Image barrier → Algorithm aversion	0.177	0.099	0.038*
Motivators → Algorithm aversion	0.269	0.092	0.002**
Motivators × Usage barrier → Algorithm aversion	0.005	0.066	0.473
Motivators × Value barrier → Algorithm aversion	-0.036	0.086	0.337
Motivators × Risk barrier → Algorithm aversion	0.054	0.094	0.283
Motivators × Tradition barrier → Algorithm aversion	-0.127	0.095	0.090
Motivators × Image barrier → Algorithm aversion	-0.038	0.092	0.339
Inhibitors → Algorithm aversion	0.027	0.102	0.396
Inhibitors × Usage barrier → Algorithm aversion	0.113	0.079	0.077
Inhibitors × Value barrier → Algorithm aversion	0.056	0.083	0.251
Inhibitors × Risk barrier → Algorithm aversion	0.015	0.101	0.439
Inhibitors × Tradition barrier → Algorithm aversion	0.113	0.121	0.174
Inhibitors × Image barrier → Algorithm aversion	-0.048	0.072	0.252

This table presents the path analysis results investigating the relationship between auditors' resistance to innovation (including perceived usage, value, risk, tradition, and image barriers) and their aversion to AI algorithms. The analysis also considers auditors' perceptions of clients' technology readiness–specifically, motivators (innovativeness and optimism) and inhibitors (discomfort and insecurity)–as moderators in the relationship between auditors' innovation resistance and their aversion to algorithms. Additionally, the model includes auditors' ages, genders, levels of AI-related education, tenure, and working positions as covariates. The results are reported as standardized path coefficients, standard errors (SEs), and *P*-values. * and ** indicate statistical significance at the 5 and 1% levels.

Therefore, my hypotheses *H4* and *H5* were supported, while the others were rejected. These results highlight three key points. First, auditors with higher levels of AI-related education exhibit greater algorithm aversion. This group of auditors possesses a deeper understanding of the limitations and potential risks associated with AI algorithms, making them more aware of issues including data bias, model interpretability, and the consequences of algorithmic errors (Dietvorst et al., 2015). Their advanced knowledge leads to skepticism about the reliability and fairness of AI systems, particularly in complex and high-stakes environments like auditing, where accuracy and ethical considerations are paramount. Additionally, their education exposes them to the details of AI development, including how algorithms are trained, validated, and potentially manipulated, fostering a critical perspective. As a result, these auditors might prefer human judgment over algorithmic solutions, believing that human expertise and intuition can better navigate the complex and context-specific challenges of auditing. Namely, auditors' understanding of AI technologies results in a more cautious and critical stance towards the adoption of these tools in their professional practices.

Second, auditors' aversion to AI algorithms is significantly influenced by their perceptions of psychological barriers, including tradition and image concerns, whereas perceived functional barriers (including usage, value, and risk) are less influential. I consider that tradition in auditing means a long-standing reliance on human judgment, expertise, and established practices that have been developed over decades (Dierynck et al., 2023). This reliance makes auditors hesitant to embrace AI, which represents a significant shift away from these trusted methodologies. Moreover, the image concerns stem from the perceived necessity to maintain a reputation for thoroughness, reliability, and professional skepticism. Auditors fear that reliance on AI could be seen as a diminishment of their expertise, potentially leading to doubts about their professional judgment and the rigor of their audits. This apprehension is strengthened by the notion that AI, being relatively new and less understood, may not yet be perceived as fully trustworthy or capable of replicating the comprehensive understanding that human auditors bring to their evaluations.

Conversely, perceived functional barriers including usage, value, and risk have less impact on auditors' aversion to AI. These functional concerns are often seen as logistical challenges that can be addressed through training, development, and technological advancements. For example, issues related to the usage of AI can be mitigated with proper education and user-friendly interfaces, while concerns about the value and accuracy of AI can be alleviated through continuous improvements and proven success stories (Glikson & Woolley, 2020; Munoko et al., 2020). Similarly, risks associated with AI, including data breaches or algorithmic errors, are considered manageable with robust safeguards and regulatory compliance measures. Since these functional barriers are viewed as tangible and solvable, they do not lead to the same level of deep resistance as psychological barriers rooted in tradition and professional image.

Third, auditors' perception of their clients' technology readiness levels does not significantly moderate the relationship between their innovation resistance and algorithm aversion. I consider that innovation resistance and algorithm aversion are deeply rooted in individual attitudes and cognitive biases that can be resistant to external influences (cf. Commerford et al., 2022). Internal factors overshadow clients' perceived readiness, meaning that even if auditors believe their clients are technologically advanced and ready to adopt new systems, this does not necessarily alleviate their personal resistance to these innovations. The introduction of algorithms and advanced technologies represents a shift towards reliance on novel processes, which can be perceived as less transparent and more prone to errors that are difficult to trace or understand. This can lead to a heightened sense of unease and resistance among auditors, independent of their clients' technology readiness. Essentially, auditors may fear that reliance on algorithms could compromise the quality and integrity of their work, leading to a persistent aversion despite external assurances of technological capability from clients.

Furthermore, auditors' assessment of their clients' technology readiness typically focuses on the clients' ability to implement and effectively utilize technology. However, this focus does not directly address auditors' concerns about the applicability, reliability, and ethical implications of using algorithms in their own work (Munoko et al., 2020). The readiness of clients to adopt technology does not alleviate auditors' worries about issues including data privacy, algorithmic biases, and the potential for reduced human oversight in the auditing process. These concerns are inherent to the auditors' role and are not easily influenced by external perceptions of readiness. The auditing profession operates within a regulatory and compliance framework that can be slow to adapt to technological advancements. Auditors will remain cautious about adopting new technologies until they are fully endorsed and standardized within the industry. Even if clients are ready and eager to embrace new technologies, auditors might resist due to a lack of clear guidelines, standards, and regulatory support for the use of algorithms in auditing practices. These results lead to my discussion and conclusions.

5.5 Chapter Conclusion

The results from these three studies collectively highlight the complex dynamics of AI adoption in audits, emphasizing the critical roles of client-side factors, internal firm dynamics, and individual auditor perceptions. Study One reveals that while qualitative findings underscore the foundational role of client-side technological collaboration, the quantitative regression results provide more robust evidence on the predictors of AI acceptance among auditors in external audits. The regression analysis shows that perceived usefulness of AI is the strongest predictor of acceptance, significantly outweighing the influence of demographic factors including age, gender, and tenure. This finding suggests that auditors prioritize the practical benefits of AI in enhancing their audit tasks. Moreover, client-related factors, particularly technological capability and willingness to adopt AI, are critical determinants of auditors' acceptance, highlighting that auditors are more inclined to embrace AI when their clients are technologically prepared and supportive of AI integration. In contrast, perceived risks, including budgetary and technological concerns, do not significantly deter auditors' acceptance, suggesting a balanced view where perceived benefits can outweigh concerns.

Study Two extends the investigation into joint audits, identifying key factors that influence auditors' acceptance of AI-augmented practices. The study finds that perceived usefulness and ease of use of AI are crucial determinants, along with the supportive attitudes of clients, regulatory bodies, and headquarters. These findings underscore the importance of a supportive organizational environment for fostering AI adoption. The study also emphasizes that client acceptance and technological readiness are particularly influential in joint audit settings, where effective collaboration and communication are essential.

Study Three examines the psychological barriers that impact auditors’ resistance to AI, providing a nuanced understanding of the interplay between individual attitudes and external factors. The study reveals that auditors with higher AI-related education levels are more resistant to AI algorithms, primarily due to their awareness of AI's limitations and risks. Psychological barriers, including concerns about tradition and professional image, further amplify this resistance, suggesting that auditors' aversion to AI is influenced by deeper professional and personal values. The study also explores the moderating effects of clients’ technological readiness, finding that while external readiness plays a role, internal factors including auditors' own cognitive biases and attitudes are often more influential in shaping their acceptance of AI.

Collectively, these studies suggest that successful AI adoption in audits requires a comprehensive approach that integrates client-side collaboration, supportive environments, and consideration of auditors' psychological readiness. By balancing technological advancements with robust human oversight, the adoption process can enhance audit quality and efficiency while maintaining the professional judgment and integrity of auditors. These findings provide valuable insights for accounting firms, auditors, and regulators as they navigate the evolving landscape of AI in audits, highlighting the importance of addressing both technological and human elements in the integration of AI.

CHAPTER SIX: DISCUSSON

6.1 Chapter Introduction

This chapter synthesizes the study's empirical, theoretical, and practical contributions, acknowledges its limitations, and proposes avenues for future research on AI adoption in auditing. Empirically, it draws on interviews and survey data from external, joint, and internal audit contexts to identify core barriers – operational disruptions, skepticism about AI's handling of complex judgments, and fears of undue reliance on automation without human oversight – and highlights the pivotal role of clear regulatory guidance, particularly in joint audits. Across all settings, auditors favour assisted AI systems that augment rather than supplant professional judgment.

Theoretically, the research refines the Technology Acceptance Model by embedding audit-specific constructs and social influences – peer attitudes, client expectations, and regulatory norms – to deepen understanding of adoption decisions in varied audit environments. It also integrates Innovation Resistance and Technology Readiness frameworks, revealing how auditors' algorithm aversion interacts with clients' readiness to deploy AI platforms, and thus shapes adoption pathways.

On the practical front, the study underscores the necessity of human-centric AI strategies: solutions must prioritize transparency, explainability, and seamless collaboration between auditors and algorithms. It calls for robust, industry-tailored regulatory frameworks and targeted training programmes to address both technical and psychological obstacles, fostering confidence in AI-supported audit processes.

Despite its contributions, this research has limitations, including reliance on self-reported proxies for client attitudes and the inherent simplification of certain survey measures. Future studies should examine richer social network dynamics, trace the evolution of algorithm aversion longitudinally, and compare adoption patterns across internal and external audit functions.

Throughout the findings, two themes recur: the inescapable need for human oversight and the enabling power of regulatory clarity. Yet divergence emerges by context – external audits emphasize risk aversion and individual judgment, joint audits highlight inter-firm coordination and collaborative accountability, and general audit settings surface diverse psychological and operational challenges. As a result, theoretical implications shift from cognitive acceptance models toward socio-institutional frameworks, and practical recommendations span from targeted training initiatives to comprehensive governance frameworks and collaborative AI ecosystems. These contextual variations affirm that effective AI integration in auditing demands models and interventions calibrated to each domain's unique challenges.

6.2 Empirical Contributions

My findings contribute to the literature on AI adoption in auditing by identifying the factors influencing auditors' acceptance of AI across different auditing contexts.

6.2.1 From the standpoint of specific audit contexts

Obstacles to AI adoption in external audits: While the literature acknowledges the potential benefits of AI in enhancing audit quality (Costello et al., 2020), this study provides an in-depth examination of the specific obstacles that auditors face when considering AI adoption in the context of external audits. External audits, which involve evaluating the financial statements of client firms to ensure accuracy and compliance, are particularly sensitive to risks associated with AI integration, including inherent, control, and detection risks. The study identifies several key barriers that auditors encounter, notably concerns about AI's capability to accurately assess complex risk scenarios, the reliability of AI-generated insights, and the operational challenges of integrating AI systems into existing audit workflows.

One significant finding is that auditors are wary of the operational disruptions that AI implementation might cause, particularly the need for extensive retraining of staff and the potential for increased complexity in audit processes. These concerns are compounded by the perception that AI systems, while capable of processing large volumes of data quickly, may not yet possess the nuanced understanding required to make complex audit judgments that involve interpreting qualitative information, notably client behaviour or industry-specific factors. This skepticism is particularly pronounced among auditors who have experienced the limitations of existing AI tools, which may not fully account for the intricacies of financial reporting and regulatory compliance in external audits.

Another critical obstacle identified in the study is the perceived risk associated with over-reliance on AI, especially in areas where human oversight is deemed essential. Auditors express concerns that an overdependence on AI could lead to complacency or a reduction in the thoroughness of audit procedures, potentially increasing the risk of undetected errors or misstatements. This is particularly relevant in the context of detection risk, where the accuracy and comprehensiveness of audit findings are paramount. The study suggests that while AI has the potential to enhance detection capabilities through advanced data analytics and anomaly detection, auditors remain cautious about fully delegating this responsibility to AI systems without adequate human oversight.

The study's contribution lies in its detailed exploration of these barriers, providing a clearer understanding of the specific challenges that hinder AI adoption in external audits. By highlighting these obstacles, the research offers a valuable perspective for auditing firms and AI developers, emphasizing the need to address these concerns through targeted strategies notably enhanced training programmes, improved AI transparency, and the development of AI systems that are specifically designed to complement rather than replace human expertise in external audits. This approach can help mitigate the perceived risks and operational challenges associated with AI adoption, ultimately fostering greater confidence and acceptance among auditors.

<u>The impact of regulatory and policy environments on AI use in joint audits:</u> Expanding on the literature that emphasizes the importance of regulatory frameworks in AI adoption (Eulerich et al., 2022), this study investigates how social factors, particularly different regulatory and policy environments influence the use of AI in joint audits. Joint audits, which involve multiple firms working together to provide assurance on an entity's financial statements, present unique challenges related to communication, coordination, and the division of responsibilities (Guo et al., 2017; Hoos et al., 2019). The study finds that auditors are more likely to adopt AI technologies in joint audits when there is clear regulatory guidance that addresses the ethical and operational use of AI, thereby reducing uncertainties and enhancing the perceived legitimacy of AI applications.

The research reveals that auditors feel more confident in integrating AI into their joint audit processes in supportive regulatory environments. These regulations provide auditors with the necessary framework to navigate the ethical considerations and compliance requirements associated with AI, ensuring that AI technologies are used responsibly and effectively. This is particularly important in joint audits, where differing regulatory interpretations among participating firms can lead to inconsistencies in AI application and audit outcomes. Clear regulatory guidance helps harmonize the use of AI across different firms, fostering a more collaborative and cohesive audit process.

Conversely, when regulatory guidance on AI in auditing is lacking or ambiguous, auditors exhibit greater reluctance to adopt AI technologies in joint audits. The absence of clear rules can lead to uncertainty about the appropriate use of AI, particularly regarding issues of accountability and data privacy. Auditors in these environments may fear that the integration of AI could expose them to legal or reputational risks if the AI systems do not comply with local standards or if their outputs are challenged by stakeholders. This reluctance is further compounded by the complexity of coordinating AI use among multiple firms with potentially different risk appetites and compliance approaches.

The study's contribution lies in its empirical exploration of how regulatory and policy environments shape AI adoption in joint audits, highlighting the critical role of regulatory clarity and support in facilitating AI integration. By providing evidence on the positive impact of well-defined regulatory frameworks, the research underscores the importance of regulatory bodies in setting clear guidelines and standards for AI use in auditing. These findings suggest that policymakers should prioritize the development of robust and adaptable regulations that address the specific needs of joint audits, including guidelines on AI accountability, transparency, and data security. Such regulatory support can help reduce barriers to AI adoption in joint audits, fostering greater innovation and enhancing audit quality through the responsible use of AI technologies.

6.2.2 From the perspective of general audit contexts

Empirical identification of AI system preferences in auditing: The study expands on the existing literature by empirically examining auditors' preferences for different modes of AI integration–assisted, augmented, and autonomous–within the auditing field. While prior research has identified the theoretical potential of these AI modes in enhancing audit quality (Munoko et al., 2020), this study provides concrete evidence showing that audit managers, particularly those from non-Big Four firms, prefer assisted AI applications in specific audit contexts, such as external audits. Assisted AI systems are designed to support auditors by automating routine tasks, such as data collection and preliminary analysis, thereby allowing auditors to focus on more complex judgmental tasks. This preference is driven by a combination of factors, including concerns about the reliability of fully autonomous AI systems, the perceived loss of human control, and the importance of maintaining professional judgment, especially in complex audits where the stakes are high.

The findings reveal that while augmented and autonomous AI systems have the potential to significantly enhance audit efficiency and accuracy, auditors are hesitant to fully embrace these technologies due to worries about accountability and transparency. In augmented AI, where human auditors and AI systems share decision-making responsibilities, auditors are concerned about the potential blurring of accountability lines, which could complicate the audit process and undermine trust in the final outcomes. Meanwhile, fully autonomous AI systems, which are capable of conducting entire audit processes independently, raise concerns about the accuracy of AI-generated decisions and the ability to effectively monitor and control these systems. Auditors are particularly cautious about using autonomous AI in contexts that require a high level of professional judgment, notably in the evaluation of complex financial statements.

This study's contribution lies in its detailed exploration of auditors' preferences across these AI modes, highlighting a significant gap between the potential capabilities of AI technologies and their practical acceptance in current auditing practices. By empirically identifying the preference for assisted AI, the study underscores the importance of developing AI systems that enhance rather than replace human judgment, aligning with the professional values and expectations of auditors. This nuanced understanding of AI mode preferences provides valuable insights for AI developers and auditing firms, suggesting that a gradual and collaborative approach to AI adoption–starting with assisted systems–may be the most effective strategy for gaining auditor acceptance. Furthermore, the study emphasizes the need for ongoing engagement with auditors throughout the AI development process to ensure that new technologies align with their professional needs and concerns, ultimately fostering greater trust and facilitating wider adoption of AI in auditing.

Client influence on AI adoption decisions in auditing: Building on the literature that emphasizes the client-oriented nature of audits (Dezoort et al., 2001), this study provides empirical insights into how client expectations and technological readiness influence auditors' decisions to adopt AI technologies. The findings indicate that auditors are significantly more inclined to integrate AI into their audit processes when their clients are receptive to AI-enabled services, even if there are some concerns about the associated risks. This aligns with the literature's assertion that client preferences play a pivotal role in shaping audit approaches, as auditors seek to meet client expectations while maintaining high standards of audit quality.

The study highlights that client influence extends beyond mere technological readiness; it also encompasses clients' trust in and comfort with AI technologies. For instance, clients who are familiar with AI and its applications in other business contexts are more receptive to AI-enabled audit services, viewing them as a means to enhance efficiency and accuracy. Conversely, clients who are skeptical of AI or lack understanding of its benefits may resist AI integration, prompting auditors to adopt a more conservative approach to AI use. This client-driven dynamic suggests that the successful adoption of AI in auditing is not solely a matter of technological capability but also hinges on the broader acceptance and support from clients.

Moreover, the study finds that clients' preferences can directly impact the scope and extent of AI integration in audits. For example, clients who prioritize rapid results and cost efficiencies are more likely to encourage the use of AI technologies that can streamline audit processes and reduce manual workloads. On the other hand, clients who value the assurance provided by human judgment may prefer audits that retain a higher degree of human involvement, even if that means foregoing some of the efficiencies offered by AI. This variation in client preferences underscores the importance of auditors being flexible and responsive to client needs, tailoring their AI adoption strategies to align with the specific expectations of each client.

This contribution provides valuable empirical evidence on the critical role of client influence in AI adoption decisions within the auditing profession. It underscores the need for auditing firms to actively engage with clients to educate them about the potential benefits and limitations of AI, thereby building trust and fostering a more supportive environment for AI-enabled audits. Additionally, the findings suggest that auditors should consider client preferences as a key factor in their AI adoption strategies, ensuring that the integration of AI technologies aligns with client expectations and contributes to enhancing overall audit quality. By prioritizing client engagement and addressing client concerns, auditors can facilitate a smoother transition to AI-enabled auditing practices, ultimately benefiting both auditors and their clients.

The role of psychological barriers in AI adoption in auditing: The study addresses the gap in the literature regarding the psychological barriers to AI adoption in auditing, specifically focusing on algorithm aversion (Liu et al., 2023). Algorithm aversion is a phenomenon where individuals, including auditors, are reluctant to trust or rely on AI systems, even when those systems have demonstrated superior performance in certain tasks. This reluctance is particularly prevalent in auditing, where professional judgment, accountability, and the ability to explain and justify decisions are critical components of the audit process.

The research identifies that auditors' algorithm aversion is largely driven by concerns over the transparency and explainability of AI systems. Auditors express discomfort with the "black box" nature of many AI algorithms, which makes it difficult to understand how the AI arrived at specific conclusions or recommendations. This lack of transparency undermines auditors' confidence in AI outputs, as they fear that they may not be able to adequately explain or defend AI-generated decisions to clients or regulatory bodies. The study finds that this concern is particularly pronounced in high-stakes auditing contexts, such as external audits of large or complex entities, where the implications of errors are significant.

Another key psychological barrier identified is the fear of losing control over the audit process. Auditors are trained to rely on their professional judgment and expertise, and the introduction of AI can be perceived as a threat to their role and authority. This fear is compounded by the perception that AI systems, while powerful, may not fully grasp the nuances of specific audit situations, notably industry-specific risks or client-specific considerations. As a result, auditors may resist adopting AI technologies, preferring to rely on traditional methods that they perceive as more controllable and reliable.

The study contributes to the literature by providing empirical evidence on the prevalence and impact of these psychological barriers, highlighting the need for human-centric AI designs that prioritize transparency, explainability, and user control. By addressing these concerns, AI developers can create systems that are better aligned with auditors' needs and preferences, fostering greater acceptance and trust in AI technologies. The findings also suggest that targeted education and training programmes that enhance auditors' understanding of AI, including how AI systems work and how they can complement rather than replace human judgment, are essential for overcoming algorithm aversion. This contribution offers valuable insights for both practitioners and AI developers, emphasizing the importance of considering psychological factors in the design and implementation of AI systems in auditing.

Cross-cultural insights from AI adoption in Chinese accounting firms: Reflecting the literature's global perspective on AI in auditing (Lennox and Wu, 2022), this study examines AI adoption in Chinese accounting firms to provide insights into how cultural and regulatory contexts influence AI integration. China's rapid technological advancements and strong governmental support for AI create a unique environment for AI adoption, offering a valuable case study for understanding the interplay between local contexts and AI implementation in auditing.

The study finds that Chinese accounting firms are enthusiastic adopters of AI, driven by a national emphasis on technological innovation and digital transformation. This aligns with broader global trends that recognize AI's potential to enhance audit quality, efficiency, and decision-making capabilities (Costello et al., 2020). However, the research also identifies unique challenges faced by Chinese firms, including concerns related to data privacy, ethical considerations, and the alignment of AI use with international auditing standards. These challenges reflect the specific regulatory and cultural landscape of China, where strong government involvement in AI development coexists with a need to harmonize local practices with global norms.

A key finding of the study is that Chinese firms view AI as a strategic tool for gaining competitive advantages in a rapidly evolving market. This strategic perspective is supported by government policies that actively promote AI adoption across various industries, including accounting and auditing. However, the study also highlights that while regulatory support is a driving force, the complexity of navigating both domestic and international regulations presents a significant challenge. Chinese firms must balance compliance with local regulations, which may be more permissive or prescriptive, with the need to meet the expectations of global clients and stakeholders who operate under different regulatory frameworks.

The contribution of this study lies in its detailed examination of how cross-cultural factors influence AI adoption in auditing. By providing empirical insights into the Chinese context, the research adds a comparative dimension to the literature, demonstrating that AI adoption is not a one-size-fits-all process but is shaped by local regulatory, cultural, and market dynamics. This contribution enriches the global understanding of AI in auditing, highlighting the need for cross-cultural research to inform the development of AI adoption frameworks that are adaptable to diverse environments.

6.3 Theoretical Contributions

My work also makes several contributions to the literature from a broader perspective. ***Extended TAM:*** My study expands the original TAM by considering different audit contexts for AI adoption. Specifically, in the context of external audits, I incorporated the impacts of auditors' perceived risks on their acceptance of AI to explore auditor-side factors in AI adoption. Additionally, I assessed the relationship between auditors and clients in external audits, integrating clients' ability and willingness to accept AI-involved audit services into the model. The results highlight the significance of client-side influences on auditors' attitudes toward AI, underscoring the appropriateness of these extensions. My enhancement of the original TAM aligns with prior research that introduces specific contexts into TAM, as demonstrated by Hasija and Esper (2022). For joint audits, I integrated social factors into TAM, significantly enriching its predictive power and practical applicability. This addresses the key facets of AI technology adoption and usage influenced by social dynamics. While the original TAM focused primarily on PU and PEOU as the main determinants influencing individual decisions to use new technologies, it showed limitations in examining practitioners' attitudes toward AI as AI adoption becomes increasingly socially embedded. By incorporating social factors, the model reflects the reality that individual AI adoption decisions are influenced by others within their social environments. Using AI adoption in joint audits as a case study, I demonstrated that integrating social factors allows TAM to evolve from explaining AI adoption through rational, cognitive assessments to considering the complex dynamics of social interactions and influences. This improvement broadens TAM's applicability across different professional contexts and deepens the understanding of the interplay between AI technology and society. It enables practitioners to better design, introduce, and market technologies in ways that align with social dynamics and user communities, enhancing the overall effectiveness of AI implementation strategies. Therefore, incorporating social factors into TAM contributes to the model's development by adding layers of complexity that reflect the social nature of AI adoption.

The refined TAM demonstrably outperforms the original model in both external and joint audit settings by addressing critical, context-specific barriers that the classic PU/PEOU specification cannot capture. In external audits, the addition of auditors' perceived risk and clients' readiness to accept AI-enabled services closes the gap left by TAM's cognitive-only focus – resolving the problem of unexplained variance in auditors' adoption decisions that stems from operational uncertainty and client resistance. In joint audits, embedding social influence variables remedies TAM's inability to account for the collaborative nature of multi-firm engagements – solving the shortfall in predictive power when interpersonal pressures and institutional norms shape technology use. By tailoring its constructs to these two professional contexts, the extended model not only yields stronger explanatory and predictive fit but also offers actionable insights for practitioners seeking to mitigate risk concerns in external audits and to leverage peer and regulatory endorsements in joint audits.

Refined IRT-TRI: My study also contributes to the literature by presenting a refined IRT-TRI model to develop a comprehensive understanding of auditors' algorithm aversion. By incorporating auditors' innovation resistance as a core element and clients' technology readiness as a moderating factor, the study deepens the understanding of the interplay between personal and external influences on resistance to technological adoption (cf.

Mahmud et al., 2023). Examining auditors' innovation resistance helps identify how an inherent reluctance to embrace new technologies might affect their willingness to adopt AI algorithms. Introducing clients' technology readiness as a moderator allows for exploring whether a client's readiness for technology adoption can mitigate or amplify auditors' resistance. However, the finding that clients' technology readiness does not moderate the relationship between auditors' innovation resistance and their aversion to AI indicates that even clients with high technology acceptance cannot influence auditors' resistance (cf. Dodgson et al., 2020). This lack of moderation suggests that auditors' personal barriers and resistance to innovation operate independently of external technological encouragement. This insight is crucial as it highlights the necessity for targeted interventions aimed directly at changing auditors' attitudes and perceptions, rather than relying on clients' readiness as a catalyst for change. By distinguishing these factors, the study emphasizes the complexity of overcoming innovation resistance and underscores the importance of addressing internal resistance mechanisms within auditors to effectively promote AI adoption.

In general audit settings, the enhanced IRT–TRI framework demonstrates superior explanatory and predictive validity by positioning auditors' innovation resistance as a focal construct and rigorously testing clients' technology readiness as a potential moderator. Whereas traditional adoption models emphasize cognitive evaluations of usefulness and ease of use, this refined approach captures the affective and identity-based reluctance that underpins algorithm aversion. The empirical evidence, showing that clients' readiness does not attenuate auditors' resistance, challenges the prevailing assumption that external technological endorsement alone can overcome professional inertia. As a result, the model brings into sharp relief the cohort of auditors whose reluctance persists despite a supportive client environment and thereby underscores the need for interventions aimed directly at modifying auditors' internal attitudes and perceptions (e.g. targeted upskilling initiatives, cognitive-reframing workshops) rather than relying solely on external incentives.

6.4 Contributions to Practice

Tailored strategies for AI adoption in diverse industries and auditing: The research emphasizes the necessity for industry-specific and client-centric AI adoption strategies. It highlights that AI adoption must address unique operational, regulatory, and social dynamics specific to each industry or client context. For instance, industries with high data sensitivity, like finance, should prioritize AI solutions that enhance data security and compliance, whereas less regulated sectors can focus on efficiency and decision-making improvements. Similarly, in auditing, firms should consider both employees' and clients' attitudes towards AI, tailoring solutions that align with professional standards and client expectations to foster trust and satisfaction (Eulerich et al., 2022; Raisch and Krakowski, 2020).

Human-centric and collaborative AI approaches: The study advocates for human-centric AI adoption approaches that emphasize transparency, explainability, and accountability, particularly in professional settings such as auditing. It suggests designing AI systems that are accessible, user-friendly, and inclusive, enhancing the collaboration between human auditors and AI tools. Emphasizing collaboration rather than replacement, these systems should foster a partnership where AI augments rather than replaces human decision-making (Costello et al., 2020). This approach helps mitigate algorithm aversion and promotes the effective integration of AI by respecting and adapting to social norms and professional standards (Munoko et al., 2020).

Incorporation of social factors in AI-augmented processes: The integration of AI in professional practices, especially in joint audit settings, requires understanding the social dynamics that influence collaboration and communication. The study suggests designing AI systems that enhance social interactions, adapt to regional and industry differences, and foster a more inclusive and responsive audit environment. By recognizing and adapting to social factors, AI can drive methodological innovation, improve teamwork, and enhance conflict management, ultimately leading to more coherent and comprehensive audit processes (Knechel & Williams, 2023; Deore et al., 2023).

<u>Policy implications and supportive frameworks for AI integration:</u> The study underscores the importance of robust ethical guidelines, adaptable regulatory frameworks, and ongoing collaboration between regulators, practitioners, and technology developers. It suggests that accounting firms and other professional entities should implement phased AI adoption strategies, allowing gradual adjustment and increasing comfort levels among professionals. Policies should support continuous evaluation and adaptation of AI tools, driven by feedback from users, ensuring alignment with professional needs and ethical standards (Nekhili et al., 2022).

<u>Psychological adaptation and training for AI adoption:</u> To foster effective AI integration, the study highlights the need for AI systems to be psychologically adapted to end-users, enhancing accountability and explainability. By creating interfaces that make AI-generated recommendations understandable and involving users in the development process, firms can promote a sense of ownership and trust. Training programmes that focus on the complementary nature of AI can empower professionals to leverage AI tools effectively, enhancing their capabilities rather than replacing them (Munoko et al., 2020).

6.5 Limitations and Future Research Directions

My studies have several limitations. In exploring AI adoption in external audits, I assumed that audit managers could effectively assess their clients' attitudes toward AI. However, clients might hide their true attitudes during audits to maintain positive relationships with auditors (Aghazadeh and Hoang, 2020), hoping auditors will tolerate their aggressive financial statements (Koch and Salterio, 2017). Future research could directly investigate client firms to measure their interest in AI. Furthermore, while Likert-scale questions enable the quantification of relevant factors in the survey experiment (Haesebrouck et al., 2021), their measurement accuracy may be limited. Participants' trust and other factors may not be accurately captured by responses on a seven-point scale. Future studies could employ larger scales to measure human attitudes toward AI more precisely.

In studying AI deployment in joint audits, it is important to consider that auditors and their firms may have complex social networks. These networks often feature global and community structures (Sytch & Tatarynowicz, 2014), which can significantly influence auditors' receptiveness to AI. The perspectives and attitudes toward AI held by peers or clients within these network layers can have diverse effects on auditors' acceptance of the technology. The differences in influence arising from individuals' positions within global or community contexts highlight the need for a deeper understanding of these structures. Additionally, auditors' social networks encompass the core or peripheral roles held by their peers or clients (Sytch & Tatarynowicz, 2014). These positions can distinctly affect auditors' willingness to embrace AI, as the opinions from central network members might carry more weight than those from peripheral members. These limitations suggest a need for future research to dig into the complexity of social networks surrounding auditors. A more detailed investigation into how these social structures and the positions within them affect auditors' acceptance of AI could enhance the understanding of factors determining effective AI adoption.

Regarding the investigation of auditors' algorithm aversion, the rapid advancement of AI technologies, particularly generative AI (e.g. ChatGPT: Wei, Wu, & Chu, 2023), may influence auditors' resistance to AI algorithms as AI becomes more integrated into professional fields. While psychological barriers remain significant in contributing to auditors' aversion, a thorough analysis using longitudinal datasets can provide a comprehensive understanding of this resistance. Such datasets can reveal how auditors' attitudes and behaviours evolve over time with continued exposure to AI technologies. By examining these trends, future research can identify specific factors that either hinder or facilitate the acceptance of AI in auditing, which is crucial for developing strategies to mitigate resistance and promote effective AI integration. Moreover, my study examined auditors' aversion to AI algorithms in general, overlooking the contextual differences between internal and external audits. Understanding these differences is essential, as each type of audit serves distinct purposes and operates under different pressures and expectations (Commerford et al., 2023). Internal audits focus on improving internal controls, risk management, and operational efficiency, often dealing with sensitive, proprietary information. Auditors might resist AI here due to fears of job displacement or concerns about the algorithm's ability to handle complex, context-specific tasks. Conversely, external audits verify the accuracy and fairness of financial statements for stakeholders under regulatory scrutiny, requiring transparent and reliable methods. Auditors might be skeptical of AI due to concerns about regulatory compliance, the transparency of AI decision-making processes, and potential errors that could undermine their credibility. Understanding these contextual differences helps tailor AI solutions that address specific concerns and enhance AI acceptance in both audit environments. Future research could explore this complexity in greater detail.

An additional limitation stems from the temporal frame of this research, which is restricted to 2021 – prior to the widespread deployment of advanced generative AI systems such as GPT-3.5, GPT-4, and contemporary multimodal platforms. Consequently, the attitudes and resistance patterns captured in this thesis pertain to interactions with early-stage AI tools and may not generalize to contexts in which auditors routinely encounter more sophisticated capabilities – namely fluent natural-language generation, automated code inspection, and prolific synthetic data synthesis. Future studies should therefore employ longitudinal designs and gather post-2021 data to evaluate how the rapid evolution of generative AI alters auditors' trust calibration, risk perceptions, and adoption behaviours. Such work will clarify whether exposure to these powerful models attenuates algorithm aversion or, alternatively, gives rise to new concerns – particularly regarding transparency, model explainability, and ethical implications – within both external and internal audit environments.

6.6 Contradictions

Despite the overall coherence of the extended TAM and refined IRT–TRI frameworks, three notable findings ran counter to theoretical expectations:

Risk perception in Study One: Although we hypothesised that higher perceived risks (inherent, control, and detection) would dampen auditors' attitudes toward AI in external audits, risk perception did not exert a significant direct effect on overall attitude. A plausible explanation is that, in the highly risk-averse domain of external auditing, auditors view risk as an intrinsic element of their work; thus, variations in perceived AI risk are subsumed under broader assessments of usefulness and reliability. In other words, auditors may treat risk concerns as baseline conditions rather than as distinct attitudinal drivers, focusing more on whether AI adds sufficient value to offset any operational uncertainties.

Peer attitude in Study Two: In joint audits, we expected that peer attitudes–reflecting social pressure from fellow auditors–would significantly influence AI adoption. However, peer attitude failed to reach significance. This may reflect the overriding impact of institutional and regulatory factors in multi-firm settings: when clear external guidance is present, auditors may defer to formal norms rather than to informal peer cues. Moreover, joint audits often involve cross-firm teams with heterogeneous peer groups, diluting any single peer group's influence and elevating the salience of standardized regulatory protocols over localized social pressures.

Client readiness in Study Three: The refined IRT–TRI model posited that clients' technology readiness would moderate the effect of auditors' innovation resistance on algorithm aversion. Contrary to expectation, no moderating effect emerged. This suggests that auditors' internal resistance to algorithmic decision-making operates largely independently of clients' openness to technology; deep-seated professional identities and affective barriers cannot be offset merely by external endorsements. In other words, even highly tech-savvy clients do not substantially alter auditors' personal reluctance to cede control to AI, underscoring the necessity of interventions targeting auditors' own beliefs and comfort levels with new technologies.

6.7 Chapter Conclusion

This study provides comprehensive insights into the factors influencing AI adoption in auditing, making significant empirical, theoretical, and practical contributions. Empirically, the research identifies key barriers to AI adoption in external and joint audits, notably operational disruptions, concerns over AI's ability to handle complex audit tasks, and the need for clear regulatory guidance to enhance AI's legitimacy and application in auditing. These findings highlight the critical role of targeted strategies that address specific challenges, notably enhancing AI transparency, improving training programmes, and developing AI systems that complement human expertise. The study underscores the importance of regulatory clarity and supportive frameworks in fostering AI adoption, especially in joint audits where multiple firms must coordinate and comply with varying regulatory standards.

Theoretically, the study advances the TAM by incorporating audit-specific factors and social dynamics, offering a more comprehensive understanding of how AI adoption decisions are influenced by both individual and collective considerations. It also refines the IRT-TRI by examining the interplay between auditors' innovation resistance and clients' technology readiness, providing insights into the complex dynamics that affect auditors' acceptance of AI technologies. These theoretical contributions enhance the predictive power and practical applicability of these models, enabling a more nuanced approach to understanding AI adoption in auditing.

Practically, the study emphasizes the importance of human-centric AI adoption strategies that prioritize transparency, explainability, and collaboration between auditors and AI systems. It advocates for tailored AI solutions that align with the specific needs and expectations of different industries and client contexts, fostering trust and enhancing the overall effectiveness of AI-enabled audit practices. The research also highlights the need for robust regulatory frameworks and ongoing engagement with auditors to address psychological barriers such as algorithm aversion, ensuring that AI systems are designed and implemented in ways that align with professional standards and values.

The chapter concludes by acknowledging the limitations of the study, including potential biases in measuring auditors' and clients' attitudes towards AI and the evolving nature of psychological barriers to AI adoption. It calls for future research to explore these limitations further, particularly the impact of social networks, the differences between internal and external audits, and the rapid advancements in AI technologies. By addressing these areas, future research can build on the study’s contributions to develop more effective strategies for integrating AI into auditing, ultimately enhancing audit quality and fostering greater acceptance of AI technologies within the profession.

CHAPTER SEVEN: CONCLUSIONS

7.1 Chapter Introduction

This concluding chapter synthesizes the study's empirical, theoretical and practical insights into auditors' AI adoption across external, joint and general audit settings. Drawing on an expanded TAM and a refined IRT-TRI framework, it demonstrates that in external audits AI uptake hinges less on auditors' own risk perceptions and more on client attitudes and digital competence. In joint audits, supportive regulatory guidance and client acceptance emerge as the primary social drivers of collaborative AI use, while peer influence plays a limited role. In broader audit contexts, AI aversion is shown to stem predominantly from personal and psychological barriers rather than functional concerns. Together, these findings highlight the necessity of aligning AI strategies with client capabilities, regulatory clarity and auditors' mindsets. The chapter concludes by outlining implications for designing transparent, trustworthy and contextually tailored AI systems that foster collaboration, accountability and sustained innovation in the auditing profession.

7.2 Research Conclusions

External Audits: In external audit engagements, I examine how auditors' acceptance of AI is shaped less by their own risk assessments and more by clients' attitudes and technical competencies. I show that when clients articulate clear expectations for AI-driven insights and demonstrate robust technological readiness, auditors become markedly more willing to deploy assisted AI applications – while remaining cautious about fully autonomous systems that may mishandle complex financial judgments. This finding indicates that audit firms should foreground client sentiment in their AI rollout plans by co-developing implementation road maps, offering joint training sessions, and establishing feedback loops to build mutual trust and understanding. For future research, I propose investigating how client characteristics, such as organizational size, industry sector, and digital maturity, moderate auditor receptivity, and whether joint governance mechanisms further smooth technology adoption. Theoretically, I argue that these insights warrant an extension of TAM to integrate client–auditor relational constructs, thereby improving its explanatory power in external audit contexts.

Joint Audits: In the context of joint audits, I explore the influence of social and institutional determinants on auditors' willingness to adopt AI-augmented methodologies. I find that client endorsement of AI-driven efficiencies and analytical insights robustly increases auditors' openness to collaborative AI applications, underscoring the imperative to align audit strategies with client expectations. Moreover, I show that a coherent regulatory and policy framework – characterized by explicit guidance and accessible resources – creates an enabling environment for joint AI deployment by mitigating uncertainty and legitimizing innovative practices. In contrast, peer norms among co-auditors exert a comparatively modest effect on AI acceptance. These findings imply that practitioners should foreground client engagement and regulatory harmonization when integrating AI into joint audit engagements, and that future research ought to investigate the mechanisms through which regulatory architectures and client–auditor relationships converge to shape technology adoption trajectories in auditing.

Auditors' Aversion to AI Algorithms: In general audit contexts, I examine the antecedents of auditors' algorithm aversion, with particular emphasis on cognitive and affective inhibitors. I demonstrate that, although functional and operational concerns remain salient components of broader innovation resistance, they exert comparatively little influence on aversion to AI-driven decision-making. Similarly, I find that client-side technology readiness, while pivotal for tool selection, fails to alleviate auditors' fundamental reluctance to cede control to autonomous systems. Instead, dispositional factors including perceived loss of agency, low algorithmic self-efficacy, and heightened uncertainty emerge as the primary drivers of aversion. These results call on practitioners to implement interventions targeting individual-level concerns – by enhancing transparency, fostering hands-on experience, and building algorithmic trust – to facilitate smoother AI integration. For future research, I advocate rigorous evaluation of such interventions and deeper inquiry into how auditor characteristics (e.g. cognitive style, risk tolerance) moderate resistance to algorithmic methodologies.

7.3 Final Reflections

This study contends that the trajectory of AI in auditing will be shaped less by algorithmic sophistication and more by the profession's capacity to cultivate systems that are trusted, transparent, and responsive to social contexts. Rather than viewing technological progress as an end in itself, auditors must position innovation within a framework of professional and relational considerations – recognizing themselves not simply as adopters of new tools but as social agents whose decisions are influenced by client expectations, peer norms, regulatory mandates, and their own ethical commitments. By adapting TAM and enhancing IRT-TRI framework to address audit-specific concerns, our findings demonstrate that cultural, psychological, and interpersonal dynamics are as critical to successful AI integration as algorithmic performance. In practice, AI will not supplant auditors; instead, those practitioners who engage with AI in a socially informed and ethically grounded manner will shape the evolution of the audit profession.

7.4 Research Dissemination

This research has been shared in management and information-systems settings through presentations that translate the findings into practical recommendations for audit practice. By illustrating how client expectations and regulatory clarity influence AI uptake, it suggests approaches – notably collaborative rollout plans, focused training initiatives, and feedback mechanisms – to support the integration of AI tools without compromising professional rigor.

Concurrently, the work has informed discussions among AI and human–computer interaction practitioners by identifying key barriers to algorithm use, including perceived loss of control and low algorithmic self-efficacy. These observations have guided the creation of prototype audit applications with features like transparency layers, interactive explanations, and hands-on walkthroughs. Ongoing collaborations are investigating how to embed ethical safeguards and user-centered checks into the development lifecycle of AI-driven audit software.

7.5 Chapter Conclusion

This chapter concludes that the thesis demonstrates auditors' AI acceptance to be driven predominantly by external influences – clients' attitudes and technical readiness in external audits; client endorsement and regulatory clarity in joint audits; and dispositional inhibitors (loss of agency, low algorithmic self-efficacy) in general contexts. By extending TAM and IRT-TRI framework to incorporate relational and cognitive dimensions, the thesis establishes a socially informed model for AI integration. Accounting firms should therefore prioritize client-centric road maps, phased rollouts, and targeted trust-building interventions. Future research must explore how organizational scale, industry sector, digital maturity, and governance structures further moderate these adoption dynamics.

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APPENDIX A. Interview and Survey Designs

Table A.1. Interview guide for senior managers at BTC on AI in external audits

Abstract
This interview guide is designed for a research study involving senior managers at BTC. The study aims to explore the practical applications of AI in external audits. The interview questions are designed to elicit detailed insights into the participants' experiences and opinions on AI-based technologies in the auditing process.

1. Interview Preparation
- **Objective:** Ensure thorough preparation to create a conducive environment for open dialogue and all necessary recording equipment is functioning properly.

2. Introduction to the Interview
- **Objective:** Provide a clear overview of the interview process.
- **Sample Script:**
    - "Welcome and thank you for participating in this interview. My name is *, and I will be conducting this interview as part of our research on the practical applications of AI in external audits. The interview will last approximately 30 minutes. I will be asking you a series of questions about your experiences and perspectives on AI-based technologies in the auditing process. Your responses will remain confidential and will be used solely for academic purposes."

3. Participant Criteria and Selection Rationale
- **Objective:** Explain the criteria for participant selection to contextualize the expertise of the interviewees.
- **Criteria:**
    - Long tenure in the firm to ensure substantial working experience.
    - Employment in core positions, directly involved in major operational decisions.
    - Specialization in various domains and experience at different levels within the firm, contributing to the firm's development.

4. Research Theme and Context
- **Objective:** Provide a detailed introduction to the research theme and context.
- **Sample Script:**
    - "Before we begin with the questions, I would like to provide some context about our research. We are exploring the practical applications of AI in external audits and how these technologies are being utilized within Baker Tilly China."

5. Consecutive and Adaptive Questioning
- **Objective:** Use a flexible approach to questioning, allowing for adaptation based on participants' previous answers.
- **Methodology:**

- Questions will follow a consecutive format, with each subsequent question building on the participant's previous response. This approach ensures that the interview remains relevant and responsive to the participant's unique experiences and insights.

6. Primary Research-related Questions

- **Objective:** Investigate the participants' opinions about the practical applications of AI in external audits.
- **Sample Questions:**
  - "How much do you know about the financial robot[3] you have developed?"
  - "Do you have any expectations for this financial robot in the short or long term?"

7. Questions from the Participant

- **Objective:** Allow participants to ask questions, demonstrating their engagement and interest in the research topic.
- **Sample Script:**
  - "We've covered various aspects of AI in external audits. Do you have any questions for me about this research or any additional thoughts you would like to share?"

8. Conclusion

- **Objective:** Summarize the interview and explain the next steps in the research process.
- **Sample Script:**
  - "Thank you for your time and valuable insights today. We appreciate your participation in this study. We will analyse the information gathered and inform you of any further steps. Your contributions are crucial to our understanding of AI applications in external audits."

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[3] The question involves an AI technology (financial robot) that automates investment advice and portfolio management through AI algorithms, optimizing asset allocation and risk management.

Table A.2. Primary survey question (Source: Authors Own)

Survey: Auditors’ Acceptance of AI-Augmented Joint Audits at Baker Tilly China

Definition of AI-Augmented Joint Audits: For the purpose of this study, AI-augmented joint audits refer to the integration of artificial intelligence (AI) technologies into joint audit processes to enhance efficiency, accuracy, and collaboration. Specifically, AI-augmentation may involve:

1. Robotic Process Automation (RPA): Automates repetitive audit tasks, streamlining data collection and ensuring standardized processes across auditors.
2. Real-Time Anomaly Detection: Identifies discrepancies across multiple datasets from different auditing parties, improving error detection and risk assessment.
3. AI-Enhanced Virtual Reality: Facilitates collaborative remote asset inspection for auditors from different firms without requiring physical presence.
4. Generative AI: Assists in producing comprehensive audit reports and predictive models to support decision-making.

Manipulation: Participants will be randomly assigned to one of three conditions, each presenting a different AI-augmented joint audit scenario:

- Condition 1 (RPA & Anomaly Detection): Participants will be introduced to a scenario where RPA automates data collection and anomaly detection swiftly flags inconsistencies.
- Condition 2 (AI-Enhanced VR Collaboration): Participants will be introduced to a scenario where AI-enhanced virtual reality is used for remote asset inspections, reducing travel needs and increasing efficiency.
- Condition 3 (Generative AI & Predictive Analytics): Participants will be introduced to a scenario where Generative AI generates detailed audit reports and predictive models to improve decision-making.

Each participant will receive a brief description of their assigned AI-augmentation scenario before responding to the survey questions.

Survey Questions:

Perceived Acceptance and Usefulness

1. How would you rate your acceptance of AI-augmented joint audits in your assigned scenario? (1 = Totally Unacceptable, 7 = Entirely Acceptable)

2. How useful do you perceive the adoption of AI augmentation to be in joint audits in your assigned scenario? (1 = Not Useful at All, 7 = Extremely Useful)
3. How would you rate the ease of use of AI technology in your assigned scenario? (1 = Very Difficult to Use, 7 = Very Easy to Use)

Perceived Organizational and Industry Acceptance

4. How would you rate your firm headquarters' acceptance of AI-augmented joint audits? (1 = Totally Unacceptable, 7 = Entirely Acceptable)
5. How would you rate your peers' acceptance of AI-augmented joint audits? (1 = Totally Unacceptable, 7 = Entirely Acceptable)
6. How would you rate your clients' technological ability to accept AI services, considering they are in the agriculture, forestry, animal husbandry, and fishery industries? (1 = Very Low, 7 = Very High)

Regulatory and Environmental Support

7. How would you rate the supportiveness of regulatory and policy environments for AI-augmented joint audits? (1 = Very Low, 7 = Very High)

Purpose of This Survey: This survey aims to examine auditors' acceptance of AI technologies in joint audits. The findings will provide insights into perceived benefits, challenges, and industry readiness for AI-augmented auditing practices.

Confidentiality Statement: All responses will remain anonymous and will be used solely for academic research purposes.

APPENDIX B. Ethical Approval

Ethical Approval

Han WU

Student ID: ETU20160366

13 November, 2023

To whom it may concern:

Rennes School of Business is an AACSB, EQUIS, AMBA accredited business school in France. Han WU conducted her PhD studies with us between 2017 and 2022. During this time, she collected data using survey and interview methods. The data collection was carried out in accordance with the appropriate ethical standards in place in Rennes School of Business at that time.

SARAH HUDSON
Director of PhD program
Full Professor
Management and Organisation Department

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Figure B.1. Ethical approval from Rennes School of Business

Research Approval

This is to certify that Han WU has conducted questionnaire surveys and relevant interviews at Baker Tilly China Certified Public Accountants, titled “Adoption of Artificial Intelligence related Technology in Accounting and Auditing.”

Through the questionnaire surveys and interviews, Han WU has gained an understanding of the current adoption of artificial intelligence technology in the fields of accounting and auditing. Further, the research explored the advantages and market challenges associated with the use of artificial intelligence in these fields. The survey and study also assessed the overall impact of artificial intelligence related technology on professional practices in accounting and auditing.

The questionnaire surveys and interviews conducted by Han WU at Baker Tilly China Certified Public Accountants were solely for the purpose of exploring and researching the development and impact of artificial intelligence related technology in the fields of accounting and auditing. The research is for academic purposes, and the questionnaire and interviews were conducted truthfully.

Hereby to certify

Date: 08/23/2024

Figure B.2. Ethical approval from Baker Tilly China