Faculty of Economics and Business

The Intention to Adopt Blockchain's Technology in the Auditing Profession

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DECLARATION

I declare that the work in this dissertation was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The dissertation has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

safirah

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ABSTRACT

Globally, blockchain technology has become popular, particularly among players in the financial industry. To maintain their leadership position in promoting the Fourth Industrial Revolution, it is clear that the majority of industrialized nations, including the European Union and G20 member states, have started to approve the application of blockchain technology. Being that case, academics acknowledged that despite several early initiatives, Malaysia had been somewhat lost when it came to the legislation and implementation of blockchain technology in the nation. Therefore, the purpose of this study was to examine how blockchain technology may affect financial reporting and auditing, as well as the potential benefits and drawbacks for the accounting industry. This study used a quantitative approach, distributing more than 300 questionnaires via the online questionnaire to 38 audit firms in Kuching, Sarawak. According to the study, the only factors that influence a person's intention to adopt blockchain technology are perception of external control (PEC), computer self-efficacy (CSE), job relevance (JR), output quality (OQ), and result demonstrability (RD). Social influence acts as a moderator for all of these factors. It therefore indicates how important it is for the industry to start using blockchain technology.

Keywords: Blockchain Impact, TAM, UTAUT, Accounting, Auditing

Kesan Penggunaan Blok Rantai dalam Profesion Pengauditan

ABSTRAK

Di peringkat global, teknologi blok rantai telah menjadi popular, terutamanya dalam kalangan pemain dalam industri kewangan. Untuk mengekalkan kedudukan kepimpinan mereka dalam mempromosikan Revolusi Perindustrian Keempat, adalah jelas bahawa majoriti negara perindustrian, termasuk Kesatuan Eropah dan negara anggota G20, telah mula meluluskan penggunaan teknologi blok rantai. Sehubungan itu, ahli akademik mengakui bahawa walaupun terdapat beberapa inisiatif awal, Malaysia agak rugi apabila melibatkan perundangan dan pelaksanaan teknologi blok rantai di negara ini. Oleh itu, tujuan kajian ini adalah untuk mengkaji bagaimana teknologi blok rantai boleh menjejaskan pelaporan dan pengauditan kewangan, serta potensi manfaat dan kelemahan untuk industri perakaunan. Kajian ini menggunakan pendekatan kuantitatif, mengedarkan lebih 300 borang soal selidik melalui "aplikasi WhatsApp" kepada 38 firma audit di Kuching, Sarawak. Menurut kajian itu, satu-satunya faktor yang mempengaruhi niat seseorang untuk mengguna pakai teknologi blockchain ialah persepsi kawalan luaran (PEC), efikasi kendiri komputer (CSE), perkaitan kerja (JR), kualiti pengeluaran (OQ), kebolehbuktian hasil (RD), jangkaan usaha (EE), dan jangkaan prestasi. Pengaruh sosial bertindak sebagai kawalan untuk semua faktor ini. Oleh itu, ia menunjukkan betapa pentingnya industri mula menggunakan teknologi blockchain.

Kata kunci: *Kesan blok rantai, TAM, UTAUT, Akaun, Audit*

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LIST OF ABBREVIATIONS

AVE	Average Variance Extracted
BT	Blockchain
CFA	Confirmatory Factor Analysis
CMV	Common Method Variance
CSE	Computer self-efficacy
EE	Effort Expectancy
F^2	Effect Size
HTMT	Heterotrait-monotrait Ratio
IBM SPSS	International Business Machines Corporation Statistical Package for the Social Sciences
IDT	Innovation Diffusion Theory
INT	Intention
ISSM	Information Systems Success Model
JR	Job Relevance
MAE	Mean Absolute Error
MIA	Malaysia Institute of Accountants
OQ	Output Quality
PE	Performance Expectancy
PEC	Perception of External Control
PEOU	Perceived Ease of Use
PLS-SEM	Partial Least Squares Structural Equation Modeling
PU	Perceived Usefulness

Q^2	Predictive Relevance
RD	Result Demonstrability
RMSE	Root Mean Square Error
R^2	Coefficient of Determination
SEM	Structural Equation Modeling
SI	Social Influence
SPM	Sijil Pelajaran Malaysia
SRMR	Standardized Root Mean Square Residual
TAM	Technology Acceptance Model
TAM3	Extended Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor
WOM	Word of Mouth

CHAPTER 1

INTRODUCTION

1.1 Introduction

Chapter 1 presents an overview of the study, detailing its background, research challenges, objectives, significance, and scope. The chapter commences by addressing the growing significance of blockchain technology in the auditing field, highlighting its capacity to improve transparency, security, and efficiency. The research problem is outlined, emphasizing the difficulties auditors encounter in using blockchain technology. Thereafter, the research objectives and questions are established, accompanied by an examination of the study's significance in both theoretical and practical domains. Finally, the study's scope and constraints are delineated to offer a clear comprehension of its boundaries.

1.2 Background of the study

In both financial and non-financial reporting, auditing is an essential process that ensures accuracy, dependability, and adherence to regulatory standards. For the public, investors, and regulatory agencies, among others, it is essential to preserve trust. To evaluate the financial accounts of a business, auditing has historically depended on sample techniques and manual verification procedures. These techniques are time-consuming, prone to human mistake, and susceptible to fraudulent manipulation, notwithstanding their effectiveness.

Internal auditing and external auditing are the two categories of auditing. Professionals in a business carry out internal audits to evaluate operational effectiveness, internal controls, and risk management. Since numerous ahead of time accounting crises, internal auditing has been a crucial component in promoting efficient controls and risk management. Furthermore, the internal auditing supports risk management in various ways through its assurance and advisory roles (Jarah et al. 2022). On the other hand, external auditing is carried out by independent auditors who assess an organization's financial statements in order to offer an objective assessment of their accuracy and fairness. The external auditor plays an important role to improving the quality of accounting information and ensuring the greatest amount of confidence in accounting information (Mohsin & Abdulkareem, 2022). To guarantee adherence to accounting and auditing standards, auditors use evidence-based approaches such as risk assessments, analytical processes, and substantive testing.

Even though auditing is governed by organized procedures, the profession still faces a number of difficulties. Regulators and business experts are concerned about fraud, financial misrepresentation, data manipulation, and inefficiencies in audit procedures. Conventional approaches frequently depend on sampling strategies, which might not always be able to identify irregularities or fraudulent activity. Furthermore, a move toward more advanced and technologically driven audit methodologies has been made necessary by the increasing degree of complexity of financial transactions, the emergence of digital assets, and worldwide regulatory changes.

To address these challenges, emerging technologies like blockchain are being explored to enhance audit reliability, transparency, and efficiency. Blockchain is a decentralized, distributed ledger technology that securely records transactions in a tamper-proof and immutable manner. Its key features, such as transparency, cryptographic security, and real-time verification, make it a promising solution for enhancing the auditing process. The rapidly evolving business landscape is undergoing a transformational shift, catalyzed by technological advancements. Among the aforementioned innovations, blockchain technology has ushered in a new era of secure and automated processes, with far-reaching implications for various industries. According to Aisyah et al. (2023), distributed ledger technology, often known as blockchain technology, is a peer-to-peer distributed asset database that may be shared between two or more entities across a network without boundary.

Blockchain technology's decentralized, transparent, and unchangeable digital ledger system has the potential to upend several industries, including accounting and auditing, healthcare, and supply chain management. By offering an unchangeable and visible record of the items' route, blockchain can guarantee authenticity and traceability. For example, Walmart's supply chain management tracks food goods from farms to shelves using blockchain, which can improve food safety and shorten recall processes. Blockchain can safely store and exchange patient medical records in the healthcare sector while protecting patient privacy. For the healthcare industry, a doctor might view a patient's whole medical history, which is maintained on a blockchain and helps with diagnosis by lowering errors. Blockchain can automate the audit trail in the accounting and auditing professions by offering a real-time, impenetrable ledger of transactions. Deloitte, for example, has investigated blockchain-based technologies to improve audit efficiency and transparency.

The method by which transactions and data are kept, validated, and subsequently carried out is also altered by blockchain technology. Because of its decentralized, transparent, and unchangeable character has enormous potential to transform a wide range of businesses, enhancing security and promoting efficiency while also building process confidence (Abdennadher et al., 2022). This is achieved through the facilitation of secure and efficient transactions without the need for intermediaries. Blockchain technology leverages advanced encryption technology to perform transactions across general ledgers shared by internal and external parties. Furthermore, blockchain technology is integrated into the main blockchain system of all stakeholders, making it a reliable and efficient solution for those who seek to optimize their business processes. It is imperative that organizations and all businesses investigate the potential applications of blockchain technology and adjust to its revolutionary nature as it continues to develop. Figure 1.1 describes blockchain technology and the factors that have exploded in popularity in the modern era.

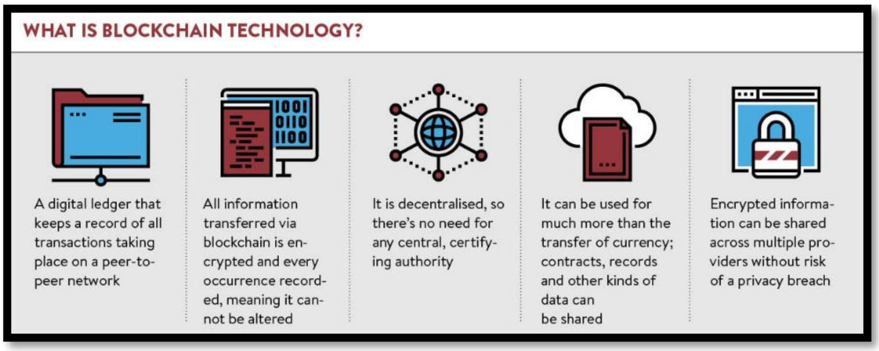

Figure 1.1: Blockchain Technology

Note: IoT World News

From a local standpoint, Malaysia is in risk since the country could be endangered by its lack of knowledge about blockchain (Yatim, 2018). Other nations are stepping up to invest in blockchain technology for their economies, which will affect Malaysia whether or not other nations choose to embrace or reject the technology (Wahab et al., 2020). Malaysians are still not as familiar with blockchain technology as people in other nations. The percentage of awareness among Malaysians from the third quarter of 2019 to the fourth quarter of 2022 is demonstrated in Figure 1.2.

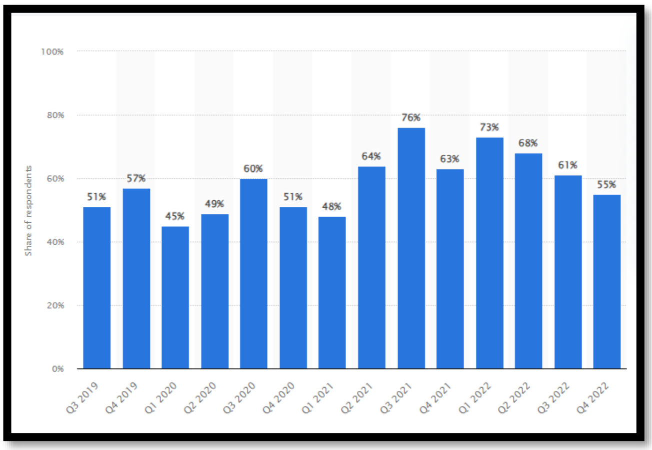

Figure 1.2: Blockchain Awareness Among Malaysians

Note: Statista

One of the roles of accountants and auditors is to stay up to date with technological advancements and take the initiative to understand how they can impact financial reporting and auditing practices. Muda and Landau (2019) found that the use of technology positively and significantly influences the quality of auditing and accounting practices. Due to its environment's natural evolution, the accounting profession has undergone several changes over the years. However, accounting practice is still adapting to emerging technologies in recent years. The accounting skills of handling financial data, understanding where the data comes from, and knowing which models are best suited to apply qualified accountants to build data mining and analytics models accurately, interpret the results, and make decisions based on information that they get. Steven (2016) discovered that emerging technology enables the efficient detection of duplicate transaction data, effectively eliminating concerns about the reliability of the transactional dataset. Additionally, it reduces the time required for data transformation through automation processes such as pairing, extraction and formatting. The implementation of emerging technology tools in the auditing process enhances productivity, improves the accumulation of sufficient and appropriate audit evidence, facilitates faster communication with stakeholders, and ensures the protection of confidential client data (Thottoli et al., 2022).

Blockchain technology seeks to revolutionize financial reporting significantly by guaranteeing the timeliness, accuracy, and transparency of financial information. With blockchain technology, financial transactions can be instantly recorded, leading to the ultimate creation of a tamper-proof audit trail. The expansion of a blockchain system may improve the security of the information flow in the network, hence improving the security of information sharing and transmission. Blockchain application implementation lowers information provision costs and enhances financial report quality. Cross-border transactions are one of the most widely recognized applications of blockchain technology worldwide in the aspect of international trade, business flow, and capital exchange. Domestic and international banks offer payment, liquidity and financial risk management services to support corporations in completing acquisition transactions (Eriksson et al., 2017). Traditional transaction methods in centralized systems have often been slow and costly for fund transfers. However, with the adoption of decentralized ledger technology, the verification and processing of cross-border transactions can be completed within seconds, regardless of time zones.

1.3 Problem Statement

Despite the transformative potential of Blockchain Technology to enhance transparency, security, and efficiency in the auditing profession, its adoption remains limited due to several barriers. These include a lack of awareness about BT’s application, insufficient technical expertise, and challenges in integrating BT with existing systems. Additionally, auditors’ willingness to adopt BT is influenced by factors such as Perception of External

Control (PEC), Computer Self-efficacy (CSE), Job Relevance (JR), Output Quality (OQ), Result Demonstrability (RD), Effort Expectancy (EE), and Performance Expectancy (PE). However, there is limited research on how these factors collectively impact the intention to adopt BT in the auditing profession.

This gap in understanding hinders the development of targeted strategies to overcome adoption barriers, potentially delaying the realization of BT's benefit for the auditing industry. Without addressing these challenges, the profession risks falling behind in leveraging innovative technologies to address evolving demands for accountability, fraud prevention, and operational efficiency. Chowdhury (2024) discusses the transformative potential of blockchain technology in modern business operations. Blockchain's decentralized and secure structure ensures transparency, traceability, and improved security. It is widely used in business areas like supply chain management, finance, and healthcare, demonstrating its proven effectiveness.

Furthermore, the lack of adoption may lead to missed opportunities for auditors to enhance their competitive edge and meet stakeholders' expectations in an increasingly digital and data-driven business environment. According to Lee et al, (2023), stakeholder expectations hold the highest normalized importance, underscoring their critical role in driving sustainable practices within the industry. Implementing technology-based auditing improves the effectiveness and capabilities of the internal audit process. As a result, the perceived relative advantage of this approach increases, making individuals more likely to invest in and adopt the technology (Lutfi & Alqudah, 2023).

Previous studies have shown that blockchain technology can facilitate data exchange among owners, operators, contractors, suppliers, and other stakeholders while maintaining data privacy and security (Deepa et al., 2022; Singh et al., 2023). Given these demonstrated benefits, it is critical to investigate the interplay of factors influencing blockchain technology adoption to provide actionable insights for practitioners, policymakers, and technology developers. To address these challenges, stakeholders should promote collaboration and communication, enhance the development of efficient blockchain technology, and implement a robust governance framework (Sigh and Kumar, 2024).

1.4 Research Questions

The questions of this study are as follows:

1. How does the Perception of External Control (PEC) influence the intention to adopt Blockchain Technology (BT)?
2. How much does Computer self-efficacy (CSE) influence the intention to use Blockchain Technology (BT)?
3. In what ways does Job Relevance (JR) impact the intention to use Blockchain Technology (BT)?
4. How does Output Quality (OQ) affect the desire to use Blockchain Technology (BT)?
5. How does the Result Demonstrability (RD) influence the intention to adopt Blockchain Technology (BT)?
6. How does Effort Expectancy (EE) influence the intention to adopt Blockchain Technology (BT)?
7. How does Performance Expectancy (PE) influence the intention to adopt Blockchain Technology (BT?

1.5 Research Objectives

The research objectives of this study are as follows:

1. To examine the relationship between the Perception of External Control (PEC) on the intention to adopt Blockchain Technology (BT).
2. To examine the relationship between Computer Self-efficacy (CSE) and the intention to adopt Blockchain Technology (BT).
3. To examine the relationship between Job Relevance (JR) and the intention to adopt Blockchain Technology (BT).
4. To examine the relationship between Output Quality (OQ) and the intention to adopt Blockchain Technology (BT).
5. To examine the relationship between Result Demonstrability (RD) and the intention to adopt Blockchain Technology (BT).
6. To examine the relationship between Effort Expectancy (EE) and the intention to adopt Blockchain Technology (BT).
7. To examine the relationship between Performance Expectancy (PE) and the intention to adopt Blockchain Technology (BT).

1.6 Significance of Study

Through this study, the objective is to assess the feasibility of intention to implementing blockchain technology in the field of auditing. This research will also contribute to a deeper comprehension of the organizational requirements for integrating blockchain technology to ensure effective management, particularly within financial systems. Given the constantly evolving technological landscape, it is imperative to recognize the importance of understanding blockchain technology, as it has the potential to mitigate cyber fraud and enhance the security of data.

In the digital transformation era, the auditing profession increasingly seeks innovative solutions to enhance transparency, security, and efficiency. Blockchain technology has emerged as a promising tool to address these needs, offering immutable records and real-time verification capabilities. The increased knowledge influences behavioral intentions towards blockchain technology in a good way. Technology user's satisfaction and understanding affect a person's intention to adopt it. This is because they will find that technology is easier to use if they understand and enjoy it, and their perception of enjoyment is crucial to accepting new technology implementation.

Understanding how external factors, such as organizational support or regulatory environments influence to adoption of BT is critical for creating enabling conditions for its implementation. This insight can help organizations and policymakers design supportive frameworks to encourage BT adoption. (PEC)

By examining the role of individuals' confidence in their ability to use BT, this study highlights the importance of training and skill development. Addressing CSE can empower auditors and professionals to embrace BT, reducing resistance to technological change.

Investigating how BT aligns with the specific tasks and responsibilities of auditors guides organizations. This ensures that BT is implemented in ways that directly enhance job performance and operational efficiency.

The study explores how the perceived quality of outcomes generated by BT influences adoption intentions. High output quality can increase trust in BT, making it a more attractive solution for auditing processes.

By analysing how the visibility and tangibility of BT's benefits impact adoption, this research helps organizations communicate the value of BT more effectively. Clear demonstrations of its advantages can accelerate acceptance and integration.

Understanding the role of ease of use and user-friendliness is essential for designing intuitive BT systems. Reducing the effort required to adopt BT can lower barriers to entry and increase its uptake among professionals.

The study examines how the perceived benefits of BT in improving performance drive adoption intentions. Highlighting these benefits can motivate organizations and individuals to invest in BT solutions.

Not only does this research contribute to the theoretical knowledge of technology adoption, but it also gives stakeholders useful tools to help BT adoption. By tackling the elements mentioned in the research questions, this study helps BT expand and become integrated into the auditing industry and beyond, which eventually promotes efficiency, innovation, and transparency in professional procedures.

1.7 Scope of Study

The present study endeavours to undertake a comprehensive analysis of the ramifications that technological advancements have had on the Accounting Profession. In particular, the study aims to shed light on the extent to which these technological changes have impacted the accounting profession, the benefits that technology has brought to the accounting profession, and the challenges that technology has posed to the field of accounting. By delving into these critical aspects, this study aims to provide a nuanced and in-depth understanding of the complex relationship that exists between technology and the accounting profession, thereby contributing to the existing literature on this subject matter.

1.8 Definitions of Key Terms

To ensure that the discussion in this research is clear and consistent, it is important to define the key terms used in this study. The purpose of this section is to provide precise definitions of the key terms, including

1.8.1 Perception of External Control

Perception of External Control (PEC) is defined as the degree to which an individual believes that organizational and technical resources exist to support the use of the system (Elshafey et al., 2020).

1.8.2 Computer self-efficacy

Computer Self-Efficacy (CSE) is defined as a judgment of one's capability to use a computer. It incorporates judgments of an individual on his or her skills to perform tasks using a microcomputer (Karsten et al., 2012).

1.8.3 Job Relevance

Job Relevance (JR) is defined as the decisions that are based on the match between jobs and people. It involves figuring out what it takes to do a particular job and then finding people who are a good fit (Peiró et al., 2020).

1.8.4 Output Quality

Output Quality (OQ) is defined as consistently producing work that not only meets but surpasses established standards (Pekkanen & Pirttilä, 2022).

1.8.5 Result Demonstrability

Result Demonstrability (RD) is defined as the degree to which the results of using a system are tangible observable, and communicable (Doo & Bonk, 2021).

1.8.6 Social Influence

Social Influence (SI) is defined as the phenomenon where an individual's behaviors, opinions, or beliefs change as a result of their network ties, often becoming more similar to those with whom they are connected (Spears, 2021).

1.8.7 Effort Expectancy

Effort expectancy refers to howe easily users believe the technology will be used. If the technology is perceived as easy to use, users are likelier to adopt it (Rizkalla et al., 2023a).

1.8.8 Performance Expectancy

Performance expectancy is the extent to which users believe that using technology will increase productivity and effectiveness in achieving their goals (Rizkalla et al., 2023a).

1.9 Conclusion

Chapter 1 has laid the groundwork for this research by outlining the study's background, objectives, and significance. It has underscored the necessity to investigate the determinants affecting blockchain adoption among auditors, specifically in Kuching, Sarawak. The chapter delineated the theoretical framework and research methods, establishing the foundation for the ensuing chapters. The subsequent chapter will offer an exhaustive examination of pertinent literature to situate the study within established research and theoretical frameworks.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Chapter 2 offers a comprehensive analysis of the literature about blockchain technology in auditing, the Unified Theory of Acceptance and Use of Technology (UTAUT), and other pertinent topics. The chapter commences with an examination of blockchain technology, its essential attributes, and its ramifications for the auditing profession. The text subsequently examines current research on technology adoption models, emphasising UTAUT and its relevance to this study. The discourse encompasses the independent variables, such as sense of external control, computer self-efficacy, job relevance, output quality, result demonstrability, effort expectancy, and performance expectancy, alongside the moderating influence of social factors. The chapter finishes by delineating research gaps and substantiating the necessity for this investigation.

2.2 Blockchain Evolution

A database that can be shared, updated, and validated by all users is what is known as a blockchain (Rusmanto et al., 2023). This provides the timely and permanent management of transactional financial records. It also guarantees openness and prevents any further adjustments. The likelihood of fraud detection is great, which is the main benefit. According to DeVries (2016), one of the newest technologies being utilized by the nation's commercial banks as well as the central bank to guarantee daily transactions is blockchain technology. Financial clients employed blockchain technology in their transactions at the beginning of 2008 as a result of the increased fear of the world financial crisis.

2.2.1 Blockchain 1.0

Maull et al. (2017) state that the initial version of blockchain, termed Blockchain 1.0, is founded on Distributed Ledger Technology (DLT). Witnesses can eliminate occurrences of duplicate spending by utilizing a distributed ledger, a database collaboratively shared by multiple parties (Mills et al., 2016). The cryptocurrency sector experienced the highest utilization of distributed ledger technology, with Bitcoin serving a pivotal function (Olnes et al., 2017). Bitcoin facilitated the emergence of the "Internet of Money" and established itself as the "digital currency for the internet." The Bitcoin network, recognized as blockchain 1.0, initiated the first iteration of the technology in 2009. The inaugural cryptocurrency was developed and launched in this era. The primary notion was payment and its potential application in the creation of cryptocurrency.

Bitcoin might potentially serve as a prototype for an innovative economic framework. Bitcoin functions as a cryptocurrency in applications for digital payments, remittances, and cash transfers that operate autonomously from central banks and rely exclusively on encryption methods. Decker and Wattenhofer (2013) asserted that multi-hop broadcasting was employed to analyze and update the ledger as information disseminated around the Bitcoin network. Regrettably, the delays induced by this propagation strategy resulted in blockchain forks and discrepancies. Due to its diminished transaction costs and relative anonymity, Blockchain 1.0 presents several advantages over traditional payment methods. Due to their vast supply, bitcoins will perpetually remain available in the market. By facilitating secure, transparent, and traceable transactions, Bitcoins eliminate both double spending and counterfeiting.

Despite its numerous accomplishments, Bitcoin has seen notable setbacks. The initial generation of blockchain is based on the Proof of Work (PoW) consensus mechanism, which necessitates the resolution of complex mathematical problems. Proof of Work is time-consuming and requires substantial energy relative to the overall profits generated due to its complexity. Ultimately, Bitcoin approaches a centralized system wholly controlled by self-serving miners.

2.2.2 Blockchain 2.0

The ineffectiveness in mining and the restricted scalability of first-generation blockchain motivated Buterin to broaden the blockchain concept beyond mere cash (Buterin, 2014). This evolution led to the emergence of the second generation of blockchain, Ethereum, which included innovative ideas such as smart contracts in conjunction with the Proof of Work consensus method. Smart contracts are self-executing, autonomous programs that function automatically according to pre-established terms between parties. These contracts possess a high level of security, rendering them impervious to hacking or alteration. Consequently, Smart Contracts markedly reduce expenses related to verification, execution, and fraud mitigation, while guaranteeing transparent and unequivocal contract terms (Macrinici et al., 2018).

Ethereum (Buterin, 2016) integrates smart contracts within the blockchain. It is a community-developed system that underpins Ether (ETH), a cryptocurrency with extensive uses across various sectors, including commerce, real estate, and electronic voting. Miners in the digital currency Ethereum compete for the digital currency Ether instead of Bitcoins (Bouoiyour and Selmi, 2017). In Ethereum, there exists a currency known as "gas," which serves to remunerate miners for including transactions in their blocks. Every execution of a smart contract necessitates the transmission of a designated amount of gas for a remote miner to incorporate into the blockchain.

The smart contract framework of Ethereum provides substantial benefits, especially regarding precision and transparency. By expressly recording contractual provisions, these self-executing contracts guarantee clarity and accessibility for all parties concerned. Moreover, possessing a processing capacity of up to 15 transactions per second, they enable swift execution while minimizing dependence on intermediaries across diverse applications. Nonetheless, smart contracts pose considerable hurdles for users owing to their intricate development process (Delmolino et al., 2016). Even minor programming mistakes can result in unforeseen and even grave repercussions (Chen et al., 2017). Once a vulnerability is exploited, mitigation becomes challenging, as rectifying the issue necessitates consensus among stakeholders and a comprehensive change of the underlying code (Marino & Juels, 2016). Therefore, optimizing the advantages of Ethereum relies on the meticulous design and secure implementation of smart contracts.

2.2.3 Blockchain 3.0

This generation of blockchains has introduced a convergence towards decentralized applications. Multiple study domains, including health, governance, the Internet of Things (IoT), supply chain management, business, and smart cities, were evaluated for the development of decentralized applications (Vora et al., 2018). At this stage, Ethereum, Hyperledger, and other platforms were utilized to program smart contracts for various decentralized applications (Palma et al., 2019; Yu et al., 2018).

A primary disadvantage of blockchain 1.0 and 2.0 is their insufficient scalability, as they predominantly depend on the Proof of Work (PoW) consensus method, leading to protracted transaction confirmation delays, frequently extending to several hours. The inefficiencies prompted the development of blockchain 3.0, aimed at improving scalability and promoting the worldwide adoption of cryptocurrencies. This third-generation blockchain not only supports smart contracts but also integrates decentralized applications (dApps) that function on a distributed blockchain network, hence removing centralized authority control. Furthermore, blockchain 3.0 facilitates inter-chain transactions via sophisticated methods like sharding, wherein each node retains only a segment of the blockchain data rather than the complete ledger. This method maximizes efficiency, minimizes network congestion, and improves security by allocating the computing workload.

Blockchain 3.0 incorporates various consensus techniques, such as Proof of Stake (PoS) and Proof of Authority (PoA), enhancing transaction processing speed and computing efficiency while obviating the necessity for distinct transaction fees (De Angelis et al., 2018). Despite being in its nascent phase, blockchain 3.0 seeks to resolve the scalability, interoperability, privacy, and sustainability issues inherent in earlier blockchain iterations. It is constructed on the "Fast, Feeless, and Minerless" (FFM) architecture, which removes reliance on miners for transaction validation and use inherent verification techniques instead. This innovation facilitates markedly increased transaction throughput and accommodates thousands of transactions per second.

The emergence of blockchain 3.0 has resulted in the creation of various platforms, each possessing distinct attributes aimed at facilitating blockchain integration in practical applications. The ICON project enables interoperability among several blockchains, ensuring transaction verification via a decentralized ledger and removing the necessity for central authority or transaction fees. Furthermore, a unique third-generation blockchain framework employs Directed Acyclic Graph (DAG) protocols (Agarwal et al., 2011; Vasseur et al., 2013), eliminating the necessity for conventional blocks, chains, and miners. This method is illustrated by platforms like IOTA, which utilizes a distributed ledger system devoid of traditional mining (Divya & Biradar, 2018). Other significant blockchain 3.0 platforms are Cardano, which incorporates its coin, ADA, and seeks to rectify Ethereum's shortcomings, and Aion, a network engineered to facilitate various blockchain architectures while promoting cross-chain interoperability (Spoke, 2017).

Notwithstanding these developments, blockchain 3.0 poses numerous hurdles. The decentralized nature complicates and prolongs bug repair and system changes. Furthermore, although enhancing efficiency, the consensus procedures employed in this generation are very complex and necessitate additional refinement for broad acceptance.

2.2.4 Blockchain 4.0

This generation mainly focused on services such as public ledger and distributed databases in real-time. This level has seamless integration of Industry 4.0-based applications. It uses smart contracts and regulates within the network by its consensus (Holland et al., 2018). A forthcoming advantageous advancement in the evolution of Blockchain is Blockchain 4.0. It seeks to provide Blockchain Technology as a commercially viable platform for the development and operation of apps, thereby rendering the technology fully mainstream. It has the potential to integrate other advanced technologies such as Artificial Intelligence with Blockchain. Blockchain 4.0 facilitates the seamless integration of diverse platforms to operate cohesively under a unified framework, addressing business and industrial requirements. Unibright serves as the foundational platform for presenting blockchain 4.0 utilities (Unibright IT UG, 2018), facilitating the integration of various blockchain business models. Another example is the SEELE Platform which facilitates integration inside the blockchain ecosystem by enabling seamless cross-communication between diverse protocols across many services (Schmidt et al., 2018). The fourth generation can provide transactional speeds of up to 1 million transactions per second, a feat now unattainable in preceding generations.

2.2.5 Summary of Blockchain Evolution

The evolution of blockchain technology from Blockchain 1.0 to Blockchain 4.0 signifies a significant revolution, transitioning from a rudimentary ledger system to an extensive ecosystem that facilitates intricate applications across several industries. Phase 1 which is blockchain 1.0, commenced with Bitcoin and concentrated on decentralized digital currencies. It facilitated secure and transparent peer-to-peer transactions, although was confined to financial applications. Blockchain 2.0 introduced by Ethereum, facilitates programmable contracts that run autonomously upon the fulfillment of specified criteria. This expanded blockchain use transcends banking, facilitating decentralized applications (dApps) in sectors such as supply chain, healthcare, and government.

Blockchain 3.0 concentrated on surmounting constraints related to velocity, expense, and interoperability among various blockchain networks. Innovations include Directed Acyclic Graphs (DAGs), sidechains, and proof-of-stake (PoS) consensus mechanisms that were developed to improve efficiency. Adoption has broadened to encompass enterprise solutions with enhanced regulatory compliance. Blockchain 4.0 seeks to enhance the user-friendliness, scalability, and practicality of blockchain for real-world enterprises. Features encompass AI integration, refined governance structures, and augmented security. Facilitates the integration of blockchain technology into mainstream enterprise use, allowing for seamless the third generation of the World Wide Web, referred to as Web 3.0 or Web3 applications.

2.3 Theoretical Model: Technology Acceptance Model (TAM)

TAM is a theory that indicates how users of a technology can accept and use a technology. TAM was first introduced by Davis (1985), when users are exposed to the new technology, some factors can affect their decision, when and how they will use it. Organizations become more dependent on information systems when they use advanced systems. For instance, when companies use this system in their business either in financial or non-financial transactions, this data is effectively managed, which leads to the idea of adopting computer technology or application in the acceptance of technology (Davis, 1989a). There are two factors in the acceptance of a technology according to TAM; 1. Perceived usefulness, where it can be said that when someone believes that using a certain system will improve their performance, 2. Perceived Ease-Of-Use, where someone believes that a certain system is effortless.

The Technology Acceptance Model (TAM) elucidates individuals' views and acceptance of new technology. Davis et al. (1989b) indicate that consumers tend to prefer simpler solutions. The attitude affects the intention to utilize a particular technology, which predicts actual system usage (Salloum et al., 2019). As stated by Brown et al. (2002), users are compelled to utilize the system, with perceived behavioral control and subjective standards reinforcing this purpose. This illustrates how user pleasure and usability of technology influence an individual's intention to embrace it. Users will find technology more user-friendly if they derive enjoyment from it, and their perception of enjoyment is essential for the acceptance of new technology (Zhong et al., 2021). Their perceptions of the technology's utility and accessibility will influence the adoption and utilization by SMEs. Davis et al. (1989b) assert that customer attitudes and intentions about the utilization of new technology are shaped by perceived usefulness and perceived ease of use.

A newly developed technology with significant functionality is more likely to be adopted (Morosan, 2011). Digitalization is the process of converting commercial processes to encompass customer management, transactions, services, and feedback inside a completely digital framework (Ikumoro & Jawad, 2019). Figure 2.1 illustrates the TAM concept.

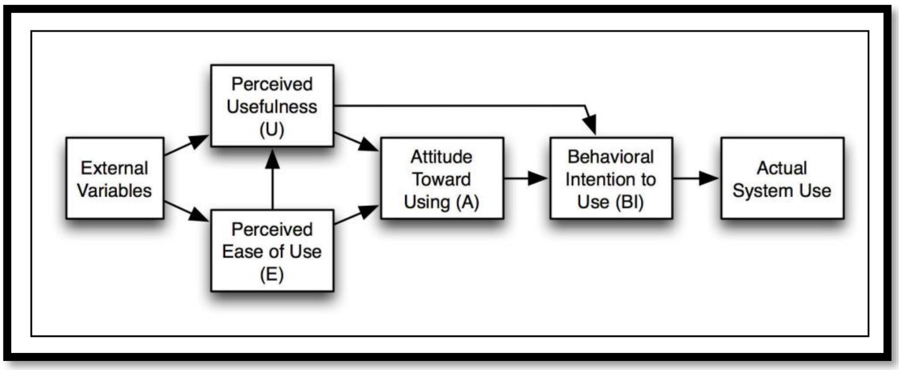

Figure 2.1: TAM Model

Note: Davis, 1985

2.3.1 Perception of External Control (PEC)

PEC is characterized as a person's subjective evaluation of the degree to which external factors or conditions affect their life and results. The impression of external control exhibited a high positive correlation with the acceptability of surveillance technologies (Wnuk et al., 2020).

Venkatesh, Smith, et al. (2003) characterize PEC as the degree to which an individual recognizes the accessibility of technology and organizational resources to support system utilization. PEC is a significant determinant affecting individuals' tendencies to engage with the e-learning system (Chu & Chen, 2016). The inclination of individuals to utilize the e-learning system is affected by PEC, a significant indicator of effort anticipation (Dwivedi et al., 2019).

2.3.2 Computer Self-efficacy (CSE)

The theory of computer self-efficacy is founded on the Technology Acceptance Model (TAM). It indicates the extent to which an individual can utilize a computer to accomplish a certain task or activity (Compeau & Higgins, 1995). Computer self-efficacy is a fundamental theoretical concept that may affect accountants' and auditors' endeavors to use technology. According to Morina & Berisha-Shaqiri (2023), all individuals possess the confidence to utilize computers effectively for task completion in the workplace. Evidence suggests that individuals may be adept at navigating an AI-driven future, considering the growing influence of artificial intelligence (AI) in defining forthcoming employment landscapes. A positive association exists between computer self-efficacy and learning outcomes when using a computer. Enhanced computer self-efficacy correlates with improved learning outcomes. (Febriati, 2021).

Thongsri et al. (2020) state that individuals with a positive feeling of computer self-efficacy are more inclined to view the system as user-friendly and to resolve issues promptly when they occur. Individuals with advanced computer skills are more inclined to utilize blockchain technology compared to those with less expertise. This is particularly applicable to utilizing computers to facilitate the learning process. Computer self-efficacy enhances organizational involvement and concurrently affects job satisfaction inside the company (Wolverton et al., 2020). Computer self-efficacy is a determinant of employee engagement and satisfaction results in technology.

2.3.3 Job Relevance (JR)

The concept that an individual's performance is influenced by the target system is referred to as job relevance (Venkatesh & Favis, 2000). Kim et al. (2009) state that consumers would be motivated to acquire further knowledge about the technology to independently assess its benefits. Knowledge and practical instructions are essential as they assist users inside the organization in leveraging technology to enhance their workplace experience (Rafique et al., 2020). A prior study indicates that those who are technologically proficient and believe in its potential to enhance education are more inclined to utilize digital tools and software compared to those who are less proficient and harbor negative views about technology (Antonietti et al., 2022).

Na et al. (2022) state that most new technologies have been chosen for their capacity to enhance end users' productivity in the workplace. In other words, when integrating new technology into an organization, the needs and relevance of end users should be prioritized in selecting a technology that enhances user benefits and performance. Users' evaluations of technology adoption are significantly affected by usability and user experience (Al-Maroof et al., 2020).

2.3.4 Output Quality (OQ)

Output quality (OQ) refers to the extent to which an individual evaluates the system's efficacy in executing responsibilities (Venkatesh, 2000). Output quality can be defined as an individual's evaluation of a system's effectiveness in fulfilling the tasks necessary for the role. As stated by Faqih and Jaradat (2015), the output quality can serve as a valuable reference for developing and executing effective real-world interventions and tactics to enhance customers' desire to use e-commerce technology. Integrating technology within the company can facilitate data gathering and processing, yielding valuable insights for situational analysis and forecasting (Petrlić & Vitezić, 2023). The output quality will benefit from enhanced data and information availability, both temporally and quantitatively, thereby improving the quality of their work.

Hariguna et al. (2021) state that the superior quality of technology employed inside an organization influences both output quality and the sustainability of facilities. The quality of input regarding skills composition is focused on enterprises that initially possess strong skill-augmenting productivity (Bas & Paunov, 2021).

2.3.5 Result Demonstrability (RD)

The phrase "result demonstrability" refers to an individual's perception that employing a method would provide tangible, observable, and communicable outcomes. A heightened degree of outcome demonstrability can enhance user confidence and satisfaction. An improved user experience and heightened acceptance and adoption of the technology may arise from users' ability to see and articulate the benefits or implications of a system. Researchers examining individuals' inclination to utilize e-learning systems found that research and development substantially enhance regarded usefulness (Hanif et al., 2018). Result demonstrability emerged as a motivator for the organization's adoption of technology in daily operations, with result demonstrability exerting the most significant influence (Izuagbe et al., 2022a).

Soodan et al. (2024) indicate that an organization's faith in technology favorably influences perceptions of its usefulness and impacts outcome demonstrability. Employees enhance their capacity to comprehend technological information, facilitating the observation and utilization of results generated by system technology (Yuan et al., 2021).

2.3.6 Effort Expectancy (EE)

Effort expectancy refers to the perceived ease of use of systems (Ghalandari, 2012). Technology successfully persuaded consumers to remain engaged and utilize these features (Tannady et al., 2024). Effort expectancy, as defined by Sang Ryu and Fortenberry (2021), refers to consumers' perceptions regarding the ease and efficiency of utilizing a technology channel interchangeably inside a specific system to accomplish tasks. "Effort expectancy" refers to an individual's perception of the ease or difficulty associated with utilizing a specific service or technology to complete designated activities (Venkatesh et al., 2003). The concept corresponds with the principle of perceived ease of use Dwivedi et al. (2017), which has been shown to exert a positive and significant impact on consumers' attitudes towards the adoption of technology in service organizations (Hung et al. (2013); Lu et al. (2010); Navavongsathian et al. (2020).

2.3.7 Performance Expectancy (PE)

The degree to which a person expects to improve their job performance through the use of a system is known as their performance expectancy (Ghalandari, 2012). According to Venkatesh et al. (2003), performance expectancy is the degree to which a person believes that utilizing a certain service or technology would enable him or her to successfully complete related tasks. The idea behind performance expectancy is that people will be more inclined to adopt new services or technologies if they believe them to be beneficial (Dwivedi et al., 2017). Several research have demonstrated that people's attitudes about embracing new and electronic technologies are positively and significantly impacted by performance expectancy (Dwivedi et al. (2017); Khalilzadeh et al. (2017); Park et al. (2007); Pynoo et al. (2011).

2.4 Theoretical Model: Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), formulated by Venkatesh et al. (2003), is a prominent framework for comprehending technology adoption. It delineates four key determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions. The model incorporates four moderators: gender, age, experience, and voluntariness of use which affect the correlations between these factors and behavioral intention. Venkatesh et al. (2003) posited that gender, age, experience, and voluntariness of usage modify the links among UTAUT categories and behavioral intention. These moderators have been thoroughly investigated in the context of technology adoption research. Nonetheless, its usefulness is contingent upon context and may lack relevance in controlled and regulated settings, such as auditing.

Age and gender influence individuals' differences in information processing such as, cue interpretation and processing, which then impacts their dependence on habits to direct action. Research indicates that elderly individuals predominantly depend on automatic information processing Hasher and Zacks (1979); Jennings and Jacoby 1993), with their established habits obstructing or inhibiting new learning (Lustig et al. 2004).

Murphy and Hassall (2019) propose a complex link between expertise and experience. Initially, there exists a positive link between expertise and experience; however, this relationship may turn negative at elevated levels of experience, maybe due to factors such as overconfidence or outdated information. Professionals in the accounting sector are regarded as experts owing to their ongoing professional development and training, which progressively augment their competencies (Jasanoff, 2003).

Voluntariness is acknowledged as a significant factor affecting both individual and communal acceptance of technology. When a customer actively transitions to a different audit firm, they may pursue an auditor whose accounting and reporting perspectives align more closely with their own (Nagy, 2005). This voluntary modification would lead to a diminished level of the auditor's professional skepticism. Chen et al. (2008) asserted a favorable correlation between audit quality and the auditor's professional skepticism.

This study alters the UTAUT model by substituting these moderators with social influence. The primary determinants of auditors' intention to utilize blockchain are performance expectancy and social influence (Ferri et al., 2021). Furthermore, auditors' effort prediction for the deployment and utilization of this technology seems to be a dependable predictor. This section offers a theoretical rationale for this adjustment grounded in existing literature and contextual factors. Mousa Jaradat and Al Rababaa (2013) state that there are direct effects between behavioral intention and the subsequent utilization of technology adoption. Culture significantly influences technology adoption (Venkatesh & Zhang, 2010). Establishing the practice of utilizing technology to enhance the learning experience will inherently enhance behavioral usage (Nair et al., 2015). The UTAUT concept is illustrated in Figure 2.2 (Venkatesh et al., 2000).

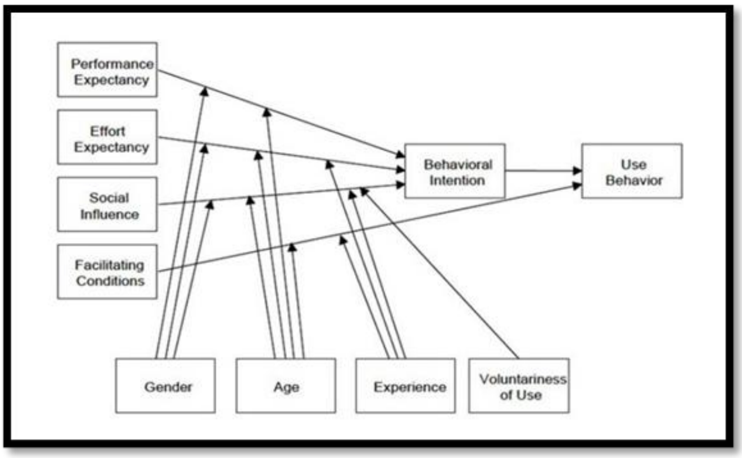

Figure 2.2: UTAUT Model

Note: Venkatesh et al., 2000

This study revises the original UTAUT model by omitting gender, age, experience, and voluntariness of usage as moderators, given their reduced significance in the auditing profession. Social influence is presented as a moderator because of its essential function in regulatory compliance and organizational decision-making. This adaptation is substantiated by previous studies highlighting the significance of contextual adjustments to UTAUT in professional environments (Dwivedi et al., 2019). This study improves the explanatory capacity of UTAUT about blockchain adoption in auditing by incorporating social impact as a moderating variable.

2.4.1 Social Influence (SI)

A theoretical concept that was developed from UTAUT, social influence (SI) examines how a director's decisions are influenced by the opinions of those in his circle of acquaintances. (Venkatesh et al., 2003), stated that by social influence, they meant the degree to which an individual perceives that others are important to him or her in using the new system. According to (Almarashdeh et al., 2021), SI is correlated with an individual's perception of how much their significant others agree with them about using new technologies. SI also influences the choices made by users of new mobile technologies (Joa & Magsamen-Conrad, 2022). Individual opinion and societal variables are the two main influencers of an individual's beliefs regarding the acceptance and use of technology (Bozan et al., 2016).

According to (Curtis & Payne, 2008), SI influences auditors' intentions to use new software solutions positively. It is especially pronounced in highly hierarchical environments like audit firms, where an individual would be more likely to consider the opinions of others who have evaluative authority over their performance. Social influence comes in two types: the first is external and includes things like expert opinions and stories from the media. Interpersonal influence, including that of superiors, colleagues, and word-of-mouth, is the second kind.

2.5 Conceptual Framework

This research investigates the determinants affecting the willingness to embrace blockchain technology within the auditing profession. The conceptual framework is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), offering a systematic method for comprehending technology adoption. This study identifies perception of external control, computer self-efficacy, work relevance, output quality, outcome demonstrability, effort expectancy, and performance expectation as crucial factors affecting auditors' preference toward embracing blockchain technology.

The perception of external control pertains to auditors' belief in their influence over the adoption process, whereas computer self-efficacy denotes their confidence in efficiently utilizing blockchain technology. Job relevance refers to the expected utility of blockchain in executing auditing functions, whereas output quality denotes expectations for the precision and dependability of blockchain-generated financial documentation. Result demonstrability refers to the degree to which auditors may perceive concrete advantages from the deployment of blockchain technology. Effort expectancy pertains to the perceived simplicity of utilizing blockchain, whereas performance expectancy pertains to the conviction that blockchain would improve auditors' job performance and efficiency.

This study includes social influence as a moderator to enhance the understanding of external forces in determining adoption intentions. Social impact denotes the perceived encouragement or expectations from peers, superiors, regulatory entities, and industry leaders concerning blockchain adoption. In heavily regulated sectors such as auditing, professional standards and institutional influences are essential in the use of technology. This study asserts that social impact moderates the correlations between the independent factors and the intention to use blockchain technology. For instance, if auditors recognize significant support from their professional networks or regulatory bodies, they may be more inclined to regard blockchain as pertinent and advantageous, hence enhancing its adoption aim. In contrast, without such influence, personal views may exert a diminished impact on adoption decisions.

Figure 2.3 presents the conceptual framework, illustrating the links among the independent factors, the moderating variable (social influence), and the dependent variable (intention to embrace blockchain technology).

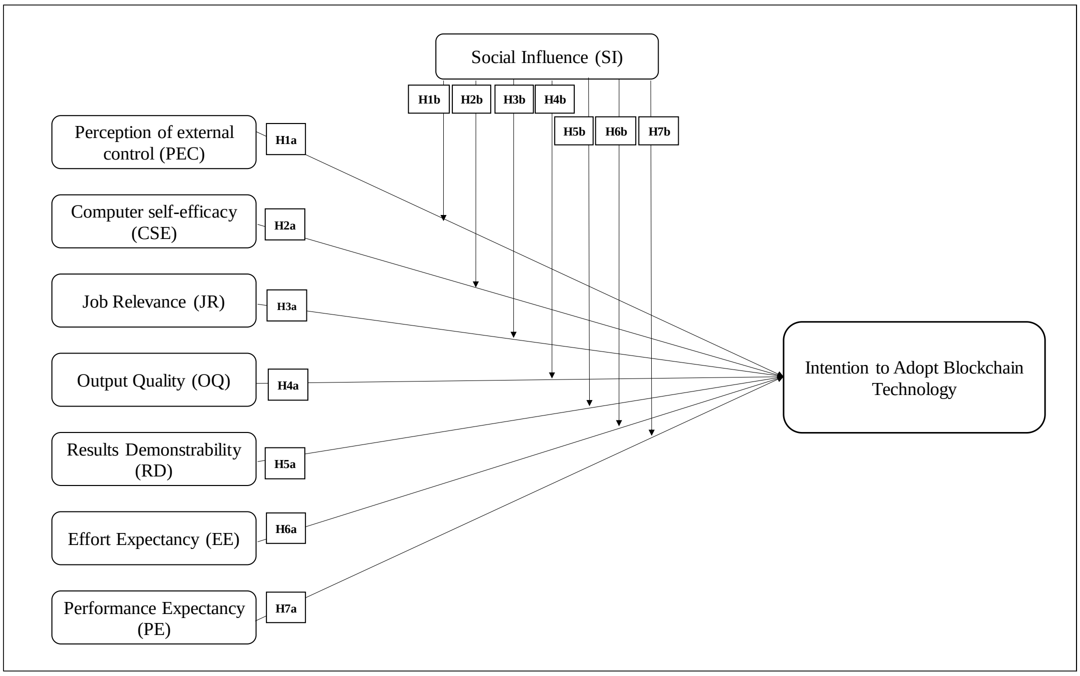

Figure 2.3: Conceptual Framework

2.6 Hypotheses Development

This procedure directs the research design and facilitates the methodical examination of the correlations among variables. The researchers can construct a hypothesis that may yield significant and dependable study results.

2.6.1 Relationship between Perception of External Control (PEC) and Intention to Adopt Blockchain Technology

Venkatesh et al. (2003) characterize TAM3 as encompassing the concept of Perception of External Control (PEC), which denotes the idea that the technological and organizational resources of the system are easily available to enhance their utilization. PEC is a crucial factor influencing adoption intention in various contexts and circumstances (Putra and Samopa, 2018).

Ferri et al. (2021) underscore that this viewpoint is supported by the auditing profession's emphasis on blockchain adoption methods. Blockchain technology has numerous advantages, like improved auditing, cost reduction, greater data provenance, and increased confidence, which encourage business organizations to adopt it (Orji et al., 2020). Most experts acknowledge that the emphasis of Blockchain technology undeniably possesses the potential to profoundly influence and revolutionize all aspects of accounting. Its capacity to automate various accounting procedures would eradicate the necessity for human participation in routine operations and markedly enhance the efficiency and efficacy of accounting processes (Kommunuri, 2022; LaLacurezeanu et al., 2020). The increasing number of blockchain technology has resulted in its extensive adoption across various sectors.

Research by Liu et al. (2022) highlights China's significant focus on the incorporation of blockchain technology across many industries and smart cities. However, contradictory research exists about the importance of PEC in technology adoption. Some research indicates a substantial beneficial impact (Ifinedo, 2012). In contrast, some argue that in highly regulated industries, external mandates and compliance obligations may take precedence over personal notions of control (Grewal et al., 2020). Considering these varied findings, additional investigation is required to evaluate PEC's influence on blockchain usage in auditing. Therefore, the following hypothesis is proposed.

Hypothesis 1 (H1a): There are positive relationship between the Perception of external control (PEC) on intention to use Blockchain Technology (BT).

2.6.2 Relationship between the Perception of External Control (PEC) on Intention to use Blockchain Technology (BT), Moderating by Social Influence

The perception of external control (PEC) significantly influences individuals' intention to embrace blockchain technology, as it indicates the accessibility of technological and organizational resources that support adoption (Venkatesh et al., 2003). Nonetheless, in addition to these structural elements, social influence (SI) is a significant driver in either increasing or diminishing the impact of PEC on adoption intention. Social influence denotes the degree to which individuals believe that significant referents, such coworkers, industry peers, or regulatory entities, advocate for or anticipate their adoption of a technology (Venkatesh et al., 2012).

Research has shown that social influence substantially affects technology adoption behaviors by influencing individuals' perceptions of external resources and support (Delfabbro et al., 2021). Auditors are more inclined to utilize existing technological resources and enhance their intention to implement blockchain when they observe significant advocacy for its adoption from their peers or superiors (Gokoglan et al., 2022). Conversely, when social influence is limited, the perceived external control may exert a reduced effect on adoption decisions, as individuals may lack the drive or confidence to utilize existing resources efficiently.

Social influence is acknowledged as a vital element in digital transformation since it impacts users' confidence in technology and promotes acceptance through peer validation and industry support (Wamba et al., 2020). Studies on online services indicate that the most efficient digital platforms incorporate social impact mechanisms, such as user evaluations and recommendations, which bolster consumer trust and promote engagement with the technology (Grewal et al., 2020). In professional contexts such as auditing, social norms, and industry trends significantly influence auditors' readiness to embrace blockchain-based technologies (Ferri et al., 2023). It is anticipated that social impact will modulate the relationship between PEC and the desire to embrace blockchain, enhancing the effect when social support for adoption is robust. Consequently, the subsequent hypothesis is posited.

Hypothesis 1 (H1b): There is a positive relationship between the Perception of external control (PEC), moderating by Social Influence (SI), and intention to adopt Blockchain Technology (BT).

2.6.3 Relationship between Computer Self-efficacy (CSE) and Intention to Adopt Blockchain Technology

Computer self-efficacy (CSE) is an important psychological factor influencing technology adoption, indicating an individual's confidence to proficiently utilize a certain technology (Hayashi et al., 2004). Self-efficacy, a term introduced by Bandura (1986), is defined as individuals' assessments of their skills to organize and implement actions necessary to achieve specific performance outcomes. Elevated levels of computer self-efficacy correlate with an increased propensity to adopt developing technologies, as individuals perceive themselves as more adept at surmounting technical obstacles and optimising the advantages of adoption (Venkatesh et al., 2012).

In auditing, blockchain technology has intricate features such as smart contracts, real-time data validation, and decentralized transaction monitoring. Consequently, risk professionals with elevated CSE may have increased confidence in investigating and incorporating blockchain solutions into their operations (Ferri et al., 2021). Comprehension of BT and elaboration of many factors that affect the use of BT in the auditing domain.

Consequently, the literature on BT is being augmented, as it is seen as a potent new methodology that substantially affects auditors' practices (Hamadeh et al., 2025).

CSE significantly influences performance expectancy and the conviction that blockchain utilization would improve auditing efficacy. Research suggests that individuals with elevated self-efficacy are more inclined to view technology innovations as beneficial rather than obstructive, hence enhancing their propensity to embrace such improvements (Putra and Samopa, 2018). Consequently, considering the impact of CSE on personal confidence and adoption choices, the subsequent hypothesis is posited:

Hypothesis 2 (H2a): There are positive relationship between Computer Self-efficacy (CSE) and Intention to Adopt Blockchain Technology.

2.6.4 Relationship between Computer Self-efficacy (CSE) and Intention to Adopt Blockchain Technology, Moderating by Social Influence.

Computer self-efficacy (CSE) significantly impacts an individual's confidence in embracing new technologies, such as blockchain. Nonetheless, in addition to individual competence, external social factors such as peer influence, managerial backing, and industry standards can either enhance or diminish the effect of CSE on the intention to embrace blockchain technology. Social impact (SI) denotes the extent to which individuals believe that significant stakeholders, including colleagues, supervisors, and regulators, anticipate or promote their utilisation of technology (Venkatesh et al., 2003).

Research indicates that in professional settings, social influence can enhance the impact of self-efficacy on technology adoption. Individuals with elevated CSE who gain substantial social support for blockchain adoption may experience increased confidence and motivation to interact with the technology (Delfabbro et al., 2021). Conversely, even professionals with robust CSE may be reluctant to embrace blockchain if they see insufficient industry-wide endorsement or if their peers exhibit skepticism (Grewal et al., 2020).

Social impact also aids in closing the confidence gap for those with diminished Core Self-Evaluations (CSE). Liu et al. (2022) showed that the new users demonstrated increased reactivity to effort expectancy, performance expectancy, social impact, facilitating conditions, and trust, which could substantially enhance the intention to utilise blockchain technology. Self-efficacy and perceived usefulness were significant factors influencing the behavioural intention to use technology (Hsieh et al., 2017). Consequently, social influence is anticipated to modify the link between CSE and the desire to use blockchain, amplifying the effect when social influence is elevated. Consequently, the subsequent hypothesis is posited:

Hypothesis 2 (H2b): There is a positive relationship between Computer Self-efficacy (CSE), moderating by Social Influence (SI), and intention to adopt Blockchain Technology (BT).

2.6.5 Relationship between Job Relevance (JR) and Intention to Adopt Blockchain Technology

Individuals are more likely to adopt a technology they regard as advantageous to their profession, whereas those deemed irrelevant may encounter opposition. In the auditing industry, blockchain technology presents advantages including increased transparency, less fraud risk, and higher efficiency in transaction verification. Nonetheless, its implementation is largely contingent upon auditors perceiving it as pertinent to their professional duties.

Previous research has demonstrated a correlation between work relevance and technology adoption. Bhattacherjee and Sanford (2006) discovered a positive correlation between job relevance and user attitudes toward technology adoption, indicating that users are more inclined to embrace technologies they perceive as beneficial for their work. In a similar vein, Kim et al. (2009) examined the influence of job relevance on the adoption of new technologies in auditing, concluding that a heightened perception of relevance correlates with an increased desire to utilise the technology. These results correspond with the Unified Theory of Acceptance and Use of Technology (UTAUT) model, which identifies job relevance as a significant predictor of technology adoption behaviour (Venkatesh et al., 2012).

Considering the increasing interest in blockchain technology in auditing, it is essential to investigate whether auditors regard blockchain as pertinent to their profession and how this impression affects their plans to embrace it. Informed by the theoretical framework and previous empirical evidence, the subsequent hypothesis is posited:

Hypothesis 3 (H3a): There are positive relationship between Job Relevance (JR) and Intention to Adopt Blockchain Technology.

2.6.6 Relationship between Job Relevance (JR) and Intention to Adopt Blockchain Technology, Moderating by Social Influence

Job relevance (JR) is a crucial factor influencing technology adoption, indicating an individual's assessment of a system's alignment with their professional responsibilities and its contribution to work productivity (Izuagbe et al., 2021). Users are more inclined to use technology when they acknowledge its potential advantages in enhancing their work processes (Wu et al., 2011).

Snicker (2013) highlights that assessing a system's efficacy in facilitating job-related tasks is essential for gauging its adoption potential. The correlation between job relevance and technology adoption may vary among individuals. Social impact (SI) the extent to which individuals believe that significant persons such as coworkers, supervisors, or industry peers endorse the adoption of technology can serve as a crucial moderating factor (Venkatesh et al., 2012). When social impact is pronounced, individuals may experience heightened pressure or motivation to embrace blockchain technology, hence strengthening their conviction in its significance and utility. Conversely, when social impact is minimal, the perceived relevance of blockchain to one's profession may not suffice to motivate adoption due to the absence of external validation.

Previous research has emphasized the moderating impact of social influence on technology adoption. Research by Bhattacherjee and Sanford (2006) demonstrated that social norms can enhance the influence of perceived usefulness on adoption intention. Van den Heuvel et al. (2020) state that employees' motivation, attitude, and positive reinforcement are fundamental elements affecting their intention to exploit technology in adapting to the new working structure. The empirical evidence demonstrates that the implementation of new technology can augment employees' job effectiveness (Okkonen et al., 2019) and can improve employees' adaptive performance (Hamid, 2022). Based on this theoretical framework, the subsequent hypothesis is presented.

Hypothesis 3 (H3b): There are positive relationship between Job Relevance (JR), moderating by Social Influence (SI), and intention to adopt Blockchain Technology (BT).

2.6.7 Relationship between Output Quality (OQ) and Intention to Adopt Blockchain Technology

In technology adoption, users frequently evaluate various systems that are equally pertinent to their work and make decisions depending on the quality of the outputs generated by each system. When technology regularly produces superior outcomes, consumers regard it as more beneficial and are more inclined to embrace it (DeLone and McLean, 2003).

Blockchain technology is valued for its safe, transparent, and unchangeable properties, which enhance trust in banking and auditing processes. A key benefit is its ability to facilitate international transactions without traditional financial intermediaries, so ensuring speed, accuracy, and cost-effectiveness. If users perceive blockchain technology as delivering high-quality and verifiable results, their faith in its effectiveness increases, influencing their adoption decisions. Most past studies have highlighted the importance of output quality in technology adoption.

DeLone and McLean (2003) proposed the Information Systems Success Model (ISSM), emphasizing that output quality is an important variable influencing system adoption and user satisfaction. Petter et al. (2008) showed that systems with higher output quality increase user trust and adoption intentions, particularly in financial and auditing sectors. Venkatesh and Bala (2008), according to the Technology acceptability Model 3 (TAM3), identified output quality as a pivotal component affecting system acceptability, especially when users rely on technology for decision-making. Dwivedi et al., (2012) underscored that output quality is a crucial determinant of technology acceptance, particularly in data-driven industries where accuracy is important. Following this theoretical framework, the ensuing hypothesis will be presented.

Hypothesis 4 (H4a): There are positive relationship between Output Quality (OQ) and Intention to Adopt Blockchain Technology.

2.6.8 Relationship between Output Quality (OQ) and Intention to Adopt Blockchain Technology, Moderating by Social Influence

The relationship between output quality and technology adoption may be modified by social influence, defined as the degree to which individuals are influenced by the views and actions of their peers, colleagues, or industry leaders. Social influence has been shown to affect the innovation adoption process directly. This result has significant implications for organizations in the efficient management of employee-driven innovation (Chang et al., 2015). The most effective web-based offerings consider social impact factors, fostering customer loyalty to technology and facilitating rapid client engagement (Ruangkanjanases et al., 2023).

When social impact is significant, individuals are more inclined to trust the quality of blockchain technology's outputs due to positive peer reinforcement and industry endorsements. Previous studies have shown that social influence can enhance the impact of perceived system effectiveness on adoption intentions (Venkatesh et al., 2012; Lu et al., 2005). Therefore, the following hypothesis is proposed.

Hypothesis 4 (H4b): There are positive relationship between Output Quality (OQ), moderating by Social Influence (SI), and intention to adopt Blockchain Technology (BT).

2.6.9 Relationship between Result Demonstrability (RD) and Intention to Adopt Blockchain Technology

Agarwal and Prasad (1999) suggest that the results of the demonstration significantly influence the acceptability of an idea. They indicated a substantial correlation between behavioral need to adopt and demonstrability (Gow et al., 2019). Result Demonstrability indicates the extent to which the effects of employing technology are perceptible and conveyable to others (Wong et al., 2022). The theory depends on the conceptual instrumental framework, wherein individuals assess the utility of technology based on the demonstrable efficacy of its advantages in practice (Zhang et al., 2010). Within the context of blockchain adoption in the auditing profession, outcome demonstrability significantly influences auditors' assessments of the system's efficacy.

Auditors have been charged with ensuring transparency, accuracy, and integrity in financial reporting. The implementation of blockchain technology provides immutable, verifiable, and decentralized records, hence improving audit reliability and fraud detection (Zhang et al., 2020). When auditors can observe and articulate the advantages of blockchain such as enhanced trust in audit outcomes, fewer errors, and heightened efficiency they are more inclined to recognize blockchain as an important resource for their profession.

Research on blockchain adoption across several industries indicates that professionals are more inclined to embrace the technology when they perceive its direct impacts (Casino et al., 2019). Research on blockchain in financial auditing indicates that companies utilizing blockchain for real-time audit verification saw enhanced trust and efficiency, resulting in greater acceptance by auditors (Zhang et al., 2020). Organizations that successfully implemented blockchain through pilot programs experienced heightened levels of acceptance from auditors and compliance officers (Dai & Vasarhelyi, 2017). Therefore, the following hypothesis is proposed.

Hypothesis 5 (H5a): There are positive relationship between Result Demonstrability (RD) and Intention to Adopt Blockchain Technology.

2.6.10 Relationship between Result Demonstrability (RD) and Intention to Adopt Blockchain Technology, Moderating by Social Influence

The influence of outcome demonstrability on performance expectancy could be different among auditors. Certain auditors may be more affected by external perspectives and peer experiences, whereas others may predominantly depend on their evaluations of the technology. Social Influence, a moderating variable in the UTAUT model, denotes the degree to which individuals perceive those significant persons, such as coworkers, industry leaders, or regulatory entities, to advocate for the adoption of a technology (Venkatesh et al., 2003).

In the framework of blockchain adoption in auditing, Social Influence can enhance the impact of Result Demonstrability. When seasoned blockchain users recount their favorable experiences and achievements to their peers, prospective users are more inclined to form enhanced impressions of blockchain's use. This corresponds with prior studies indicating that peer recommendations, expert endorsements, and industry trends substantially affect views of a technology's efficacy (Alharthi et al., 2020). This is a recommendation for hypothesis 5b.

Hypothesis 5 (H5b): There are positive relationship between Result Demonstrability (RD), moderating by Social Influence (SI), and intention to adopt Blockchain Technology (BT).

2.6.11 Relationship between Effort Expectancy (EE) and Intention to Adopt Blockchain Technology

According to (Thusi and Maduku, 2020), effort expectancy is consumer confidence that technology is easy to learn and easy to use. Effort expectancy can be seen as the ease with which users can make outcomes and monitor data usage only the application (Liveon.id, 2022). Consumers tend to use applications that can provide them with maximum benefits with the ease of operating the application (Davis et al., 1989). Studies show that performance expectancy significantly influences trust and the inclination to use technology. Consequently, the findings indicate that the respondents recognize the performance expectation and effort expectancy associated with utilizing blockchain technology in management. (Nguyen and Nguyen, 2021). Effort expectancy relates to the perceived ease of use, recognizing that people are more inclined to adopt smart technologies that require low operational effort (Almaher et al., 2024). This is a recommendation for hypothesis 6a.

Hypothesis 6 (H6a): There are positive relationship between Effort Expectancy (PE), and intention to adopt Blockchain Technology (BT).

2.6.12 Relationship between Effort Expectancy (EE) and Intention to Adopt Blockchain Technology, Moderating by Social Influence

Effort Expectancy (EE) is a crucial factor in the adoption of new technologies, denoting the perceived simplicity of usage and the effort necessary to operate a system (Fedorko et al., 2021). Users frequently encounter difficulties with blockchain technology due to its intricacy, technical characteristics, and requirement for specialized expertise (Wamba & Queiroz, 2019). The Technology Acceptance Model (TAM) and its extensions indicate that people are more inclined to accept a technology when they see it as user-friendly (Davis et al., 1989).

Investigations across multiple sectors have substantiated this correlation. Leong et al. (2020) identified that entrepreneurial orientation (EO) was a strong predictor of blockchain adoption within the financial sector. Wong et al. (2020) similarly established that EE directly affects trust and behavioral intention toward blockchain technology. Based on these findings, it is plausible to assume that persons who view blockchain technology as user-friendly will have a greater propensity to embrace it.

Karahanna and Straub (1999) suggest that social influence exerts a more significant impact on rookie technology users compared to experienced users. Furthermore, the social influence component underscores the impact of peers and colleagues on individual adoption decisions, particularly pertinent in corporate settings (Kapnissis et al., 2022). This is a recommendation for hypothesis 6b.

Hypothesis 6 (H6b): There are positive relationship between Effort Expectancy (EE), moderating by Social Influence (SI), and intention to adopt Blockchain Technology (BT).

2.6.13 Relationship between Performance Expectancy (PE) and Intention to Adopt Blockchain Technology

Performance Expectancy (PE), as stated by Venkatesh et al. (2003), denotes the perceived utility of a technology and the advantages it affords consumers. It indicates the user's assurance that embracing the technology will augment efficiency and elevate performance. Within the realm of blockchain technology, PE is essential since customers anticipate that blockchain will deliver secure, transparent, and efficient solutions for diverse applications (Thusi and Maduku, 2020).

Studies indicate that enhanced usability and anticipated advantages propel technology adoption (Compeau and Higgins, 1995). When individuals perceive that blockchain can enhance their work processes or confer a competitive edge, their propensity to use the technology escalates (Rizkalla et al., 2023b). Furthermore, Almaher et al. (2024) emphasize that the adoption of blockchain is profoundly affected by its capacity to improve efficiency and optimize operations.

Hypothesis 7 (H7a): There are positive relationship between Performance Expectancy (PE), and intention to adopt Blockchain Technology (BT).

2.6.14 Relationship between Performance Expectancy (PE) and Intention to Adopt Blockchain Technology, Moderating by Social Influence

Performance expectancy significantly positively influences the behavioral desire to adopt technology (Al-Saedi et al., 2020). The acceptance of technology by users or customers is influenced by performance expectancy and social influence, while simultaneously hindered by perceived risk and cost (Hongxia et al., 2011). Multiple prior authors have demonstrated the advantageous impact of performance expectancy on the behavioral intention of customers to utilize the service (Luo et al., 2010). PE pertains to the extent of an individual's confidence that utilizing a specific system will enhance their job performance (Almarashdeh et al., 2021).

Hypothesis 7 (H7b): There are positive relationship between Performance Expectancy (PE), moderating by Social Influence (SI), and intention to adopt Blockchain Technology (BT).

2.7 Conclusion

Chapter 2 has offered a comprehensive examination of the theoretical and empirical literature pertinent to blockchain adoption in auditing. The review encompasses current technological acceptance models, emphasizing UTAUT and its principal constructs. The review emphasized the significance of external control, self-efficacy, work relevance, output quality, and result demonstrability in shaping adoption decisions. The moderating function of social influence was examined concerning blockchain implementation. This chapter identifies research gaps, establishing the necessity for additional empirical examination, which will be addressed using the research technique outlined in Chapter 3.

CHAPTER 3

METHODOLOGY

3.1 Introduction

Chapter 3 defines the research approach employed in this study. The discussion initiates with the research design, rationalizing the application of a quantitative methodology to investigate blockchain acceptance among auditors. The chapter subsequently delineates the population, sampling methodology, and determination of sample size. The subsequent section elucidates the questionnaire development process, encompassing the operationalization of variables derived from verified measurement scales. The protocols for the pilot test, in addition to evaluations of reliability and validity, are also provided. The chapter concludes by outlining the data-gathering methodology and the analytical approaches utilised, specifically Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS software.

3.2 Research Design

This study utilises a quantitative research design to comprehensively examine the factors affecting auditors' inclination to use blockchain technology in audit businesses in Kuching. Considering the growing importance of blockchain technology in the auditing field, it is essential to evaluate the determinants of its acceptance, especially in organisational contexts where technology installation is frequently intricate and affected by several factors. The study seeks to furnish actual knowledge concerning the factors influencing blockchain adoption, so contributing to academic research and practical applications for audit firms.

A cross-sectional survey method was employed to gather data from auditors at a specific moment. Cross-sectional studies are extensively utilised in social science and business research, as they facilitate the analysis of correlations among various variables at a certain point in time (Creswell, 2014). This method is especially appropriate for this study as it facilitates the identification of critical factors influencing blockchain adoption without necessitating a longitudinal approach, which may be impractical due to time and resource limitations. Moreover, cross-sectional surveys provide extensive data gathering, allowing for the analysis of patterns and trends that may not be readily apparent using qualitative or case study methodologies.

The research employed structured questionnaires to guarantee standardised data collection, facilitating uniform measurement of essential constructs. This methodology improves the study's reliability and validity, as structured surveys reduce interviewer bias and guarantee that all participants are presented with identical questions. The questionnaire was created to assess constructs like job performance, output quality, outcome demonstrability, effort expectancy, performance expectancy, and social impact, recognised as essential elements in technology adoption research (Venkatesh et al., 2003). The study utilises a standardised survey instrument, allowing for quantitative analysis of replies, facilitating statistical hypothesis testing, and offering objective insights regarding blockchain adoption in audit companies.

A quantitative approach was selected instead of qualitative or mixed method approaches because it offers generalizable results. Quantitative research facilitates hypothesis testing through statistical methods, hence empirically validating correlations between variables (Babbie, 2010). This methodology selection corresponds with the study's aim of comprehending the predictive capacity of perception of external control, computer self-efficacy, job relevance, output quality, result demonstrability, effort expectancy, performance expectancy, and social effect on the intention to use blockchain technology. Furthermore, the application of statistical analysis strengthens the study's accuracy by providing numerical evidence that substantiates theoretical progress in blockchain adoption research.

The study utilises a quantitative, cross-sectional survey research design to investigate the adoption of blockchain technology among auditors in Kuching. This method employs a systematic questionnaire and statistical analysis to guarantee that the results are scientifically rigorous and practically applicable, hence enhancing the existing information on technology adoption within the auditing profession.

3.3 Population

The study's target demographic comprises professional auditors working in audit firms situated in Kuching, Sarawak. The choice of this group is warranted by the escalating significance of blockchain technology in the auditing field and the rising necessity for technological innovations to improve audit quality, fraud detection, and regulatory adherence. The Malaysian Institute of Accountants (MIA) reports that 38 registered audit firms are functioning in Kuching, offering an adequate pool of participants for this study.

Auditors are essential in financial reporting, guaranteeing that organisations comply with accounting rules, statutory mandates, and ethical standards. The incorporation of blockchain technology in auditing could transform data verification, transparency, and real-time reporting. This study aims to investigate the degree to which auditors regard effort expectancy, performance expectancy, and other pertinent variables as factors influencing their decision to use blockchain technology.

The justification for choosing auditors as the target demographic arises from their direct participation in audit processes, encompassing activities such as financial statement analysis, fraud risk evaluation, and compliance oversight. Auditors' viewpoints on the usability, job relevance, and general practicality of adopting blockchain technology are essential for comprehending the difficulties and enablers of its application in the auditing profession.

This study concentrates on auditors' readiness and desire to utilise blockchain technology; thus, selecting persons actively involved in auditing guarantees the contextual relevance of the obtained data. Consequently, by delineating the population as professional auditors within registered audit firms in Kuching, the study guarantees that the findings are pertinent, dependable, and tailored to the auditing profession in Malaysia.

3.4 Sample Size

G*Power was employed as the principal instrument to ascertain the necessary sample size, hence ensuring the validity and reliability of the statistical analysis in this study. G*Power is a reputable statistical software that allows researchers to do power analysis by calculating the minimal sample size necessary for hypothesis testing. This methodology guarantees that the research attains adequate statistical power, hence reducing both Type I (false positive) and Type II (false negative) mistakes (Erdfelder et al., 1996; Cohen, 1992). This strategy ensures that the sample size is neither inadequate, which might lead to inaccurate findings, neither unreasonably significant, hence avoiding unnecessary data gathering and resource expenditure.

Power analysis is a crucial component of research design that determines the appropriate number of samples for studies involving continuous variables. Berger (2008) defines power analysis as comprising four interrelated components, Power (1 - β or Type II error probability): This denotes the likelihood of accurately rejecting a faulty null hypothesis. A widely recognized benchmark in social sciences and behavioural research is 0.80, indicating that the study has an 80% probability of identifying a genuine effect. Effect size (f^2): The effect size denotes the magnitude of the association between the independent and dependent variables in the research. It is generally categorised as small (0.02), medium (0.15), or large (0.35) (Cohen, 1992). This study employs a medium effect size ($f^2 = 0.15$), commonly utilised in behavioural and business studies. Significance level (α or Type I error probability): This denotes the likelihood of erroneously rejecting a valid null hypothesis. A standard significance level is 0.05, indicating a 5% likelihood of a Type I error occurring.

Sample size (N): The number of individuals necessary to guarantee that the study possesses enough statistical power. This is the principal outcome derived from the G*Power test based on the previously mentioned three factors. Through the integration of these components, G*Power offers a methodical approach for calculating the sample size that enhances the study's dependability while maximizing efficiency in data collecting (Faul et al., 2009).

The F-test has been selected as the relevant statistical test in G*Power for this study. The study employed "Linear multiple regression: Fixed model, R^2 deviation from zero" as the testing methodology. This decision is predicated on the study framework's presence of several independent variables (predictors) affecting the dependent variable, hence providing multiple regression the most appropriate analytical method.

The G*Power parameters for this investigation were established as follows: Effect size (f^2) = 0.15 (moderate effect), and Significance level (α) is set at 0.05. Statistical power equals 0.80 (80%), Number of predictors = 14 (derived from the number of hypotheses for independent variables influencing blockchain adoption)

G*Power calculations indicate that a minimum sample size of 135 respondents is necessary to attain sufficient statistical power for this study. Collecting responses from a minimum of 135 auditors in audit firms in Kuching will yield adequate power to identify significant relationships between variables, hence ensuring the robustness of the study's conclusions.

Although G*Power determines the minimum necessary sample size, it is frequently prudent to strive for an elevated response rate. In empirical research, certain participants may fail to finish the questionnaire, provide incomplete responses, or withdraw from the project. Kock and Hadaya (2018) state that although power analysis establishes a minimal sample size, it may remain inadequate owing to issues related to data quality. Consequently, to improve the statistical reliability and generalisability of the results, this study intends to gather responses from a sample bigger than the requisite 135 participants. An increased sample size diminishes sampling error and enhances the reliability of statistical estimates.

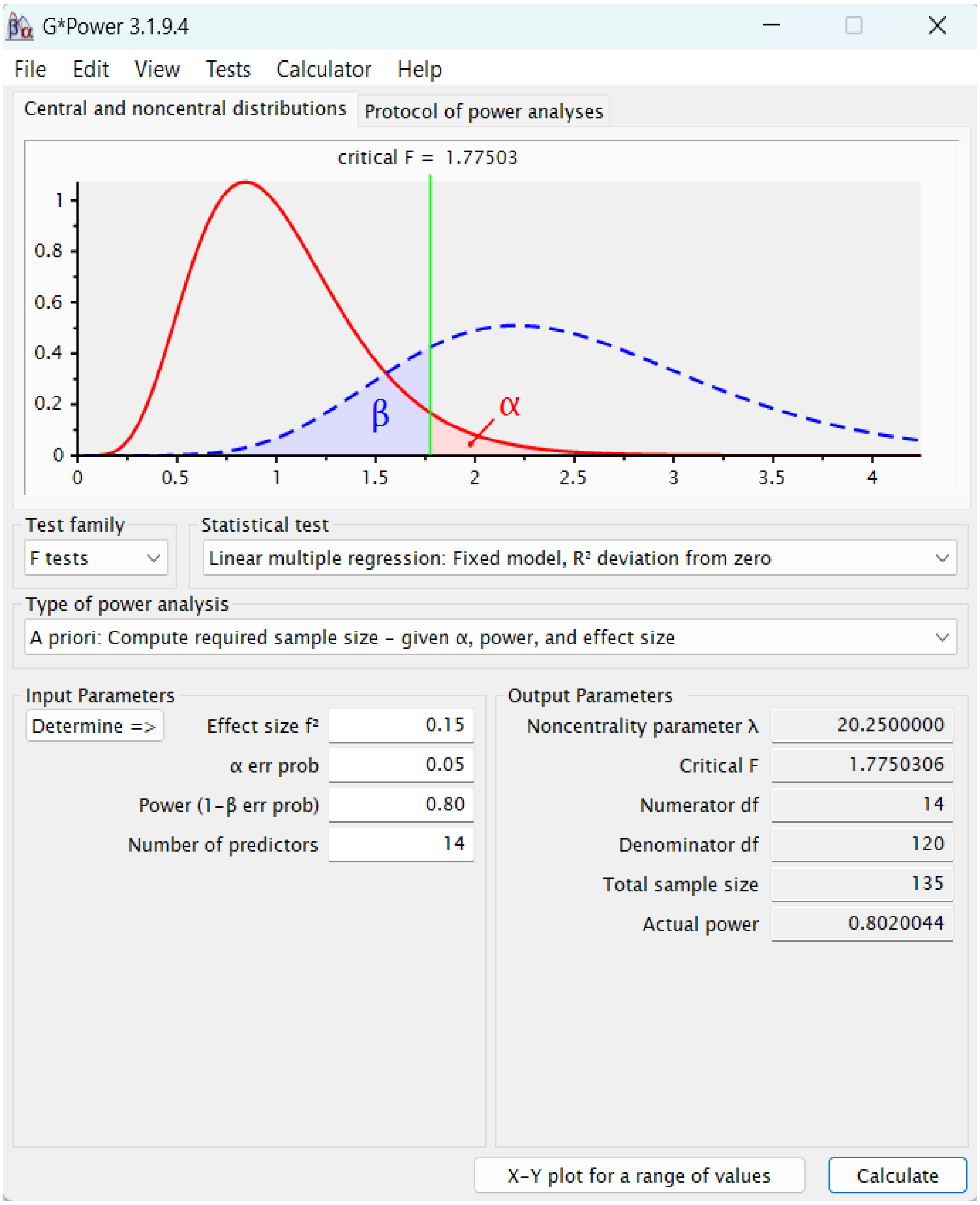

Figure 3.1: G*Power Test

3.5 Sampling Technique

This study adopted a purposive sample strategy, often referred to as judgemental sampling, to fulfil the research objectives. Purposive sampling is a non-probability sampling method wherein participants are chosen based on certain factors that render them particularly qualified to yield pertinent data for the research (Kumar et al., 2013). In contrast to random sampling, which provides every member of a population an equal opportunity for selection, purposive sampling targets individuals with specialised knowledge, experience, or skill pertinent to the research issue.

The employment of purposive sampling in this study is warranted due to the specialised nature of blockchain technology adoption in auditing, necessitating respondents with a robust background in accounting and financial auditing. Given that not all auditors possess expertise with evolving technologies, purposive sampling guarantees the selection of individuals with adequate professional experience and industry exposure, hence enhancing the quality of the responses gathered.

The criteria for selecting respondents in this study were meticulously established to guarantee that participants were suitably qualified to furnish precise, dependable, and insightful data concerning blockchain technology adoption. The subsequent inclusion criteria were delineated:

Age Requirement: Participants must be a minimum of 20 years old to guarantee they possess the requisite educational and professional experience in accounting and auditing. Professional experience: Participants must possess accounting and financial experience to ensure they have the requisite technical understanding for assessing blockchain's application in auditing. Employment Status: Participants must be presently engaged as accountants in an audit firm situated in Kuching. This encompasses auditors employed full-time, part-time, or on a contractual basis. Minimum Work Experience: Participants must possess a minimum of two years of experience in the auditing field to ensure a comprehensive understanding of auditing procedures and technical applications. This criterion excludes persons who are inexperienced in the industry and may lack the proficiency to evaluate the significance of blockchain. Gender and Educational Qualifications: There were no limitations for gender or the highest attained educational qualifications, as long as respondents possessed an accounting and financial background. This inclusive methodology guarantees a diversity of opinions while preserving the sample's relevance.

Purposive sampling, grounded in the researcher's judgment rather than chance, is especially appropriate for studies aimed at acquiring profound, significant insights from field experts rather than generalizing results to a broader population. This study used purposive sampling to guarantee that participants possess the requisite knowledge, experience, and ability to furnish data that directly addresses the research objectives.

Moreover, although purposive sampling presents difficulties, including the possibility of selection bias, its application in this study is strategically warranted. The peculiarity of blockchain use in auditing necessitates the selection of auditors who fulfil established criteria to enhance the validity and trustworthiness of the results. The study seeks to gather data from persons actively involved in auditing activities, rendering them the most suitable cohort to evaluate blockchain's usability, advantages, and potential obstacles within the auditing field.

This study used purposive sampling to guarantee that its respondents are closely aligned with the research aims, resulting in more accurate, relevant, and significant insights regarding the usage of blockchain technology in the auditing profession.

3.6 Unit of Analysis

This study employs the individual as the analytical unit, primarily concentrating on auditing professionals employed in audit businesses located in Kuching, Sarawak. The choice of using individual auditors as the analytical unit is based on the aim of comprehending their perceptions, experiences, and behavioural objectives concerning the integration of blockchain technology in auditing procedures.

The intended respondents for this study are professionals possessing an accounting and financial background who are currently involved in auditing positions. This inclusion requirement is essential for multiple reasons. First, the significance of Blockchain Implementation in Auditing. Auditors possessing accounting and financial acumen are essential for maintaining financial integrity, guaranteeing regulatory compliance, and preventing fraud. The perspectives and experiences of auditors significantly impact the viability and adoption of blockchain technology in auditing organisations, which provides advantages including real-time data verification, immutability, and automated audit trails. Evaluating the feedback of specialists possessing direct expertise in auditing augments the study's practical significance and guarantees that the results are contextually pertinent.

Second, comprehending Individual-Level Determinants. This study facilitates a detailed analysis of critical factors affecting blockchain adoption by using individual experts instead of organisations as the unit of analysis. Factors such as effort expectancy, work relevance, output quality, and result demonstrability are fundamentally individual perceptions, indicating that their influence on adoption decisions may differ markedly among various auditors. Examining these personal and occupational aspects yields empirical insights into auditors' perceptions of the utility, usability, and relevance of blockchain technology to their professional duties.

Third, guaranteeing Data Reliability and Validity. Concentrating on individuals as the analytical unit facilitates the acquisition of precise, measurable data using organised questionnaires, thus augmenting the study's reliability and validity. Utilising approved survey instruments guarantees that the data gathered reliably represents auditors' impressions of blockchain adoption. Responses at the individual level can thereafter be gathered and statistically analysed to discern overarching patterns and trends (Creswell, 2014).

Lastly, conformity with Quantitative Research Methodology. This study utilises a quantitative research methodology, optimal for analysing individual-level data. The quantitative method facilitates the empirical examination of hypotheses, demonstrating statistical correlations among critical factors such as effort expectancy, performance expectancy, and social influence. As individual auditors constitute the decision-making entities concerning technology adoption inside their organizations, their viewpoints offer significant predictive insights into blockchain adoption patterns in the auditing profession.

3.7 Development of Questionnaire

The questionnaire for this study was carefully constructed to guarantee precision, validity, and reliability in assessing the components associated with blockchain adoption among auditors in Kuching. The instrument was created using validated scales from previous studies to ensure alignment with known research frameworks. The development process entailed meticulous evaluation of the study objectives, construct definitions, measurement scales, and the methodological rigor required for empirical research in technology adoption.

The questionnaire was organized into multiple important sections, each focussing on distinct characteristics pertinent to the study. These variables correspond with the Unified Theory of Acceptance and Use of Technology (UTAUT) framework and its expansions, which are extensively utilized in technology adoption research (Venkatesh et al., 2003).

This part comprises enquiries regarding respondents' age, gender, educational attainment, years of experience, and employment status. These factors offer context for the sample population and enable subgroup analysis (Creswell, 2014). PEC denotes a person's conviction that external elements, like organizational support, rules, and resource accessibility, affect their capacity to utilise blockchain technology (Venkatesh et al., 2003). This section's questions evaluate auditors' perceptions of their resource adequacy and technical assistance for implementing blockchain in their operations.

Computer self-efficacy assesses an individual's confidence in their capacity to utilise blockchain technology proficiently (Compeau and Higgins, 1995). This section assesses auditors' assessed competence in managing blockchain-related duties independently. Enhanced self-efficacy is anticipated to elevate the probability of adoption (Bandura, 1986).

Effort anticipation refers to the anticipated simplicity of utilising and mastering blockchain technology (Venkatesh et al., 2003). Participants evaluate assertions concerning the user-friendliness of blockchain systems and the extent of work required to understand their usage. Performance expectation denotes the perceived use of blockchain in enhancing job performance (Davis, 1989; Venkatesh et al., 2003). Enquiries evaluate auditors' perceptions of blockchain's capacity to improve efficiency, diminish errors, and promote data integrity inside the auditing process.

Job relevance evaluates the extent to which blockchain technology corresponds with auditors' professional responsibilities (Venkatesh & Davis, 2000). This section addresses the integration of blockchain within audit workflows and its compatibility with existing practices. Output quality pertains to auditors' assessments of the precision, clarity, and dependability of blockchain-derived audit data (Almaher et al., 2024). This section assesses the perception of the quality of blockchain-generated financial records and audit trails. Result demonstrability pertains to the concrete advantages and visible outcomes of employing blockchain technology in auditing (Venkatesh & Davis, 2000). Participants evaluate the tangible benefits of blockchain technology, including enhanced fraud detection and regulatory compliance.

Social influence evaluates the degree to which peers, professional organisations, and institutional norms affect auditors' decisions to embrace blockchain (Karahanna and Straub, 1999; Kapnissis et al., 2022). Inquiries examine the influence of peer endorsements, regulatory requirements, and industry trends on views toward blockchain adoption.

The dependent variable assesses auditors' propensity and probability to implement blockchain technology in their practice (Ajzen, 1991; Venkatesh et al., 2003). Participants concur with assertions regarding their future usage goals, commitment to adoption, and preparedness to include blockchain in their auditing processes.

The questionnaire predominantly utilizes a 5-point Likert scale (from 1 = Strongly Disagree to 5 = Strongly Agree) for all items relevant to the constructs. The Likert scale is extensively utilized in behavioural research to measure changes in attitudes and perceptions (Krosnick & Presser, 2010). Before comprehensive data collection, the questionnaire was subjected to pre-testing by a team of academic experts and auditors to ascertain content validity. Preliminary research was performed with a limited cohort of auditors to assess:

3.7.1 Demographic Information

Section A in the questionnaire focused on the respondent’s demographic information including their gender, age, highest education levels, work status in the organization, their current position, and how long they have been working in the auditing profession. Respondents were informed that this information would be used solely for analysis purposes. Collecting this data enabled the researcher to explore and summarize the information more effectively, providing a clearer understanding of the respondent's characteristics and facilitating a more detailed analysis of the study's findings.

First, respondents were asked to select their gender. Then, they were asked about their age from the following options: 20-30 years, 31-41 years, 42-52 years, and 53 years and above. Respondents were also asked to select their highest education levels from options: Sijil Pelajaran Malaysia (SPM), Diploma/Advance Certificate/Skilled Certificate, bachelor's degree, and Post Degree. Respondents also were asked about their work status from the options: Part-time, Contract, Full-time, and Others. The respondent's current position in the organization also was asked with the options: Senior Auditor, Junior Auditor, Manager, and Partner. The final concern that was asked in section A is how long has been respondents working with the options: less than one year, 1-3 years, 4-6 years, and more than seven years.

3.7.2 Rating Scale

This research relies upon a Likert-based questionnaire (Likert,1932) to gather data. In line with previous authors, the questionnaire was composed of 34 questions divided into 3 different sections which are to collect information about the respondents and a section devoted to each theoretical construct. The type of measurement of the 5-point Likert Scale will be used in Section C to answer each category. According to (Zikmund et al., 2013), 5-point Likert Scale can be used because this scale can indicate how respondent ranks their agreement with the answers or statements on the questionnaire. The respondent will rank each statement from 1 to 5 from strongly disagree to strongly agree.

Table 3.1: 5-Point Likert Scale

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

The 5-point Likert scale utilized in this study is detailed in Table 3.1. The scale ranges from 1 to 5, with each point representing a different level of agreement or disagreement. Specifically, a rating of 1 denotes “Strongly Disagree”, 2 denotes “Disagree”, 3 denotes "Neutral”, 4 denotes "Agree”, and 5 indicates “Strongly Agree”. This scale provides a structural framework for respondents to express their opinions or perceptions on the various constructs under investigation, ensuring consistency and precision in the measurement of variables throughout the study.

3.7.3 Measurement of Constructs

Items from the constructs were adopted from existing research. The summary of these adopted questions for section C is shown in Table 3.2.

Table 3.2: Measurement of Constructs

Theoretical Construct	Label	Question
Computer self-efficacy	CSE1	I could BT if someone showed me how to do it first
	CSE2	I could use BT in auditing activities if I had just the built-in help facility for assistance
	CSE3	I think that I can use BT for auditing activities if my firm will organize a good training
	CSE4	I could use BT if I had used similar application before this one
Perception of external control	PEC1	I have control over using BT
	PEC2	I have the resources necessary to use BT
	PEC3	Given the resources, opportunities and knowledge it takes to BT, it would be easy for me to use the system
	PEC4	I can master BT thanks to my ICT skills
Job relevance	JR1	In auditing activities blockchain can be massively used
	JR2	In auditing activity, blockchain usage is relevant
	JR3	BT is relevant for future auditing service
	JR4	The future of auditing activities is BT

Table 3.2 continued

Output quality	OQ1	I expect the quality of the output I get from using BT will be high
	OQ2	By using BT, I will not have any problem with the quality of auditing activities
	OQ3	I expect BT will improve the quality if my job
	OQ4	I expect the results from using BT to be excellent
Result demonstrability	RD1	In my opinion, the results of using BT are apparent to me
	RD2	I have no difficulty telling others about the results of using BT
	RD3	I believe I could communicate to others the consequences of using blockchain for auditing activities
	RD4	In my opinion, the results of blockchain usage will be tangible for everyone
Social influence	SI1	People who influence my behavior (would think/think) that I should use blockchain
	SI2	People who are important to me (would think/think) that I should use BT in auditing activities
	SI3	My Boss thinks I should learn how to use BT for auditing activities
Intention	INT1	I intend to start using BT for auditing activities
	INT2	I plan to start implementing blockchain in my auditing activities

Note: Ferri et al., (2020)

3.8 Expert Validation

Before being tested in the pilot test, the questionnaire was subjected to expert validation to determine its content validity and suitability for assessing the constructs associated with blockchain adoption among auditors. The instrument underwent evaluation by academic supervisors and an auditing expert to determine the clarity, relevance, and congruence of the questionnaire items with the study's theoretical framework.

The objective of expert validation was to verify that each questionnaire item precisely represents the intended concept. Enhance the wording to improve clarity and eliminate ambiguity. Ensure that the questionnaire effectively encompasses the research variables as established in existing literature. Expert comments were integrated into the questionnaire by clarifying problematic terminology, enhancing response possibilities, and assuring consistency with the study's objectives. Following this validation process, the amended questionnaire was considered prepared for pilot testing to evaluate its clarity and usefulness among the intended respondents.

Each item in the questionnaire was expert-validated to eliminate confusion and ambiguity, ensuring reliable and validated questions. The questionnaire will be improved based on the outcome of the expert validation. The pilot test aimed to ensure that the instructions were clear, allowing for valid and reliable answers from the respondents. Additionally, expert validation enables researchers to identify defective questions that are not relevant to the respondents. Questionnaires were distributed to supervisors to review and comments, and one person from auditing professionals from the audit firm.

The final version of the questionnaires was revised and approved by the supervisor to ensure the reliability and validity of the items for actual data collection. Expert validation results are shown in Table 3.3. All feedback from the respondents was considered and the questions were amended accordingly.

Table 3.3: Expert Validation

Item No.	Theoretical Construct	Question	R1	R2	R3	R4	R5	Comments/Changes Made
1.	Computer self-efficacy	I could BT if someone showed me how to do it first	Agree	Agree	Agree	Agree	Agree	
		I could use BT in auditing activities if I had just the built-in help facility for assistance	Agree	Agree	Agree	Agree	Agree	
		I think that I can use BT for auditing activities if my firm will organize a good training	Agree	Agree	Agree	Agree	Agree	
		I could use BT if I had used a similar application before this one	Agree	Agree	Agree	Agree	Agree	
2.	Perception of external control	I have control over using BT	Agree	Agree	Agree	Agree	Agree	
		I have the resources necessary to use BT	Agree	Agree	Agree	Agree	Agree	
		Given the resources, opportunities, and knowledge it takes to BT, it would be easy for me to use the system	Agree	Agree	Agree	Agree	Agree	

Table 3.3 continued

		I can master BT thanks to my ICT skills	The variable appears to lack relevance to the specified variables.	Agree	Agree	Agree	Agree	Amended accordingly.
3.	Job relevance	In auditing activities, blockchain can be massively used	Agree	Agree	Agree	Agree	Agree	
		In auditing activity, blockchain usage is relevant	Agree	Agree	Agree	Agree	Agree	
		BT is relevant for future auditing service	Agree	Agree	Agree	Agree	Agree	
		The future of auditing activities is BT	Agree	Agree	Agree	Agree	Agree	
4.	Output quality	I expect the quality of the output I get from using BT will be high	Agree	Agree	Agree	Agree	Agree	
		By using BT, I will not have any problem with the quality of auditing activities	Agree	Agree	Agree	Agree	Agree	
		I expect BT will improve the quality if my job	Agree	Agree	Agree	Agree	Agree	
		I expect the results from using BT to be excellent	Agree	Agree	Agree	Agree	Agree	

Table 3.3 continued

5.	Result demonstrability	In my opinion, the results of using BT are apparent to me	Agree	Agree	Agree	Agree	Agre	
		I have no difficulty telling others about the results of using BT	Agree	Agree	Agree	Agree	Agree	
		I believe I could communicate to others the consequences of using blockchain for auditing activities	Agree	Agree	Agree	Agree	Agree	
		In my opinion, the results of blockchain usage will be tangible for everyone	Agree	Agree	Agree	Agree	Agree	
6.	Social influence	People who influence my behavior (would think/think) that I should use blockchain	Agree	Agree	Agree	Agree	Agree	
		People who are important to me (would think/think) that I should use BT in auditing activities	Agree	Agree	Agree	Agree	Agree	
		My Boss thinks I should learn how to use BT for auditing activities	Agree	Agree	Agree	Agree	Agree	

Table 3.3 continued

7.	Intention	I intend to start using BT for auditing activities	Agree	Agree	Agree	Agree	Agree	
		I plan to start implementing blockchain in my auditing activities	Agree	Agree	Agree	Agree	Agree	
		Benefits and challenges impact the intention to integrate blockchain technology into auditing activities	Add two more questions to further enhance it is comprehensiveness.	Agree	Agree	Agree	Agree	Amended accordingly.
		Role do organizational and individual factors play in shaping the intention to implement blockchain technology in auditing practices	Add two more questions to further enhance it is comprehensiveness.	Agree	Agree	Agree	Agree	Amended accordingly.

Notes: (R1: Respondent 1), (R2: Respondent 2), (R3: Respondent 3), (R4: Respondent 4), (R5: Respondent 5)

3.9 Pilot Test

A pilot test was undertaken before to sending the questionnaire to the entire sample of respondents to evaluate the validity, reliability, and clarity of the study instrument. This initial phase was crucial to confirm that the questionnaire precisely assessed the targeted constructs, was understandable to the target demographic, and could efficiently gather pertinent data for analysis. The pilot test facilitated the detection of ambiguities, inconsistencies, and potential difficulties within the instrument, allowing for essential adjustments before comprehensive data gathering.

10 auditors participated in the pilot test, representing the study's target group. Their feedback was assessed to enhance the questionnaire, augmenting clarity, readability, and alignment with study goals. The pilot test enabled an initial evaluation of reliability via Cronbach's Alpha (α) and content validity through expert review.

A pilot test was conducted in June 2024 preceding the actual data collection. This phase is crucial for evaluating the effectiveness of the questionnaire with the target respondents Hunt et al., (1982). Zaltman and Burger (1975) assert that a pilot test may employ a limited sample size, with prior research suggesting that 10 to 30 respondents are sufficient for detecting substantial issues in survey instruments (Hertzog, 2008; Johanson and Brooks, 2010). For this study, the feedback from these 10 respondents was meticulously analyzed, leading to essential revisions to improve the questionnaire's validity and reliability before widespread distribution. Reliability indicates the internal consistency of the questionnaire, guaranteeing that the measurement items for each construct yield stable and uniform findings. Cronbach's Alpha (α) was employed to evaluate internal dependability, with a satisfactory threshold set at 0.70 (Hair et al., 2014).

3.10 Data Collection Procedure

Following the quantitative methodology, a questionnaire survey was used to gather data from auditors across 38 audit firms in Kuching, Sarawak. Figure 3.2 illustrates the steps were taken for the data collection.

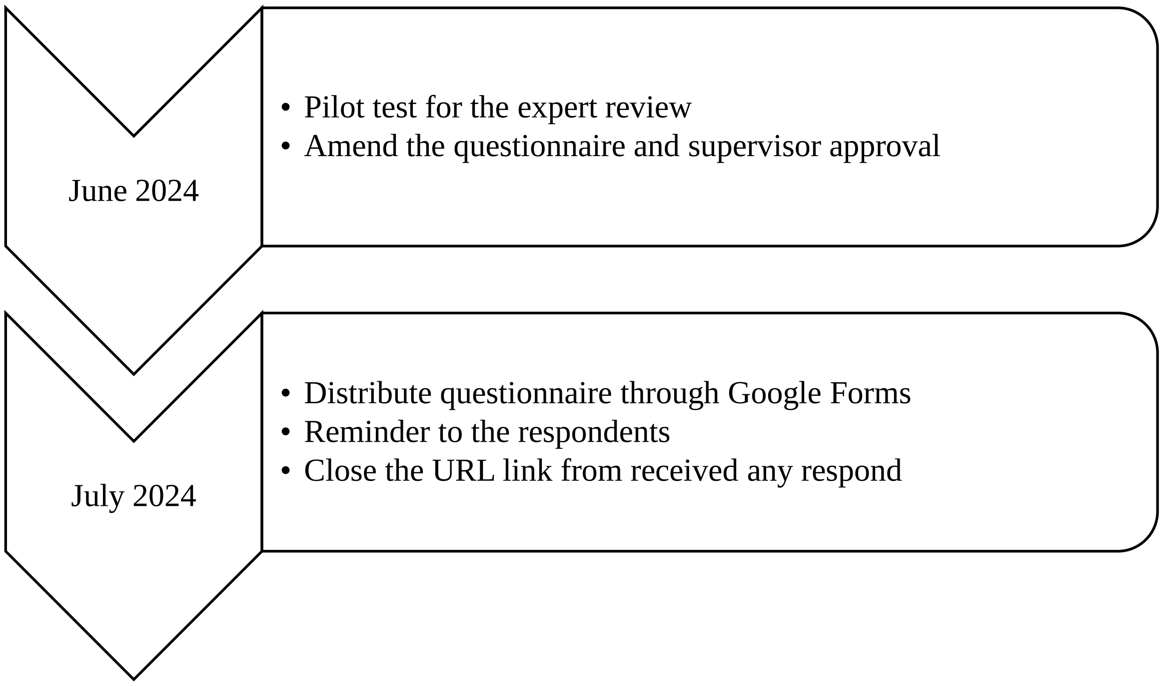

Figure 3.2: Steps Collecting Data

Initially, in June 2024, the researcher sent an invitation through online questionnaire and *word of mouth (WOM)* for a pilot test expert review since the sample needed for expert review only for the small value. Respondents were given one month to complete the survey. Regular monitoring was conducted to ensure that the minimum sample size was achieved. Due to limited time, the researcher decided to push the respondents to complete the survey as soon as possible. After achieving the minimum sample size, the survey was closed at the end of July 2024. Since the data was collected within a short time, there was no need to perform a response bias test, as a consistent time frame can help mitigate the risk of response bias (Podsakoff at al., 2003).

3.11 Data Analysis Techniques

This section provides a detailed explanation of the data analysis techniques employed in this study. It includes the selection of software, data analysis methods, and the step-by-step analysis process. The analysis begins with a preliminary analysis, followed by descriptive statistics, an assessment of the measurement models, and ultimately assessment of the structural model. Each stage of the analysis is elaborated upon to ensure a clear understanding of the analysis procedures undertaken in this study.

3.10.1 Data Analysis Tools

This study employed two data analysis tools which is IBM SPSS Statistics and SmartPLS 4.0. IBM SPSS Statistics was utilized to conduct preliminary data analysis and to examine respondents' demographics, producing descriptive analyses for the variables. While SmartPLS was employed to assess both the measurement and structural models.

3.10.2 Preliminary Analysis

Preliminary analysis is the inspection, scrutiny, and analysis that is conducted on data before the main analysis which is to detect, manage, and detect errors. In this phase, frequencies were computed to identify missing data and suspicious response patterns were examined using the mean and standard deviation for each indicator based on the respondents' answers. The researchers might suspect that an outlier represents some other kind of error, misunderstanding, or lack of effort by a respondent such as in a reaction time distribution in which most respondents took only a few seconds to respond, a respondent who took 3 minutes to respond would be an outlier. However, since respondents only can choose from a set of given answers, no outliers were found in the data. Data distribution analysis was conducted by checking the skewness and kurtosis. Additionally, to avoid common method bis in this study, Harman single factor test was applied (Hair et al., 2022).

3.10.3 Descriptive Statistics

In any research study, descriptive statistics are an integral part of understanding and characterizing the data set under investigation. These statistics offer a succinct yet insightful summary of the sample and its measurements, providing a deeper understanding of the data's characteristics. Among the three commonly used types of descriptive statistics, including mean, median, and mode, they help determine a data set's central tendency. The computation of the statistic involves adding all of the data set's values and dividing the result by the total number of respondents. This calculation provides a central location for the data and helps to determine its distribution. When dealing with datasets that have extreme values or outliers that could distort the results if the mean is used as a measure of central tendency, this statistic is especially helpful. Descriptive statistics help researchers to get a better understanding of their data and make informed conclusions.

3.10.4 Partial Least Squares Structural Equation Modelling (PLS-SEM)

This study utilised PLS-SEM, a statistical software tailored for Partial Least Squares Structural Equation Modelling (PLS-SEM), a variance-based technique extensively applied in social science research, especially for predicting essential target constructs and examining intricate relationships among latent variables. PLS-SEM was selected as the optimal analytical method for this investigation because of its capacity to manage intricate structural models, its appropriateness for research focused on enhancing predictive accuracy, and its resilience when applied to small to intermediate sample sizes (Hair et al., 2017).

The adoption of PLS-SEM as the preferable analytical method in this study is warranted by numerous critical methodological factors. PLS-SEM is a predictive methodology that prioritizes the maximisation of the explained variance (R^2) of the dependent variable over assessing overall model fit, rendering it especially appropriate for research focused on theory development and hypothesis testing in nascent domains, such as blockchain adoption among auditors (Hair et al., 2019). In contrast to covariance-based SEM (CB-SEM), which necessitates large sample sizes and presumes multivariate normality for model fit assessment, PLS-SEM is a non-parametric approach adept at managing small sample sizes and non-normal data distributions, thereby maintaining the robustness of statistical results even when conventional parametric assumptions are violated (Sarstedt et al., 2017).

Moreover, PLS-SEM is especially appropriate for investigations with intricate research models that encompass numerous independent variables, a moderating variable, and a dependent variable, as seen in this study. The proposed conceptual framework includes external control perception, computer self-efficacy, job relevance, output quality, result demonstrability, effort expectancy, and performance expectancy as independent variables, with social influence serving as a moderating variable, and the intention to adopt blockchain technology as the dependent variable. Due to the complex interconnections among these constructs, PLS-SEM offers a sophisticated methodological framework that can estimate both direct and indirect effects concurrently, while accommodating moderating effects, thus facilitating a more thorough comprehension of the factors affecting blockchain adoption in the auditing field (Henseler et al., 2016).

Moreover, PLS-SEM is beneficial in contexts where theory is in flux, as it enables researchers to engage with intricate models that incorporate both formative and reflective measurement components. This flexibility is especially advantageous in research aimed at generating new theoretical insights rather than simply validating existing theories, rendering PLS-SEM the most suitable methodological option for this study (Hair et al., 2021).

PLS-SEM is a second-generation multivariate analytical technique enabling researchers to concurrently analyse both measurement models (outer models) and structural models (inner models). The measurement model evaluates the reliability and validity of constructs, confirming that observed indicators accurately reflect their latent variables, whereas the structural model analyses the proposed relationships among independent, moderating, and dependent variables (Hair et al., 2017). PLS-SEM allows researchers to calculate route coefficients that reflect the strength and direction of correlations between constructs, as well as evaluate the significance of these relationships through bootstrapping methods. Furthermore, it facilitates the computation of the coefficient of determination (R^2), predictive relevance (Q^2), and effect size (f^2), collectively offering a thorough assessment of the model's explanatory and predictive efficacy (Sarstedt et al., 2017).

This research systematically employed PLS-SEM utilizing SmartPLS software, referring to a standardised analytical protocol to guarantee the reliability, validity, and robustness of the statistical results. The data analysis procedure was executed in several phases, data coding and cleaning, and assumption verification. Before performing the primary analysis, the raw data was meticulously examined closely for completeness, absent values, and discrepancies. Instances with significant missing data or incorrect responses were excluded to maintain the dataset's accuracy and dependability. Assumption Verification: While PLS-SEM does not necessitate multivariate normality, exploratory data analysis was performed to identify extreme outliers and confirm that the data adhered to fundamental quality standards essential for rigorous analysis.

3.10.5 Assessment of Measurement Model

Information on learning and performance between latent variables and the observed indicators is gathered through the technique of assessment of measurement, which was employed in this study. Interpreting the data and forming conclusions about what has been learned is the process of evaluation. Allocating numerical values to indicate the extent to which a specific outcome's quality has been proven is the process of measurement. To guarantee the link between latent variables and observed variables while using partial least squares structural modeling (PLS-SEM), the measurement quality approach will be applied. To guarantee the precision and dependability of the measurements, it entails evaluating the factor loadings, standardized estimates, and correlations.

Evaluating the reflecting measurement model begins with an analysis of the indicator loading. It is recommended to utilize loadings larger than 0.708 since this indicates that more than 50% of the indicator's variance is explained by the construct, leading to acceptable item dependability. better numbers often correspond to better degrees of dependability when evaluating the internal consistency reliability utilizing Joreskog (1971) composite reliability. Values above 0.95, however, raise warning flags because they appear to indicate item repetition, which calls into question the validity of the concept. Furthermore, straight line responses and other undesirable response patterns may be present in cases where reliability ratings exceed 0.95. This could result in an overabundance of correlations between the indicator's error components.

Cronbach's alpha is another metric used to assess internal consistency reliability, but it generally provides lower results than composite reliability. This is because the components in Cronbach's alpha are not weighted, making it a less accurate indicator of reliability. In contrast, individual loadings and reliability are higher than Cronbach's alpha when using composite reliability, as the items are weighted according to the construct indicators. The genuine dependability of the construct is usually considered to be between these two extreme values, with Cronbach's alpha being too conservative and composite reliability being too liberal.

The third step involves evaluating the convergent validity of each construct measure. The average variance extracted (AVE) is used to assess the convergent validity of each construct for all of its elements. An AVE of 0.50 or above indicates that the construct accounts for at least 50% of the variation of the components comprising the construct.

Lastly, discriminant validity is evaluated in the fourth step of the measuring model evaluation. The conventional metric for discriminant validity, recommended by Fornell and Larcker (1981), involves comparing the AVEs of each construct to the squared inter-construct correlation. However, the Fornell-Larcker criterion performs poorly, especially when used to prove that the indicator loadings on a construct only differ by a small amount.

Henseler et al. (2015) proposed the heterotrait-monotrait ratio (HTMT) as an alternative. Discriminant validity problems are present when HTMT values are high. For example, for structural models with conceptually comparable dimensions, a threshold value of 0.90 is recommended. Bootstrapping can also be used to determine whether the HTMT value differs considerably from 1.00 or a lower cutoff value.

3.10.6 Assessment of Structural Model

Assessing the structural model is the next stage in analyzing the PLS-SEM results. The coefficient of determination R^2, the blindfolding-based cross-validated redundancy measure Q^2, and the statistical significance and applicability of the path coefficients are examples of standard assessment criteria that are to be taken into account. Assuming a large sample size, researchers should evaluate the out-of-sample prediction capability of their model using the PLS predict approach (Shumueli et al., 2016).

To get the structural model coefficients for the connections between the constructs, a series of regression equations are computed. Before assessing the structural correlations, it is necessary to ensure that the presence of collinearity does not distort the results of the regression. This process is similar to assessing formative measurement models, except the exogenous constructions' latent variable scores are used to calculate the VIF values. Mason and Perreault (1991) and Becker et al. (2015) state that collinearity issues can also occur at lower VIF levels, such as 3 to 5. VIF values above 5 are indicative of potential collinearity issues among the predictor constructs. The VIF values ought to be near 3 or less, ideally. Making higher-order, theoretically supported models is an often employed solution when collinearity is an issue (Hair et al., 2017).

The endogenous construct's R^2 value is examined in the following step. The variance is measured by the R^2 and is a measure of the explanatory power of the model since it is explained by each of the endogenous factors (Shmueli and Koppius, 2011). According to Rigdon (2012), the R^2 is also known as in-sample predictive power. More values of R^2 indicate a stronger explanatory ability; the value ranges from 0 to 1. According to Heseler et al. (2009) and Hair et al. (2011), it is generally accepted that R^2 values of 0.75, 0.50, and 0.25 correspond to significant, moderate, and weak levels. According to Raithel et al. (2012), acceptable R^2 depends on the context and can be as low as 0.10 in certain areas. Another sign that the model overfits the data is when R^2 is excessively high. The possibility that the model overfits the data stems from its potential overcomplication.

Determining the Q^2 value is an additional technique to assess the PLS path model's predictive accuracy (Geisser, 1974; Stone, 1974). The blindfolding method, which is the basis for this statistic, estimates the model parameters by taking one point out of the data matrix and imputing it with the mean (Ringdon, 2014; Sarstedt et al., 2014). Small differences between the original and anticipated numbers convert into a larger Q^2 value, which indicates a higher prediction accuracy." In general, Q^2 values for a given endogenous construct should be greater than zero to show how well the structural model predicts that construct. As a general rule, Q^2 values greater than 0, 0.25, and 0.5 indicate the PLS-path model's small, medium, and substantial predictive importance.

3.11 Conclusion

This chapter explained the study approach employed to examine the adoption of blockchain technology by auditors. The justification for employing a quantitative approach has been provided, detailing the choice of the survey method and the target demographic. The development of the questionnaire, execution of a pilot test, and evaluation of reliability and validity have been addressed. The rationale for using PLS-SEM for data analysis was elucidated, emphasising its appropriateness for forecasting adoption behaviour and managing intricate interactions among variables. The subsequent chapter will delineate the conclusions and findings of the data analysis, offering empirical insights into the study's hypotheses.

CHAPTER 4

RESULTS

4.1 Introduction

Chapter 4 explores the findings from the data analysis undertaken to investigate the adoption of blockchain technology by auditors. The chapter commences with an examination of the data preparation process, encompassing data cleaning, coding, and assumption verification. Descriptive statistics are thereafter presented to encapsulate the demographic attributes of the respondents. Subsequently, reliability and validity assessments are conducted to evaluate the measurement model, so ensuring the robustness of the research instrument. The chapter subsequently conducts structural model analysis utilising Partial Least Squares Structural Equation Modelling (PLS-SEM), which assesses the interactions among independent variables, the moderating variable, and the dependent variable. The results are accompanied by statistical evidence that either corroborates or refutes the offered hypothesis. The chapter finishes with a summary of essential findings and their implications for the implementation of blockchain in auditing.

4.2 Preliminary Data Analysis

Preliminary data analysis proceeded with the calculation of frequencies to identify any missing data. A total of 135 valid replies were obtained, with no missing data, as all survey items were compulsory. Additionally, response patterns that elicited suspicion were evaluated by computing the mean and standard deviation for each indicator based on participant replies.

Table 4.1 displays the mean values of the indicators, ranging from 3.94 to 4.46, indicating that respondents predominantly concurred with the assertions pertaining to each concept. The elevated mean scores suggest that participants viewed the assessed constructs favorably. The standard deviation values vary from 0.693 to 1.037, indicating substantial heterogeneity in responses. This degree of dispersion indicates that although replies differed, they did not display significant inconsistencies, so affirming the data's dependability.

Subsequently, the lowest and maximum values of each indicator were analyzed to detect any probable outliers. Since respondents were restricted to a predetermined set of responses, no outliers were identified. Prior to conducting the measurement model analysis, an evaluation of data distribution was performed by analyzing skewness and kurtosis values to ascertain the normality of the dataset.

A skewness score between -1 and +1 is typically regarded as optimal, whereas values ranging from -2 to +2 are considered acceptable for normality (George & Mallery, 2019). Values surpassing these criteria signify a markedly non-normal distribution. The skewness values in this study range from -1.101 to -0.452, indicating a pronounced negative skewness, suggesting that respondents predominantly favored higher response alternatives such as "Agree" or "Strongly Agree."

A kurtosis number greater than +2 implies a leptokurtic distribution, characterized by excessive peakness, whereas a value less than -2 signifies a platykurtic distribution, marked by excessive flatness. The kurtosis values in this dataset span from -1.057 to 1.259, remaining within the permitted limits. Some indicators, such as PE02 = 0.478 and SI01 = 0.365, demonstrate a mild peaked tendency, but others, such PE04 = -0.863 and SI04 = -1.057, indicate a somewhat flatter distribution. Nonetheless, as no values beyond the ±2 range, the data does not exhibit significant deviations from normality and is suitable for subsequent statistical analysis.

Table 4.1: Mean, Std. Deviation, Skewness, and Kurtosis

Construct	Item	N	Mean	Std. Deviation	Skewness	Kurtosis
Computer self-efficacy	CSE01	140	4.43	0.760	-1.101	0.320
	CSE02	140	4.39	0.745	-0.976	0.233
	CSE03	140	4.46	0.693	-1.029	0.322
	CSE04	140	4.27	0.872	-1.220	1.259
Perception of external control	PEC01	140	2.98	0.978	-0.191	-0.121
	PEC02	140	2.87	1.010	0.049	-0.279
	PEC03	140	4.17	0.944	-1.027	0.634
	PEC04	140	4.18	0.892	-1.101	1.236
Job relevance	JR01	140	4.13	0.847	-0.538	-0.684
	JR02	140	4.16	0.810	-0.392	-1.132
	JR03	140	4.33	0.744	-0.723	-0.460
	JR04	140	4.29	0.782	-0.751	-0.377
Output quality	OQ01	140	4.33	0.753	-0.729	-0.514
	OQ02	140	4.14	0.934	-0.828	-0.041
	OQ03	140	4.37	0.713	-0.804	-0.156
	OQ04	140	4.35	0.758	-0.785	-0.476
Results demonstrability	RD01	140	4.13	0.880	-0.705	-0.048

Table 4.1 continued

	RD02	140	4.06	1.012	-0.932	0.322
	RD03	140	4.09	0.966	-0.965	0.661
	RD04	140	4.16	0.892	-0.871	0.577
Effort expectancy	EE01	140	4.19	0.856	-0.802	0.201
	EE02	140	4.09	0.956	-0.775	-0.165
	EE03	140	4.15	0.881	-0.812	0.203
	EE04	140	3.94	1.037	-0.552	-0.757
Performance expectancy	PE01	140	4.27	0.803	-0.702	-0.581
	PE02	140	4.26	0.851	-0.947	0.478
	PE03	140	4.26	0.836	-0.757	-0.521
	PE04	140	4.25	0.841	-0.649	-0.863
Social influence	SI01	140	4.08	0.937	-0.849	0.365
	SI02	140	4.09	0.936	-0.828	0.292
	SI03	140	4.15	0.897	-0.605	-0.795
	SI04	140	4.13	0.872	-0.452	-1.057
Intention	INT01	140	4.20	0.867	-0.872	0.329
	INT02	140	4.16	0.892	-0.809	0.105
	INT03	140	4.26	0.828	-0.761	-0.459
	INT04	140	4.39	0.801	-1.068	0.208

Common Method Variance (CMV) poses a possible problem when self-reported survey data is gathered from identical respondents simultaneously. Common method variance (CMV) occurs when systematic measurement mistakes distort the relationships between variables due to shared technique bias instead of genuine conceptual correlations (Podsakoff et al., 2003).

A primary factor contributing to CMV is common rater bias, wherein respondents consistently answer items influenced by social desirability or cognitive consistency tendencies, rather than offering independent evaluations for each construct. Moreover, contextual influences on items, like analogous phrasing, sequencing effects, or insufficient separation among constructs, may exacerbate common method variance (CMV).

The presence of CMV was evaluated using Harman's Single Factor Test, as shown in Table 4.2. This test assesses whether a singular latent factor explains the bulk of the variance within the sample. If a single factor accounts for over 50% of the overall variance, common method variance (CMV) is deemed troublesome. The findings revealed that the primary component represented 64.265% of the overall variation, indicating that common method variance (CMV) was a concern in this research.

To alleviate the impacts of CMV, a range of procedural and statistical solutions may be employed. Procedural remedies encompass the assurance of anonymity, the randomization of item order, and the utilization of varied scale formats to mitigate response biases. Statistical methodologies, including the incorporation of a marker variable or the implementation of latent variable factor modeling, can assist in mitigating common method variance in forthcoming studies.

Table 4.2: Harman's Single-factor Test (Total Variance Explained)

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative**
1	23.136	64.265	64.265	23.136	64.265	64.265
2	1.945	5.402	69.668			
3	1.867	5.187	74.855			
4	1.164	3.233	78.087			
5	0.848	2.356	80.444			
6	0.763	2.121	82.564			
7	0.664	1.843	84.408			
8	0.606	1.684	86.091			
9	0.543	1.507	87.599			
10	0.458	1.273	88.872			
11	0.392	1.090	89.962			
12	0.364	1.012	90.974			
13	0.340	0.945	91.919			
14	0.330	0.915	92.834			
15	0.288	0.800	93.634			
16	0.260	0.721	94.355			
17	0.233	0.647	95.002			
18	0.213	0.592	95.594			
19	0.182	0.505	96.099			
20	0.167	0.464	96.563			

Table 4.2 continued

21	0.155	0.430	96.994
22	0.141	0.391	97.384
23	0.130	0.362	97.746
24	0.110	0.306	98.053
25	0.103	0.287	98.340
26	0.089	0.248	98.588
27	0.074	0.206	98.794
28	0.071	0.198	98.992
29	0.066	0.184	99.176
30	0.063	0.174	99.351
31	0.056	0.156	99.506
32	0.045	0.126	99.632
33	0.044	0.121	99.753
34	0.036	0.101	99.854
35	0.029	0.082	99.936
36	0.023	0.064	100.00

Extraction Method: Principal Axis Factoring.

4.3 Overview of Respondents

The demographic characteristics of the respondents are presented in Table 4.3. The findings indicate that the respondents are from audit firms in Kuching. The researcher concluded that female respondents (59.30%) have a greater number than male respondents (40.70%), and most respondents are around 31 to 41 years old (52.10%). Most respondents who work as auditors have a working experience of more than 4 years (32.10%), and their current position in an audit firm is as a senior auditor (42.10%). The majority of respondents (57.90%) have a bachelor's degree as their educational background, and (81.40%) of respondents are in full-time employment. Respondent awareness regarding blockchain technology (53.6%), and majority of respondents (82.90%) still in beginner level of knowledge in blockchain technology. Most of the respondent's intent to learn about blockchain technology (90%) compared to not interested in learning about blockchain technology (10%).

Table 4.3: Demographic Profile of Respondents

Demographic Profile	**Category**	**Frequency (N=140)**	**Percentage (%)**
Gender	Male	57	40.70
	Female	83	59.30
Age	20-30 years	51	36.40
	31-41 years	73	52.10
	42-52 years	12	8.60
	53 years and above	1	2.90
Education Background	Sijil Pelajaran Malaysia (SPM	2	1.40
	Diploma/Advanced Certificate/Skilled Certificate	38	27.10
	Bachelor's Degree	81	57.90

Table 4.3 continued

	Post Degree	19	27.10
Work Status	Part-time	2	1.40
	Contract	21	15.00
	Full-time	114	81.40
	Others	3	2.10
Current Position	Senior Auditor	59	42.10
	Junior Auditor	50	35.70
	Manager	18	12.90
	Partner	13	9.30
Working Experience	Less than one year	19	13.60
	1-3 years	32	22.90
	4-6 years	45	32.10
	More than seven years	44	31.40
Awareness of Blockchain Technology	Yes	75	53.60
	No	65	46.40
Level of Knowledge about Blockchain Technology	Beginner	116	82.90
	Intermediate	24	17.10
	Expert	-	-

Table 4.3 continued

Prevent from being aware of Blockchain Technology	Doesn't have info about Blockchain	76	54.30
	Doesn't know about Blockchain	21	15.00
	Never heard about Blockchain Technology	43	30.70
Intend to learn about Blockchain Technology	Yes	126	90.00
	No	14	10.00

4.4 Assessment of Measurement Model

This study used a reflective measurement model. Tests for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity were performed to assess this model.

4.4.1 Indicator Reliability

The dependability of specific indicators was evaluated by examining outer loadings. The widely recognized benchmark for outer loadings is 0.708 or above, as this guarantees that each indicator accounts for a minimum of 50% of the variance in its corresponding construct (Hair et al., 2022). Hulland (1999) observed that outer loadings below 0.70 are frequently seen in social science research, and their retention is contingent upon their influence on internal consistency reliability and convergent validity.

Indicators with Loadings Exceeding 0.70. The majority of indicators achieved the suggested 0.708 level, so affirming robust reliability and construct validity. Indicators with Loadings Ranging from 0.40 to 0.70, certain indicators exhibited loadings within this range. Hair et al. (2022) assert that these indications should be eliminated alone if their removal markedly enhances reliability (Cronbach's alpha, composite reliability) or convergent validity (AVE).

In this investigation, the elimination of these markers did not yield a significant enhancement in reliability or validity. Furthermore, these indicators were preserved owing to their theoretical significance and empirical usefulness in elucidating blockchain adoption within the auditing profession.

4.4.2 Internal Consistency Reliability

The study's theoretical framework outlines the analysis of the item answers' measurement model component, with a thorough explanation of the internal consistency reliability coefficient provided as an additional benefit.. A methodological approach comprising three sequential stages is propounded to ascertain its estimation: the preliminary elucidation of descriptive data, the rigorous evaluation of pertinent measurement models, and the meticulous computation of internal consistency coefficients concomitant with their attendant confidence interval. The following formulas are presented in detail: (a) Cronbach's alpha and omega coefficients for unidimensional measures that exhibit quantitative item response scales; (b) ordinal omega, ordinal alpha, and nonlinear reliability coefficients concerning unidimensional measures that contain dichotomic and ordinal items; and (c) the omega and omega hierarchical coefficients for essentially unidimensional scales that demonstrate method effects.

Cronbach's alpha, renowned as the preeminent internal consistency measure, is conventionally derived as the arithmetic mean of all feasible split-half coefficients (Cortina, 1993). It inherently denotes the total number of factors encompassed by the scale as well as the potency of their intercorrelations. It is widely acknowledged that, in the course of devising a novel measure, values surpassing 0.70 are customarily deemed appropriate; however, for research pursuits, values exceeding 0.80 are deemed acceptable. The reliability coefficient seamlessly resides within the domain of a numeric spectrum between 0 and 1. The comprehensive account presented in the composited reliability outcomes of Table 4.4 distinctly attests to the corrosion of internal consistency reliability requirement, each latent variable incontrovertibly surpassing the specified benchmark with a corresponding score exceeding the commendable threshold of 0.70.

4.4.3 Convergent Validity

Convergent validity is established when the constituent elements of a given measure coalesce to accurately represent the underlying construct. The Average Variance Extracted (AVE) serves as the average of the squared loadings of each indicator linked to a construct, offering a determinant of convergent validity. Statistical convergent validity is confirmed when the AVE surpasses 0.50. Upon review of the data in Table 4.4, it is observed that each AVE value, spanning from 0.780 to 0.873, met the minimal criterion of 0.50, thereby signifying that the measurement models exhibited adequate convergent validity.

The achievement of convergent validity hinges on the AVE surpassing 0.50, a proposition substantiated by studies conducted by Fornell & Larcker (1981), Chin (2010), Hair et al. (2017), and Hair et al. (2022). An AVE exceeding 0.50 implies that the construct may account for a minimum of 50% of the variability in the item (Chin, 1999; Hair et al., 2022). As revealed in Table 4.4, all AVE values fulfilled the requisite threshold of 0.50, with values spanning from 0.543 to 0.814, thus affirming the presence of adequate convergent validity within the measurement models, notwithstanding the AVE of PEC at 0.494.

Table 4.4: Results for Reflective Measurement Model

Latent Variable	Indicators	Convergent Validity: Loadings >0.70	Convergent Validity: Indicator Reliability >0.50	Convergent Validity: AVE >0.50	Internal Consistency Reliability: Cronbach's Alpha 0.60-0.90	Internal Consistency Reliability: Reliability (rho_a) 0.60-0.90	Internal Consistency Reliability: Composite Reliability (rho_c) >0.70	Discriminant Validity: HTMT Significantly Lower than 0.85 [0.90]?
CSE	CSE01	0.900	0.896					
	CSE02	0.912	0.908	0.780	0.906	0.912	0.934	Yes
	CSE03	0.899	0.892					
	CSE04	0.819	0.800					
PEC	PEC01	0.394	0.432					
	PEC02	0.467	0.503	0.494	0.706	0.839	0.777	Yes
	PEC03	0.901	0.890					
	PEC04	0.890	0.870					
JR	JR01	0.900	0.895					
	JR02	0.933	0.929	0.841	0.937	0.938	0.955	Yes
	JR03	0.937	0.938					
	JR04	0.898	0.888					
OQ	OQ01	0.931	0.928					
	OQ02	0.840	0.822	0.839	0.935	0.943	0.954	Yes
	OQ03	0.959	0.959					
	OQ04	0.929	0.924					
RD	RD01	0.858	0.851					
	RD02	0.939	0.936	0.839	0.935	0.930	0.954	Yes
	RD03	0.931	0.927					

Table 4.4 continued

	RD04	0.932	0.927					
EE	EE01	0.908	0.902					
	EE02	0.942	0.943	0.854	0.943	0.947	0.959	Yes
	EE03	0.947	0.946					
	EE04	0.898	0.893					
PE	PE01	0.931	0.929					
	PE02	0.906	0.898	0.873	0.951	0.952	0.965	Yes
	PE03	0.953	0.951					
	PE04	0.946	0.944					
SI	SI01	0.937	0.931					
	SI02	0.925	0.920	0.848	0.940	0.942	0.957	Yes
	SI03	0.879	0.865					
	SI04	0.941	0.940					
INT	INT01	0.934	0.934					
	INT02	0.938	0.934	0.848	0.940	0.944	0.957	Yes
	INT03	0.949	0.948					
	INT04	0.860	0.859					

4.4.4 Discriminant Validity

Discriminant validity evaluates whether theoretically distinct constructs genuinely differ in empirical observations. The Heterotrait-Monotrait Ratio (HTMT) is a prevalent method for assessing discriminant validity in Partial Least Squares Structural Equation Modeling (PLS-SEM). Henseler et al. (2015) assert that HTMT values under 0.90 signify enough distinctiveness among conceptions. In more conservative contexts, a more stringent criterion of 0.85 is advised to provide enhanced discriminant validity (Gold et al., 2001).

Table 4.5 displays the HTMT values for this investigation, which range from 0.589 to 0.940. The predominant results are below 0.85, hence affirming discriminant validity. Nonetheless, certain ratios surpass the 0.85 barrier, with one value (0.940 between Performance Expectancy and Result Demonstrability) exceeding the more permissive 0.90 level. Values less than 0.85 such as 0.589, 0.628, and 0.651, demonstrate robust discriminant validity, signifying that the constructs are separate and assess different concepts. Principles Between 0.85 and 0.90, for instance, 0.873, and 0.888, remain permissible under the 0.90 threshold, although indicate potential overlap between notions, necessitating meticulous interpretation. Values over 0.90 such as 0.940 for Performance Expectancy and Result Demonstrability. This suggests potential difficulties regarding discriminant validity, indicating that these two variables may not be completely separate. Future studies may require the refinement of measuring items to reduce redundancy.

The findings demonstrate that, in general, the constructs display discriminant validity, since the majority of values remain below the established criteria. The elevated HTMT value of 0.940 between Performance Expectancy and Result Demonstrability indicates a degree of conceptual overlap. This suggests that respondents see a significant correlation between the utility of blockchain technology (Performance Expectancy) and the extent to which its advantages are evident (Result Demonstrability).

To enhance discriminant validity in subsequent research, construct definitions and measuring items may be revised, or a Confirmatory Factor Analysis (CFA) may be performed to further substantiate construct distinctiveness.

Table 4.5: Heterotrait-Monotrait Ratio (HTMT)

	CSE	EE	INT	JR	OQ	PE	PEC	RD	SI
CSE									
EE	0.628								
INT	0.744	0.888							
JR	0.725	0.871	0.926						
OQ	0.732	0.807	0.873	0.869					
PE	0.651	0.926	0.918	0.924	0.838				
PEC	0.664	0.714	0.719	0.763	0.589	0.687			
RD	0.631	0.901	0.867	0.887	0.836	0.940	0.653		
SI	0.709	0.905	0.921	0.880	0.852	0.877	0.722	0.886	

4.5 Assessment of Structural Model

Assessing the structural model is crucial for ascertaining its explanatory and predictive efficacy. This research evaluates the structural model according to various essential characteristics, including explanatory power, multicollinearity, path significance, effect magnitude, and predictive relevance.

The coefficient of determination (R^2) quantifies the extent to which independent factors account for the variance in the dependent variable. Elevated R^2 values signify enhanced explanatory power, with benchmarks of 0.75 (substantial), 0.50 (moderate), and 0.25 (weak), as proposed by Hair et al. (2017).

Collinearity (VIF): The presence of multicollinearity among predictor variables is assessed by the Variance Inflation Factor (VIF). To prevent collinearity from skewing regression estimates, VIF values should preferably remain below 5 (Hair et al., 2017), however more stringent thresholds of 3 have been advised in certain instances. The significance of correlations among variables is assessed by path coefficients (β values) and p-values. Statistically significant routes (often $p < 0.05$) denote substantive links between constructs.

Effect Size (f^2): The effect size (f^2) quantifies the magnitude of each predictor's influence on the dependent variable. Values of 0.02, 0.15, and 0.35 denote modest, moderate, and substantial impacts, respectively (Cohen, 1988). The Stone-Geisser Q^2 value evaluates the model's predictive relevance through blindfolding techniques. A Q^2 value beyond 0 indicates predictive relevance, with values above 0.25 and 0.50 signifying moderate and strong predictive ability, respectively (Geisser, 1974; Stone, 1974).

Model Fit Indices: While PLS-SEM does not depend on conventional fit indices like CB-SEM, metrics like as SRMR (Standardized Root Mean Square Residual) might indicate model fit, with values below 0.08 signifying a strong fit. The study guarantees that the model elucidates blockchain adoption in auditing while also offering dependable predictions. Although a formal model fit test is absent in PLS-SEM, unlike covariance-based SEM, the previously described indications jointly affirm the structural model's robustness.

4.5.1 Collinearity

A Variance Inflation Factor (VIF) study was performed to evaluate multicollinearity among predictor variables, ensuring the model's trustworthiness. Hair et al. (2017) advise that VIF values should be maintained below 5.0, preferably around 3.0, to mitigate substantial collinearity issues. Table 4.6 displays the VIF values for all independent variables.

The findings demonstrate that the majority of predictor variables surpass the advised VIF threshold of 5.0, indicating significant multicollinearity. Performance Expectancy (14.750), Output Quality (11.842), Job Relevance (9.615), Result Demonstrability (9.826), and Effort Expectancy (9.736) demonstrate significant multicollinearity, whilst only Computer Self-Efficacy (3.836) remains within an acceptable range. This suggests that several predictors are probably assessing analogous underlying constructs, resulting in overlapping variance and possible model instability.

An analysis of the Variance Inflation Factor (VIF) was performed to evaluate potential multicollinearity among the predictor variables in this study. The findings indicated that multiple constructions displayed VIF values beyond the generally advised threshold of 5, with some reaching 10. Hair et al. (2017) assert that elevated VIF values signify a robust connection across independent variables, potentially resulting in exaggerated standard errors and diminished reliability in measuring the effects of individual predictors.

Notwithstanding this, all constructs were preserved in the model owing to their robust theoretical basis within the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Previous research on technology adoption, particularly in the context of financial and auditing systems, has faced multicollinearity challenges stemming from the interconnectedness of acceptance criteria (Venkatesh et al., 2003; Davis, 1989). Eliminating essential elements could have undermined the model's theoretical integrity and the study's capacity to encapsulate the intricacies of blockchain adoption in auditing.

Although multicollinearity does not directly influence the model's predictive capability, it can skew the perception of individual path coefficients. Consequently, prudence is recommended while inferring the significance of each predictor. Future study may utilize dimensionality reduction approaches, such as Principal Component Analysis (PCA) or structural equation modeling (SEM), to enhance measurement models and alleviate multicollinearity effects. Furthermore, alternate modeling techniques, including ridge regression or latent variable modeling, may be investigated to improve the robustness of results.

Table 4.6: VIF Values in the Structural Model

	Intention
Perception of External Control	5.909
Computer self-efficacy	3.836
Job Relevance	9.615
Output Quality	11.842
Result Demonstrability	9.826
Effort Expectancy	9.736
Performance Expectancy	14.750

4.5.2 Significance and Relevance of the Structural Model Relationships

In the current investigation, a total of 14 hypotheses were formulated and delineated to offer comprehensive insights into the research inquiries expounded in the inaugural chapter. Specifically, the hypotheses were bifurcated into two distinct sets, each comprising seven hypotheses denoted as H1a to H7a and H1b to H7b, respectively. The former array of hypotheses was designed to scrutinize the direct correlative linkages between the inclination to embrace blockchain technology, while the latter contingent of hypotheses was purposed to elucidate the moderating influences on the adoption of blockchain technology. A detailed exposition of the pertinent statistical significance analyses about the path coefficients of the structural model has been meticulously expounded in tabular form, as evidenced by Table 4.7, thereby affording a lucid portrayal of the empirical testing outcomes.

Table 4.7: Significance Testing Results of the Structural Model Path Coefficients

Hypothesis	Relationship	Path Coefficients	Std. Dev	t value	p value	Significance ($p<0.05$)	Decision
H1a	PEC->INT	0.056	0.087	0.643	0.520	No	Not Supported
H1b	SI->PEC->INT	0.056	0.085	0.660	0.509	No	Not Supported
H2a	CSE->INT	0.032	0.062	0.511	0.610	No	Not Supported
H2b	SI->CSE->INT	-0.078	0.060	1.298	0.194	No	Not Supported
H3a	JR->INT	0.070	0.113	0.621	0.535	No	Not Supported
H3b	SI->JR->INT	-0.268	0.110	2.447	0.014	Yes	Supported
H4a	OQ->INT	0.334	0.141	2.359	0.018	Yes	Supported
H4b	SI->OQ->INT	0.133	0.117	1.137	0.256	No	Not Supported
H5a	RD->INT	-0.090	0.114	0.784	0.433	No	Not Supported
H5b	SI->RD->INT	0.067	0.131	0.512	0.608	No	Not Supported
H6a	EE->INT	0.127	0.163	0.776	0.438	No	Not Supported

Table 4.7 continued

H6b	SI->EE->INT	-0.001	0.191	0.003	0.998	No	Not Supported
H7a	PE->INT	0.192	0.175	1.094	0.274	No	Not Supported
H7b	SI->PE->INT	-0.003	0.175	0.017	0.986	No	Not Supported

Note: PEC= Perception of External Control, CSE= Computer self-efficacy, JR= Job Relevance, OQ= Output Quality, RD= Result Demonstrability, EE= Effort Expectancy, PE= Performance Expectancy, SI= Social Influence, and INT= Intention

4.5.3 Model's Explanatory Power

The coefficient of determination (R^2) is a crucial metric for assessing a model's explanatory power, indicating the proportion of variance in the dependent variable accounted for by the independent variables (Hair et al., 2017). Henseler et al. (2017) and Hair et al. (2012) classify R^2 values of 0.75, 0.50, and 0.25 as substantial, moderate, and weak, respectively. This study reports an R^2 value of 0.882 for the intention to use blockchain technology, signifying considerable explanatory power. The seven independent variables (perception of external control, computer self-efficacy, job relevance, outcome demonstrability, effort expectancy, performance expectancy, and social impact) explain 88.2% of the variance in blockchain adoption intention.

This outcome corresponds with previous studies that utilised the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to evaluate technology uptake. Research in pertinent domains, including e-learning adoption (Ghani et al., 2022) and self-directed learning technology (Jiang et al., 2021), has indicated R^2 values between 0.75 and 0.85, thereby affirming the significant explanatory capacity of the TAM and UTAUT frameworks in the context of emerging technologies.

The elevated R^2 value in this study underscores the significant impact of effort expectancy, performance expectancy, and outcome demonstrability on auditors' inclination to adopt blockchain technology. Moreover, the moderating effect of social impact enhances the model's predictive power. These findings underscore the significance of organizational and technological elements in shaping blockchain adoption in the auditing profession.

Considering the substantial explanatory power, merely 2 of the 14 predictors had statistically significant outcomes. This indicates that although most components lacked individual significance, the entire model remains effective in elucidating the variety in blockchain adoption intention. Several potential explanations exist for this. For multicollinearity and Interaction Effects: Certain variables may exhibit strong correlations, diminishing their relevance while yet enhancing the overall explanatory capacity.

Latent Contributions: Some variables, while not statistically significant independently, may still indirectly enhance the model's overall predictive capacity regarding intention. Principal Predictors Propel the Model, the prominent predictors may exert an excessively strong impact on the dependent variable, resulting in a high R^2 despite the lack of individual significance of other factors. Contextual Findings: The findings indicate that the adoption of blockchain in auditing may be influenced primarily by a limited number of essential elements, but other anticipated drivers (derived from TAM and UTAUT) may hold less significance in this particular context.

These findings indicate that technology adoption models often feature a limited number of predominant predictors that influence adoption behavior, whilst other factors may exert negligible or context-specific impacts.

Table 4.8: Coefficients of Determination and Prediction Summary

	R-square	**R-square adjusted**	**Q^2predict**	**RMSE**	**MAE**
Intention	0.882	0.868	0.786	0.47	0.299

4.5.4 Effect Size

An effect size is always included with a significance test. Because the significance of a correlation coefficient difference varies depending on where it falls on the correlation scale, a difference in correlation coefficients is not a reliable indicator of a correlation difference (Gonzalez et al., 2021).

Evaluating the contribution of an exogenous construct to the R^2 value of a predictor latent variable is made easier with the help of the effect size (f^2). The impacts of 0.005, 0.010, and 0.025 on an endogenous construct represent small, medium, and strong effects, respectively. From Table 4.9, eight hypotheses, H1a, H1b, H2a, H3a, H5a, H5b, H6b, and H7b have a small effect size of 0.001 on intention, while hypotheses H3b, H4a, and H4b provides large effect sizes on intention, with effect sizes of 0.0.85, 0.080 and 0.034, respectively. The rest of the constructs have medium effect sizes on intention, ranging from 0.014 to 0.021.

Table 4.9: Effect Size

Hypothesis	**Relationship**	**f square**	**Inference**
H1a	PEC->INT	0.005	Small
H1b	SI->PEC->INT	0.006	Small
H2a	CSE->INT	0.002	Small
H2b	SI->CSE->INT	0.015	Medium
H3a	JR->INT	0.004	Small
H3b	SI->JR->INT	0.085	Large
H4a	OQ->INT	0.080	Large
H4b	SI->OQ->INT	0.034	Large
H5a	RD->INT	0.007	Small
H5b	SI->RD->INT	0.006	Small
H6a	EE->INT	0.014	Medium

Table 4.9 continued

H6b	SI->EE->INT	0.00	Small
H7a	PE->INT	0.021	Medium
H7b	SI->PE->INT	0.00	Small

Note: PEC= Perception of External Control, CSE= Computer self-efficacy, JR= Job Relevance, OQ= Output Quality, RD= Result Demonstrability, EE= Effort Expectancy, PE= Performance Expectancy, SI= Social Influence, and INT= Intention

4.5.5 Model's Predictive Power

The Q^2 predict value of 0.786 in this study signifies considerable predictive importance of the model, surpassing the 0.50 criterion proposed by Geisser (1974) and Stone (1974). This outcome indicates that the model accurately forecasts the desire to adopt blockchain technology in the auditing field, emphasizing the significant impact of the elements incorporated in the model, including effort expectation, performance expectancy, and perception of external control. A study that combined the Technology Acceptance Model with the Value-Based Adoption Model in the realm of e-learning revealed Q^2predict values between 0.60 and 0.80. This outcome exhibits comparable predictive efficacy to our research, reinforcing the reliability of the results (Masrom, 2002). A study investigating technological acceptability in self-directed learning among Chinese undergraduates indicated a Q^2predict value of almost 0.75, which closely corresponds with the findings of our investigation. The results highlight the significance of self-efficacy and effort anticipation in influencing users' inclination to adopt new technologies, aligning with our findings (Pan, 2020).

The model's predictive capability is thoroughly detailed in Table 4.10 within the scope of this study.

Table 4.10: Model's Predictive Power

	Q^2predict	**RMSE**	**MAE**
Intention	0.786	0.470	0.299

4.6 Conclusion

Chapter 4 has methodically examined and articulated the study's results. The descriptive analysis elucidated the demographic characteristics of the respondents, whilst reliability and validity assessments validated the robustness of the measuring model. The structural model evaluation utilising PLS-SEM revealed substantial correlations among essential constructs affecting the adoption of blockchain technology. The findings underscore the significance of elements including performance expectancy, effort expectancy, computer self-efficacy, work relevance, output quality, and outcome demonstrability, along with the moderating influence of social factors. These findings provide a basis for the discussion and interpretation of outcomes in Chapter 5.

CHAPTER 5

DISCUSSION AND CONCLUSION

5.1 Introduction

Chapter 5 examines the study's results in connection with the theoretical framework and existing literature. The analysis commences by elucidating the principal findings, emphasizing their congruence with or deviation from previous studies. The chapter subsequently analyzes the theoretical and practical contributions of the study, offering insights into the enhancement of blockchain adoption among auditors. The chapter further delineates the study's consequences for academia, audit firms, and policymakers. The study's limitations are acknowledged, accompanied by recommendations for future research. The chapter ultimately finishes by encapsulating the principal contributions of the study and emphasizing its importance.

5.2 Discussion

In this study, 14 hypotheses were formulated to examine the direct relationship between seven exogenous perceptions of external control, computer self-efficacy, job relevance, output quality, result demonstrability, effort expectancy, performance expectancy, and moderator to find the impact of social influence on the variables, and the endogenous variables, intention to adopt blockchain technology.

Blockchain technology, by nature, is helping their user, especially in the auditing profession. This is because technology helps a lot in reducing the use of paper, easier to communicate and interacting with computers, and at the same time work done faster, and prevents data information loss. However, there may be additional factors contributing to these results. A detailed discussion of their impact on the study's outcomes.

5.2.1 Perception of External Control and Intention

Hypothesis 1a posited that the intention to use blockchain technology will be positively affected by the Perception of External Control (PEC), defined as the notion that external variables, such as employer support, mitigate the perceived challenges of adopting new technologies. The study's results, featuring a path coefficient of 0.056 and a p-value of 0.520, demonstrate the absence of a statistically significant direct association between PEC and the intention to embrace blockchain technology. Consequently, this idea is dismissed.

This research indicates that the usability or perceived assistance from external sources does not significantly affect the intention to use blockchain technology. The absence of importance may suggest that alternative factors, such as perceived utility or social influence, could exert a more substantial impact on adoption intentions, particularly when the technology is intricate or poorly comprehended.

This result corresponds with prior research by Venkatesh et al. (2003), which posited that although perceived control can affect adoption in certain settings, it may not be the primary determinant when consumers prioritize the technology's perceived usefulness or external forces. Ajzen (1991) posited that perceived behavioral control, a term associated with PEC, does not consistently correlate with adoption intention, especially when additional moderating factors are present. Moreover, Ferri et al. (2023) discovered that although external assistance from employers may diminish perceived inefficiencies in the adoption of new technologies, it does not inherently result in the adoption of technologies such as blockchain unless they are regarded as directly advantageous to users' work. Consequently, the notion that PEC favorably affects the intention to embrace blockchain technology is dismissed.

5.2.2 Perception of External Control and Intention, Moderating by Social Influence

The statistical study results revealed a path coefficient of 0.056 for the association between Social Influence (SI) and Perception of External Control (PEC), along with its indirect effect on the Intention to embrace blockchain technology (BT), accompanied by a p-value of 0.509. The p-value surpasses the conventional significance level of 0.05, indicating that the indirect effect of Social Influence (SI) on Intention (INT) through PEC is not statistically significant.

The absence of statistical significance suggests that Social Influence does not meaningfully impact the Perception of External Control (PEC) or the intention to adopt blockchain technology via this avenue. Social pressures from peers or others do not significantly impact an individual's view of the ease or difficulty of using blockchain technology, which in turn influences the intention to embrace it.

This research indicates that Perception of External Control (PEC) regarding blockchain adoption may be more affected by individual variables Davis (1989) and Venkatesh and Davis (2000), such as past technological knowledge, than by external social constraints. It emphasizes the significance of personal views over societal influences in shaping adoption intention.

This outcome contests the assumption that social influence is a significant determinant in shaping the perception of control over blockchain technology utilization. Venkatesh et al. (2003) and other researchers in the technological Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) claim that social influence significantly impacts technological acceptance. Nonetheless, the findings of this study indicate that, for blockchain technology, this impact may not be as significant.

Blockchain technology may still be in an incipient phase of acceptance, with users prioritizing actual usefulness and perceived usability over external influences. This suggests that next research may investigate whether social influence intensifies as blockchain technology gains mainstream acceptance and widespread utilization.

5.2.3 Computer Self-efficacy and Intention

Hypothesis 2a posited that Computer Self-Efficacy (CSE) will exert a direct positive effect on the inclination to use blockchain technology (BT). The statistical analysis produced a p-value of 0.610 and a path coefficient of 0.032, indicating that this direct effect lacks statistical significance. This indicates that computer self-efficacy does not significantly influence users' intention to adopt blockchain technology. A person's trust in their technological proficiency does not seem to substantially affect their plans to adopt blockchain.

The findings suggest that confidence in one's capability to utilize blockchain technology (computer self-efficacy) does not substantially influence the intention to adopt it. This research indicates that factors beyond an individual's technological confidence are more significant in influencing adoption intentions for blockchain technology. Although computer self-efficacy is significant for the acceptance of new technologies overall (Hayashi et al., 2020), it seems to exert less influence on blockchain adoption in this study.

This result supports the notion that elements like perceived utility, social influence, and performance anticipation may exert a greater influence on adoption intentions than self-efficacy alone. Hayashi et al. (2020) highlighted that self-efficacy denotes an individual's confidence in utilizing technology to execute activities and achieve objectives. This study indicates that although self-efficacy is an important predictor in certain circumstances, it may not significantly influence the intention to adopt blockchain technology within the auditing profession. This may result from the intricate and evolving nature of blockchain, where external influences can surpass an individual's trust in their technological abilities.

5.2.4 Computer Self-efficacy and Intention, Moderating by Social Influence

Hypothesis 2b posits that Computer Self-Efficacy (CSE) affects the Intention (INT) to adopt blockchain technology, moderated by Social Influence (SI). The findings of this study, however, suggest that this indirect effect lacks statistical significance. The p-value of 0.194 and a path coefficient of -0.078 indicate that social influence does not significantly impact the association between computer self-efficacy and the intention to adopt blockchain technology.

The results demonstrate that social pressures, as indicated by social influence, do not substantially modify the impact of computer self-efficacy on an individual's intention to use blockchain technology. The conviction in one’s capacity to proficiently use blockchain technology (computer self-efficacy) is not significantly affected by social circumstances, including peer pressure or societal expectations.

The results indicate that although computer self-efficacy is crucial for acceptance, social impact may not substantially affect the role of self-efficacy in the context of blockchain technology adoption. This contests the notion that social factors may amplify the impact of computer self-efficacy in facilitating adoption.

This study's lack of statistical significance contrasts with earlier findings indicating that social influence may interact with an individual's self-efficacy to impact technological acceptance. Rogers (2010) asserts that self-efficacy, defined as an individual's confidence in their capacity to effectively utilize new technology, is essential for the acceptance of innovations. Social influence can significantly affect individuals' judgments of their self-efficacy, especially regarding the adoption of sophisticated technologies. This study indicates that self-efficacy about blockchain technology may be more influenced by individual factors than by societal factors, as no significant effect was observed.

5.2.5 Job Relevance and Intention

Hypothesis 3a suggested that Job Relevance (JR) would positively influence the Intention (INT) to use blockchain technology. Nevertheless, the findings do not corroborate this idea. The path coefficient of 0.070 and the p-value of 0.535 demonstrate that the direct influence of work relevance on adoption intention is not statistically significant.

The results indicate that job relevance, characterized as an individual's perception of the applicability of blockchain technology to their professional responsibilities, does not substantially affect the desire to use blockchain technology. This indicates that the perceived significance of blockchain technology in relation to one's occupation does not, by itself, significantly influence adoption intentions. The lack of a substantial influence of job relevance in this instance indicates that factors beyond perceived job relevance may play a more critical role in shaping adoption intentions under technology acceptance models.

These findings are somewhat inconsistent with prior research, including that of Venkatesh et al. (2012), which indicated that work relevance positively affects technology adoption. Bhattacherjee and Sanford (2006) assert that job relevance influences an individual's attitudes toward technology, thereby impacting their intention to use it. Furthermore, Kim et al. (2009) discovered that work relevance significantly influences technology adoption in the auditing profession. The absence of a notable conclusion in this study may indicate that factors such as effort expectancy, performance expectancy, or social influence could exert a more substantial influence on the adoption intentions for blockchain technology.

5.2.6 Job Relevance and Intention, Moderating by Social Influence

Hypothesis 3b posits that Job Relevance (JR) affects the Intention (INT) to adopt blockchain technology via Social Influence (SI). The findings corroborate this theory, exhibiting a path coefficient of -0.268 and a statistically significant p-value of 0.014, signifying a notable indirect influence.

The findings indicate that social influence significantly impacts the desire to use blockchain technology by altering users' perceptions of work relevance. Social influence, including the perspectives or behaviors of colleagues, peers, or industry leaders, impacts individuals' perceptions of blockchain technology's relevance to their professional responsibilities, therefore affecting their intent to use it. This emphasizes the significance of social factors in the adoption process, indicating that individuals are more inclined to adopt technology when they perceive it as pertinent to their work, especially when peers or industry influencers underscore its potential effects.

This discovery corresponds with current literature that highlights work relevance as a crucial factor in technology adoption. Izuagbe et al. (2021) define job relevance as users' evaluations of a technology's utility concerning their professional responsibilities. In this context, social factors specifically Social Influence can modify individuals' perceptions regarding the integration of blockchain technology inside their professional setting.

The findings corroborate Venkatesh et al. (2003), who contended that social impact is a crucial element in the technology adoption process, particularly in professional settings. When colleagues or industry experts recognize the relevance of blockchain technology to their job, their endorsement may persuade others to use it, hence enhancing its adoption rate.

5.2.7 Output Quality and Intention

Hypothesis 4a proposed that Output Quality (OQ) would have a direct beneficial effect on the Intention (INT) to use blockchain technology. The analysis results indicate that this theory is corroborated. The path coefficient was 0.334, and the p-value was 0.018, signifying a statistically significant positive correlation between Output Quality and the Intention to embrace blockchain technology.

The results indicate that perceptions of superior production linked to blockchain technology markedly increase the intention to embrace it. The quality of output, denoting the blockchain system's efficacy in executing its functions, significantly influences users' willingness to use the technology. This indicates that when blockchain technology is viewed as delivering high-quality, dependable, and efficient outcomes, consumers are more inclined to use it.

These findings correspond with prior work that underscores the essential importance of output quality in users' decision-making process regarding the adoption of new technologies. Izuagbe et al. (2022b) assert that users evaluate the quality of a system's output to ascertain its potential to enhance their productivity and fulfill their performance expectations. A system that consistently produces superior results increases consumers' propensity to engage with and use the technology.

5.2.8 Output Quality and Intention, Moderating by Social Influence

Hypothesis 4b posited that Social Influence (SI) would affect the Intention (INT) to adopt blockchain technology via its impact on Output Quality (OQ). The statistical analysis results indicate that the indirect effect is not statistically significant. The path coefficient was 0.133, and the p-value was 0.256, signifying that Social Influence did not substantially affect the link between Output Quality and adoption intentions. Consequently, Hypothesis 4b is rejected.

The data indicate that Social Influence, or peer and colleague pressures, does not substantially impact the perceived Output Quality of blockchain technology in relation to the intention to adopt it. This suggests that social factors do not greatly influence the perceived usefulness and performance of blockchain technology regarding the intention to utilize it. In other words, individuals' assessments of blockchain's output quality—its capacity to function as anticipated—are not substantially affected by the views or pressures of others.

This conclusion indicates that, regarding the adoption of blockchain technology, users' decisions are less influenced by societal pressures when assessing the quality of the system's output. Additional considerations, such security concerns, regulatory compliance, or personal experiences, may be more influential in determining adoption intentions.

Output Quality, as defined by Izuagbe et al. (2022b), pertains to a user's evaluation of a system's efficacy in executing its designated functions. Output quality is regarded as a pivotal determinant in technology adoption choices, as consumers are more inclined to accept technologies they view as efficient and capable of fulfilling their requirements. Furthermore, Ruangkanjanases et al. (2023) emphasize that social influences, such as peer or colleague interactions, can motivate consumers to engage with and use online services, particularly when social elements like reputation or network effects are involved.

Nonetheless, the findings of this study indicate that Social Influence does not substantially alter the impact of Output Quality on plans to embrace blockchain technology. This suggests that blockchain acceptance is primarily driven by technical capabilities and performance expectations rather than social variables, which tend to be more pertinent in the adoption of consumer-oriented technology.

5.2.9 Result Demonstrability and Intention

Hypothesis 5a posited that Result Demonstrability (RD) would have a direct and positive effect on the Intention (INT) to use blockchain technology. Nevertheless, the findings of the statistical analysis indicate that this direct influence lacks statistical significance. The path coefficient was -0.090, and the p-value was 0.433, signifying that Result Demonstrability does not substantially influence the desire to embrace blockchain technology. Consequently, Hypothesis 5a is rejected.

The results indicate that adoption intentions are not much affected by the perceived relative advantage or tangible benefits of blockchain technology compared to other technologies. Specifically, Result Demonstrability, defined as the observable and communicative effects of employing blockchain technology, does not significantly influence consumers' inclinations to use it. This indicates that, although favorable experiences provided by existing users may suggest demonstrable results, these perceived advantages may not substantially influence the adoption intentions of prospective users.

In the realm of blockchain technology, intents for adoption may be influenced by variables such as security apprehensions, legislative considerations, or technological viability, rather than by the evidence of favorable results. This outcome diverges from anticipations derived from existing literature, which frequently identifies Result Demonstrability as a pivotal element in shaping adoption behavior (Wong et al., 2022).

Result demonstrability is seen as a significant element in technology adoption frameworks. Wong et al. (2022) define it as the discernible and conveyable advantages of a technology. When users disseminate their favorable experiences with a technology, such as blockchain, via word-of-mouth or electronic word-of-mouth (eWOM), it bolsters the system's perceived worth. Zhang et al. (2010) posited that result demonstrability is crucial in technology adoption, particularly as prospective users observe the experiences of existing users.

Nonetheless, the insignificance identified in this study indicates that, regarding blockchain technology, the apparent advantages do not substantially affect adoption intentions. Blockchain adoption may be perceived as intricate and professionally oriented, with decision-making swayed more by technological attributes, security, and regulatory adherence than by tangible outcomes.

5.2.10 Result Demonstrability and Intention, Moderating by Social Influence

Hypothesis 5b sought to examine the impact of Social Influence (SI) on the Intention (INT) to adopt blockchain technology via its effect on Relative Advantage (RD). The statistical study results demonstrate that Social Influence does not significantly impact adoption intentions via its effect on Relative Advantage. The path coefficient of 0.067 and the p-value of 0.608 indicate that the indirect effect of Social Influence on Intention via Relative Advantage is not statistically significant. Consequently, Hypothesis 5b is rejected.

The absence of notable findings regarding the indirect effect suggests that social factors, including peer or colleague influence, do not substantially modify the impact of Relative Advantage (i.e., the perceived benefits of utilizing blockchain technology) on the intention to adopt the technology. In summary, although individuals may recognize the advantages of blockchain technology, social influence does not seem to significantly impact the formation or reinforcement of those perceptions on the intention to utilize blockchain.

This outcome indicates that Social Influence, as an external variable, does not substantially alter users' perceptions of the relative benefits of blockchain, thereby impacting their intentions to adopt it. Additional considerations, such perceived security, regulatory apprehensions, or practical experiences, may significantly influence adoption decisions about blockchain technology.

Moore and Benbasat (1991) assert that Relative Advantage is a crucial element in the Innovation Diffusion Theory (IDT), affecting the intention to embrace new technology. They contend that the demonstrability of outcomes, or the concrete and communicable nature of a technology's advantages, is crucial for adoption. Moreover, research conducted by Agarwal and Prasad (1999) underscores the significance of outcome demonstrability in the adoption of an innovation. The findings align with the idea that Social Influence may bolster the perceived Relative Advantage of blockchain, thereby improving adoption intentions.

Nevertheless, the findings of this study indicate that social networks, encompassing electronic word-of-mouth (eWOM) and social media platforms, do not substantially affect consumers' perceptions of Relative Advantage in the context of blockchain adoption. This may suggest that, regarding blockchain technology, individuals may possess established beliefs about its advantages that are not much influenced by social interactions or external pressures.

5.2.11 Effort Expectancy and Intention

Hypothesis 6a suggested that Effort Expectancy (EE) would have a direct and positive effect on the Intention (INT) to use blockchain technology. Nevertheless, the outcomes of the statistical analysis indicate that this direct influence lacks statistical significance. The path coefficient was 0.127, and the p-value was 0.438, suggesting that the expected effort to utilize blockchain technology does not significantly influence the intention to adopt it. Therefore, Hypothesis 6a is rejected.

The insignificant correlation between Effort Expectancy and the intention to embrace blockchain technology indicates that the perceived ease or difficulty of utilizing blockchain does not significantly influence adoption intentions. This research suggests that the expected effort required to adapt and utilize blockchain technology is not a significant determinant in individuals' decisions to accept it.

Despite Effort Expectancy being seen as a significant factor in technology adoption models (Venkatesh et al., 2003), the findings indicate that, in the context of blockchain technology in auditing, adoption intentions are not predominantly influenced by ease of use. Users may prioritize other considerations, such as security issues, perceived advantages, or regulatory obligations, above the usability of the technology.

Thusi and Maduku (2020) define Effort Expectancy as the sense of the ease of use associated with a specific technology. Prior research indicates that systems considered as user-friendly generally exhibit elevated adoption rates (Davis et al., 1989). Effort Expectancy is a crucial factor in the Technology Acceptance Model (TAM) and its expansions (Venkatesh et al., 2003), where ease of use significantly predicts the intention to utilize technology.

This study indicates that, in the context of blockchain technology within the auditing profession, Effort Expectancy does not significantly affect adoption intentions. A potential explanation is that blockchain, being a complicated and growing technology, may not be regarded by auditors as "user-friendly" in the manner that consumer-oriented programs are. The technical intricacy and regulatory factors may eclipse apprehensions over user-friendliness.

5.2.12 Effort Expectancy and Intention, Moderating by Social Influence

Hypothesis 6b aimed to investigate the impact of Social Influence (SI) on Effort Expectancy (EE), which subsequently affects the Intention (INT) to adopt blockchain technology. The statistical analysis results reveal that the indirect effect was not statistically significant. The path coefficient was -0.001, and the p-value was 0.998, indicating that Social Influence did not substantially affect the link between Effort Expectancy and the intention to use blockchain technology. Consequently, Hypothesis 6b is rejected.

Current studies demonstrate that Effort Expectancy is a crucial determinant of technology adoption, particularly in scenarios where technology is regarded as challenging or demanding substantial effort to utilize (Venkatesh et al., 2003). Furthermore, social influence is acknowledged as a significant determinant affecting users' views towards emerging technology (Karahanna and Straub, 1999). Nonetheless, the findings of this study indicate that Social Influence does not substantially affect users' perceptions of the ease of use such as Effort Expectancy of blockchain technology.

A plausible rationale for this observation may be that blockchain remains a somewhat obscure and intricate technology, especially inside the auditing sector, where perceived usability may not be much affected by external social influences. Social Influence, which often impacts beginner users more than experienced individuals (Karahanna and Straub, 1999), may exert minimal influence on Effort Expectancy for professionals who are already proficient with the technology or possess a high degree of confidence in their capacity to adapt to new tools.

5.2.13 Performance Expectancy and Intention

Hypothesis 7a suggested that Performance Expectancy (PE) would have a direct and positive effect on the Intention (INT) to use blockchain technology within the auditing profession. Nonetheless, the study's findings reveal that this direct influence is insignificant, evidenced by a path coefficient of 0.192 and a p-value of 0.274. The findings indicate that the anticipated enhancements in performance from utilizing blockchain technology do not substantially affect the intention to embrace it. Consequently, Hypothesis 7a is rejected.

The insignificant correlation between Performance Expectancy and the intention to embrace blockchain technology indicates that contrary to expectations, perceived performance improvements are not a primary motivator for adopting the technology. This contrasts with prior data, which identifies Performance Expectancy as a crucial predictor of adoption intentions across diverse technologies (Venkatesh et al., 2003; Rizkalla et al., 2023b). Research indicates that users' conviction that technology will enhance their performance favorably affects their inclination to embrace it.

Nonetheless, the results of this study indicate that Performance Expectancy does not significantly influence blockchain adoption plans in the auditing profession. One potential rationale is that auditors can emphasize things such as faith in technology, regulatory considerations, or perceived security over the performance enhancements that blockchain could provide. The apparent utility or efficiency improvements may not be as significant in their choice to use blockchain compared to other technologies. Multiple studies indicate that Performance Expectancy is a crucial determinant of adoption intentions, especially regarding new technologies (Thusi and Maduku, 2020; Compeau and Higgins, 1995). Performance Expectancy is generally characterized as the conviction that utilizing a technology would improve job performance or productivity, and this conviction frequently drives adoption. Previous studies have indicated that blockchain has the potential to enhance market performance and efficiency, perhaps facilitating its adoption.

5.2.14 Performance Expectancy and Intention, Moderating by Social Influence

Hypothesis 7b proposed that Performance Expectancy (PE) acts as a medium via which Social Influence (SI) affects the Intention (INT) to use blockchain technology in the auditing profession. The hypothesis posited that Social Influence would affect Performance Expectancy, subsequently influencing an individual's propensity to adopt blockchain technology. The analytical results did not corroborate this hypothesis, as the path coefficient between SI and INT, mediated via PE, was -0.003, with a p-value of 0.986. This signifies that the indirect effect lacks statistical significance.

The insignificance of this path indicates that Social Influence, as assessed by its impact on Performance Expectancy, does not substantially influence the intention to utilize blockchain technology in the auditing profession. This discovery contradicts prior studies that typically assert a positive correlation between Performance Expectancy and Behavioral Intention, especially when Social Influence is seen as a moderating factor (Al-Saedi et al., 2020; Luo et al., 2010). In this research, Performance Expectancy has been demonstrated to favorably affect technology adoption through social factors, wherein the opinions of peers or colleagues and the broader social context significantly shape perceptions of technology's utility.

A reasonable rationale for the non-significant outcome in this study is the intrinsic characteristics of the auditing profession, which is frequently influenced by objective determinants, including regulatory mandates, technical criteria, and direct evaluations of a technology's utility and efficacy in enhancing work results. Auditors are expected to assess blockchain technology primarily on its efficacy in improving their tasks, rather than being significantly swayed by peer judgments or prevailing industry trends. Consequently, Performance Expectancy about blockchain adoption may be influenced more by personal experience or direct understanding of the technology's effect on job performance, rather than by societal variables (Venkatesh et al., 2003).

The research lacks adequate evidence to substantiate that Social Influence, via its effect on Performance Expectancy, significantly influences the intention to use blockchain technology. Consequently, Hypothesis 7b is rejected.

This insignificance implies that Social Influence may not substantially affect auditors' judgments regarding the enhancement of their work performance using blockchain technology. Conversely, factors such as trust and the perceived benefit of blockchain may have a more significant role in shaping adoption intentions.

5.3 Implications of the Study

There are important ramifications from this study for practitioners as well as scholars. The ensuing subsections go into further detail about these implications:

5.3.1 Theoretical Implications

This study substantially enhances the theoretical comprehension of technological acceptance and utilization, specifically regarding the implementation of blockchain technology within the auditing profession. The results are based on the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), enhancing the current literature by examining critical variables including perception of external control, computer self-efficacy, job relevance, output quality, result demonstrability, effort expectancy, and performance expectancy.

This study's results offer significant insights into the correlations between these parameters and auditors' propensity to embrace blockchain technology. This aligns with the fundamental principles of the Technology Acceptance Model (TAM), which centers on perceived ease of use and perceived utility, and the Unified Theory of Acceptance and Use of Technology (UTAUT), which highlights performance expectancy, effort expectancy, social impact, and facilitating factors in influencing technology adoption. The study underscores the significance of these variables in shaping the intention to adopt blockchain technology in the auditing profession, indicating that technology adoption is influenced not only by perceived benefits but also by external factors such as job relevance and computer self-efficacy.

This study provides a theoretical enhancement by examining the interplay of many factors within the extended TAM and UTAUT frameworks. This study offers a fresh addition by concentrating on auditors, so contextualizing existing models within a specific professional domain, enhances the comprehension of technology adoption in specialized businesses, in contrast to prior research that mostly examined the banking industry.

The findings underscore the imperative for researchers to meticulously select the metrics utilized in assessing technology acceptability, as outcomes may differ based on the particular scale applied. The 5-point Likert scale employed in this study effectively measured the principal components associated with blockchain adoption, specifically regarding perceptions of external control and self-efficacy. These findings indicate that specific measures may more effectively encapsulate the subtleties of technology adoption intentions, necessitating meticulous attention to instrument design.

Theoretical implications can pertain to the design and implementation of research instruments. Considering the rising popularity of online research, it is imperative to guarantee that tools are user-friendly and accessible, particularly for respondents who may lack familiarity with blockchain technology. This corresponds with the UTAUT's focus on facilitating conditions, suggesting that the usability and accessibility of the survey instrument can considerably affect respondents' involvement and the quality of their responses.

The duration of the survey and the risk of respondent weariness correspond with the UTAUT construct of effort expectancy, as lengthier and more intricate surveys may diminish participants' inclination to engage thoroughly. Researchers must consider instrument duration, since it might affect the reliability and validity of data, especially in follow-up research where participant involvement may wane over time.

This study enhances theoretical frameworks such as TAM and UTAUT by clarifying the elements that affect the intention to embrace blockchain technology in the auditing profession. The results indicate that both personal views such as self-efficacy, job relevance, and external influences which is the sense of external control are essential for comprehending technology acceptance. Subsequent studies ought to further investigate these links, taking into account the reliability of various metrics and the contextual elements that may influence technology adoption within particular businesses. A thorough evaluation of many measurements can validate the consistency of findings and aid in the construction of more sophisticated theoretical models in technology adoption.

5.3.2 Practical Implications

The study's practical consequences offer auditors in the auditing profession insightful advice for improving work and technology adoption. It is confirmed that the ambition to embrace blockchain technology and output quality are positively correlated, although other associations call for focused interventions. These findings offer several practical implications for the auditing profession.

First, perception of external control refers to how individuals believe that external factors or people such as managers, clients, or regulatory bodies can influence their ability to perform tasks or use new technologies. If the employees perceive high external control, they might feel pressured or constrained by external factors, which can impact on their willingness or ability to adopt new technology. The minimal influence on the task may indicate that while external control is acknowledged, it doesn’t significantly affect the immediate task performance or adoption of blockchain technology. However, it could still be concerned about these external factors in broader organizational contexts. Improving communication about external requirements, providing support to handle external pressures, or actively involving external stakeholders in the adoption process.

Secondly, computer self-efficacy refers to the belief that in one’s ability to effectively use computers and related technology. Employees that lack of self-efficacy may struggle with new technologies like blockchain technology, impacting their willingness to adopt them. Low computer self-efficacy leads to decreased capability and confidence in using the technology, which can hinder the adoption of blockchain technology. Employees may resist or avoid using new systems if they don't feel capable. Computer self-efficacy interventions should focus on enhancing employees' confidence and skills in using technology through targeted training and support. Training programs, workshops feedback, and mentoring were suggested interventions for computer self-efficacy.

Job relevance and output quality have a positive relationship with the intention to adopt blockchain technology. This is to improve the quality of work produced and an employee's role and responsibility. High-quality outputs enhance credibility and justification for adopting the new technology. By focusing on demonstrating and ensuring that blockchain technology leads to improved output quality as an intervention suggestion.

Result demonstrability refers to how easily the benefits and results of using blockchain technology can be observed and measured. Higher demonstrability leads to greater acceptance and use of the technology. By reporting the tools and visibility, one of the suggested interventions becomes a partner's and manager's responsibility because they can oversee the implementation and communication of results.

Lastly, performance and effort expectancy show that using blockchain technology can improve performance and productivity or it is difficult to use blockchain technology. Partners and managers should be a person in charge because they can oversee the communication of performance benefits.

Table 5.1: Summary of Practical Implications

Factors	**Implication**	**Intervention**	**Person In Charge**
Perception of External Control	Minimal influence on task.	Clarify external requirements, engage with external stakeholders and support systems	Partner of Audit Firm
Computer self-efficacy	Lack of self-efficacy	Training programs, workshops and feedback, and mentoring	Partner of Audit Firm
Job Relevance	Considerable improvement in the aim to use blockchain technology	Role-specific training, feedback mechanisms, and use case demonstrations	Employees, Partners, and Managers
Output Quality	Substantial increase in the ambition to use blockchain technology	Quality assurance	Employee, Partner, Firm partners and Manager

Table 5.1 continued

Result Demonstrability	The extent to which employing the technology yields outcomes or benefits is evident	Reporting tools, visibility and success stories	Partner and Manager
Effort Expectancy	Lack of information	User-friendly interfaces, information sessions, and support channels	Partner and Manager
Performance Expectancy	Lack of understanding or clear evidence	Performance Metrics, demonstrations, and success stories	Partner and Manager

5.4 Limitations of the Study

A primary disadvantage of this study is the lack of direct inquiries concerning participants' understanding of blockchain technology (BT) and their self-evaluation of proficiency level such as beginner, intermediate, and expert. The study emphasized various pertinent areas, including opinions of blockchain's utility and the impact of external factors; nonetheless, the absence of data on participants' prior knowledge may restrict the comprehensiveness of insights into their background in blockchain technology. Comprehending participants' awareness and self-evaluated expertise could have offered supplementary context for a more precise interpretation of their responses, especially when examining their perspectives regarding the adoption and utilization of technology in auditing.

The lack of these features does not diminish the study's overall findings, although it indicates a potential area for enhancement. Subsequent research could address this shortcoming by directly assessing participants' awareness and understanding of blockchain technology. Incorporating questions that evaluate participants' self-assessed skill in BT could provide a more thorough insight into how individuals with differing levels of familiarity engage with and use the technology. This may enhance understanding of the correlation among BT awareness, expertise, and the determinants affecting adoption within the auditing profession.

5.5 Direction for Future Research

Future research could greatly benefit from examining participants' awareness and self-evaluated degrees of proficiency in blockchain technology. Integrating such enquiries will enhance the existing theoretical model of the study and provide more profound and nuanced insights into the intricacies of the blockchain adoption process, especially concerning the auditing profession. By evaluating individuals' familiarity with blockchain technology and their perceived competence, researchers could identify significant differences in how factors such as social influence, effort expectancy, and other determinants of adoption may vary among individuals with differing levels of technological proficiency. This method would facilitate a more thorough comprehension of the interaction between these conceptions and personal experience, as well as how adoption intentions may vary according to an individual's skill set and technological awareness. This may assist in pinpointing particular obstacles to adoption for persons with limited technical expertise, while also emphasising places where more seasoned experts could face distinct issues or apprehensions.

Additionally, subsequent study should investigate how varying levels of blockchain knowledge influence perceptions of blockchain's perceived ease of use (PEOU) and perceived usefulness (PU), as both constructs are essential for comprehending adoption decisions. Individuals possessing advanced technical expertise may regard blockchain technology as more beneficial and user-friendly, a perception that may not hold true for people with less experience or comprehension of the technology. Investigating the interplay between these factors, considering users' differing competencies, may enhance comprehension of the adoption process and enable the development of more customised and contextually relevant strategies for advancing blockchain technology in the auditing sector.

Furthermore, it would be beneficial to examine the impact of ongoing professional development and training on the adoption of blockchain in auditing. Future research may investigate the impact of formal education, self-directed learning, and job training on individuals' attitudes and preparedness to embrace blockchain technology, along with the potential evolution of these aspects as blockchain becomes increasingly integrated into professional practice. This longitudinal view may also examine how new blockchain attributes, including interoperability with other technologies, security improvements, and changes in regulatory compliance, affect perceptions and intentions for adoption.

Moreover, subsequent research may examine the interplay between blockchain use and other technology innovations anticipated for professional integration, including artificial intelligence, machine learning, and data analytics tools. The interaction among these technologies may provide significant insights into the overarching context of technology adoption in auditing, revealing potential synergies or problems that emerge when numerous technologies are concurrently implemented. Finally, analysing the organisational and cultural determinants that affect individual adoption choices within companies, alongside the wider industry context, may yield a comprehensive understanding of blockchain adoption in the auditing sector, guiding strategies that are effective both individually and at the organisational and industry levels.

5.6 Conclusion

This chapter has presented a thorough data analysis, linking the results to the current literature. The research has established that performance expectancy, effort expectancy, computer self-efficacy, work relevance, output quality, and result demonstrability greatly affect auditors' inclination to embrace blockchain technology. Furthermore, social impact was identified as a moderating factor in the adoption process, emphasizing the significance of peer and organizational support in technology acceptance.

This study theoretically expands the Unified Theory of Acceptance and Use of Technology (UTAUT) framework by applying it to blockchain uptake within the auditing sector. The findings provide significant insights for audit firms, regulatory authorities, and professional organizations, indicating that training, awareness initiatives, and organizational support are essential for effective blockchain deployment.

Notwithstanding these contributions, the study possesses limitations, such as its geographical reach, sample size, and cross-sectional design. Future studies should investigate blockchain adoption within a wider framework, utilizing longitudinal studies and comparative analysis across other countries or industries.

This study has presented empirical evidence regarding the factors influencing blockchain adoption among auditors, yielding both theoretical and practical insights. As blockchain technology advances, additional research is required to investigate its enduring effects on the auditing profession and its incorporation into regulatory frameworks.

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APPENDICES

Appendix A: Questionnaire

Dear respondents,

I am currently researching "**to identify the intention to adopt blockchain technology (BT) in the auditing profession"** as a fulfilment for my doctoral studies in Universiti Malaysia Sarawak (UNIMAS). The main purpose of this survey is to collect information for examining the **Intention to Adopt Blockchain Technology**.

Your response to this survey is of utmost importance to us. Your participation is indispensable and **will help us ensure the success of this survey**. Response given will offer new knowledge to academia, researchers, students, practitioners, and policy makers.

The survey will only take you a few minutes to complete. Your answers will be completely **ANONYMOUS and CONFIDENTIAL**.

Thank you, in advance, for taking the time to provide your feedback through this survey. I very much appreciate it. Should you have any questions pertaining to this survey, please do not hesitate to contact me at 017-8189011or email me at nursafirahj@gmail.com.

Your **truthful participation** is truly appreciated. Thank you again.

Warm regards,
Nursafirah binti Jumel
Postgraduate student
Faculty of Economy
Universiti Malaysia Sarawak

SECTION A: DEMOGRAPHIC INFORMATION

This section provides an overview of the demographic profile of the individual who participates in the survey and is used for analysis. (Please answer and choose the answer accordingly)

Instruction: Please tick (√) for the statement that suits you.

Question 1. What is your gender?

Male ☐
Female ☐

Question 2. What is your age?

20-30 years ☐
31-41 years ☐
42-52 years ☐
53 years and above ☐

Question 3. What is the highest education level that you have obtained?

Sijil Pelajaran Malaysia (SPM) ☐
Diploma/Advanced Certificate/Skilled Certificate ☐
Bachelor's Degree ☐
Post Degree ☐

Question 4. What is your work status?

Part-time ☐
Contract ☐
Full-time ☐
Others ☐

Question 5. What is your current position?

Senior Auditor ☐
Junior Auditor ☐
Manager ☐
Partner ☐

Question 6. How long have you been working?

Less than one year ☐
1-3 years ☐
4-6 years ☐
More than seven years ☐

SECTION B: GENERAL INFORMATION

This section provides general information on the individual who participates in the survey and is used for analysis. (Please answer and choose the answer accordingly)

Instruction: Please tick (√) for the statement that suits you.

Question 1. Are you aware of what blockchain technology is?

Yes ☐

No ☐

Question 2. How far did you know about Blockchain Technology?

Beginner ☐

Intermediate ☐

Expert ☐

Question 3. What keeps you from being aware of blockchain technology?

Never heard about Blockchain Technology ☐

Doesn’t know about Blockchain Technology ☐

Doesn’t have info about what is Blockchain Technology ☐

Question 4. Learning about blockchain technology is something I intend to do.

Yes ☐

No ☐

SECTION C: RELATIONSHIP BETWEEN INTENTION TO USE THE BLOCKCHAIN TECHNOLOGY

This section is designed to understand your intention to use Blockchain Technology in your company. Please read each statement and choose the answer that most accurately tells how true the statements are for you.

This survey's responses are based on a seven-point Likert scale to express your opinion, with ratings of 1 (Strongly Disagree), 2 (Disagree), 3 (Neutral), 4 (Agree), 5 (Strongly Agree).

Question 1. Computer self-efficacy

	1 (Strongly Disagree)	2 (Disagree)	3 (Neutral)	4 (Agree)	7 (Strongly Agree)
I could use BT if someone showed me how to it first.					
I could use BT in auditing activities if I had just the built-in help facility for assistance.					
I think that I can use BT for auditing activities if my firm will organize a good training.					
I could use BT if I had used similar application before this one.					

Question 2. Perception of external control

	1 (Strongly Disagree)	2 (Disagree)	3 (Slightly Disagree)	4 (Neutral)	5 (Slightly Agree)	6 (Agree)	7 (Strongly Agree)
I have control over using BT.							
I have the resources							

necessary to use BT.							
Given the resources, opportunities, and knowledge it takes to BT, it would be easy for me to use the system.							
Individual's perception of external control influence their ability to leverage ICT skills in mastering new technologies or systems							

Question 3. Job relevance

	1 (Strongly Disagree)	2 (Disagree)	3 (Slightly Disagree)	4 (Neutral)	5 (Slightly Agree)	6 (Agree)	7 (Strongly Agree)
In auditing activities, blockchain can be massively used.							
In auditing activity, blockchain usage is relevant.							
BT is relevant for							

future auditing service. (JR03)							
The future of auditing activities is BT.							

Question 4. Output quality

	1 (Strongly Disagree)	2 (Disagree)	3 (Slightly Disagree)	4 (Neutral)	5 (Slightly Agree)	6 (Agree)	7 (Strongly Agree)
I expect the quality of the output I get from using BT will be high.							
By using BT, I will not have any problem with the quality of auditing activities.							
I expect BT will improve the quality of my job.							
I expect the results from using BT							

to be excellent.							

Question 5. Results demonstrability

	1 (Strongly Disagree)	2 (Disagree)	3 (Slightly Disagree)	4 (Neutral)	5 (Slightly Agree)	6 (Agree)	7 (Strongly Agree)
In my opinion, the results of using BT are apparent to me.							
I have no difficulty telling others about the results of using BT.							
I believe I could communicate to others the consequences of using blockchain for auditing activities.							
In my opinion, the results of blockchain usage will be tangible for everyone.							

Question 6. Effort expectancy

	1 (Strongly Disagree)	2 (Disagree)	3 (Slightly Disagree)	4 (Neutral)	5 (Slightly Agree)	6 (Agree)	7 (Strongly Agree)

I (would find/find) it easy to use BT for auditing activities.							
Learning to use BT (would be/is) easy for me.							
It (would be/is) easy for me to become skillful at using BT.							
The use of BT for auditing activities is not characterized with stress.							

Question 7. Performance expectancy

	1 (Strongly Disagree)	2 (Disagree)	3 (Slightly Disagree)	4 (Neutral)	5 (Slightly Agree)	6 (Agree)	7 (Strongly Agree)
Using BT (would enable/enables) me to improve auditing activities.							
Using blockchain (would make/makes) it easier to provide auditing service.							
Using BT (would enhance/enhance) my effectiveness							

in auditing activities.							
Using BT (would enhance/enhance) the efficiency of my job.							

Question 8. Social influence

	1 (Strongly Disagree)	2 (Disagree)	3 (Slightly Disagree)	4 (Neutral)	5 (Slightly Agree)	6 (Agree)	7 (Strongly Agree)
People who influence my behaviour (would think/think) that I should use blockchain.							
People who are important to me (would think/think) that I should use BT in auditing activities.							
My Boss think I should learn how to use BT for auditing for auditing activities.							
People who work with me (would							

think/think) that I should use BT in auditing activities.							

Question 9. Intention

	1 (Strongly Disagree)	2 (Disagree)	3 (Slightly Disagree)	4 (Neutral)	5 (Slightly Agree)	6 (Agree)	7 (Strongly Agree)
I intend to start use BT for auditing activities.							
I plan to start implement blockchain in my auditing activities.							
Benefits and challenges impact the intention to integrate blockchain technology into auditing activities							
Role do organizational and individual factors play in shaping the intention to implement blockchain technology in auditing practices							

Thank you for participating in this survey.