

**Perception of The Adoption of Artificial Intelligence Tools on Audit Quality in the Lebanese
Private Sector: A Perspective from Internal Auditors.**

**This Thesis is submitted with the requirements of Haigazian University for the degree of
Master of Business Administration in Accounting”**

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Thesis

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Private Sector: A Perspective from Internal Auditors.**



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Business Administration with a specialization in accounting*

Dedication

This thesis is dedicated to my friends and family, whose love and support was truly needed throughout this journey.

To my friends, who stood by my side during moments of doubt, stress and exhaustion and celebrated every small win with me, thank you for your kindness and understanding.

To my work colleagues and especially my manager, who were all understanding of the time and effort I must put in to complete this thesis even if it takes away from my work-life balance.

And finally, to anyone who has ever inspired me to dream big and work hard, this work is a testament to your influence in my life.

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Abstract

This thesis investigates the factors influencing internal auditors' adoption of artificial intelligence (AI) tools in the Lebanese audit sector, with a particular emphasis on the mediating role of perceived audit quality (AQ). Grounded in the Technology Acceptance Model (TAM), the study examines how perceived usefulness (PU) and perceived ease of use (PEOU) affect auditors' behavioral intention (BI) to adopt AI, both directly and indirectly through AQ. Data were collected via a structured survey distributed to 300 internal auditors, yielding 100 valid responses from professionals with work/experience in AI auditing. The analysis employed PROCESS Model 4 for mediation, controlling demographic and contextual variables. The findings reveal that both PU and PEOU are positively associated with BI, but these effects are fully mediated by AQ: auditors are only likely to adopt AI tools when they perceive tangible improvements in audit quality. While the mediation effect for PU was statistically significant, its magnitude was modest, indicating a cautious interpretation is warranted. The results underscore the importance of audit quality as the decisive mechanism linking technology perceptions to adoption intention, differing from studies in other contexts where direct effects of PU and PEOU are often reported. The thesis contributes to the literature by highlighting the centrality of AQ in technology acceptance among auditors and by providing region-specific insights relevant for emerging markets. Practical recommendations for audit firms, technology developers, and policymakers are offered, emphasizing the need to demonstrate quality improvements to drive effective AI adoption in the auditing profession.

Keywords: Artificial Intelligence, Audit Quality, Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Behavioral Intention (BI).

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CHAPTER ONE: INTRODUCTION

1.1 Background

One of the fastest-growing transformational forces in modern business reality is Artificial Intelligence (AI), which has reformed most industries and processes (Uctu et al., 2024). In the auditing field, machine learning, natural language processing (NLP) and robotic process automation (RPA) are among the automation tools utilised in AI that increase audit quality by improving accuracy, effectiveness, and even increasing fraud detection (Issa et al., 2016; Aitkazinov, 2023). All these technologies can be used to do repetitive tasks, analyse enormous amounts of data in real time and alert auditors to abnormalities that might have remained undiscovered with the traditional methods (Al-Omush et al., 2025).

AI is already starting to shape global audit practices, but this is not without its challenges and opportunities when it comes to the Lebanese private sector. Like many emerging markets, Lebanese audit firms and internal auditors work in a context of economic complexities, moving regulatory structures, and limited technological infrastructure (Rizk, 2020). However, auditing in Lebanon has not yet covered comprehensive governance guidelines for AI; therefore, audit professionals lack a clear set of guidelines for compliance, liability, and responsibility (Abdallah et al., 2024; Bou Reslan & Jabbour, 2024).

Additionally, due to the wide proliferation of AI, internal auditors (who provide essential third-party control to ensure corporate governance and prevent fraud) must adapt their skills to have and the processes they enact. According to Albawwat & Frijat (2021), many internal auditors may not have formal training in AI techniques, which may result in scepticism, underutilization, or wrong use of AI tools. It raises the need for a deep empirical investigation of this tension between the

often irresistible benefits of AI on the one hand and real-world problems of its implementation on the other, in the Lebanese context.

To give some context, this thesis looks at how Perceived usefulness (PU) and Perceived Ease of Use (PEOU) affect Behavioural Intention (BI) to use AI, through the mediating variable of Perceived quality (PQ) of AI, using a sample consisting of 100 internal auditors in Lebanon. The study applies the classical TAM model to the Lebanese case, as there are not many studies about how AI is used in Lebanese auditing. It tries to understand how an auditor's opinion of using AI could help in finding errors, stopping fraud and maintaining reliable audits. The study aims to provide useful information that helps managers and practitioners use AI in auditing by looking at data about the views of auditors on this subject.

1.2 Research Problem and Research Question

According to the recent discourse on the use of AI in auditing, it presents several improvements such as speed, accuracy, and improved fraud detection (Rane et al., 2024). Yet, there remain critical gaps. Traditional methods of auditing rely mainly on human skill, judgment, and sense in reading financial information and uncovering inaccuracies (Tiron Tuder & Deliu, 2022). However, AI provides an alternative data-driven paradigm that automates labour-intensive tasks and reduces human error, but then brings with it concerns of transparency, algorithm bias, skill gaps when auditors and AI work together, and security vulnerability (Munoko et al., 2020; Mokander et al., 2024).

These tensions are magnified in Lebanon. Partial or outdated regulatory guidance, economic volatility, and scarcity of resources to deliver training on advanced technology create a situation where AI needs to be adopted, but is full of difficulty (Moustafa Abdallah et al., 2024). There is

much that regulators and auditors must work through to figure out how to take advantage of AI's potential to improve audit quality (Benjelloun, 2024; Diab & El Hajj, 2024).

The central research problem that arises from this dilemma, is: given that Lebanon has its own set of challenges regarding regulation, auditor competencies and firm level resource constraints, there was a need to understand the perception of Lebanese auditors on how the adoption of AI impacts the quality of their work regarding auditing in Lebanese private sector organizations due to the gap in empirical evidence on this matter in the case of Lebanon. Consequently, the question that underlies my research program is:

How do internal auditors perceive AI adoption in the auditing process and its role in audit quality in Lebanon?

This leads to the following sub-questions:

RQ1: How do internal auditors perceive the usefulness of AI in auditing quality?

RQ2: How do internal auditors perceive the ease of use of AI for improving auditing quality?

RQ3: How do internal auditors perceive the impact of PU and PEOU on behavioural intentions to adopt AI tools mediated by PQ of AI?

1.3 Research Objectives

Based on the research problems and questions, the key objectives of this thesis are as follows:

RO1: To examine internal auditors' perceptions of the potential usefulness of Artificial Intelligence (AI) in improving audit quality.

RO2: To assess how internal auditors perceive the ease of use of AI technologies is perceived to impact auditing quality.

RO3: To evaluate how auditors perceive the impact of PU and PEOU on behavioural intentions to adopt AI tools mediated by PQ of AI.

1.4 Research Implications

However, despite the amount of research on AI and how it regulates accounting and financial management, specific investigations enlightening on the way auditors see how AI transforms audit quality in emerging economies such as Lebanon are not as numerous. The contributions of this thesis can be categorised into theoretical understanding and practical applications.

1.4.1 Theoretical Implications

It mainly adds to theory by studying how auditors feel about adopting AI in times of economic and regulatory changes, using the variables of PEOU and PU from the TAM model and the impact of BI of AI through PQ of AI in auditing. Most of the work on this topic looks at developed areas with strong government systems, but this study takes place in Lebanon, where AI is used without clear and strong governance. Moreover, the study expands scholarly discussions using the lens of the TAM to examine auditor attitudes towards AI in a circumstance with limited resources, cultural differences, and diverse regulatory approaches. Furthermore, a quantitative methods research design is used, which provides a holistic insight into how auditors do their work in utilising an AI-driven solution, closing the gap between the numeric performance indicators (e.g., error reduction) and what happens in practice when these solutions are used in practice.

1.4.2 Practical Implications

From a practical standpoint, this study contributes actionable guidance to International and Lebanese internal auditors and audit firms on how to leverage AI technologies to improve the ability to detect errors and fraud and operate an audit. It also gained insight into potential

challenges posed by AI, data security, technology cost, and resisting change, and can help practitioners take advantage of the benefits of AI rather than get derailed by its complexities. The guidance of these findings may also encourage policymakers and professional bodies to create laws and standards governing innovation, promoting ethical and professional integrity preserving. One last thing is identifying the emerging skill sets that need to be developed in an AI augmented audit environment, including data analytics proficiencies and AI literacy. The study recommends that auditors adopt continuous learning to facilitate the adoption of advanced technologies in the current audit practices.

1.5 Thesis Outline

To present a coherent analysis, the thesis is structured into the following chapters:

Chapter 1: Introduction → Introduces the research background, identifies the research problem and research questions, delineates the specific objectives, and highlights the theoretical and practical contributions. This chapter also provides an overview of the thesis structure.

Chapter 2: Literature Review → Offers a detailed examination of relevant scholarly work on AI and auditing, including foundational theories, the historical evolution of AI in auditing, and current debates on the ethical, regulatory, and professional implications. The chapter also situates the study within the TAM and develops a research Hypothesis.

Chapter 3: Research Methodology → Presents research design, covering data collection instrument (questionnaire), sampling strategies, and analytical procedures. Justifies the focus on Lebanese internal auditors and explains how reliability and validity concerns are addressed.

Chapter 4: Data Analysis and Findings → Reports the quantitative findings. It interprets survey statistics (e.g., descriptive analysis, correlations, regression tests), emphasising key patterns that reveal how AI adoption influences audit quality and what barriers firms encounter.

Chapter 5: Discussion → Synthesises the results considering the research objectives and relevant literature. Evaluate how the findings support or challenge existing studies on AI in auditing, drawing attention to regional nuances in Lebanon.

Chapter 6: Conclusion and Recommendations → Summarises the entire study, highlighting the main insights into AI's impact on audit quality. Presents practical guidelines for auditors, regulators, and policymakers, and identifies areas for future research, including limitations of the current study and suggestions for extended or comparative research designs.

1.6 Conclusion

This chapter has introduced the central focus of the thesis by outlining the background, research problem, and key questions that anchor the study. It has also clarified the objectives of guiding the investigation and highlighted the theoretical and practical contributions that the work aspires to make. Taken together, the chapter underscores that while AI holds the promise of transforming internal auditing practices, by uses the classical TAM model as a compass for this study. The subsequent chapters will expand on these themes by reviewing the relevant literature, detailing the quantitative approach employed in this study, and analysing empirical findings to illustrate how AI both challenges and enriches the traditional contours of audit quality. This thesis attempts to contribute to the discussion by proposing insights that might assist Lebanese auditors, policymakers, and scholars in leveraging responsibly and responsibly AI's power.

Chapter 2: Literature Review

2.1 Introduction

In this chapter, the literature review is meant to offer a critical overview of how internal auditors use artificial intelligence (AI) tools. The literature review aims to check earlier studies, theories and research results that influence the current study. Therefore, this part of the paper places the research within the wider academic field, points out important discussions, changes in the area, and clarifies where current knowledge is lacking. In the end, the review of literature supports the research objectives by making it clear that further work on AI in auditing, especially in the Lebanese context, is important and required now.

This chapter begins by introducing the main ideas and the history of AI in auditing, which helps set the stage for the rest of the discussion. The chapter then looks at the main theories, highlighting the Technology Acceptance Model (TAM), which guides this study, as well as its extensions (TAM2 and TAM3), both of which have been commonly used to explain people's decisions about new technology use. The review then summarises studies on what influences auditors to use AI, focusing on PU, PEOU, BI and the changes in audit quality. It ends with a summary of the main research problem, the conceptual framework used and a link between the findings of the literature review and the aims of the study.

The literature does not provide much information on audit quality, which has been referred to as the perceived quality (PQ) of AI, as a link in the relationship between TAM and the use of AI in auditing. Studies so far have mostly looked at the direct effects of perceived usefulness and perceived ease of use on behavioural intention, but rarely consider how audit quality affects this relationship. Not many studies have looked at whether the perceived quality of AI tools can affect

the relationship between PU and PEOU and internal auditors' willingness to use AI. In Lebanon, there is not much research yet on applying AI in auditing, and the studies that exist do not often consider mediation models. Therefore, this study considers how perceived quality of AI acts as a link between the independent variables (PU and PEOU) and the dependent variable (behavioural intention to adopt AI), adding something new to both research and practice.

2.2 Artificial Intelligence in Auditing

2.2.1 Definition and Scope of AI in the Accounting and Auditing Profession

Artificial intelligence involves computer systems that can handle activities that usually require human intelligence, like solving problems, spotting patterns, understanding language and making decisions (Davenport & Ronanki, 2018). In accounting and auditing, AI is used to describe a group of technologies, like machine learning (ML), natural language processing (NLP) and robotic process automation (RPA), each one helping to improve different parts of assurance and audit activities. AI includes simple automation and more complex analytics, but in auditing, today's use is mostly limited to the basic automation side. These systems can carry out many routine, rule-driven tasks in large quantities, helping auditors handle large data, work more efficiently and improve the accuracy of their audits (Mökander & Axente, 2023; Mashrur et al., 2020).

The field of AI is growing in auditing because firms are using technology to ensure quality, follow regulations and fulfil clients' expectations for faster and more accurate results (Rane et al., 2024). AI is now a key part of both internal and external audits, changing old methods and allowing auditors to use data more effectively and focus on risks (Gautam, 2023). Importantly, while AI can automate many routine audit functions, it is not a replacement for human professional judgment;

rather, it acts as a complementary tool that augments the auditor's ability to interpret complex evidence and exercise critical thinking (Afrin et al., 2024).

2.2.2 Applications of AI in Internal and External Audit

AI is used in auditing for data review, risk analysis and many other purposes within and outside the organisation. An important way machine learning is used is for risk assessment, in which it looks at transaction data to recognise any unusual behaviour that suggests fraud or an error (Antwi et al., 2024). AI is also used to find unusual activities in financial transactions by checking large numbers of records and datasets, which in the past required manual review of a sample of the data (Issa et al., 2016). Using NLP, auditors can review contracts, emails and audit reports quickly and easily find areas where rules are not followed or inconsistent risks are present (Qatawneh, 2024; Mokander et al., 2024).

In AI-enhanced auditing, Robotic Process Automation (RPA) is used to automate routine tasks such as processing data, checking invoices and reconciling accounts so that auditors can concentrate on more complex work requiring judgment (Afrin et al., 2024). Additionally, Machine Learning (ML) makes use of statistical models on large data to support activities like detecting fraud, creating risk models and spotting errors (Mashrur et al., 2020). Natural Language Processing (NLP) helps to study and interpret the text in contracts and communications, which assists auditors in spotting risks and assessing whether things are in compliance (Mokander et al., 2024). Lastly, Analytics Platforms are software that bring together different AI abilities, allowing users to review all audit activities, keep track of them regularly and report on them in real time (Mohammed Ismail & Abdul Hamid, 2024).

Now, these tools are being added to normal audit processes, which make audits more complete, less prone to errors and easier to carry out (Onwubuariri et al., 2024).

2.2.3 Motivations and Challenges in Adopting AI in Audit Practice

AI is being adopted in auditing for various reasons. To start, AI can greatly improve the accuracy of audits and help cover more data, which makes it easier to detect fraud (Aitkazinov, 2023; Issa et al., 2016). By automating regular work, auditors have more time to analyse and evaluate difficult issues, which improves the quality of the audit. AI also helps with regulations by quickly identifying any issues or anomalies, and it allows for both regular audits and real-time assurance, which are very important in the current business world (Appelbaum et al., 2021).

Even so, there are also difficulties when using AI in auditing. A major challenge is that there are no clear standards for AI governance in places like Lebanon, which makes it unclear how and when to use AI in audits (Benjelloun, 2024; Abdallah et al., 2024). Since many people in the profession do not have adequate knowledge about AI, auditors may encounter difficulty in using or accepting AI technologies (Albawwat & Frijat, 2021). Because financial information is sensitive, there are major problems with data privacy and security during audits (Aitkazinov, 2023). High costs and reluctance to accept change among organisations can prevent many smaller audit firms from fully adopting new technology (Alayli, 2023; Diab, 2021).

In general, AI has the potential to change audit practice, but realising its benefits means dealing with technical, organisational and regulatory challenges and regularly training auditors and creating strong ethical and governance plans.

2.3 Theoretical Foundation

To analyse the drivers and barriers to AI adoption within auditing, the TAM model is used to explain the perception of auditors in the adoption of AI through highlighting the role of PU and POEU from TAM1 as independent variables impacting the dependent variable BI, mediated by PQ of AI. The discussion of professional adoption and acceptance of AI systems is grounded in several established adoption and innovation theories, particularly Davis et al. (1989), which help us explain how new technologies diffuse through professional domains and how end-users (like auditors) develop trust in and acceptance of an AI system.

2.3.1 Overview of TAM, TAM2, UTAUT

The research of the study is based on the TAM developed by Davis et al. (1989). In the work of Sabek et al. (2024), the model explains how auditors come to accept and understand AI technologies through their work. Two key aspects of usability and user-friendly design constitute acceptance by the auditor of AI integration of operational procedures. In the Technology Acceptance Model, Perceived Usefulness (PU) and Perceived Ease of Use (PEU) are the two key factors for determining adoption behaviours for any technology. AI seems to add value to the audit quality as it offers the auditors the capacity to detect fraud where audit quality is compromised by fraud and reduce mistakes, and enhance the efficiency of financial statement analysis (Albawwat & Frijat, 2021). PEU shows that it is easy to embed AI systems within auditors' work with minimal or no additional training for the auditors and without altering their traditional audit procedures (Fedyk et al., 2022). An AI system is more likely to gain adoption by auditors when they perceive high levels of usefulness and ease of use, and the resistance to the adoption of the system stems from scepticism or unfamiliarity with AI tools.

PU and PEU are affected by several external elements since they condition the auditors to use AI in their auditing activities. The support received from within the organisation stands as an essential requirement. Organisations that support AI implementation through training initiatives boost both the practical value and operational simplicity for auditors (Almaqtari et al., 2024). Additionally, regulatory and ethical concerns can either facilitate or hinder adoption; unclear guidelines on AI-generated audit reports may create uncertainty, while concerns about algorithmic bias and data security may lead to distrust (Munoko et al., 2020). Auditor trust in AI systems plays a significant role because they will resist using AI insights that differ from their human judgment. AI tools will gain wider adoption if they display their decision-making methods clearly and follow auditing standards recognised by professionals (Al-Omush et al., 2025). Auditors must develop positive behavioural intentions about AI adoption because their confidence in AI's accuracy and reliability, and ethical aspects will determine their willingness to use it. To gain widespread acceptability by auditors, AI auditing quality improvements need both regulatory definition and system integration into current audit work processes, in combination with ongoing auditor skill advancement (Almagrashi et al., 2023; Abdullah & Almaqtari, 2024). Professional auditing practices will be optimally enhanced through partnerships between firms and regulatory bodies. The application of AI solutions shows promise to enhance audit quality through proper management of current obstacles that protect professional auditing standards and public accountability (Fedyk et al., 2022).

The TAM2 model is also important in psychology. Venkatesh and Davis (2000) brought TAM2 by building on the original TAM of Davis et al. (1989) by adding factors that represent social and cognitive influence. The TAM2 approach also includes the subjective norm (the social pressure people feel to use or refrain from using technology), image, job relevance, output quality and result

demonstrability. Because of these additions, TAM2 can take into account both personal beliefs and external factors, like workplace culture and what peers expect, so it is highly fitting in workplaces where social influence is key.

A basic model for studying human behaviour is the Theory of Reasoned Action (TRA), which Fishbein and Ajzen introduced in 1975. TRA states that a person's intention to act is influenced by their opinion about the behaviour and by subjective norms (i.e., opinions about whether important people in their life expect them to behave a certain way). In the same way, TRA underlies models such as TAM by stressing that intention is important in influencing actual action.

UTAUT, which was proposed by Venkatesh et al. (2003), combines important components of eight main technology acceptance models, for example, TAM and TRA. UTAUT outlines that four essential reasons for intention and usage are performance expectancy, effort expectancy, social influence and facilitating conditions and that there are other factors involved, such as age, gender, experience and whether usage is voluntary. UTAUT best demonstrates why organisations adopt certain technologies, since it recognises that many things play a role.

Even though many extended TAM models exist, this study bases its conceptual framework on the original TAM (TAM1), looking at the main elements of PU, PEOU and BI. The choice is made from a foundation of theory and real-life observations. Even though TAM was first introduced, it still works well and has been validated many times, especially for auditing, by showing how users' judgments about technology affect their decision to use it (Hamadeh et al., 2025). When auditing is seen through the lens of AI, the importance of PU and PEOU becomes clear, since they both reflect auditors' opinions about the usefulness and accessibility of AI tools, which are key in fast-changing technical contexts with limited budgets (Almaqtari et al., 2024). By focusing on TAM1, researchers can gain a clearer picture of what impacts internal auditors' decisions about using AI,

since factors from outside the business are less relevant locally (e.g., Wu & Chen, 2017). By using this method, we can investigate in detail how perceived quality (PQ) of AI connects user opinions to how they intend to act in the future, which is an area that has not been explored enough.

2.3.2 Technology Acceptance Model 3 (TAM3)

The *Technology Acceptance Model 3 (TAM3)* is an advanced and integrative model developed by Venkatesh and Bala (2008) to address the limitations of its predecessors—TAM and TAM2—by incorporating a broader set of determinants that influence an individual's acceptance of technology. While the original TAM focused on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as the core predictors of Behavioural Intention (BI), TAM3 enhances the model by introducing new constructs, moderators, and antecedents, particularly about job relevance, perceived enjoyment, and facilitating conditions.

TAM3 merges TAM2's cognitive instrumental processes (such as job relevance and result demonstrability) with PEOU determinants (such as computer self-efficacy and anxiety). This comprehensive approach makes TAM3 particularly valuable in professional and enterprise contexts—like auditing—where users must balance perceived benefits with usability concerns and organisational influences.

TAM3 retains the foundational components of TAM: (i) *Perceived Usefulness (PU)*: the belief that using a system will enhance job performance. (ii) *Perceived Ease of Use (PEOU)*: the belief that using a system will be free of effort. (iii) *Behavioural Intention (BI)*: the likelihood of adopting or continuing to use technology. For the sake of auditor availability and feasibility of the study, the study extends these with an *additional dimension*:

Output Quality – the extent to which the system performs tasks well. In the case of auditors, it could be about how reliable AI tools are in analysing large datasets or analysing anomaly reports.

This study redeems TAM3 as an effective framework to understand the formation of the perception of AI adoption by the internal auditors (Bou Reslan & Jabbour, 2024). Internal auditors' acceptance of AI tools does not depend solely on determining whether the tools are useful or easy to use (Al-Omush et al., 2025). However, acceptance also relies on whether auditors perceive AI tools to result in demonstrable benefits (result demonstrability) and to be enjoyable or motivating to use (perceived enjoyment). Also, their behavioural intention might reflect their confidence in using AI (self-efficacy), having training and support (external control), or a tendency to worry that AI will disturb audit process control (Benjelloun, 2024).

Because it brings together social and cognitive instrumental factors in a smooth way, TAM3 is an excellent model for observing how auditors adopt new technologies in their work (Saravanos et al., 2022). TAM3 goes beyond previous versions by including other important determinants: job relevance, output quality, proving the results and computer self-efficacy, which are closely linked to how technology is applied in auditing. When working with AI, auditing professionals are required to evaluate its helpfulness, how easy it is to operate, how well it aligns with daily tasks, the accuracy of its outputs and their proficiency with it (Hamadeh et al., 2025). When these things are factored in, TAM3 lets us discuss the recognition or avoidance of AI innovations by auditors in a meaningful way. Especially in auditing settings, it matters a lot since making the wrong decision can lead to big problems and following regulatory requirements is crucial while deciding to use complex technology.

2.3.3 The Use of TAM1 Reference Framework Instead of TAM3

The research here is grounded on the original Theory of Acceptance and Use of Technology (TAM1), not TAM3 as some may expect. While TAM3 adds factors like job relevance, output quality and feelings about the technology to the original version (from Davis & Granić, 2024), TAM1 is recognised as the key and most researched model among experts in technology adoption in auditing and accounting fields (Rosli, 2012).

Many choose TAM1 primarily because it can be applied and is relevant to professional users in organisational situations. A large amount of relevant research on how technology is adopted in auditing relies on TAM1 as the main model (Ajibade, 2018). These studies keep showing that PU and PEOU are the key elements that encourage BI to use new technologies. TAM1 looks at only a few main factors which allow it to clearly explain user acceptance behaviours that are not easily influenced by other, less important factors in real-world settings.

Alternatively, TAM3 looks at variables such as job relevance and perceived enjoyment, which are believed to be valuable in general, but may not be as useful for auditors. Enjoyment or personal fulfilment are less important reasons for using advanced technology in auditing than factors like efficiency, accuracy and compliance (Rosli et al., 2012; Curtis & Payne, 2008). Since AI tools are often part of the auditor's key tasks, job relevance is already covered by perceived usefulness and ease of use. For these reasons, including these extra elements from TAM3 might add extra complexity without really helping explain the present study's findings.

This study does not attempt to cover all of the connections proposed by the TAM or its extensions, and it does not try to validate or expand the TAM3 model. In its place, TAM1 is used as a reference framework, supplying a well-developed base for the conceptual model. The study uses the main

ideas from TAM1, which say that PU and PEOU influence people's intention to use new technology, to look at what affects AI adoption among internal auditors. Practical methods help clarify the concepts and make it easier to compare the research with what has already been done.

For this reason, the study concentrates on PU and PEOU as the independent variables and BI as the dependent variable. These constructs, job relevance and perceived enjoyment, are not included because they are seen as less significant to Lebanese audit firms. The framework here is based on what most experts agree on and makes the study more valuable for those who want to encourage AI adoption among professionals, managers and policymakers.

All in all, choosing TAM1 instead of its updated versions is influenced by principles of simplicity, what others have studied and the way the theory applies in different settings. By relying on the key ideas of TAM1, the research keeps its approach focused and thorough, using the model's well-known strengths to help examine AI adoption in auditing that is both well-founded and useful for practising auditors.

2.3.4 Summary of Empirical Findings on Factors Affecting Behavioural Intention

Many studies have regularly shown that PU and PEOU are among the top factors that influence BI to adopt new technologies. In the TAM, these two constructs consistently predict if professionals will accept and make use of technology in various industries. It has been established in multiple studies in auditing that PU and PEOU play a major role in shaping auditors' decisions to use advanced technologies. A study by Issa et al. (2016) revealed that auditors who believed AI-enabled tools could help with efficiency and accuracy in their job were more willing to use them. Also, Fedyk et al. (2022) found that the simplicity of using AI in current audit procedures greatly determined how willing auditors were to work with these technologies. Similar results were found

by Appelbaum et al. (2022), suggesting that both PU and PEOU are strong factors in determining whether accounting and audit professionals adopt technology, mainly when the technology is intended for error detection, data analysis and compliance supervision.

PU and PEOU can be used to make predictions in other areas besides auditing. According to studies, how useful and easy to use electronic health records are seen by clinicians can powerfully influence their intention to use them (Holden & Karsh, 2010). Also, in government and administration, studies have found that individuals are more willing to use e-government services or platforms if they think the technology enhances the service and if they feel comfortable using the system (Venkatesh et al., 2012).

2.4 Perceived Audit Quality as a Mediator

2.4.1 Defining Perceived Audit Quality

Perceived audit quality is when internal auditors assess how accurately, consistently and fairly the audit has been performed, as well as how well it detected any fraud (Rane et al. 2024; Aitkazinov, 2023; Issa et al., 2016). Essentially, how well an audit is done is measured by how much it meets professional standards and gives dependable, objective proof of the financial information (Antwi et al., 2024; Aitkazinov, 2023; Tiron-Tudor & Deliu, 2022; Earley, 2015). When audit quality is high, the audit process finds and fixes errors, is timely, efficient and ensures clients and regulators trust the audit. For AI tools to be accepted in technology-enabled audits, they should help with accuracy, error reduction, fraud detection and improve the flow of processes, without losing the credibility or transparency of the audit results.

2.4.2 Theoretical and Empirical Support for Mediation

Studies are increasingly indicating that the way users perceive the outcome quality can act as a mediator for the link between technology perceptions (PU and PEOU) and behavioural intention (Al-Fraihat et al., 2020; Aboelmaged, 2010; Lin et al., 2007). Theoretically, if users think a system is easy to use and helpful, they are more likely to see their results as of high quality, which may then lead to their desire to use the technology. For instance, Lin et al. (2007) showed that people's satisfaction and intention to use e-learning were influenced by how easy they found it and how useful they thought it was, and these were further mediated by how they perceived the system and information quality. Aboelmaged (2010) showed, in a study of ERP systems, that how useful a system is seen and how much it improves outcomes are what affect the decision to adopt it. Al-Fraihat et al. (2020) also found that, in the case of online learning platforms, TAM constructs affected users' intention to use digital tools mainly through service quality and how users perceived the outcomes.

The results indicate that, in cases of adopting technology for health, education and organisations, people's beliefs about system quality (PQ) often play a key role in transforming positive perceptions of a system (PU and PEOU) into an increased intention to use it. Although mediation through AI is used in various industries, it is a new idea in auditing and its use is not well established.

Audit quality serves as a mediating variable between PU and PEOU on one hand, and behavioural intention (BI) on the other, because PU and PEOU significantly enhance the effectiveness, efficiency, and trustworthiness of audit processes, thereby improving audit quality (Al-Ateeq et al., 2022). Enhanced audit quality, in turn, builds trust in the audit function and increases the likelihood of continued or future adoption of AI tools in auditing, aligning with the behavioural

intention construct (Hachem & Sujud, 2020; Qader & Cek, 2024). This is consistent with prior IS success and TRAM-based studies, which recognise quality-related constructs as mediating variables between system perceptions and user behaviour (Lin et al., 2007; Al-Fraihat et al., 2020).

The rationale for positioning audit quality as a mediating variable is supported by extended TAM and IS success models (e.g., DeLone & McLean, 2003; Lin et al., 2007; Al-Fraihat et al., 2020).

These frameworks assert that technology perceptions not only influence behavioural intention directly but also operate through perceptual or performance-related outcomes, such as system quality, output quality, or satisfaction, which in turn shape the user's intention to continue using the system.

In this vein, PU and PEOU positively influence the perceived improvement in audit processes, such as increased accuracy, timeliness, fraud detection, and decision-making support. These improvements directly enhance the perceived or actual audit quality, which acts as a reputational and professional benefit in the auditor's context, ultimately increasing their behavioural intention to adopt or rely on the technology in question.

This logic aligns with the model (Lin et al., 2007), which supports the integration of domain-specific outcome constructs (like AQ) into the TAM framework as mediators between perceptions and intentions.

2.4.3 Gaps in Literature

While studies in other sectors show that perceived audit quality affects behavioural intention, there are few investigations of this relationship in the auditing sector. A lot of the studies that use TAM3 or similar tools in auditing only examine the direct effects of systems on adoption intentions or

don't include outcome quality as a variable. Because of this, it is unclear how internal auditors' opinions about using AI in audits affect their readiness to adopt AI-driven tools. Empirically examining perceived audit quality as a mediator helps address a missing point in the literature and provides fresh explanations for how technology affects professional auditors' behaviour.

2.5 Lebanese Context: AI Adoption in Local Auditing Firms

The adoption of AI-driven audit methodologies encounters multiple obstacles that Lebanese audit firms must overcome (Almaqtari et al., 2024). The main challenge stems from the scarcity of skilled auditors who possess AI expertise and training capabilities. Lebanese audit professionals lack formal training in AI technologies; because of this, they struggle to incorporate AI effectively into their professional work (Moustafa Abdallah et al., 2024). Auditing professionals face a skills deficit because they either do not accept AI technology due to their unfamiliarity or use AI systems improperly because they do not comprehend their capabilities (Wolniak & Stecuła, 2024).

Lebanese auditing firms face significant resistance against adopting changes among their personnel. Traditional auditors view AI as a danger to their employment security because they believe robotic systems will take over important auditing choices. The resistance to AI adoption tends to slow down implementation, especially in organizations which do not receive sufficient leadership backing for technological innovation (Bou Reslan & Jabbour, 2024). Audit firms need to demonstrate that AI functions as a tool which enhances human auditor capabilities instead of replacing human auditors. Training programs focused on AI technology together with organizational support for technological evolution will help auditors understand AI as a tool that enhances their work instead of disrupting their tasks (Anomah et al., 2024).

The implementation of AI technology in Lebanon faces major difficulties due to privacy concerns related to data security and confidentiality. As Diab and El Haj (2024) have reported, Auditing becomes necessary to access large amounts of financial information, driven by AI and necessitating compliance with international data protection standards such as the General Data Protection Regulation (GDPR), raising privacy concerns with cybersecurity threats. Lebanese audit firms need to deploy strong cybersecurity systems alongside encryption standards, data governance structures to protect against AI auditing risk. In the absence of security measures, AI adoption can cause any audit firm to face punitive legal actions or adverse reputational consequences in the event of any form of data breach (Sutisna, 2025).

High implementation costs coupled with the limited financial capabilities of small to medium audit firms are the reasons why many Lebanese audit firms are struggling to implement AI systems. AI-powered auditing tools need a lot of expenses in terms of software systems, infrastructure development, as well as employee training programs (Alayli, 2023; Diab, 2021). Large international firms are likely to have the means to invest in the implementation of AI technology; however, smaller firms could struggle to invest in AI technology, as this would create a digital divide in the auditing industry. To bridge this gap, government incentives, industry collaborations, or academic partnerships could potentially offer affordable AI solutions or training programs for the Lebanese auditing firms (Alayli, 2023; Diab, 2021).

2.6 Conceptual Model and Hypotheses Development

Given the rising integration of Artificial Intelligence (AI) into audit functions, there has been a huge spike in academic interest in understanding the implications for audit quality. In this section, by employing the theoretical background discussed earlier, namely the TAM, hypotheses are formulated addressing the impact of AI on different aspects of audit quality. Existing empirical

and conceptual evidence upholds the hypothesis that AI leads to better audit quality in three ways: Enhancing accuracy, fraud detection capability and operational efficiency (Issa et al., 2016; Fedyk et al., 2022; Kokina et al., 2025). The subsequent subsections are a synthesis of literature to justify the Hypothesis for this study.

2.6.1 Conceptual Model Diagram

The main idea behind this research is to explore the impact of AIs on how well audits are executed in Lebanese private sector organisations. It sets out how PU, PEOU and BI are connected, using perceived AI quality as a driver, in view of the limitations posed by regulations, knowledge and resources in Lebanese auditing. It begins with the Technology TAM and demonstrates the way internal auditors include AI in their work based on their attitudes and experiences. The conceptual framework maps out these relationships to offer a structured way to study AI practice adoption in auditing and what enables organisations to implement auditing practices with AI without disrupting their auditing practices. This research contributes to the conversation on digital transformation in auditing while furthering empirical research to guide AI integration strategies in Lebanon’s niche auditing space.

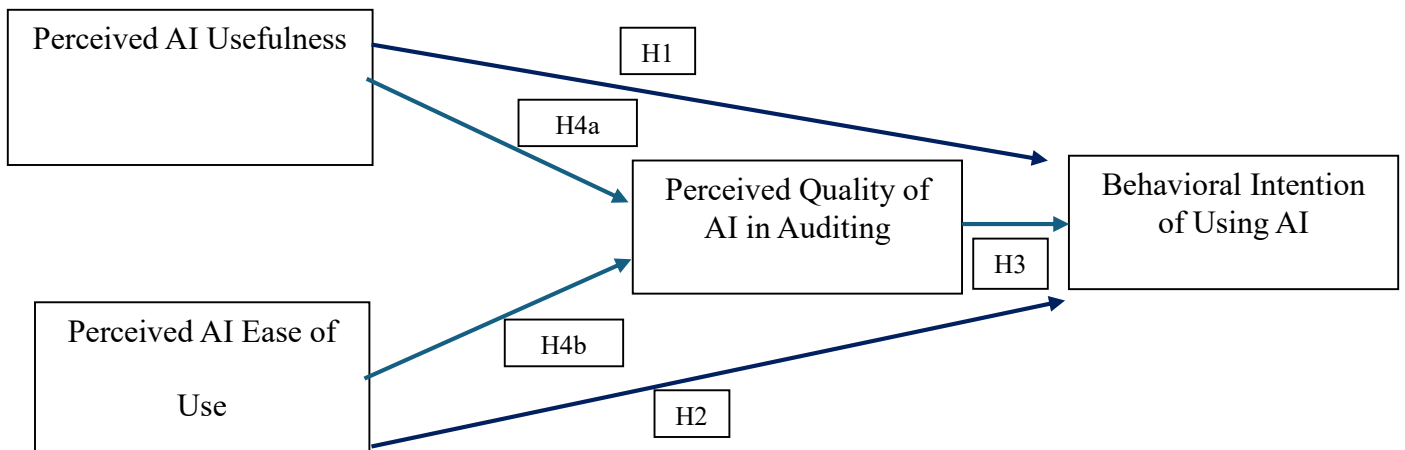


Figure 1: Research Conceptual Framework

2.6.2 Hypotheses Development

2.6.2.1 Perceived Usefulness (PU) and Internal Auditors' Behavioural Intention: Internal Auditors' Behavioural Intention to Adopt AI

According to the Technology Acceptance Model, Perceived Usefulness can be considered one of the core constructs. To the extent to which an employee believes that the use of specific technology will lead to the enhancement of the performance of his/her job. In terms of auditing, PU shows internal auditors' expectations that AI tools would provide benefits in terms of efficiency, accuracy, risk detection, and audit work quality overall.

In fact, according to the research, auditors consider that AI can be used to automate more routine tasks such as data extraction and risk assessment, which can save time and boost efficiency. For example, in the United Arab Emirates (UAE), a study links auditors' preference for AI in fraud detection and risk assessment (El Alaoui & Izza, 2024; Al-Shboul & Al-Shboul, 2022). Also in Jordan, auditors find Assisted and Augmented AI useful but have lower confidence in Autonomous AI systems. As in Lebanon, where there will only be scarce resources for auditors, they might be of the same opinion but choose those that relate to their local issues, for instance, gaps in regulations (El Alaoui & Izza, 2024; Al-Shboul & Al-Shboul, 2022).

PU has throughout been found to be a strong predictor of technology adoption in auditing, based on empirical research. Issa et al. (2016) found that it was more likely to use AI tools (BI) for analytics tasks was found in auditors who thought it beneficial. Similarly, Kokina et al. (2025) found that AI allows auditors to manage complex datasets, as well as illuminate hidden risks, and so improve the functioning of the audit. From a theoretical perspective, if auditors consider AI as

useful for identifying errors, eliminating bias, or automating basic time-consuming procedures, they are likely to consider it as contributing to increased audit quality outcomes (Munoko et al., 2020; Al-Omush et al., 2025).

While audit tasks become more data-intensive, auditors' belief in the value of AI becomes of utmost importance. However, their perception of audit quality in the integrated AI environment is positively affected when they expect AI to result in more thorough and trustworthy audits (Aitkazinov, 2023; Gautam, 2023; Antwi et al., 2024).

Thus, PU directly affects behavioural intention to use a system. The TAM framework indicates that users will adopt technology if they think it will improve their job performance (Whiting et al., 2012; Onwubuariri et al., 2024, etc.). Out of the many studies that validate this relationship in the auditing domain, a few include Vasarhelyi et al. In 2015, research showed that auditors who viewed AI as having an advantage in fraud detection, data analysis, and reporting encouraged more of its use in their routines.

The fact that usefulness is related to intention is a key determinant for long-term adoption. Auditors are more likely to make an investment of time and effort to adopt AI tools, even in challenging environments, if they believe the tools can improve audit quality and depth (Appelbaum et al., 2021). In a transitional economy, such as Lebanon, where infrastructure is limited and often resistance to change is still found in its wake, the perception of the utility may overshadow initial scepticism.

Based on this body of literature, the following research hypothesis is expected:

H1: There is a positive relationship between internal auditors' perceived usefulness of AI tools and their BI for AI Adoption.

2.6.2.2 Perceived Impact of Perceived Ease of Use (PEOU) on Internal Auditors' Behavioural Intention to Adopt AI

In other words, it is the degree to which a person believes that using that system will be effortless (Davis, 1989). In the field of auditing, this construction represents the degree to which internal auditors perceive AI tools to be intuitive and easily accessible for them. TAM propose that apart from PEOU impacting behavioural intention directly, it is also a determinant of PU, especially in the first steps of technology adoption (Fedyk et al., 2022; Al-Omush et al., 2025).

This relationship is supported by several studies conducted in the accounting and auditing area. In a recent experiment by Appelbaum et al. (2021), they found that if AI systems are easy to learn, can be learned quickly, and are user-friendly, auditors are more receptive to the idea. Those auditors who see AI technologies as harder to use tend to use less of their functionality and therefore tend to have a lower usage intention with respect to the AI technologies (Venkatesh & Davis, 2000). In the Lebanese audit context, ease of use becomes very important as it will be a barrier to adoption (Bou Reslan & Jabbour, 2024), given the limited training resources and infrastructure challenges.

This is especially so for professional domains, such as auditing, where decision makers make adoption strategies based on perceived training effort, system complexity, and compatibility with existing tools (Kokina et al., 2025). This relationship is supported by prior studies (Earley, 2015; Afrin et al., 2024). For example, auditors in the audit profession are more likely to adopt and continue to use the AI tools if they think that the learning curve is low and the interface is easy and convenient to use (Sabek et al., 2024). In a place such as Lebanon, where AI is just starting, perceived ease of use can either be the facilitator or the psychological barrier to future adoption.

The more internal auditors believe AI tools are easy to use in future audit processes, the more likely they will realise the benefits of those AI tools and link them with improved audit outcomes.

H2: There is a positive relationship between internal auditor' perceived ease of use of AI tools and their BI for AI Adoption.

2.6.2.3 Perceived Impact of Audit Quality of AI on Auditors' Behaviour Intention Towards AI

Although AI is changing the way auditors conduct their work, its effectiveness in this area will be judged by whether it significantly enhances audit quality (Fedyk et al., 2022; Celestin & Vanitha, 2019). In this situation, perceived audit quality includes the accuracy and reliability of the findings, the uniformity and efficiency of the audit approach, the capacity to find fraud efficiently and, most importantly, the way to preserve or raise stakeholder trust. Using AI is important for internal auditors because they trust it will help them achieve the main objectives of their field (E.g., Babalola et al., 2022; Holm & Zaman, 2012).

According to previous studies, people are more likely to accept new technology if it improves how they do their main tasks (Putrevu & Mertzanis, 2024; Schweisfurth & Herstatt, 2016; Nambisan et al., 1999). As the consequences of errors can be severe in auditing, the opinions people have about quality are especially important. Given that AI tools are believed to lower error rates, speed up audits and produce reliable evidence, auditors are more eager to use them as part of their routine (Kordzadeh & Ghasemaghaei, 2022; Munoko et al., 2020). If the effect of AI on audit quality is seen as minor or unclear, then people are less willing to adopt it, no matter what trends are happening in technology. It underlines the fact that the acceptance of technology by auditors largely depends on their perception of audit quality.

In addition, research and practical experience confirm that how auditors are seen can directly influence a company's willingness to use AI. Auditors work in an area governed by both professional standards, laws and concerns about their reputation (Dixon et al., 2004). Being confident that AI tools do not harm the quality of audits is what makes auditors willing to use them

(Murikah et al., 2024). At times, not trusting AI's secrets, worrying about data quality or being unsure about the transparency of AI-made evidence can make people less willing to use it, despite its other benefits (Labajová et al., 2023). So, to use AI in auditing successfully, it is essential to prove that audit quality has increased.

Based on these considerations, the following hypothesis is proposed:

H3: Perceived Audit Quality of AI positively influences Behavioural Intention (BI) to adopt AI in auditing.

2.6.2.4 PQ of Artificial Intelligence Mediation Between PU, POEU and Auditors' BI on AI Usage

Apart from this, the literature indicates that auditors' perceived audit quality helps explain the connection between how they view AI and its usefulness and their real plan to integrate it into their practice (Tritama et al., 2025; Almaptari et al., 2024). TAM and research from similar areas confirm that PU and PEOU are important beliefs that affect how people first feel about new technology. But in auditing and similar fields, these beliefs become adopted when they are seen to improve the quality of the results (Al-Ateeq et al., 2022). In short, a tool may be easy to use and helpful, but unless it is believed to enhance the quality of audits, people might not feel motivated to use it (Almaptari et al., 2024).

It has been observed in many empirical studies from different industries. Studies in health informatics, enterprise resource planning and digital learning environments have found that the relationship between PU and PEOU and adoption intention is commonly mediated by how good people think the technology is (Lin et al., 2007; Aboelmaged, 2010; Al-Fraihat et al., 2020). This insight matters a lot in auditing because there is a strong focus on professional standards and results

that can be proven. Merely being seen as useful or easy to use is not enough; what encourages auditors to use an AI tool is its actual or predicted effect on their work.

Since organisations in Lebanon may face limited resources and changing laws, the mediation effect plays a bigger role. Some auditors may not be convinced to use AI only because of the buzz or because they are told to do so by managers. Rather than relying on AI itself, these stakeholders expect to see that AI tools will improve the quality and efficiency of their audits. This explains why how AI is perceived in audit processes is so important for deciding whether to use AI in actual behaviour.

Accordingly, this study advances the following mediation hypotheses:

H4: Perceived Audit Quality of AI mediates the relationship between Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioural intention (BI).

- H4a: Perceived Audit Quality mediates the effect of PU on BI.
- H4b: Perceived Audit Quality mediates the effect of PEOU on BI.

2.7 Challenges and Ethical Considerations

2.7.1 Regulatory Standards and Compliance (e.g., IAASB)

Onwubuariri et al. (2024) noted that regulatory compliance is a huge hindrance to the adoption of AI in auditing since the existing auditing standards do not enable AI-based decision making. That is, the International Auditing and Assurance Standards Board (IAASB) and Public Company Accounting Oversight Board (PCAOB) are in the process of determining appropriate standards for the implementation of AI in auditing (Li & Goel, 2025; Munoko et al., 2020). However, there are hindrances in the implementation of AI in Lebanon as audit firms face legal uncertainties about the use of AI in financial reporting (Rizk, 2020). If there are no specific guidelines for AI audits

from regulatory bodies, that may pose a risk of legal challenges that companies may face and prevent them from adopting full AI technology.

Since Lebanon does not have the needed AI regulation frameworks in place, it blocks the implementation of AI in auditing. In Lebanon, there are no yet established rules defining the proper procedures to follow for the execution of AI-driven audit, and verification and validation methods. Because of the lack of AI-specific audit regulations, there will be legal uncertainties in general situations related to the possibility of AI generating an audit report and the potential liability of the auditors when those AI-based tools are utilised for making decisions. Besides, an automated decision-making risk emerges.

The Lebanese audit sector operates by the standards of International Standards on Auditing (ISA) as well Lebanese Association of Certified Public Accountants (LACPA) issued guidelines. However, there are no explicit guidelines to utilise the methods for AI-driven auditing. When it comes to the application of AI for risk assessment and fraud identification procedures and financial statement validation procedures, the audit firms are faced with ambiguity as to how AI fits within auditing standards. Because there are no clear regulations on AI use, companies may refrain from deploying complete AI-driven audit systems, which could bring opportunities for AI in auditing.

The complex economic environment in Lebanon makes it difficult for businesses and their financial institutions to operate, as the country has experienced financial instability, currency fluctuations, and inconsistent regulations. The unstable economic situation in the region makes it difficult to apply AI because of the need for audit firms to deal with regulatory uncertainty and certify that their AI systems comply with local compliance rules. To implement AI in auditing, we demand the creation of an AI policy via audit regulations directed at AI and governance mechanisms and training programs for auditors to learn about the ethics of AI and professional

standards. Regular monitoring of audits executed utilising AI would lead to coherent audit practices and maintain professional standards within their ranks.

2.7.2 Data Privacy and Security Risks

The auditing process with AI technology requires extensive processing of confidential financial data, which creates privacy and security risks for both auditors and their clients (Aitkazinov, 2023). Audit firms have the responsibility to confirm that their AI tools match the requirements of the General Data Protection Regulation (GDPR) and all Lebanese data privacy laws. The deployment of AI systems faces challenges regarding cybersecurity because hackers may make them vulnerable through data breaches or successful attacks against their algorithms or seek access to protected financial information. To minimise security risks, firms need to establish strong security systems which combine data encryption with access control protocols (Tikkinen-Piri et al., 2018).

2.7.3 Ethical Concerns

The ethical dimensions of using AI in auditing represent a significant obstacle for auditing professionals. Algorithmic bias represents a main ethical issue because AI systems can inadvertently show a preference for specific outcomes from biased training information (Kordzadeh & Ghasemaghahi, 2022). The use of incomplete or unrepresentative datasets for training AI systems will produce unintended biases within audit risk assessments that might result in discriminatory or false conclusions (Krause, 2024). Auditors face ethical dilemmas regarding their professional judgment when they heavily depend on AI systems in auditing processes. Auditors should avoid accepting AI recommendations without a proper assessment because this practice weakens the human oversight required to maintain professional auditing standards (Adelakun, 2022). The adoption of ethical AI demands that organisations find an equilibrium

between machine automation and human expertise, so AI helps auditors make decisions rather than taking over their functions entirely.

2.8 Conclusion

This chapter's literature review reveals that, despite the growing interest in AI in auditing, most studies focus on the primary factors influencing its uptake: perceived usefulness (PU) and perceived ease of use (PEOU). Across many years, studies in auditing, health information systems and public administration have shown that both perceived ease of use and usefulness are reliable at predicting intention to use new technology (BI). In addition, real-world research proves that AI tools can improve audit quality by making tasks more accurate, efficient and effective in detecting fraud and several theories, for example, TAM, TAM2 and UTAUT, have been applied to explain why professionals use new technologies.

Even so, there are still some major unknowns. There is not much knowledge about the details of how people's attitudes toward AI translate into its use in the auditing context. Not many studies have specifically explored how perceived audit quality, which consists of accuracy, uniformity, efficiency and trust, affects the technology acceptance of internal auditors. Most studies have examined the direct outcomes of audits, and when mediation models are used, they usually do not link perceptions of audit outcomes to behavioural intention in a clear, specific way. Lebanon and other developing countries show a bigger gap, since research on how people perceive AI, its impact on auditing, and the intention to adopt it is not yet well established.

By making audit quality the main focus of the link between PU, PEOU and BI, this study addresses a major gap in the literature. Instead of the regular TAM framework, this conceptual model looks at the professional priorities of auditors, giving a better explanation of the reasons and means by

which AI is integrated into auditing. This approach helps by testing the impact of technology perceptions on audit quality, which is not covered by previous research, and is beneficial for firms and officials. This research gives useful information to those who audit, develop technology and create regulations, explaining which conditions make it more likely for AI to improve audit quality and help organisations meet their aims.

Chapter Three: Research Methodology

3.1 Introduction

The methodology adopted to investigate the impact of Artificial Intelligence (AI) on audit quality in the Lebanese private sector organisations, from the viewpoint of internal auditors, is outlined in this chapter. It first presents the form of the research enterprise, and in justifying that form, it explains its philosophical orientation and the methodological structure of the rationale. Aligns the study's objectives, research questions, and Hypothesis with the study's methodological selections are also discussed.

Quantitative research design is adopted as the method of inquiry because of the nature of the research and objectives, which aim at testing Hypotheses based on empirical data. The advantage of this approach is that it allows for the systematisation of the collection and statistical analysis of numeric data that is essential for discovering the relationships between the tools of AI and the different dimensions of audit quality. Structured survey instruments were given to a sample of 100 internal auditors working in the Lebanese private sector firms to support the quantitative design.

Chapter Two: Hypothesis, AI-driven accuracy, fraud detection and efficiency are directly tested using the chapter two survey data. In such a way, the methodology design is deductive, based on starting the study from a hypothesis directly derived from theory and moving on to empirical testing.

3.2 Research Philosophy and Approach

3.2.1 Research Paradigm: Realism

Philosophically, this study is based on the position of realism, that what lies 'out there' is independent of man, but that man's knowledge of the world is influenced by the context,

institutional, and social factors. For auditing research, realism presents a balanced philosophical perspective in that audit quality can be observable and it provides evidence of this fact, but can also be influenced by a wider organisation and technological environment. This philosophical stance allows the researcher to engage the real world in the real world: to deal with phenomena such as AI- AI-empowered audits, without resorting to simplification and discounting of the complexity of professional and institutional settings in which these phenomena emerge.

The realist paradigm advocates for quantitative methodologies which uncover generalizable patterns and test out theoretical constructs with empirical data. To operate realism, a structured survey is used as an instrument that helps to identify auditors' perceptions of how AI tools would impact the accuracy, efficiency, and reliability of accounting audit procedures. The research hopes to contribute to evidence-based practice in an area where technical innovation is advancing very quickly by focusing on measurement and statistically verifiable results.

3.2.2 Justification for the Chosen Methodological Approach

The core methodology adopted in this research is **quantitative**. The primary data collection tool is a **structured questionnaire** administered via Google Forms to a purposive sample of internal auditors. The use of standardised survey items allows for statistical comparison across participants and enhances the reliability and replicability of the findings.

The quantitative design is justified for several reasons:

- It allows for hypothesis testing using measurable indicators (e.g., perceived audit accuracy, fraud detection effectiveness).
- It facilitates generalisation within the studied population (i.e., internal auditors in Lebanon's private sector).

- It supports the use of statistical techniques (e.g., correlation, regression) that can establish the strength and direction of relationships between variables.

3.2.3 Deductive Approach

This research follows a **deductive reasoning approach**, wherein the investigation is guided by a Hypothesis developed from existing theories and prior empirical research. As presented in Chapter Two, four hypotheses were formulated based on the literature: that AI enhances audit quality through accuracy, fraud detection, and efficiency.

In line with this deductive logic:

- The study begins with a theoretical framework rooted in the Technology Acceptance Model (TAM) and innovation diffusion literature.
- This study adopts TAM3 as a reference framework and focuses on its core constructs—PU, PEOU, and BI—while excluding other extensions such as Job Relevance and Perceived Enjoyment for reasons of contextual relevance and model parsimony.
- Hypotheses are formulated based on identified gaps and relationships in the literature.
- Quantitative data is collected to test these Hypotheses through statistical analysis.

The deductive approach is consistent with the study's objectives of confirming or refuting proposed relationships using empirical data, and it supports the broader goal of contributing to generalizable knowledge on the role of AI in audit practice.

3.3 Research Design

The research adopts a **cross-sectional design**, which involves collecting data at a single point in time to examine the relationship between specific variables—in this case, the integration of

Artificial Intelligence (AI) into the auditing process and its impact on audit quality. This design is particularly suitable for the study's objective, which is to evaluate how different AI functions—such as error detection, fraud analysis, and automation—correlate with auditors' perceptions of audit quality. A cross-sectional approach is efficient, time-sensitive, and well-suited for gathering quantitative data from a professional population, such as internal auditors operating under dynamic technological and organisational conditions.

The original proposal supported the potential integration of mixed-method insights, yet the final research approach uses a quantitative foundation only. All qualitative components included in surveys, such as open-ended commentary or participant clarifications, exist to provide additional context that does not support dual analytical approaches. Although the research model incorporates the lessons from depth and contextual analysis, it chooses over breadth and generalizability attributes, which define quantitative studies.

The research explores the relationship between AI and audit outcomes across various firms and sectors in the Lebanese private sector through statistical analysis of structured survey responses. The research data undergoes statistical analysis through descriptive and inferential methods, which enables the researcher to validate the predefined Hypothesis by adopting methodological standards. The research method creates consistency in data collection and enables comparisons between demographic categories and different AI adoption levels and audit quality perception dimensions.

3.4 Population and Sampling

3.4.1 Target Population

Internal auditors from Lebanese private sector organisations make up the complete audience for this research. Internal auditors remain the optimal choice because they work inside organisations, which makes them the first ones to experience the implementation of emerging technologies, including artificial intelligence, during audit functions. As auditors maintain direct visibility into audit processes, they can deliver decisive information about the impact of AI tools on audit tasks that seek compliance and risk evaluation and fraud prevention activities.

Studying the Lebanese private sector brings essential background information to this research project. The economic turbulence alongside regulatory changes and dissimilar levels of technological readiness define Lebanon as a special market environment. Auditors who operate within this region face distinct challenges because of the difficulties in implementing and adapting AI-based systems. Internal auditors from Lebanese organisations provide essential insights about the technological opportunities and obstacles that AI presents during this time of varying digital transformations across the region. The study specifically includes this population to ensure its findings align with both the needs of audit professionals and the requirements of policymakers working in conditions of transition and constrained resources.

3.4.2 Sampling Technique

The study required participants through convenience sampling as a non-probability sampling approach. The research method selection emerged from two practical demands: the inability to access a centralised auditor database and a requirement to collect data quickly. Professional

networks, alongside LinkedIn, enabled researchers access to participants who voluntarily joined the study, along with direct communication with audit departments in private firms.

The convenience sampling method produces results with constrained generalizability for the whole Lebanese internal auditing sector but provides efficient methods for testing out initial relationships and theoretical testing. The standardised survey questions maintain analytical strength for describing statistics and conducting inferential statistics on the gathered data.

In addition, the sample was monitored for diversity across sectors and firm sizes to enhance the representativeness of the findings. Where possible, auditors from various industries—such as finance, manufacturing, healthcare, and retail—were included to capture a broad view of AI implementation in the Lebanese private sector.

3.4.3 Sample Size

The sample size for this study is *100 internal auditors*, consistent with the scope and scale of a master s-level or early-stage doctoral research project. This number balances feasibility with the need for sufficient statistical power to test the study’s three core hypotheses using basic inferential techniques, such as correlation and linear regression analysis.

The sample size is justified on both practical and methodological grounds. First, access to internal auditors in Lebanon is limited by organisational gatekeeping and confidentiality concerns, which restrict large-scale random sampling. Second, many prior studies exploring similar themes, particularly in the context of emerging economies or niche professional groups, have achieved meaningful results with samples in the range of 100 participants (e.g., Munoko et al., 2020; Al-Omush et al., 2025). As such, the sample size is sufficient to identify key patterns and draw

preliminary conclusions about AI's perceived impact on audit quality, while acknowledging the study's exploratory nature.

Efforts were made to ensure a balance of demographic and professional characteristics, such as years of experience, industry type, and level of AI exposure, to enhance the reliability and applicability of the findings.

Because of this, the research used a sample selected for its relevance, consisting of internal auditors carrying out work in Lebanon's audit sector. The survey was open to people who work in auditing and have some experience or training with artificial intelligence or digital systems used in auditing. Professional audit networks, industry associations and contacts in audit firms were used to spread invitations, so the study's sample covered a wide range of perspectives. They were informed to survey on their own, without discussing the questions with anyone else at work. Moreover, the survey introduction told participants what the research was trying to achieve and stressed that each response should be honest and individual. Just those surveys that met the qualifying standards were used in the study. These procedures were designed to minimise bias, reduce the risk of common method variance, and enhance the credibility of the resulting data, supporting the study's empirical robustness.

3.5 Data Collection Methods

A structured self-administered questionnaire is used as the main data collection tool in this study for the collection of quantitative data from internal auditors in Lebanese private sector organisations. From literature-derived constructs and the Hypothesis developed in Chapter Two, the questionnaire was developed to be in alignment with theory and empirical inquiry.

Close-ended questions via the five-point Likert scale survey instrument are used to gauge the AI adoption rate and promote the mechanism's impact on audit quality. Auditor perceptions can be ascertained with a Likert scale, such that our response ranges from 1 (strongly disagree) to 5 (strongly agree) and can be more rigorously analysed, both in terms of central tendency and variability. The questionnaire also contains multiple-choice questions to assess demographic and professional characteristics of the participants, including age, gender, years of audit experience, industry sector, and familiarity with AI tools, in addition to Likert scale items. Used to segment the data and to examine some potential moderating effects.

Academic and professional experts reviewed the English questionnaire to ensure that the questionnaire was clear, and its face validity ensured that it aligned with the objectives of the study. Upon finalisation, the surveys were distributed using Google Forms, which is an easy-to-use online tool for distribution and data collection purposes. Given the geographical dispersion of participants and ongoing logistical constraints in terms of access to organisations, this method was particularly appropriate. The survey link was distributed through email and professional networks (LinkedIn) to populate this survey with responses from current professionals in the field of internal auditing.

3.6 Design, Measurement Techniques, and Validity and Reliability of the Questionnaire

Carefully structured design of the questionnaire is used to measure the perceptions of internal auditors about the adoption of AI in enhancing audit quality among the Lebanese private sector. It includes a series of sections for the overall evaluation, including demographic and professional information, and independent variables like PU, PEOU, BI to use AI, and the mediation impact of PQ of AI in Auditing. The objective of the dependent variable is the BI of AI usage as a tool to enhance audit quality. The language used in the questionnaire is clear and concise, and therefore easily understood by participants. Most statements are measured with a Likert scale that ranges

from 'Strongly Disagree' to 'Strongly Agree,' allowing accurate measurement of respondents' attitudes. To get an overview of your familiarity with AI tools, categorical and binary questions are also included, along with demographic questions.

Accuracy and reliability of responses are maintained using various measurement techniques. A Likert scale is used for quantifying participants' perceptions systematically, which is then subjected to statistical analysis of trends and correlations. Binary questions are used to gauge basic experience/work with AI, and categorical questions are used to give context on the demographic and experience of the respondents. The responses should be based on the beliefs and knowledge of participants to use self-reported data. Also, every questionnaire is pre-tested before administering the questionnaire to ensure clarity and comprehension of every item. A pilot study may include further work on the wording and structure of questions so that they capture the relevant information.

Some methodological approaches are undertaken to ensure the validity and reliability of the questionnaire. Questions are designed upon well-known theories, for example, the TAM, and validated with panel members of experts in auditing and AI for relevance. Survey items are aligned to the theoretical frameworks that measure the BI towards adoption of AI in professional settings to maintain construct validity, so that the questionnaire captures conceptualisations of perceived usefulness and ease of use. Methods to test reliability include Cronbach's alpha to check the internal consistency, whether responses for similar items remain stable from one participant to another. In addition, test-retest reliability could be conducted by administering the questionnaire to some of the respondents at different times to determine the reliability of their responses.

This table (Table 1) provides a structured overview of the research instrument, detailing its components, purpose, question types, and measurement scales.

Table 1: Variables Measurement

Section	Purpose	Type of Questions	Measurement Scale	Source
Introduction	Provides an overview of the study and invites participation.	Informational, Consent Agreement	Binary (Agree/Do Not Agree)	-----
Sampling Questions	Assess participants' experience/work with AI types.	Multiple-choice (Yes/No)	Binary (Yes/No)	-----
Independent Variables	Evaluate perceptions of AI adoption in auditing.	Likert scale-based statements	5-point Likert Scale (1–5)	TAM model
Perceived Usefulness (PU)	Measures the expected benefits of AI in auditing.	Likert scale statements	5-point Likert Scale (1–5)	TAM model
Perceived Ease of Use (PEOU)	Assesses the anticipated ease of AI adoption.	Likert scale statements	5-point Likert Scale (1–5)	TAM model
Behavioural intention to Use AI (BI)	Evaluates the likelihood of adopting AI in audit processes.	Likert scale statements	5-point Likert Scale (1–5)	TAM model
Demographic & Professional Information	Collects background details about respondents.	Multiple-choice, Categorical	Nominal Categories	-----

3.7 Data Analysis Techniques

Once the data is collected, it is extracted to Google Sheets and cleaned for accuracy and completeness. In this regard, the Statistical Package for the Social Sciences (SPSS) was used to analyse data, because it is the most common statistical software used to analyse data in quantitative research. In the next two stages, the data analysis is carried out as follows: descriptive statistics and inferential statistics.

The basic features of the dataset are summarised and described using descriptive statistics. Key variables were analysed to provide a basic look at auditor response measures (e.g., mean, standard

deviation, frequency distributions) and trends. These summaries provided some initial insights into how internal auditors see AI's effect on their work.

Inferential statistical techniques were used to test the research Hypothesis. The TAM dimensions (PU and PEOU) and BI through BI are examined by investigating the strength and direction of the relationship between them. Second, linear regression analysis was applied to determine the degree to which each AI-related variable predicts audit quality. With these techniques, the researcher was able to accept or reject the hypothesis as a function of statistical significance and model fit.

This research uses descriptive and inferential statistical analyses to conduct the study using SPSS. The application of these techniques allows for a full examination and testing of the relationships between study variables.

3.7.1 Descriptive Statistics

Initially, descriptive statistics are conducted to summarise and describe the data that is collected. It entails calculating measures such as mean, median, standard deviation, minimum, maximum, frequency distributions, percentages, and range of all variables and demographic characteristics of respondents. Descriptive analysis yields insight into the central tendencies and variability of collected data, provides an overview of the characteristics of a sample, and guides subsequent analytical procedures.

3.7.2 Reliability Analysis

The internal consistency and stability of the measurement scales used in the study will be analysed using reliability analysis. The primary measure of reliability is Cronbach's alpha coefficient (α). Generally, a Cronbach's alpha coefficient of over 0.70 is judged acceptable as the measurement instrument provides a reliable measurement of the underlying construct (Hair et al., 2019).

3.7.5 Multiple Regression Analysis and PROCESS

The principal statistical method for testing the Hypothesis in Chapter 2 is multiple regression analysis. The results of this analysis indicate the extent how which each one of these independent variables independently predicts the fluctuations of perceived audit quality.

By calculating the regression coefficients (β), the magnitude and significance of each of the independent variables in influencing the dependent variable can be determined. Significance tests (t-tests) are performed on observed relationships to ensure that these relationships are statistically significant ($p\text{-value} < 0.05$). Furthermore, the regression model is assessed on the overall explanatory power of the model using the coefficient of determination (R^2) to know the proportion of variance in employee performance that is jointly explained by the independent variables (Hair et al., 2019).

Model 4 from the PROCESS macro for SPSS was employed, as it can test the mediating impact of perceived audit quality (AQ) in the connection among perceived usefulness (PU), perceived ease of use (PEOU) and behavioural intention (BI) to adopt AI. PROCESS Model 4 is well known for being both strong and easy to use when running tests on single-mediator models using ordinary least squares (OLS) regression. As a result of using this statistical technique, the study could figure out how AQ affects the relationship between PU and PEOU and BI. Using 5,000 samples for the bootstrapping, we created reliable, bias-corrected confidence intervals for the indirect effects to be sure the mediation analysis results were accurate. This method makes it possible to test the mediating effects of variables and improves understanding of the factors driving AI adoption by internal auditors.

The mediation analysis controlled a number of demographic and contextual variables to take into consideration the possible confounding effects. The control variables, which include age, gender, industry sector, years of professional experience, and previous usage of AI tools, were dummy-coded to allow inclusion in regression-based models. No control variable was included for education level, as the participants had similar educational backgrounds being internal auditors. In particular, age was recoded so that age of the respondents who were younger than 40 years was coded as 0 and 40 or older were coded as 1; gender was recoded so that female respondents were coded as 0 and male as 1; and industry was recoded so that the manufacturing organizations were coded as 0 and non-manufacturing organizations as 1. The other categorical controls were coded similarly in binary. By including these dummy variables in the PROCESS Model 4 analyses, the study was capable of accounting for background differences and identifying the unique influence of each of the perceived usefulness, perceived ease of use, and perceived audit quality on behavioural intention. This will increase the validity and strength of the mediation results as the impact of extraneous variables will be reduced.

3.8 Ethical Considerations

In order to protect the rights of the participants and the integrity of the research process, this research abides by the standard set of ethical guidelines that pertain to social science research. Consent was obtained from all participants by exposing them to a clear consent statement at the start of the survey, explaining the purpose of the study, the voluntariness of participation, and the anonymity of their answers.

No identifying information, such as a name, organisation name or contact details, is collected in order to maintain confidentiality. The responses were stored securely on a password-protected

device that only the researcher had access to. The data collected will be kept only for academic purposes and will be deleted after a period of time as per the data protection guidelines.

Formal Institutional Review Board (IRB) approval was not required for this study due to its minimal risk classification and the absence of vulnerable populations, but ethical approval was granted by the supervising institution, and all ethical protocols followed those expected by the university research standards.

3.9 Chapter Summary

This chapter is presented as a study of the influence of Artificial Intelligence on audit quality in the Lebanese private sector. To test empirically the stated three hypotheses (i.e., AI-driven accuracy in sales projections, fraud detection, and efficiency) of the study, a cross-sectional, quantitative design was implemented. Based on the realist paradigm, the study used deductive logic and structured questionnaires for collecting quantifiable data for internal auditors.

The sampling techniques, sample size justification, the target population, the data collection tools, as well as the distribution of the tools, were all detailed in the chapter. It also described the statistical methods used to analyse the data, such as descriptive and inferential methods and put measures in place to ensure validity and reliability. Ultimately, it discussed the ethical issues that informed participant recruitment, data management, and study conduct.

In the next chapter, the data is analysed based on Hypothesis Testing and its implications for the results in terms of the research objectives and the Hypothesis.

Chapter Four: Data Analysis and Hypothesis Testing

4.1 Introduction

For the last section, the chapter presents the outcomes of the analysis on how AI influences internal auditors, examining the role of faith in the outcome. The purpose of the first part is to give a demographic overview of the respondents; the second part provides basic statistics of key study factors. Instruments were tested again by using both reliability and validity tests to ensure the instruments are valid for measuring the variables they are designed for. To analyse the relationships among the key variables and with our research Hypothesis, we carried out correlation analysis and regression analysis. In addition, the article discusses how hypothesis testing and the associated results from the Hypothesis test relate to the underlying theory and previous studies. This chapter, therefore, serves as the basis upon which, in Chapter Five, discussion, conclusions and recommendations are drawn.

4.2 Demographic Frequencies

It explains the demographics of the internal auditors, including their gender, how old they are, how much work experience they have, their sector of employment and if they use AI in their jobs. Knowing these features helps us identify if the sample is typical and how varied the respondents were. Screening for AI knowledge was carried out so that people without AI backgrounds could not take part in the study. This is probably the criterion for being familiar with AI technologies. After completing the demographics, it was clear that these criteria helped to pick an effective and reflective group for the research project.

You can find the ‘demographic’ numbers of the internal auditors who took part in the study, with statistics on gender, age, experience, their field and how much they used AI tools. It is helpful to

check the demographic groupings of the respondents to help judge the scope and reliability of the sample. Below are the results:

The respondents were distributed between 36% females and 64% males, as indicated in Table 2.

Table 2: Gender

Gender		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	36	36.0	36.0	36.0
	Male	64	64.0	64.0	100.0
	Total	100	100.0	100.0	

Most respondents in the survey were aged 30 to 39 (46%), and the group aged 40 to 49 was second with 26%. This tendency means that most respondents are already in mid-career, which suggests they have a better understanding of and access to tools that use AI.

Table 3: Age Range

Age Range		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	20-29	14	14.0	14.0	14.0
	30-39	46	46.0	46.0	60.0
	40-49	26	26.0	26.0	86.0
	50+	14	14.0	14.0	100.0
	Total	100	100.0	100.0	

Table 3 gives details about the professional backgrounds of the auditors. About half of those surveyed (54%) had worked in internal auditing for 3 to 5 years, and 26% had spent 6 to 10 years in the field. A relatively smaller portion had experience with teaching that lasted 10 years or over (12%), while just around 8% had experiences of 3 years or fewer. Most respondents with mid-level

experience agree with the participants' age and underline that they can properly explain and discuss AI use in auditing.

Table 4 Year of Auditor Experience

Years of Internal Audit Experience		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 3	8	8.0	8.0	8.0
	3-5	54	54.0	54.0	62.0
	6-10	26	26.0	26.0	88.0
	More than 10	12	12.0	12.0	100.0
	Total	100	100.0	100.0	

A range of industries were covered by the respondents, as is shown in Table 5. Most employers (50%) came from the manufacturing business, then 22% from banking and 20% from retail, leaving 8% to be classified as “Other.” Most of the study’s participants come from manufacturing, so the results may explain practices mostly from that area, but adding other industries helps the findings apply to a broader group of people.

Table 5: Auditor Industry

Industry Sector		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Banking	22	22.0	22.0	22.0
	Manufacturing	50	50.0	50.0	72.0
	Retail	20	20.0	20.0	92.0
	Other	8	8.0	8.0	100.0
	Total	100	100.0	100.0	

In Table 6 below, you can see that one-third of auditors (30%) are just starting with AI tools, another third (32%) have intermediate knowledge, and the final section (22%) has high-level

experience. Surprisingly, only 16% of people said that they had no religion. Most people who answered the survey are familiar with using AI tools. Still, it looks like most respondents understood AI tools, which support using them in auditing processes and continue the focus on the following parts of the questionnaire.

Table 6 Level of Work/Experience with AI Tools

Level of Work/Experience with AI Tools		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	None	16	16.0	16.0	16.0
	Basic	30	30.0	30.0	46.0
	Intermediate	32	32.0	32.0	78.0
	Advanced	22	22.0	22.0	100.0
	Total	100	100.0	100.0	

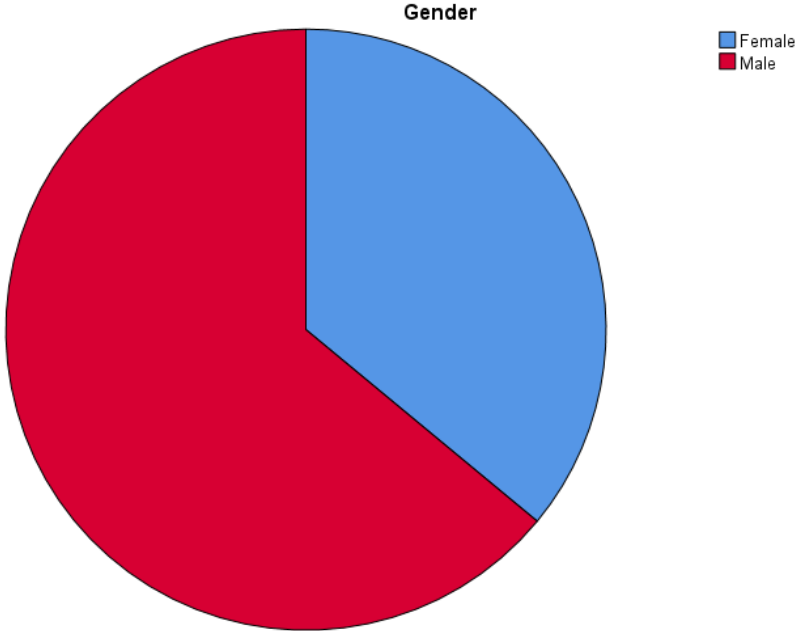


Figure 2: Gender

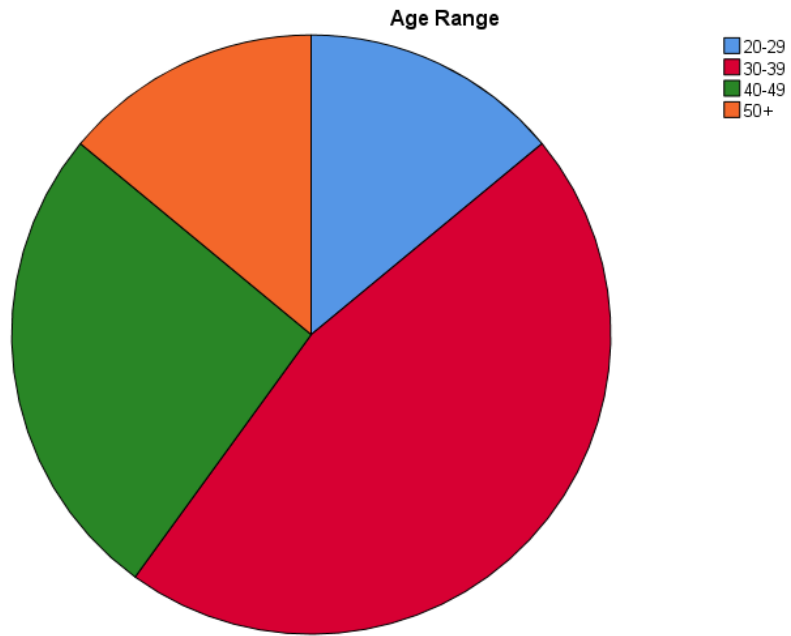


Figure 3: Age

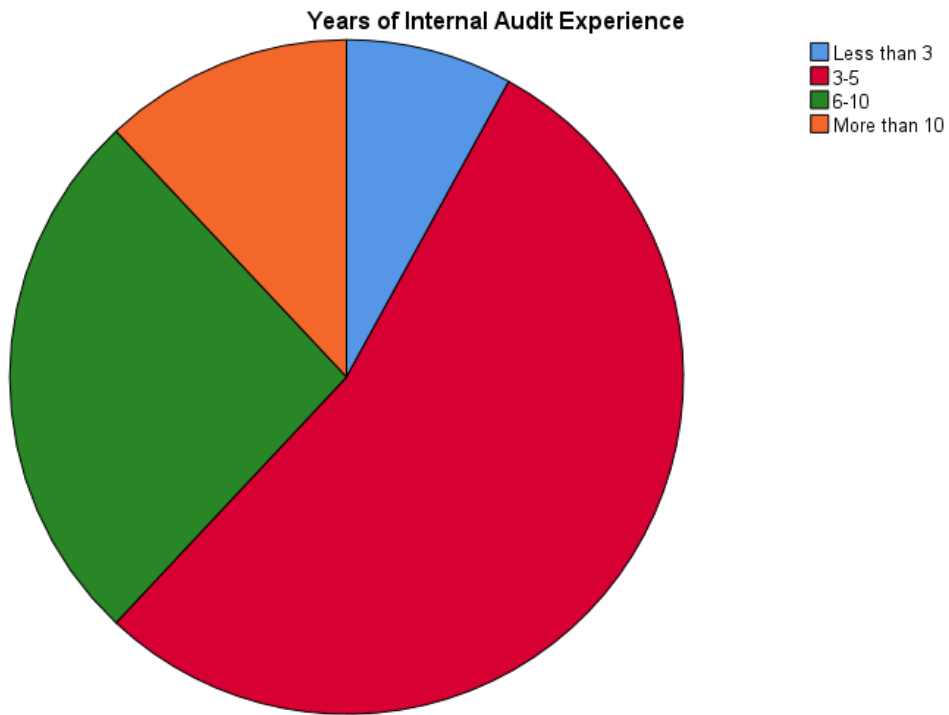


Figure 4: Audit Experience

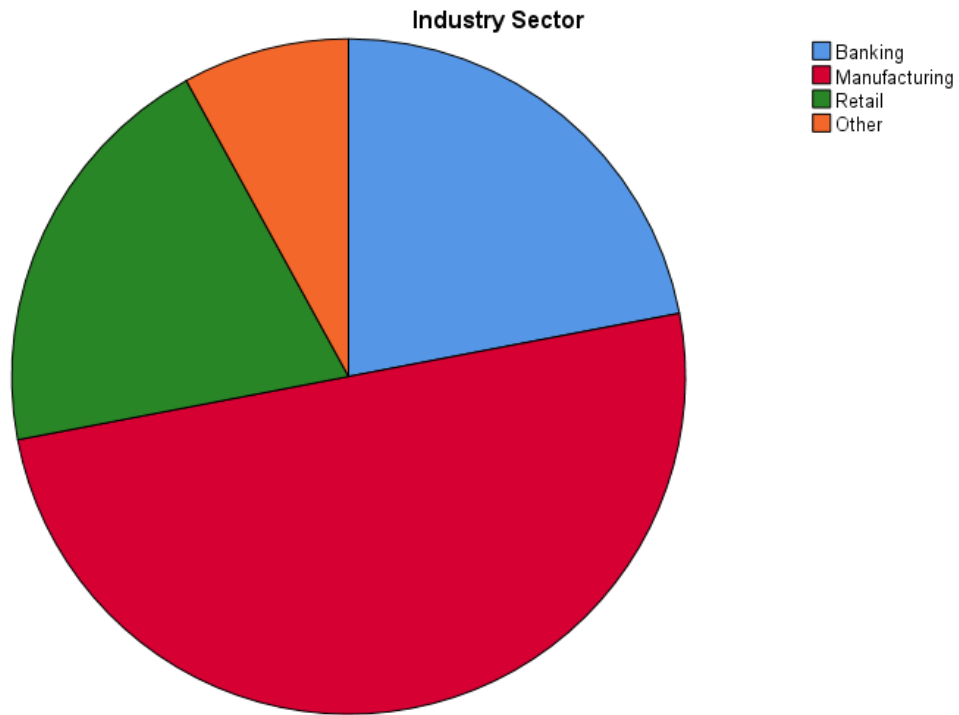


Figure 5: Industry Sector

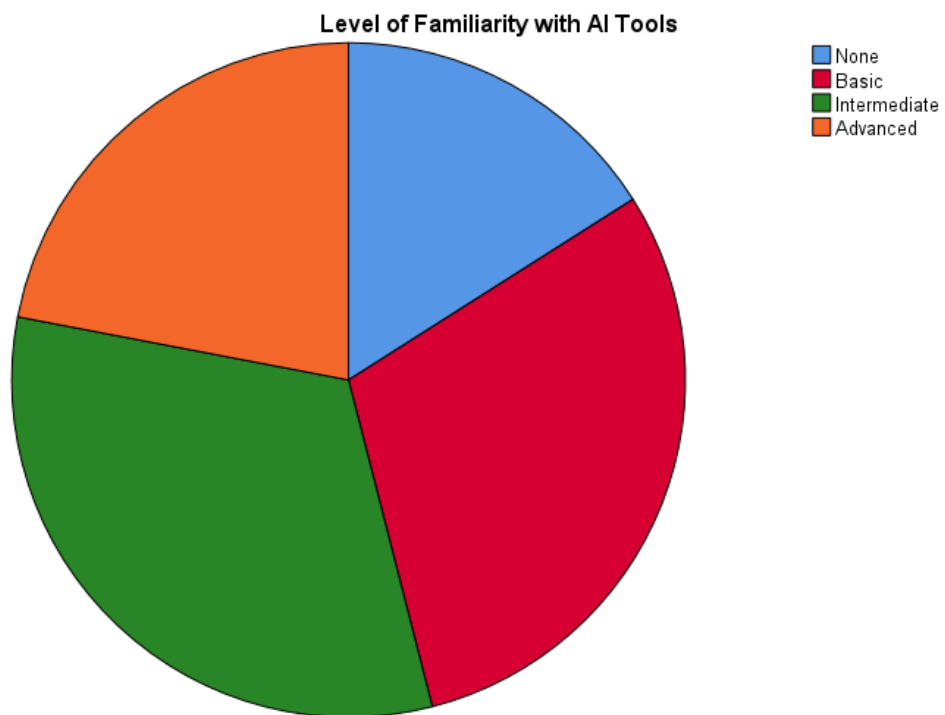


Figure 6 Familiarity with AI

4.3 Descriptives

Table 7 contains descriptive statistics that give us a summary of the distribution for each main variable: PU, PEOU, BI and AQ. Each one was measured using many pieces of information, and a group of 100 internal auditors was questioned. The range of results from the tools agrees, and average scores for PU, PEOU, BI and AQ items are greater than 4 out of 5. It appears that the participants see AI tools positively, considering their usefulness, how easy they are to handle and the outcomes they produce during an audit. Looking at the consecutive numbers in the lists reveals that a fair degree of variation occurred: lower scores were recorded as 1, and some higher responses were 5. Such variations between auditors are likely due to their own experiences or the level of preparation within their firms toward using AI.

Primarily, looking at distributional properties, some concerns were raised by the initial checks for skewness and kurtosis. More specifically, several measures (e.g., PU3, PEOU3, PEOU4, AQ1, AQ2) showed negative skewness and positive kurtosis, suggesting that their scores are unevenly distributed and that outliers or groups of high scores are present. Accordingly, and following commonly used methods, the analysis brought together each person's score for every item to get a new mean score representing each construct (PU, PEOU, BI and AQ). After computing the mean scale scores, both kurtosis and skewness at the item level were greatly lowered, which improved the distribution of the composite variables. It made it possible to apply parametric statistical techniques in the later analysis.

Because the responses were not all normal and varied widely, this tells us some crucial details. First, the different ways auditors view AI adoption reflect that the current tech landscape in Lebanon is complex and always changing. It also emphasises why using standard ways to measure variables helps stabilise the results and maintain the accuracy of analysis methods. Dealing

sensibly with non-normality strengthens the findings and adds credibility to any mediation analysis that is conducted.

Table 7: Descriptives

Descriptive Statistics	N	Minimum	Maximum	Mean		Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error	Statistic	Std. Error
PU1	100	3.00	5.00	4.6900	.05449	.54486	-1.573	.241	1.597	.478
PU2	100	3.00	5.00	4.5000	.06742	.67420	-1.009	.241	-.171	.478
PU3	100	1.00	5.00	4.4800	.07451	.74508	-1.650	.241	3.726	.478
PU4	100	3.00	5.00	4.5300	.06106	.61060	-.932	.241	-.119	.478
PU5	100	3.00	5.00	4.5000	.06742	.67420	-1.009	.241	-.171	.478
PEOU1	100	3.00	5.00	4.6600	.05724	.57243	-1.483	.241	1.252	.478
PEOU2	100	3.00	5.00	4.6300	.05801	.58006	-1.318	.241	.777	.478
PEOU3	100	1.00	5.00	4.6200	.06321	.63214	-2.424	.241	9.767	.478
PEOU4	100	1.00	5.00	4.5500	.06872	.68718	-1.994	.241	6.201	.478
PEOU5	100	3.00	5.00	4.6300	.05801	.58006	-1.318	.241	.777	.478
BI1	100	1.00	5.00	4.1600	.09070	.90699	-.656	.241	-.336	.478
BI2	100	1.00	5.00	4.0400	.08752	.87525	-.447	.241	-.315	.478
BI3	100	1.00	5.00	4.0500	.09031	.90314	-.435	.241	-.544	.478
BI4	100	1.00	5.00	4.0600	.09516	.95155	-.696	.241	.127	.478
BI5	100	1.00	5.00	4.1600	.09070	.90699	-.656	.241	-.336	.478
AQ1	100	1.00	5.00	4.6700	.06675	.66750	-2.625	.241	9.072	.478
AQ2	100	1.00	5.00	4.5700	.07000	.70000	-2.058	.241	6.025	.478
AQ3	100	1.00	5.00	4.4300	.08439	.84393	-1.370	.241	1.494	.478
AQ4	100	1.00	5.00	4.5300	.07447	.74475	-1.826	.241	4.224	.478
AQ5	100	3.00	5.00	4.5300	.06269	.62692	-.994	.241	-.044	.478
AQ6	100	1.00	5.00	4.4300	.08905	.89052	-1.667	.241	2.828	.478
Valid N (listwise)	100									

4.4 Reliability Statistics

The reliability of the instrument was investigated by carrying out a reliability analysis. The primary assessment was based on Cronbach's Alpha, and according to the standard in social science research, an acceptable result is typically around 0.70 (Hair et al., 2014).

The internal consistency of the study's constructs was assessed using Cronbach's Alpha. As per social science standards, values above 0.70 indicate acceptable reliability (Hair et al., 2014). All scales used in the study demonstrated high reliability, and no items were removed as all contributed meaningfully to their respective constructs. These results confirm that the measurement instruments are internally consistent and suitable for further analysis. More details are available in Appendix B. All of the reliability tests were done after calculating the average.

Table 8: Reliability Statistics

Scale	Cronbach's Alpha	Number of Items
Perceived Usefulness (PU)	.916	5
Perceived Ease of Use (PEOU)	.865	5
Behavioural Intention (BI)	.955	5
Audit Quality (AQ)	.870	6

4.4.6 Descriptive Average

All variables have average scores of more than 4, reaching a maximum of 4.6180 (AvPEOU) and dropping below the average only for AvRE (4.3460) and AvBI (1.40) as per Table 9. This suggests that the majority of internal auditors believe AI is easy to use, valuable and of high quality, leading them to plan using it. Most variables had moderate negative skewness, which means the majority of answers were higher on the scale. The reduced range of kurtosis (between -0.67 and 0.425) suggests that the distributions are balanced and not too peaked or flat. This shows a big difference

from the individual items, where both measures of skewness and kurtosis were problems earlier on. Thus, using an average for scores dealt with the concern of non-normality. They are better for some statistical analyses and add more validity to later tests.

The calculated averages for each variable create reliable, normally distributed composite measures, satisfying key assumptions for mediation and regression analysis. This step was critical for ensuring the accuracy and interpretability of subsequent statistical procedures, such as those involving PROCESS Model 4 for mediation testing.

Table 9 Variables Average Statistics

Descriptive Statistics	N	Minimum	Maximum	Mean		Std. Deviation	Skewness		Kurtosis	
				Statistic	Std. Error		Statistic	Std. Error	Statistic	Std. Error
AvPU	100	3.20	5.00	4.5400	.05653	.56533	-.821	.241	-.670	.478
AvPEOU	100	3.00	5.00	4.6180	.04933	.49326	-1.058	.241	.154	.478
AvBI	100	1.40	5.00	4.0940	.08363	.83628	-.483	.241	-.658	.478
AvRE	100	2.20	5.00	4.3460	.06933	.69332	-.841	.241	-.165	.478
AvAQ	100	2.83	5.00	4.5267	.05854	.58542	-1.160	.241	.425	.478
Valid N (listwise)	100									

4.5 Hypothesis Testing: Simple and Multiple Linear Regression

In the following sections, the simple linear regression testing the impact of the independent variables on the dependent variable is presented. All assumptions for the regression were met (see Appendix B).

4.5.1 H1: PU → BI

H1: There is a positive relationship between internal auditors' perceived usefulness (PU) of AI tools and their behavioural intention (BI) to adopt AI.

For Hypothesis 1, a basic linear regression was performed, where AvPU (perceived usefulness) was used as the independent variable and AvBI (behavioural intention) was the dependent variable. The purpose of this model is to analyse whether higher perceptions regarding how useful internal auditors think AI will be drive their willingness to start using it in the audit process.

According to the regression model, there is a moderate positive correlation between how much a person believes a technology is useful and the intention to use it. Perceived usefulness alone explains close to 11.6% of the differences seen in behavioural intention (Table 10). However, this significant effect for one predictor in a social science study also suggests that other factors not considered in this model help explain the variation in intention.

Table 10: Pu → BI Model Summary

Model Summary ^b				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.340 ^a	.116	.107	.79039

a. Predictors: (Constant), AvPU

b. Dependent Variable: AvBI

From the ANOVA table (Table 11), we can see that the regression model is significantly different from a simple regression model, $F(1, 98) = 12.829, p = .001$. This shows that perceived usefulness is an important factor in deciding to use AI, as predicted by the Technology Acceptance Model (TAM).

Table 11: PU → BI ANOVA

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.014	1	8.014	12.829	.001 ^b
	Residual	61.222	98	.625		
	Total	69.236	99			

a. Dependent Variable: AvBI

b. Predictors: (Constant), AvPU

In the coefficients table (Table 12), the unstandardized B for perceived usefulness is .503 (SE = .141) and the Beta is .340. The t-value turns out to be 3.582 (p = .001), which proves that there is a significant and positive relationship present. According to the findings, behavioural intention to adopt AI may rise by about 0.5 units for each extra point a user sees AI as useful. The result is also important (B = 1.809, p = .006), showing what the predicted BI would be if perceived usefulness were not taken into account.

Table 12: PU → BI Coefficients

Model	Coefficients ^a					
	Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.	
	B	Std. Error				
1	(Constant)	1.809	.643		2.814	.006
	AvPU	.503	.141	.340	3.582	.001

a. Dependent Variable: AvBI

The residual data (Table 13) demonstrate that the model estimates behavioural intention with values from 3.42 to 4.33, which gives a mean rating of 4.09, aligning well with the previously reported averages. The fact that moderate dispersal is shown by the residuals (Std. Deviation = .78639) and that extreme outliers are not visible in the standardised residuals indicates the regression model is well-suited. Even though the model only explains a little of the variance, no major assumptions in regression seem to be broken.

It relates to the hypothesis that auditors' views on how useful AI is correlate well with their intention to use AI tools at work. Previous studies and this finding agree that the view of how useful technology is helps determine if someone in auditing will adopt it. The effect size demonstrates that usefulness matters in shaping intentions.

Table 13: PU → BI Residuals Statistics

	Residuals Statistics ^a				
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3.4196	4.3255	4.0940	.28452	100
Residual	-2.92551	1.27843	.00000	.78639	100
Std. Predicted Value	-2.370	.814	.000	1.000	100
Std. Residual	-3.701	1.617	.000	.995	100

a. Dependent Variable: AvBI

4.5.2 H2: PEOU → BI

H2: There is a positive relationship between internal auditors' perceived ease of use (PEOU) of AI tools and their behavioural intention (BI) to adopt AI.

The study used a simple linear regression to see how perceived ease of use (PEOU) impacts behavioural intention (BI) in internal auditors. Auditors who find AI easy to use are potentially more willing to integrate AI into their work practices.

There is a modest positive connection found between how easy someone finds a system and how likely they are to use it, and that is named in the regression model's R value, which is .259 (Table 14). Practical experience of using AI accounts for 6.7% of what predicts behavioural intention to adopt AI. With perceived usefulness, this has only a moderately less effect, but it is still significant in research about people's attitudes and behaviour.

Table 14 PEOU → BI Model Summary

Model	Model Summary			
	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.259 ^a	.067	.058	.81177

a. Predictors: (Constant), AvPEOU

b. Dependent Variable: AvBI

From Table 15, the results show that the entire model is statistically significant: $F(1, 98) = 7.066$, $p = .009$. Thus, perceived ease of use influences how likely someone is to use the system; however,

perceived usefulness's effect is much stronger. The importance of this finding confirms the main claim of TAM, that how easy technology is to use leads to greater acceptance of it.

Table 15: PEOU → BI ANOVA

		ANOVA ^a				
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.657	1	4.657	7.066	.009 ^b
	Residual	64.580	98	.659		
	Total	69.236	99			

a. Dependent Variable: AvBI

b. Predictors: (Constant), AvPEOU

The coefficients table (Table 16) indicates that the unstandardized coefficient (B) for perceived ease of use is .440 and its standardised Beta is .259. There is a significant relationship, shown by $t(98) = 2.658$, and the probability is $p = .009$. A one-unit rise in perceived ease of use usually increases behavioural intention to adopt AI by 0.44 units. The intercept ($B = 2.064$, $p = .008$) signifies the estimated behavioural intention when perceived ease of use is at its lowest.

Table 16: PEOU → BI Coefficients

		Coefficients ^a				
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.064	.768		2.686	.008
	AvPEOU	.440	.165	.259	2.658	.009

a. Dependent Variable: AvBI

Reviewing the residuals statistics (Table 16), results from statistical analyses suggest that BI ranges from 3.38 to 4.26 and the mean is 4.09, which agrees with the descriptive findings. The residuals are distributed equally, and their variation is measured by .80766, meaning they do not indicate significant outliers or heteroscedasticity, which means the simple regression assumptions have not been broken.

This strongly supports Hypothesis 2; how easy internal auditors believe AI tools are to use leads to a strong and significant desire to use them. Nevertheless, the PU → BI model has a higher R Square than this model, which points to perceived usefulness being more important than ease of use in Lebanese auditing. In addition, PEOU continues to play a key role in practice and theory, since using simple and easy systems makes adopting new technologies much less complicated for professionals to start out.

The significance of this relationship affirms TAM’s foundational logic in the audit context and signals to practitioners and policymakers that training, intuitive interface design, and supportive onboarding procedures may enhance the adoption of AI by auditors.

Table 17 PEOU → BI Residuals Statistics

	Residuals Statistics ^a				
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3.3826	4.2620	4.0940	.21688	100
Residual	-2.86196	1.17772	.00000	.80766	100
Std. Predicted Value	-3.280	.774	.000	1.000	100
Std. Residual	-3.526	1.451	.000	.995	100

a. Dependent Variable: AvBI

4.5.3 H3: PQ → BI

H3: Perceived Audit Quality of AI positively influences Behavioural intention (BI) to adopt AI in auditing.

For Hypothesis 3, linear regression was used to study how perceived audit quality (AvAQ) impacted behavioural intention (AvBI). The analysis checks if auditors who believe AI tools lead to higher quality audits are more willing to use them.

Perceived audit quality and behavioural intention had an R value of .377, which signifies a moderate, positive relationship (Table 18). With an R-squared value of .142, it is clear that almost

14.2% of how much behaviour changes is explained by how well the audit is seen by the manager. At least in this dataset, audit quality is a better predictor of perceived quality and user satisfaction, compared to perceived usefulness and perceived ease of use.

Table 18: AQ → BI Model Summary

Model Summary ^b				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.377 ^a	.142	.134	.77844

a. Predictors: (Constant), AvAQ

b. Dependent Variable: AvBI

The information in Table 19 shows that $F(1, 98)$ is 16.258 and p is less than .001, proving the regression model is statistically significant. Such significance proves that auditors' views about audit quality play an important role in deciding whether to include AI.

Table 19: AQ → BI ANOVA

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9.852	1	9.852	16.258	.000 ^b
	Residual	59.385	98	.606		
	Total	69.236	99			

a. Dependent Variable: AvBI

b. Predictors: (Constant), AvAQ

The unstandardized coefficient for audit quality in the coefficients table (Table 27) is .539 (SE = .134), equaling a standardized Beta of .377. A strong and significant positive link is found, as the t -value is 4.032 ($p < .001$). With every additional unit in the way audit quality is perceived, behavioural intention to try AI approaches rises by 0.54 units. The intercept is also important ($B = 1.655$, $p = .008$) since it provides the basic value of BI for situations where the perceived audit quality is the least.

Table 20: AQ → BI Coefficients

Model	Coefficients ^a			t	Sig.	
	Unstandardized Coefficients	Standardized Coefficients				
	B	Std. Error	Beta			
1	(Constant)	1.655	.610		2.713	.008
	AvAQ	.539	.134	.377	4.032	.000

a. Dependent Variable: AvBI

The remaining statistics (Table 20) indicate that our predicted BI values are between 3.18 and 4.35, with an average of 4.09, just like the previous observations. As seen in Appendix B, there are no remarkable outliers and no signs of unwanted heteroscedasticity in the way residuals are spread. The standard deviation of the residuals (.77450) is comparable to that observed in previous regression models, supporting the adequacy of the fit.

The findings from these experiments make Hypothesis 3 very likely to be correct. How internal auditors see the quality of AI is a big factor in their intent to use it. Besides, this result is incredibly meaningful from a statistical standpoint and perceived audit quality is the main factor that explains differences in BI. It points out that high-quality audits help support technology adoption in the professional auditing field.

This shows that it is important for organisations and those providing AI tools to guarantee and show users that their tools make the audit process more accurate, reliable and consistent than before. Making sure that AI helps produce accurate and reliable audit results tends to encourage auditors to use these systems, mainly where professionalism and trust play important roles.

It is strongly supported by the results that perceived audit quality plays a significant and positive role in encouraging people to adopt AI in auditing. This backs up H3 and emphasises that audit quality matters a lot in accepting any new technology within this field.

Table 21: AQ → BI Residuals Statistic

	Residuals Statistics ^a				
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3.1815	4.3491	4.0940	.31545	100
Residual	-2.85925	1.21846	.00000	.77450	100
Std. Predicted Value	-2.893	.809	.000	1.000	100
Std. Residual	-3.673	1.565	.000	.995	100

a. Dependent Variable: AvBI

4.5.4 Combined Effect: Multiple Linear Regression

A multiple linear regression was conducted to examine the influence of perceived usefulness (AvPU), perceived ease of use (AvPEOU), and audit quality (AvAQ) on behavioural intention (AvBI). The overall model was statistically significant, $F(3, 96) = 6.193$, $p = .001$, and explained approximately 16.2% of the variance in behavioural intention ($R^2 = .162$). Among the predictors, only audit quality (AvAQ) had a significant positive effect on behavioural intention ($B = .394$, $p = .035$). Neither perceived usefulness ($p = .147$) nor perceived ease of use ($p = .919$) significantly predicted behavioural intention. These results suggest that audit quality is a more influential factor in shaping internal auditors' intentions to adopt AI tools, potentially acting as a mediator between TAM constructs and adoption behaviour.

Table 22: Model Summary

Model	R	R Square	Model Summary ^b	
			Adjusted R Square	Std. Error of the Estimate
1	.403 ^a	.162	.136	.77734

a. Predictors: (Constant), AvAQ, AvPU, AvPEOU

b. Dependent Variable: AvBI

Table 23: ANOVA

		ANOVA ^a				
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11.227	3	3.742	6.193	.001 ^b
	Residual	58.009	96	.604		
	Total	69.236	99			

a. Dependent Variable: AvBI

b. Predictors: (Constant), AvAQ, AvPU, AvPEOU

Table 24: Coefficient

		Coefficients ^a				
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.198	.786		1.524	.131
	AvPU	.267	.183	.181	1.461	.147
	AvPEOU	-.022	.211	-.013	-.102	.919
	AvAQ	.394	.184	.276	2.141	.035

a. Dependent Variable: AvBI

4.6 Mediation Analysis: The Role of Perceived Audit Quality (H4a)

To test whether the link between perceived usefulness (PU) and intention to adopt AI in auditing is affected by perceived audit quality (AQ), a mediation analysis (Model 4 of Hayes' PROCESS) was carried out. To consider factors that might confuse the results, the analysis used gender, age, years of experience, industry and previous AI tool experience as control variables.

Path a (PU → AQ)

First, researchers examined how PU changes audit quality. The link between usefulness of AI tools and audit quality was found to be statistically significant (B = .595, SE = .090, t = 6.64, p < .001, 95% CI [.417, .772]), so as auditors perceive AI tools as more useful, they also see improvements

in audit quality. The results indicate that the impact lasts after you account for important population and company features.

Path b (AQ → BI, controlling for PU)

The analysis then applied regression to test the relationship between BI, AQ and PU. AQ was still a strong factor associated with BI (B = .384, SE = .169, t = 2.27, p = .026, 95% CI [.048, .720]).

The direct relationship between PU and BI (with AQ controlled) was not found to be statistically significant (B = .221, SE = .176, t = 1.24, p = .217).

Indirect (Mediation) Effect

The critical result is the indirect effect of PU on BI via AQ:

- Effect = .228
- SE = .091
- CI = [.0715, .4284]

Since zero is not part of the interval, the mediation is deemed significant by many statistical rules.

Critical Interpretation and Nuance

Although the result is statistically significant, the lower part of the confidence interval (.0715) is nearly zero. It needs to be understood in more detail.

Small in scale, the indirect effect can still be found in the data. The lower confidence bound is close to zero, which shows that the mediation effect is still significant, yet weak and could change quite easily depending on small samples or if statistical assumptions are only slightly violated. This means that with a different sample, a slightly different measure or more uncontrolled factors,

we might not observe an effect that is significant. Hence, even though this evidence strongly supports PU leading to AQ, which then leads to BI, there are still doubts about its robustness.

5.7 Mediation Analysis: AQ as Mediator Between PEOU and BI (H4b)

H4b: Perceived Audit Quality mediates the effect of Perceived Ease of Use (PEOU) on Behavioural Intention (BI).

PROCESS Model 4 was applied, where:

- **Y** (Dependent variable): Behavioural Intention (AvBI)
- **X** (Independent variable): Perceived Ease of Use (AvPEOU)
- **M** (Mediator): Perceived Audit Quality (AvAQ)
- **Covariates:** Gender, Age (dummy coded), Years of Experience, Industry, and Prior AI Tool Use

Path a: Effect of PEOU on AQ

The first regression assessed the impact of PEOU on AQ. The model was significant ($R = .692$, $R^2 = .478$, $F(6, 93) = 14.21$, $p < .001$), indicating that 47.8% of the variance in AQ was explained by PEOU and the covariates.

- PEOU was a very strong, significant predictor of AQ ($B = .716$, $SE = .091$, $t = 7.87$, $p < .001$, 95% CI [.553, .897]), confirming that as internal auditors perceive AI tools as easier to use, they also perceive greater improvement in audit quality.

Among covariates:

- **Age** had a small but significant negative effect on AQ ($B = -.293$, $p = .004$), suggesting older auditors perceived less improvement in audit quality from AI, all else equal.
- **Industry** (non-manufacturing) was a positive predictor ($B = .256$, $p = .009$), indicating slightly higher perceived AQ in non-manufacturing contexts.

Path b and c': Effect of AQ and PEOU on BI

The second model regressed BI on both AQ and PEOU, including controls. The model was significant ($R = .402$, $R^2 = .162$, $F(7, 92) = 2.53$, $p = .020^*$).

- Direct effect (c'): The direct effect of PEOU on BI was not significant ($B = .027$, $SE = .214$, $t = .13$, $p = .900$, 95% CI $[-.398, .452]$).
- Effect of AQ on BI (b path): AQ was a significant positive predictor ($B = .521$, $SE = .189$, $t = 2.76$, $p = .007$, 95% CI $[.146, .896]$).

None of the covariates (including gender, age, experience, industry, prior AI tool use) significantly predicted BI in this model, indicating the results are robust across demographic groups.

Mediation Effect (Indirect Path)

The indirect effect of PEOU on BI through AQ was:

- Effect = .373, BootSE = .144, 95% BootCI $[.137, .712]$.

Analysis with covariates

To examine whether audit quality (AvAQ) mediates the relationship between perceived usefulness (AvPU) and behavioral intention (AvBI), a mediation analysis was conducted using PROCESS Model 4 (Hayes). The model also controlled for several covariates: perceived ease of use

(AvPEOU), age (AgeR), years of experience (YOE_R), industry (IND_R), and AI tool familiarity (AITOOL_R).

The first regression model assessed the effect of AvPU on AvAQ. Results revealed a significant model ($R^2 = 0.5755$, $F(6, 93) = 21.0151$, $p < .001$), indicating that approximately 58% of the variance in audit quality is explained by the independent variables and covariates. Importantly, AvPU was found to have a strong and statistically significant positive effect on AvAQ ($\beta = .4208$, $p < .001$). Additionally, AvPEOU also significantly predicted AvAQ ($\beta = .4395$, $p < .001$), confirming that both TAM variables contribute meaningfully to the perceived quality of audits. Among the covariates, age had a negative effect on audit quality ($\beta = -2.169$, $p = .0201$), while working in a relevant industry (IND_R) had a significant positive effect ($\beta = .3502$, $p < .001$).

The second regression model examined the influence of AvPU and AvAQ on AvBI. This model was also significant ($R^2 = .1769$, $F(7, 92) = 2.8239$, $p = .0104$), although it explained a more modest portion (18%) of the variance in behavioral intention. In this model, AvPU did not significantly predict AvBI ($\beta = .2723$, $p = .1786$), suggesting that the direct relationship between perceived usefulness and behavioral intention weakens when audit quality is introduced as a mediator. Conversely, the coefficient for AvAQ approached significance ($\beta = .3951$, $p = .0599$), indicating that perceived improvements in audit quality may positively influence internal auditors' intention to adopt AI tools, although the evidence is marginal.

The mediation effect was further tested using a bootstrap confidence interval approach. The indirect effect of AvPU on AvBI through AvAQ was statistically significant ($\beta = .1663$), with a 95% bias-corrected bootstrap confidence interval that did not include zero (LLCI = .0185, ULCI = .3676). This finding confirms that audit quality fully mediates the relationship between perceived usefulness and behavioural intention. In other words, while perceived usefulness alone does not

directly lead to higher intention to adopt AI tools, it significantly increases the perceived quality of auditing, which in turn increases adoption intention.

Since the confidence interval does not include zero, the mediation effect is statistically significant.

Perceived Ease of Use increases Behavioural intention to adopt AI only to the extent that it raises Perceived Audit Quality. Moreover, the direct path from PEOU to BI becomes non-significant when AQ is included, indicating a full mediation.

These findings offer strong empirical support for Hypothesis *H4b: Perceived Audit Quality fully mediates the relationship between Perceived Ease of Use and Behavioural Intention.*

So, even if AI tools are simple to use, this won't convince auditors to use them, unless they also think these tools make their audits more effective. In this setting, how easy an audit tool is to use alone doesn't motivate accountants to choose it, if its use does not also result in better audits.

Firms and technology providers in the auditing sector face noticeable challenges because of this.

It demonstrates that the perceived usefulness of AI (PU) plays a key role in improving the perceived audit quality (AQ), and then the improved AQ increases the desire to use AI (BI). There is an indirect (mediation) effect that is considered statistically significant, but the confidence interval's lower limit is very close to zero, highlighting that the effect is minor and must be interpreted with caution. When AQ is added, PU's direct effect on BI disappears, which suggests AQ is the main way usefulness relates to intention.

Table 25 Mediation Analysis Summary

Path	Effect (B)	Boot SE	95% Boot CI	Sig.	Interpretation
PU → AQ (a)	0.595	0.090	[0.417, 0.772]	✓	PU strongly and significantly increases AQ.

AQ → BI (b)	0.384	0.169	[0.048, 0.720]	✓	AQ significantly increases BI, controlling PU.
PU → BI (direct, c')	0.221	0.176	[-0.132, 0.573]	✗	No significant direct effect when AQ is included
PU → AQ → BI (indirect)	0.228	0.091	[0.0715, 0.4284]	✓(*)	The indirect (mediation) effect is statistically significant, but the lower CI is very close to zero.

Chapter Five: Conclusion and Future Studies

5.1 Introduction

In the final chapter, the main research findings are gathered, set about past studies and their implications for both theory and practice are outlined. In addition, this chapter gives targeted suggestions to parties such as auditors, technology vendors and policymakers who want to make sure AI is used correctly and ethically in auditing. At the end of the chapter, the authors share ideas for future studies, using the current research to address unanswered questions in the field.

5.2 Discussion

The findings from this research highlight important new ideas about what helps internal auditors adopt AI in Lebanon, mainly focusing on how audit quality affects the process. The study using a TAM-based model found that both usefulness and ease of use influence BI to adopt AI tools mainly through their impact on AQ. It underlines AQ's key role in both theory and practice during adoption.

Interpretation of Results Based on the Mediation Model

This analysis pointed out that how people view the audit process is a main connection between their technology views and their decision to adopt technology. It was found that adding AQ as a mediator made the links between PU, PEOU and BI no longer significant. The link between PU and PEOU, and BI was almost all through other mechanisms, not directly. Most auditors chose to use AI because its usefulness and simple use made them believe it would enhance how they perform audits. Even though the indirect effects were significant, the strength of the mediation (especially for PU) was quite low and required careful interpretation due to the upper bound being close to zero.

The results demonstrate that how an audit is perceived has a major impact on the actions of the audit profession. Because there are professional requirements, regulations and great emphasis on reliability and accuracy, auditors do not adopt new technologies just because they are different or convenient. It is believed that AI tools will make audit work more precise, uniform, and better at finding fraud and enhance trust among stakeholders. This finding builds on existing TAM research by positioning audit quality as a decisive mechanism for technology acceptance within professional practice, especially in high-stakes and trust-sensitive fields like auditing.

The study's results are like and go beyond what other international studies revealed. In studies done in countries beyond Lebanon, especially in Western and East Asian regions, both ease of use and usefulness have been consistently linked to people's willingness to take up AI and information systems. But, although a link between outcome or service quality and customer satisfaction has been found in e-learning and healthcare (for example, Lin et al., 2007; Aboelmaged, 2010; Al-Fraihat et al., 2020), it has not been studied as often in auditing and has not been highlighted as much.

What makes the Lebanese setting special, as shown by this review, is the major importance given to the perceived effectiveness of audits. International research sometimes shows that auditors use technology to gain efficiency, meet external requirements or act in line with their company's policy, but the Lebanese participants mainly focused on how AI can make the job of auditing easier and produce better results. So, in Lebanon, people see improvements in quality as a crucial factor for them to start using new technologies.

Certain unique aspects of Lebanon's audit sector cause this trend. In the first place, Lebanon is struggling with its economy and facing political unrest, which has led to more people looking at the auditing process and expecting solid and effective results. There is also a common doubt about

technology that is not proven to enhance productivity, since there are not many resources, and professionals have been very traditional for a long time. Besides, higher scrutiny from regulators and stakeholders in Lebanon requires audit firms to focus on earning trust, which is why claims of better audit work made with AI can stand out.

It is also true that Lebanon's digital evolution has been slow compared to wealthier nations, raising new worries about both the costs and the effects of adopting new technologies. Because of this condition, auditors likely check the usefulness of new tools to their jobs, instead of just counting on their innovativeness.

Overall, studies done in other places frequently find a clear relationship between PU, PEOU and BI, yet in the Lebanese case, this effect is seen only when perceived audit quality is taken into account. It highlights the importance for researchers and practitioners to consider the local work environment, business climate and regulations when bringing well-known models into a different place. In this way, the study adds to the worldwide understanding of AI adoption in auditing and explains how certain contextual factors shape people's actions.

5.3 Research Contributions

The study gives meaningful insights and practical ideas on adopting technology in auditing. The results point out that the relationship between PU, PEOU and auditors' intention is fully affected by perceived AQ. It points out that how practitioners feel about audit outcomes is crucial for trying new technologies, especially in the important and trust-based field of auditing. The research makes it clearer that BI depends on AQ, which is shaped by standards related to the profession, rather than on the user alone. The study gives one of the first empirical accounts of the adoption of AI by internal auditors in Lebanon, which helps fill a gap in both regional and global research and

supports those in similar contexts. Moreover, using proven analytical approaches like the PROCESS macro for mediation and making sure only suitable samples are used, this research paves the way for further studies in the audit profession.

5.4 Research Limitations

Nevertheless, this study brings up some limitations that must be kept in mind while going through the results. Firstly, over 300 auditors received the survey, but the number of responses was only 100, so the response rate was low. Since it is ordinary for studies among specialised professionals, this can cause doubts about whether the results are affected by non-response bias. Concerns about the expertise of the participants were met by including filter questions to include only those internal auditors with knowledge of AI in the survey. Because of this criterion and global evidence about auditors' unified acceptance of technology, it is reasonable to trust the reliability of the survey answers. Still, the fact that respondents are very familiar with AI might have influenced the noted strong agreement, limiting the shows of more distinguishable or different opinions among people.

Also, although the relationship between AQ and the association between PU and BI was statistically significant, it was small, and the confidence interval almost touched zero on the lower end. It appears that the mediation is small and easily influenced by differences between samples. Research should continue to involve more and more diverse groups of participants to confirm that this is not just a single sample result. Additionally, both the data and the questions are taken at a single moment, which can result in common method bias and prevent drawing strong conclusions about cause and effect. Because Lebanon has certain economic, law and cultural factors, it is unlikely that results obtained here would work for other regions.

5.5 Avenues for Future Research

Based on what was discovered in this study and its limitations, experts suggest doing more research in several areas. It is important for future studies to try the mediation analysis on a bigger and more diverse set of auditors, in Lebanon as well as overseas, to see if the AQ mediation is valid and stable. Longitudinal research might help explore how audit professionals' views and desires change as AI is adopted. Considering other factors, the study could investigate how organisational culture, changing regulations and trust influence the adoption of new technology. Looking at how different countries' technology, regulations and auditing traditions impact technology acceptance in accounting would help better define the influencing factors of such acceptance. In addition, qualitative methods, like interviews or focus groups, could help explain further the perceptions auditors have about the good qualities of AI in auditing.

5.6 Recommendations

The study makes clear several actions that different individuals can take to encourage the use of AI in auditing:

- 1. Prioritise Demonstrable Audit Quality Improvements:* Both audit firms and AI providers should highlight the way AI helps make the audit more effective. Showing concrete results like better accuracy, improved fraud catching and streamlined audits is likely to convince auditors more than statements about a company being useful or modern.
- 2. Develop User-Centred, Quality-Focused Training:* Training programs should, apart from showing auditors how AI is used, also highlight situations where AI enhances the usefulness and quality of audit work. Case studies, pilot tests and experiences of the first users help people see the added value.

3. *Engage Auditors in Implementation and Evaluation:* Audit firms should make sure internal auditors assist with the process of selecting, piloting and reviewing AI tools. By involving professionals, solutions meet their needs, and they show more support, as they see the audit project aims to maintain quality and standards.
4. *Strengthen Stakeholder Communication and Transparency:* Due to how much trust depends on good audit practices, businesses need to make sure clients and stakeholders understand that AI supports, rather than replaces, auditors' work. Pointing out the issue of reliability, bias and transparency from the start can make adoption more acceptable.
5. *Encourage a Culture of Continuous Learning and Ethical Awareness:* Both AI-powered technology and changes in audit methods require auditors to keep exploring new knowledge, stay ethical and be critical in their approach. Professional growth and knowing current resources will keep auditors up-to-date with technology advances and dedicated to the highest ethical standards.

5.7 Summary

All in all, the research's important findings indicate that auditors' perception of high audit quality leads them to be ready to use AI tools. Both the theoretical and practical findings are explained, plus the study's methods and the distinctive features of the Lebanese audit sector. It has been advised that firms, technology vendors and regulators focus on ensuring that using AI leads to better audit results and more trust from stakeholders. The chapter concludes by naming several areas where future research could be effective, because AI in auditing continues to evolve and covers many aspects. Taken together, these approaches provide a reliable starting point for research as well as for new ideas in management.

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Appendix A: Questionnaire

The Impact of Artificial Intelligence on Audit Quality

Introduction

Dear Participant,

You are invited to participate in an academic research study titled “*Perception of The Adoption of Artificial Intelligence Tools on Audit Quality in the Lebanese Private Sector: A Perspective from Internal Auditors.*” This study explores how different AI tools influence key aspects of audit quality, such as accuracy, fraud detection, and efficiency.

Your participation is voluntary, and your responses will remain completely anonymous. The survey will take approximately 7–10 minutes to complete. The information you provide will be used solely for academic purposes.

The responses will be stored for 6 months until the data analysis and research project approval phases end. The data will be stored for academic research purposes solely and will remain confidential.

Consent Form

By proceeding with this questionnaire, you confirm that:

- You are an internal auditor working in the Lebanese private sector.
- You have read and understood the purpose of this research.
- You voluntarily agree to participate in this study.
- You understand that your responses will remain confidential and anonymous.

I agree to participate

I do not agree to participate

Sampling Questions

Eligibility Screening

The following questions are to confirm your eligibility to participate in this study.

This research focuses on how internal auditors perceive the use of Artificial Intelligence (AI) in audit processes. To ensure the relevance of your participation, please indicate whether you are familiar with the following common types of AI technologies used in auditing. A brief description of each is provided to help guide your response.

Are you familiar with the following AI technologies?

AI Type	Description	Yes	No
Generative AI	AI systems that can produce new content, such as text, reports, summaries, or images. Examples include ChatGPT or tools that draft audit memos automatically.	<input type="checkbox"/>	<input type="checkbox"/>
Natural Language Processing (NLP)	AI that can understand, analyze, or extract information from text, such as reviewing audit documentation, contracts, or client communications.	<input type="checkbox"/>	<input type="checkbox"/>
Robotic Process Automation (RPA)	Software robots that automate routine and repetitive audit tasks, like data extraction, reconciliation, or report generation.	<input type="checkbox"/>	<input type="checkbox"/>

IMPORTANT

You may proceed if you are familiar with at least one of these AI types.

SECTION 1

1.1 Perceived Usefulness (PU) of AI in Auditing Tasks

The following statements relate to your perceptions and expectations regarding using Artificial Intelligence (AI) in auditing processes. Please indicate the extent to which you agree or disagree with each statement, based on your professional experience and expectations. There are no right or wrong answers—your honest opinions are highly valued.

Please indicate your level of agreement with the following statements based on the following scale:

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

Statement	1	2	3	4	5
I believe AI will assist me in completing audit tasks more quickly and with less effort.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I expect AI tools to support me in analyzing large datasets more effectively.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I believe AI will help me focus on more complex or judgment-based audit areas by automating routine tasks.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I anticipate AI will help reduce repetitive work in my day-to-day audit responsibilities.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I expect AI tools to enhance my confidence in making audit decisions based on data-driven insights.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

1.2 Perceived Ease of Use (PEOU) of AI Tools

The following statements explore how easy or difficult it will be to use AI tools in future auditing tasks. Please indicate your level of agreement based on your expectations of interacting with AI technologies in your professional role.

Please indicate your level of agreement with the following statements based on the following scale:

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

Statement	1	2	3	4	5
I believe it will be easy for me to learn how to use AI tools in future audits.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I expect AI tools to be user-friendly in future auditing environments.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I anticipate that using AI in auditing will not require excessive effort on my part.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I think I will quickly become comfortable using AI technologies in my audit work.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I believe the interface of future AI audit systems will be intuitive and easy to navigate.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

1.3 Behavioral Intention to Use AI (BI)

This section focuses on your intentions and willingness to use AI tools in your future audit work. Please indicate how likely it is to adopt and engage with AI technologies as they become more integrated into auditing practices.

Please indicate your level of agreement with the following statements based on the following scale:

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

Statement	1	2	3	4	5
I intend to use AI tools in future audit engagements.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I am likely to adopt AI technologies in my auditing practices as they become more available.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I will actively seek opportunities to apply AI in future audits.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I plan to enhance my skills in AI-based auditing tools soon.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I would support my organization's adoption of AI for audit functions in the coming years.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

SECTION 2:

Adoption of AI for Improving Audit Quality

Instructions: The following statements relate to how Artificial Intelligence (AI) is expected to influence the **quality and integrity** of audits conducted in your organization. Please indicate your level of agreement. Please indicate your level of agreement with the following statements regarding the overall quality of audits when AI tools are used.

Please indicate your level of agreement with the following statements based on the following scale:

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

Statement	1	2	3	4	5
I believe that adopting AI will enhance the overall quality of audits.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I expect AI-assisted audits to be more accurate in identifying misstatements or errors .	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
AI use will improve auditors' ability to detect fraudulent or anomalous financial activities .	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
AI will contribute to greater consistency and objectivity in audit outcomes.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Stakeholders (e.g., clients, management, regulators) will place more trust in audit results generated with AI tools.					
I believe AI adoption will lead to faster audit cycles without compromising quality .	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Section 3: Demographic and Professional Information

Question	Options
Gender	<input type="checkbox"/> Male <input type="checkbox"/> Female <input type="checkbox"/> Prefer not to say
Age Range	<input type="checkbox"/> 20–29 <input type="checkbox"/> 30–39 <input type="checkbox"/> 40–49 <input type="checkbox"/> 50+
Years of Internal Audit Experience	<input type="checkbox"/> Less than 3 <input type="checkbox"/> 3–5 <input type="checkbox"/> 6–10 <input type="checkbox"/> More than 10
Industry Sector	<input type="checkbox"/> Banking <input type="checkbox"/> Manufacturing <input type="checkbox"/> Retail <input type="checkbox"/> Other: _____
Level of Familiarity with AI Tools	<input type="checkbox"/> None <input type="checkbox"/> Basic <input type="checkbox"/> Intermediate <input type="checkbox"/> Advanced

Appendix B

Reliability Test

Table 26: PU Overall Scale Reliability

Cronbach's Alpha	N of Items
.916	5

Table 27: PU Items Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PU1	18.0100	5.848	.700	.915
PU2	18.2000	4.929	.871	.879
PU3	18.2200	4.981	.738	.911
PU4	18.1700	5.415	.775	.900
PU5	18.2000	4.929	.871	.879

Table 28: PEOU Overall Scale Reliability

Cronbach's Alpha	N of Items
.865	5

Table 29: PEOU Items Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PEOU1	18.4300	4.288	.619	.853
PEOU2	18.4600	3.806	.857	.795
PEOU3	18.4700	4.373	.496	.884

PEOU4	18.5400	3.847	.654	.848
PEOU5	18.4600	3.806	.857	.795

Table 30: BI Overall Scale Reliability

Cronbach's Alpha	N of Items
.955	5

Table 31: BI Items Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
BI1	16.3100	11.125	.915	.937
BI2	16.4300	11.803	.817	.953
BI3	16.4200	11.418	.860	.946
BI4	16.4100	11.113	.861	.946
BI5	16.3100	11.125	.915	.937

Table 32: AQ Overall Scale Reliability

Cronbach's Alpha	N of Items
.870	6

Table 33: AQ Items Total Statistics

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
AQ1	22.4900	9.444	.597	.860
AQ2	22.5900	8.871	.714	.842
AQ3	22.7300	8.280	.689	.846
AQ4	22.6300	8.680	.707	.842
AQ5	22.6300	9.347	.678	.849
AQ6	22.7300	8.118	.675	.850

Regression Residual Outputs

PU → BI

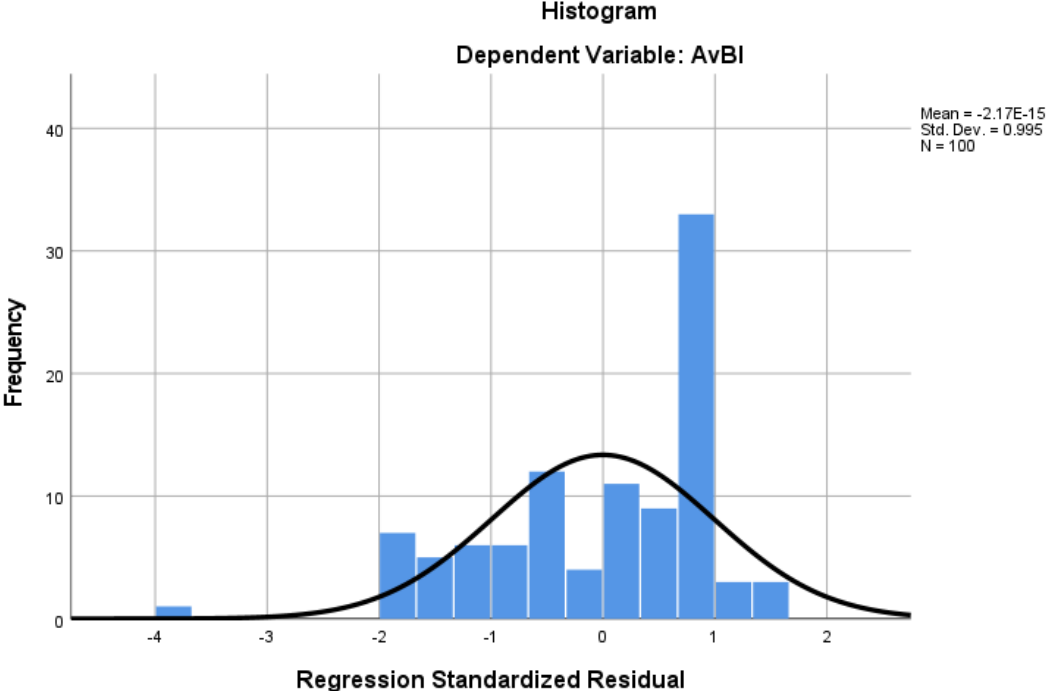


Figure 7: Standardized Residuals

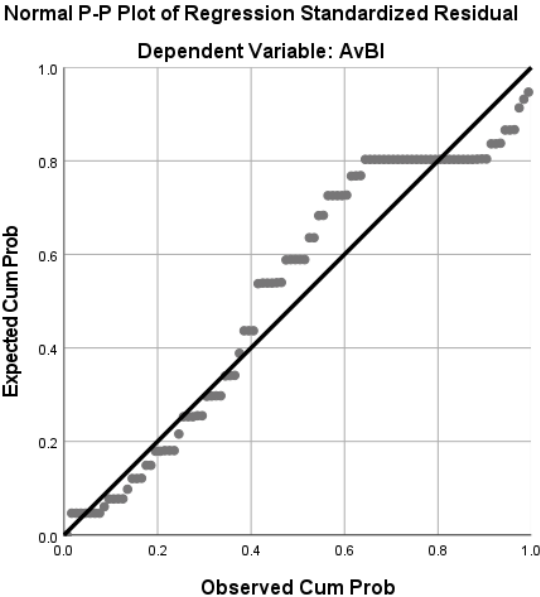


Figure 8: Normality P-P Plot

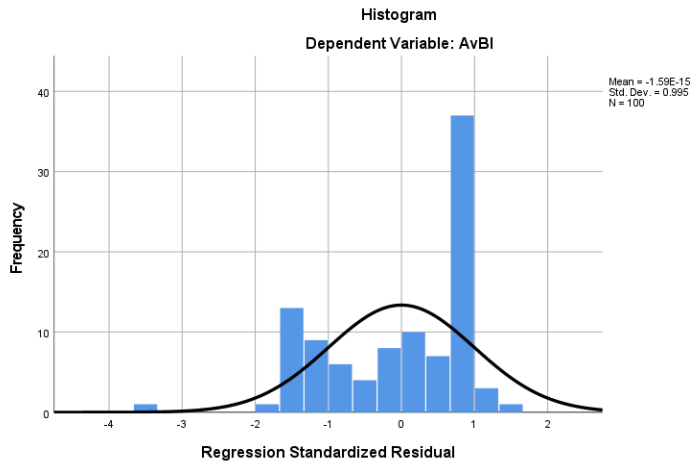


Figure 9: Standardized Residuals

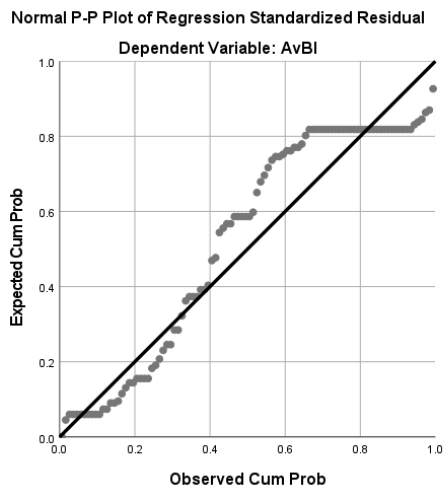


Figure 10: Normality P-P Plot

PQ → BI

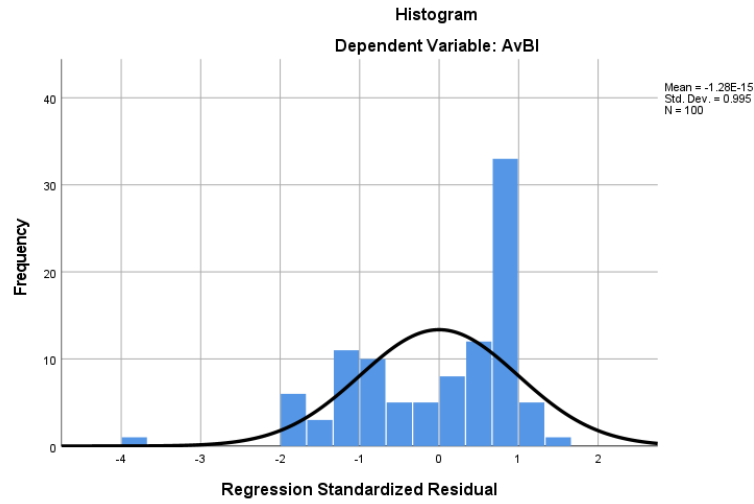


Figure 11: Standardised Residuals

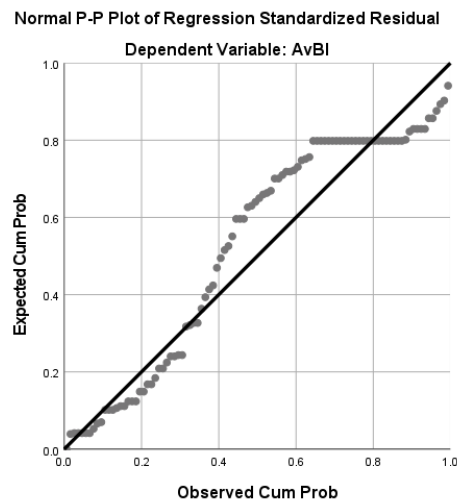


Figure 12: Normality P-P Plot

Mediation Tests

Table 34: Mediation 1 – PU → AQ → BI

```

*****
Model   : 4
  Y     : AvBI
  X     : AvPU
  M     : AvAQ

Covariates:
  AITool  IND    GEN    AGE    YOY

Sample
Size: 100

*****
OUTCOME VARIABLE:
  AvAQ

Model Summary
      R      R-sq      MSE      F      df1      df2      p
      .6187   .3828   .2252   9.6145   6.0000   93.0000   .0000

Model
      coeff      se      t      p      LLCI      ULCI
constant  1.9294   .5237   3.6843   .0004   .8895   2.9694
AvPU      .5945   .0895   6.6421   .0000   .4168   .7723
AITool    .0020   .0489   .0414   .9670  -.0951   .0991
IND      -.0427   .0587  -.7269   .4691  -.1593   .0739
GEN       .0978   .1040   .9398   .3497  -.1088   .3044
AGE      -.0457   .0582  -.7858   .4340  -.1612   .0698
YOY      -.0266   .0658  -.4046   .6867  -.1574   .1041

*****

```

OUTCOME VARIABLE:

AvBI

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4491	.2017	.6008	3.3208	7.0000	92.0000	.0034

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.5135	.9157	1.6527	.1018	-.3052	3.3322
AvPU	.2206	.1775	1.2424	.2172	-.1320	.5732
AvAQ	.3842	.1694	2.2685	.0256	.0478	.7206
AITOOOL	.0865	.0799	1.0832	.2815	-.0721	.2452
IND	-.1302	.0962	-1.3537	.1791	-.3212	.0608
GEN	-.0848	.1707	-.4964	.6208	-.4239	.2544
AGE	.0835	.0953	.8757	.3835	-.1058	.2728
YOE	-.0336	.1076	-.3122	.7556	-.2474	.1802

***** DIRECT AND INDIRECT EFFECTS OF X ON Y *****

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
.2206	.1775	1.2424	.2172	-.1320	.5732

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
AvAQ	.2284	.0913	.0715	.4284

***** ANALYSIS NOTES AND ERRORS *****

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

----- END MATRIX -----

Table 35: Mediation 2: PEOU → AQ → BI

Model : 4
 Y : AvBI
 X : AvPEOU
 M : AvAQ

Covariates:
 GEN AgeR YOER IND_R AITOOOL_R

Sample
 Size: 100

OUTCOME VARIABLE:
 AvAQ

Model Summary

	R	R-sq	MSE	F	df1	df2	p
	.6916	.4783	.1903	14.2105	6.0000	93.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.2714	.4272	2.9760	.0037	.4230	2.1197
AvPEOU	.7160	.0910	7.8664	.0000	.5352	.8967
GEN	-.0511	.0999	-.5114	.6103	-.2495	.1473
AgeR	-.2932	.1000	-2.9310	.0043	-.4918	-.0945
YOER	-.1397	.0992	-1.4091	.1621	-.3367	.0572
IND_R	.2561	.0955	2.6816	.0087	.0664	.4457
AITOOOL_R	.0442	.1122	.3944	.6942	-.1785	.2670

Table 36: Mediation with Covariates

OUTCOME VARIABLE:

AvBI

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4019	.1615	.6310	2.5315	7.0000	92.0000	.0199

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.6254	.8141	1.9966	.0488	.0086	3.2422
AvPEOU	.0270	.2139	.1260	.9000	-.3978	.4517
AvAQ	.5206	.1888	2.7574	.0070	.1456	.8956
GEN	.0628	.1822	.3449	.7309	-.2990	.4247
AgeR	.1256	.1904	.6597	.5111	-.2525	.5037
YOE_R	-.1504	.1825	-.8239	.4121	-.5128	.2121
IND_R	-.1096	.1805	-.6072	.5452	-.4680	.2488
AITOOL_R	.1205	.2044	.5893	.5571	-.2855	.5264

***** DIRECT AND INDIRECT EFFECTS OF X ON Y *****

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
.0270	.2139	.1260	.9000	-.3978	.4517

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
AvAQ	.3727	.1441	.1376	.7117

***** ANALYSIS NOTES AND ERRORS *****

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

Model : 4
 Y : AvBI
 X : AvPU
 M : AvAQ

Covariates:
 AvPEOU AgeR YOE_R IND_R AITOOOL_R

Sample
 Size: 100

OUTCOME VARIABLE:

AvAQ

Model Summary

	R	R-sq	MSE	F	df1	df2	p
	.7586	.5755	.1549	21.0151	6.0000	93.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.5160	.4133	1.2485	.2150	-.3047	1.3367
AvPU	.4208	.0905	4.6499	.0000	.2411	.6005
AvPEOU	.4395	.1012	4.3420	.0000	.2385	.6405
AgeR	-.2169	.0917	-2.3648	.0201	-.3991	-.0348
YOE_R	-.1025	.0852	-1.2028	.2321	-.2716	.0667
IND_R	.3502	.0854	4.0997	.0001	.1806	.5198
AITOOOL_R	.0961	.1007	.9550	.3421	-.1038	.2960

OUTCOME VARIABLE:

AvAQ

Model Summary

R	R-sq	MSE	F	df1	df2	p
.7586	.5755	.1549	21.0151	6.0000	93.0000	.0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	.5160	.4133	1.2485	.2150	-.3047	1.3367
AvPU	.4208	.0905	4.6499	.0000	.2411	.6005
AvPEOU	.4395	.1012	4.3420	.0000	.2385	.6405
AgeR	-.2169	.0917	-2.3648	.0201	-.3991	-.0348
YOE_R	-.1025	.0852	-1.2028	.2321	-.2716	.0667
IND_R	.3502	.0854	4.0997	.0001	.1806	.5198
AITOOL_R	.0961	.1007	.9550	.3421	-.1038	.2960

OUTCOME VARIABLE:

AvBI

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4205	.1769	.6195	2.8239	7.0000	92.0000	.0104

Model

	coeff	se	t	p	LLCI	ULCI
constant	1.3431	.8335	1.6114	.1105	-.3123	2.9985
AvPU	.2723	.2009	1.3554	.1786	-.1267	.6714
AvAQ	.3951	.2074	1.9050	.0599	-.0168	.8070
AvPEOU	-.0604	.2220	-.2719	.7863	-.5013	.3806
AgeR	.1412	.1889	.7475	.4567	-.2340	.5163
YOE_R	-.1713	.1717	-.9975	.3211	-.5122	.1697
IND_R	-.0373	.1856	-.2008	.8413	-.4060	.3314
AITOOL_R	.1458	.2023	.7208	.4729	-.2560	.5477

***** DIRECT AND INDIRECT EFFECTS OF X ON Y *****

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
.2723	.2009	1.3554	.1786	-.1267	.6714

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
AvAQ	.1663	.0894	.0185	.3676

***** ANALYSIS NOTES AND ERRORS *****

Level of confidence for all confidence intervals in output:

95.0000

Appendix 5A: Report on Thesis Defense



To: Registrar's Office

From : Thesis Committee- Advisor

Name of student: Sally Bakir Agha ID: 2225006

Title: Perception of The Adoption of Artificial Intelligence Tools on Audit Quality in the Lebanese Private Sector: A Perspective from Internal Auditors.
Thesis Defense:

The above student has done the thesis defense on June 25, 2025

Date : July 10, 2025

and was evaluated as:

- Pass
 Fail
 Conditional Pass

Thesis Committee: Dr. Mohamad Abou El Hassan
Chair

July 10, 2025
Date

Dr. Annie Tortian, 2nd Advisor
Committee Member *Annie Tortian*

10 July 2025
Date

Committee Member

Date

Committee Member

Date


Department Chair

Date

cc. Copy to student
Copy to advisor


Appendix 5B: Report on Thesis Defense

This is to certify that the candidate has fulfilled the requirements and has completed the recommended amendments by the Thesis Committee.

Advisor: Dr. Mohamad Abou El Hassan 

Dr. Annie Tortian, 2nd Advisor *Annie Tortian*

Date: June 10, 2025


Signature of the Dean of Faculty

** This form must be sent to the Registrar's office to have a Pass for the thesis on the transcript.*

Authorize Haigazian University to supply copies of my thesis to libraries or individuals upon request

Do not authorize Haigazian University to supply copies of my thesis to libraries or individuals for a period of two years starting with the date of the thesis defense

Signature

A handwritten signature in blue ink, appearing to be 'S. J.', with a stylized flourish at the end.

Date

July 18, 2025

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