BEHAVIOURAL INTENTION TO USE ARTIFICIAL INTELLIGENCE (AI) AMONG ACCOUNTING STUDENTS: EVALUATING THE EFFECT OF TECHNOLOGY READINESS AND JOB RELEVANCE

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DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ACCOUNTING (REPORTING AND MANAGEMENT ACCOUNTABILITY)

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BEHAVIOURAL INTENTION TO USE ARTIFICIAL INTELLIGENCE (AI) AMONG ACCOUNTING STUDENTS: EVALUATING THE EFFECT OF TECHNOLOGY READINESS AND JOB RELEVANCE

ABSTRACT

This study investigates the determinants affecting Malaysian accounting students' behavioural intention to use Artificial Intelligence (AI) using an extended Technology Acceptance Model (TAM) framework. Amidst the expanding integration of AI in Asia's accounting industry, this research seeks to discern the perceptions and projected use of AI by future professionals. A survey-based methodology involved third and fourth-year undergraduate students from four leading Malaysian universities, assessing technology readiness dimensions (optimism, innovativeness, discomfort, insecurity) and job relevance, with mediating variables of superior functionality and perceived usefulness. Data from 136 participants were analysed with Smart PLS 4, exploring direct and indirect influences on students' AI usage intentions. The empirical results reveal that optimism and innovativeness significantly influence the perception of AI's superior functionality, with optimism further impacting its perceived usefulness. Notably, superior functionality serves as a pivotal mediator, connecting positive perceptions with the intent to use AI. In contrast, discomfort with AI presents a significant obstacle, negatively affecting the inclination to employ AI in accounting practices. Furthermore, job relevance directly impacts both the perceived usefulness of AI and the intention to utilise it without necessitating any mediating factors. These insights enable universities to align theory and practice in accounting education, ensuring programs remain current and prepare students for the evolving, technology-centric field.

Keywords: Artificial Intelligence, Accounting Education, Behavioural Intention, Technology Readiness Dimensions, Job Relevance.

NIAT TINGKAH LAKU UNTUK MENGGUNAKAN KECERDASAN BUATAN (AI) DALAM KALANGAN PELAJAR PERAKAUNAN: MENILAI KESAN KESEDIAAN TEKNOLOGI DAN RELEVAN KERJA

ABSTRAK

Kajian ini meneliti faktor-faktor yang mempengaruhi niat tingkah laku pelajar perakaunan Malaysia untuk menggunakan Kecerdasan Buatan (AI) menggunakan kerangka Model Penerimaan Teknologi (TAM) yang diperluas. Dalam konteks integrasi AI yang berkembang di industri perakaunan Asia, kajian ini bertujuan untuk mengenal pasti persepsi dan penggunaan AI yang diramalkan oleh profesional masa depan. Metodologi kajian berdasarkan tinjauan melibatkan pelajar tahun ketiga dan keempat dari empat universiti terkemuka di Malaysia, menilai dimensi-dimensi kesediaan teknologi (optimisme, inovatif, ketidakselesaan, ketidakpastian) dan relevansi pekerjaan, dengan pembolehubah perantaraan fungsi unggul dan tanggapan kebergunaan. Data daripada 136 peserta dianalisis menggunakan Smart PLS 4 untuk memahami pengaruh langsung dan tidak langsung terhadap niat penggunaan AI oleh mahasiswa. Hasil kajian menunjukkan optimisme dan inovatif mempengaruhi secara signifikan persepsi fungsi unggul AI, dengan optimisme tambahan meningkatkan tanggapan kebergunaan. Fungsi unggul AI berperanan sebagai pengantara utama, mengaitkan persepsi positif dengan niat penggunaan AI. Ketidakselesaan terhadap AI memberi kesan langsung pada kecenderungan penggunaan AI dalam amalan perakaunan secara negatif. Relevansi pekerjaan bertindak secara langsung pada tanggapan kebergunaan AI dan niat penggunaannya, tanpa pengantara. Temuan ini membimbing universiti menyelaraskan teori dan praktikal dalam pendidikan perakaunan, memastikan program relevan dan mempersiapkan mahasiswa untuk bidang perakaunan berteknologi.

Kata Kunci: Kecerdasan Buatan, Pendidikan Perakaunan, Niat Tingkah Laku, Dimensi Kesiapan Teknologi, Relevansi Pekerjaaan.

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LIST OF SYMBOLS AND ABBREVIATIONS

AI	:	Artificial Intelligence
AIS	:	Accounting Information Systems
ANN	:	Artificial Neural Networks
ACCA	:	Association of Chartered Certified Accountants
AVE	:	Average Variance Extracted
BI	:	Behavioural Intention
CIMA	:	Chartered Institute of Management Accountants
DOI	:	Diffusion of Innovations
DS	:	Discomfort
ERP	:	Enterprise Resource Planning
EY	:	Ernst & Young
HTMT	:	Heterotrait-Monotrait
HEP	:	Higher Education Providers
ICT	:	Information and Communication Technology
IT	:	Information Technology
IN	:	Innovativeness
IIOT	:	Industrial Internet of Things
IS	:	Insecurity
IDC	:	International Data Corporation
JR	:	Job Relevance
LMS	:	Learning Management Systems
MIA	:	Malaysian Institute of Accountants
ML	:	Machine Learning
MMU	:	Multimedia University
MQA	:	Malaysian Qualifications Agency

OLAP	:	Online Analytical Processing
OP	:	Optimism
PBC	:	Perceived Behavioural Control
PU	:	Perceived Usefulness
PwC	:	Pricewaterhouse Coopers
RPA	:	Robotic Process Automation
SF	:	Superior Functionality
SU	:	Sunway University
TAM	:	Technology Acceptance Model
TR	:	Technology Readiness
TRAM	:	Technology Readiness Acceptance Model
TRI	:	Technology Readiness Index
TPB	:	Theory of Planned Behaviour
TRA	:	Theory of Reasoned Action
UM	:	University Malaya
UKM	:	University Kebangsaan Malaysia
UTAUT	:	Unified Theory of Acceptance and Use of Technology
VIF	:	Variance Inflation Factor

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CHAPTER 1: INTRODUCTION

1.1 Background of Study

The rapid evolution of technology has reshaped the trajectory of the accounting sector, with businesses weaving these advancements seamlessly into their core processes. According to a report by the International Data Corporation (IDC), a consistent growth pattern has been observed in the uptake of Artificial Intelligence (AI) across Asia. Notably, countries like Indonesia, Thailand, Singapore, and Malaysia are at the forefront of this technological revolution. While Malaysia's AI adoption pace in 2018 lagged behind some of its regional peers, the narrative shifted remarkably by 2022. IDC's recent data highlights an impressive escalation in AI investments in the Asia Pacific, hitting $17.6 billion, with projections to soar to $32 billion by 2025 (Malaysian Investment Development Authority, 2022). Notably, Malaysia emerges as the region's second-largest AI investor. This significant influx of capital, combined with an increasing acknowledgement of AI's potential and the imperative for businesses to carve out a competitive advantage, signals an imminent, more aggressive AI adoption wave in Malaysia and its neighbouring regions in the coming years (Digital News Asia, 2018).

The swift advancement of AI and its various subsets has catalysed significant transformations in the field of accounting, heralding a new era marked by shifts in human roles and responsibilities. This evolution is driven by the urgent necessity to redefine and enhance the function of human capital within the accounting profession, paving the way for a future rich in potential and innovation. The impact of AI in the workplace is profound, underscoring the imperative for aspiring accountants to acquire proficiency in digital tools and technologies integral to their future roles. The accounting sector, characterised by a high volume of repetitive and time-consuming tasks, stands on the cusp of a revolution. AI systems are poised to assume these functions, liberating human talent for more complex and strategic endeavours. This fusion of machine intelligence and human insight is expected to manifest across a spectrum of tasks, ranging from specific, well-defined activities to broader, more comprehensive assignments. While this paradigm shift presents potential challenges and uncertainties, it also opens doors to unprecedented opportunities, redefining the role of accountants as they transition from routine tasks to more analytical and advisory capacities. Contrary to the perception that AI adoption is the exclusive domain of industry giants like PWC, KPMG, or Ernst & Young, research conducted by Lee and Tajudeen (2020) reveals a burgeoning trend among small businesses leveraging AI-driven tools. These tools are instrumental in streamlining and optimising processes such as invoice image storage and data collection, underscoring the democratising influence of AI across the entire spectrum of the business landscape.

Moreover, AI and data analytics tools ease the arduous tasks of analysing and structuring extensive financial and non-financial performance data, thus facilitating more streamlined audit procedures. Audit firms have widely recognised the advantages of AI in enhancing client consultations, detecting fraud and material misstatements, and refining internal procedures. This acknowledgement, as observed by Noordin et al. (2022), has resulted in significant improvements in the precision, effectiveness, and timeliness of the auditing process. These advancements are especially crucial in the detection of fraudulent activities within client records, thereby markedly elevating the quality of audits. Building on this, Raji and Buolamwini (2019) emphasised the profound influence of AI's automation capabilities on diverse auditing functions historically dependent on human labour, notably in data entry operations. Unlike conventional methodologies, AI systems conduct thorough data analysis, produce audit tests and scripts, and markedly diminish human errors. This evolution not only enhances the accuracy and trustworthiness of audit results but also denotes a fundamental transformation within the auditing field, elevating the significance of AI and prompting a reassessment of the traditional reliance on human labour. Nevertheless, it is imperative to recognise that auditors should not always be held accountable for the failure to uncover fraud in a client's financial accounts, considering the significant obstacles posed by expertly crafted forgeries and various detection deterrents. AI presents an opportunity to tackle this challenge by efficiently analysing the entire dataset and identifying high-risk transactions (Salem, 2012). Integrating AI into auditing allows auditors to redirect their focus towards value-adding client responsibilities, leveraging AI's precise fraud detection capabilities to enhance the overall quality of the audit.

Numerous reports indicate that AI is exerting a transformative influence on the restructuring of the accounting sector. In his work, Reid (2019) underscored the prowess of Xero's cloud-based accounting system, which incorporates AI-enabled features to bolster efficiency and curtail repetitive tasks. The projection indicates that within a mere half-decade, AI will be deeply ingrained in diverse business practices, anchoring numerous software tools employed daily. Additionally, the emergence of AI-enhanced regulatory technologies, known as RegTechs, introduces a wide range of advancements. These encompass the utilisation of AI for predicting liquidity, the implementation of fortified systems for fraud detection, the integration of blockchain technology to streamline the process of bond and debenture issuance through digital auctions, the proactive identification of potential litigation risks, and the evaluation of restatement disclosures to address both intentional and inadvertent discrepancies (Ding et al., 2020).

The rapid proliferation of AI within the accounting domain has necessitated a profound transformation in the essential competencies required for accountants. This revolution encompasses not only the automation of routine tasks but also the sophisticated analysis of large datasets and enhanced decision-making processes (Bakarich & O'Brien, 2020; Gambhir & Bhattacharjee, 2021). Moreover, the evolving nature of advisory roles demands that accountants possess strategic insights and adeptness in utilising AI tools to facilitate data-informed decision-making (Yigitbasioglu et al., 2023). To maintain a competitive edge in this dynamic environment, accountants must consistently develop their expertise in an array of digital technologies, including AI, data analytics, and blockchain (Faizal et al., 2022). This continuous professional development ensures that accountants are proficient in navigating and capitalising on technological advancements to deliver heightened value to their clients and organisations.

Employers are progressively mandating new hires demonstrate an extensive understanding of AI and related technologies (Ahmad, 2020), thus potentially placing recent and future graduates with limited proficiency and knowledge in these areas at a competitive disadvantage. While experienced professionals gain from structured training programs provided by their employers, students must rely on academic institutions to ameliorate this shortfall. The evolving demands of the accounting profession present a significant challenge for current accounting students, as academic training may only partially align with the rapidly changing skills sought by employers. This disparity underscores the pivotal role of universities in addressing the skills gap within the accounting sector, ensuring that graduates are adequately prepared to meet the technological demands of the contemporary workplace (Oliveira & Bastos, 2023).

According to recent scholarly research (Elo et al., 2023; Gunarathne et al., 2021; Qasim & Kharbat, 2020), accounting educators play a pivotal role in harmonising the content of accounting programs with the expectations of the professional field. However, educators often encounter the challenge of striking a balance between delivering fundamental curriculum content and integrating contemporary issues and technological advancements pertinent to the field. A notable impediment presently faced by accounting educators is the absence of AI knowledge and skills in university curricula. This discrepancy between industry requisites and current educational practices in accounting underscores the necessity to modernise pedagogical approaches to encompass the escalating adoption of recent technologies, such as AI (Damerji & Salimi, 2021).

The Malaysian Qualifications Agency (MQA) has emphasised the importance of integrating essential technological skills into accounting programs offered by Higher Education Providers (HEPs) to address this gap. In the face of escalating demands for responsibility, HEPs are required to metamorphose into adaptable educational bodies proficient at navigating the constantly evolving landscape moulded by technological advancements, science, and the global dissemination of knowledge (Malaysian Qualifications Agency, 2014). However, the absence of comprehensive guidelines poses challenges in conducting prompt and crucial educational framework modifications. Educators can facilitate the convergence of academia and industry by effectively integrating traditional accounting principles with emerging technological trends. This harmonisation will equip graduates to operate proficiently within an accounting environment dominated by AI.

The absence of clear directives for universities in this domain could impede the timely implementation of necessary changes. To effectively tackle this issue, it is crucial to acquire a comprehensive understanding of students' intentions in embracing AI and related technologies in accounting (Chen et al., 2021). Evaluating these behavioural intentions and identifying influencing factors yield valuable insights, empowering universities to strategically shape their curricula to meet the evolving demands of the accounting industry. The behavioural intention acts as a robust predictor of the actual usage of technology, thereby permitting academic institutions to proactively mitigate potential impediments and cultivate an affirmative disposition towards integrating AI in accounting pedagogy. This holistic approach ensures that the forthcoming cohort of graduates is thoroughly primed to navigate and adapt to technological vicissitudes (Kwak et al., 2022). Consequently, it endows them with the requisite competencies to excel in the industry's dynamic and incessantly evolving landscape, effectively leveraging the advantages proffered by the assimilation of AI in accounting.

1.2 Statement of the Problem

The widespread application of AI in the financial sector, significantly more pronounced than in other industries, has instigated a fundamental shift in accounting and auditing practices (Biallas & O'Neill, 2020). This shift is marked by AI tools progressively undertaking tasks traditionally reserved for accountants, leading to a transformation in their professional roles. Correspondingly, organisational expectations of accountants have evolved, with recent studies emphasising the growing demand for accountants to possess advanced technological competencies (Chang & Hwang, 2003; Cory & Pruske, 2012). The transformation of professional duties necessitates a fundamental realignment of the academic curriculum for accountants. Such recalibration is imperative to address the existing disparity in disseminating requisite knowledge and skills and to synchronise academic instruction with the exigencies of the rapidly evolving financial industry.

The augmented prominence of AI in the accounting sector necessitates further scholarly inquiry of two critical dimensions: the grasp of this technology by forthcoming accounting graduates and the role of accounting curricula in fostering both the understanding and practical application of AI tools (AACSB, 2014). As AI is poised to redefine the future of accounting, assessing the intention of accounting students to embrace and adapt to such cutting-edge technologies becomes paramount. Extensive research within the accounting sector has been dedicated to examining the implications of AI on the evolving roles of auditors and accountants, delineating a paradigm shift in their professional responsibilities (Gambhir & Bhattacharjee, 2021; Holmes & Douglass, 2022; Kommunuri, 2022; Mohammad et al., 2020). Nevertheless, there exists a notable dearth in the literature concerning the engagement of accounting students with AI. Initial studies, such as those conducted by Damerji and Salimi (2021), have commenced shedding light on the technological readiness and perception of AI adoption among university students. However, the investigation into their behavioural intention to utilise AI in their educational and professional practice is conspicuously scant. Rectifying this research disparity is paramount, offering crucial insights for seamlessly integrating AI into accounting education and equipping future professionals for an AI-driven landscape, thus aligning education with dynamic industry needs (Kwak et al., 2022).

In an endeavour to bridge the existing research gap, the present study augments the Technology Acceptance Model (TAM) by incorporating external variables, notably technology readiness dimensions and job relevance, as independent variables. Additionally, superior functionality is incorporated as a mediating variable, concomitant with perceived usefulness, to elucidate students' behavioural intention towards utilising AI. The technology readiness dimensions, as delineated by Parasuraman (2000), are deployed to appraise critical perceptions within the financial sector. This evaluation is crucial for guiding strategic decisions pertaining to the integration of AI into educational frameworks, thus nurturing effective AI engagement. Concurrently, the notion of job relevance, articulated by Venkatesh and Davis (2000), probes into students' perceptions of AI's alignment with their future professional duties.

Elevating existing literature, this research intertwines AI system characteristics, especially superior functionality and job relevance, to illuminate the intricate interplay within the accounting sphere. The findings of this study not only chart a path for future academic inquiry but also establish a robust foundation for continued research in this dynamically evolving field. Furthermore, with an objective to stimulate technological progress in Malaysia, the study unveils novel perspectives on the confluence of AI and accounting, accentuating the behavioural intentions of accounting students towards AI integration.

1.3 Purpose of the Study

The purpose of this study is to investigate the factors that influence the behavioural intention to use AI among accounting students using an extended Technology Acceptance Model (TAM).

1.4 Research Objectives

This study meticulously examines the dynamics between technology readiness dimensions, job relevance, and their impact on the behavioural intention to use AI. The exploration is systematically arranged into several objectives:

Objective 1: To understand the influence of technology readiness dimensions (optimism, innovativeness, discomfort, and insecurity) on the behavioural intention to use AI.

Objective 2: To investigate the influence of job relevance on the behavioural intention to use AI.

Objective 3: To explore the mediating effect of superior functionality on the relationship between technology readiness dimensions and the behavioural intention to use AI.

Objective 4: To assess the mediating effect of perceived usefulness on the relationship between technology readiness dimensions and the behavioural intention to use AI.

Objective 5: To explore the mediating effect of perceived usefulness on the relationship between job relevance and the behavioural intention to use AI.

Through these systematically structured objectives, the study aspires to provide an in-depth understanding of the critical factors influencing behavioural intentions towards using AI.

1.5 Research Questions

Corresponding to the objectives, the study poses the following focused research questions:

Research Question 1: Does each dimension of technology readiness (optimism, innovativeness, discomfort, and insecurity) significantly influence the behavioural intention to use AI?

Research Question 2: Does job relevance influence the behavioural intention to use AI?

Research Question 3: Does superior functionality mediate the relationship between technology readiness dimensions and the behavioural intention to use AI?

Research Question 4: Does perceived usefulness mediate the relationship between technology readiness dimensions and the behavioural intention to use AI?

Research Question 5: Does perceived usefulness mediate the relationship between job relevance and the behavioural intention to use AI?

This ensures that each objective and research question is framed consistently, focusing on how the independent variables influence the behavioural intention to use AI.

1.6 Significance of the study

This study represents a significant contribution to the academic exploration of AI's role in accounting education. It is poised to offer invaluable insights for navigating the intricacies of this continuously evolving domain. The primary aim of the study is to integrate AI into educational frameworks, thereby broadening the spectrum of influences on accounting students' interaction with AI in their academic and professional pursuits. This endeavour seeks to enhance the Technology Acceptance Model (TAM) by incorporating unprecedented variables, leading to a more profound and nuanced comprehension of AI's academic impact. The refined TAM framework is anticipated to enrich scholarly discussions and establish a robust foundation for future research. This enhancement has the potential to redefine perspectives on technology integration in educational contexts, making it a pivotal contribution to the field.

Furthermore, the study's strategic advocacy for the assimilation of AI within accounting education addresses critical factors influencing students' perceptions and attitudes towards AI. By striving to transcend traditional curricular limitations, the research aspires to align educational strategies with the evolving requisites of the accounting profession. The study emphasises the importance of enhancing student engagement with AI and highlights the critical need to synchronise educational content with ongoing technological advances. This strategic approach ensures that graduates are comprehensively prepared and adeptly equipped for the contemporary professional landscape.

Additionally, the study is poised to offer indispensable guidance for formulating strategies that enhance AI engagement among accounting students, a direction deemed crucial for equipping them to navigate the challenges of the Industry 4.0 labour market effectively. The research places notable emphasis on a curriculum integrating AI competencies, underscoring its substantial practical implications and emphasising the imperative for both organisations and governments to accord priority to AI investments. Such strategic investments are anticipated to act as catalysts for economic growth and productivity, thereby positioning these entities as vanguards of the industry, sustaining competitive advantage, and fostering economic progress.

1.7 Scope of the study

This investigation assesses the behavioural intentions of third—and fourth-year undergraduate accounting students in Malaysia regarding their utilisation of AI. The research is conducted at four distinguished Malaysian universities: University Malaya, University Kebangsaan Malaysia, Sunway University, and Multimedia University. An online questionnaire has been meticulously chosen as the primary methodology for data collection, ensuring the efficient accumulation of requisite information.

A critical component of this study is the comparative analysis of AI usage intentions among students from both public and private universities. It is imperative to elucidate that the research focus is strictly limited to advanced undergraduate students, deliberately excluding first—and second-year students. Furthermore, this investigation is confined to students enrolled within accounting programs, thus not encompassing individuals from other disciplines or educational institutions outside the four specified.

Although this selective methodology may impose certain constraints, the expected outcomes aim to furnish pivotal insights into AI usage among senior accounting undergraduates at these Malaysian universities. The findings are anticipated to contribute towards the formulation of strategic frameworks for the integration of AI into accounting education, thereby elevating the professional readiness of accounting students within the Malaysian context.

1.8 Chapter Organisation

The forthcoming sections of this scholarly study are systematically organised as follows. The study commences with an introductory chapter that rigorously delineates the research focus. It underscores the imperative nature of examining the behavioural intention to utilise AI among third and fourth-year undergraduate accounting students in Malaysia. This foundational segment establishes a contextual framework, underscoring the paramount significance of this inquiry within the realm of AI integration in accounting education. Following the introduction, a comprehensive literature review on AI's integration in accounting is expounded. This review is methodically structured around the pivotal variables central to this study, systematically analysing existing research to establish a robust theoretical foundation for the ensuing analysis and to cultivate a thorough comprehension of the variables under scrutiny.

The subsequent section of the study presents the theoretical framework that underpins the research. This segment includes a visual depiction of the framework, effectively illustrating the interconnections among the variables and research questions. The model is thoroughly expounded to elucidate its relevance to the study, followed by a meticulous formulation and presentation of hypotheses derived from it. Building on the theoretical underpinnings, the following chapter delves into research methodology and data collection procedures. This section elaborates on the chosen methodological approach, delineates the intricacies of the sampling techniques, and discusses using an online questionnaire survey for data acquisition from the targeted student cohort at selected universities.

Following the exposition of the methodology, the study shifts its focus to the data analysis process. This section provides a comprehensive elucidation of the methodologies utilised for analysing the survey results and evaluating the research hypotheses. It employs pertinent statistical tools to unravel the intricate interrelations between the variables and the students' behavioural intention to utilise AI. Subsequently, the study presents and meticulously examines the outcomes derived from the hypotheses testing. It thoughtfully highlights key findings, offering insightful interpretations and drawing informed conclusions regarding the factors influencing accounting students' behavioural intention to use AI, including the mediating roles of perceived usefulness and superior functionality.

In its culmination, the study synthesises its principal discoveries, engaging in an erudite discourse about their theoretical and practical bearings on the integration of AI in accounting education. While recognising its limitations, the study also extends sage recommendations for future academic inquiries, thus contributing to the ongoing evolution of this field.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The digital revolution has consistently occupied a prominent place in discussions across diverse sectors, evidenced through numerous publications, modules, debates, and meetings. This trend has left a profound imprint on the business realm, engendering notable shifts in the work milieu. A significant portion of contemporary literature grapples with the man-versus-machine paradigm, addressing burgeoning concerns about AI potentially supplanting human roles and its transformative impact on human tasks. Intriguingly, the accounting sector's engagement with AI is far from a recent development. As early as the 1980s, trailblazing scholars and practitioners embarked upon rigorous research endeavours pertaining to AI applications in areas such as auditing, management accounting, taxation, and personal financial planning (Baldwin et al., 2006).

It merits emphasis that the genesis of AI lies in the depths of human analytical prowess and discernment. With its robust computational abilities, AI is envisioned not as a substitute for humans but as a complement. This harmonious synergy allows machines to manage vast, repetitive, and intricate tasks with unwavering efficiency. Consequently, accountants find opportunities to reorient their roles around AI integrations, elevating their service delivery standards. The mounting prominence of AI in accounting underscores the imminent need for a metamorphosis in both contemporary accounting practices and academic curricula.

Given the escalating integration of AI within major global and public entities, a horizon replete with opportunities beckons future accounting graduates. These budding professionals often turn to university curricula to fortify their competencies in accounting, auditing, and technology. Academic instruction plays a pivotal role in moulding the behavioural intention of students to assimilate AI applications (Damerji & Salimi, 2021). Nevertheless, it is imperative to acknowledge that the meticulous integration of AI into the fabric of accounting hinges on more than sheer technological prowess. Students' predisposition and intent to harness AI in their impending professional ventures become critical markers for the sector's trajectory. By assigning paramount importance to this domain in academia, the ensuing generation of accounting professionals stands poised to adeptly manoeuvre through the dynamic, tech-infused terrains of their industry, fortifying their resilience and adaptability in an environment enriched by AI. Within this tapestry, the behavioural intention to use AI crystallises as a salient axis of inquiry.

As emerging accounting professionals steer through this evolving scenario, two pivotal facets emerge that shape their inclination towards AI: technology readiness (TR) and job relevance (JR). The former encompasses the infrastructural and mental readiness to embrace and maximise AI's expansive capabilities, while the latter probes the pertinence and resonance of AI within modern accounting roles. Perceived usefulness (PU) seeks insights into the students' convictions, questioning whether AI is discerned as an instrumental asset capable of augmenting professional performance. Concurrently, superior functionality (SF) extends this interrogation, scrutinising if AI is perceived as a superior alternative to traditional, AI-absent methodologies. A detailed exploration of these determinants not only elucidates the prospective path of the accounting sector but also charts a directive for academic bodies, ensuring the forthcoming cadre of accountants is not merely acquainted with AI but possesses profound fluency in it. This literature review aims to illuminate these intricate facets, laying the groundwork for an exhaustive exploration of the behavioural intention to use AI among accounting students.

2.2 Artificial Intelligence (AI)

Artificial intelligence (AI) has been characterised in an array of ways, with the majority of definitions referring to robots with the capacity to learn and reason exhibiting characteristics of human intelligence. According to Haenlein and Kaplan (2019), AI is the ability of a system to precisely interpret external data, absorb and learn from the data, and use the new information to achieve particular goals and tasks with flexibility and adaptation. AI can be categorised based on intelligence, including cognitive-analytical, emotional-human-inspired, and social-humanised. This classification reflects the various aspects of intelligence that AI can mimic or replicate from human behaviour. The birth of AI dates back to 1942, with Isaac Asimov's short tale on the three laws of robotics and Alan Turing's development of The Bombe, a machine designed to decrypt the German Enigma Code during World War II. The term 'Artificial Intelligence' was first established in 1956 by Marvin Minsky and John McCarthy during a workshop that brought together academics from a variety of disciplines for one purpose: to create new research on a computer that mimics human intelligence (Haenlein & Kaplan, 2019).

Machine learning (ML) constitutes a component of AI distinguished by its systems' ability to glean insights from data and render decisions without explicit programming for predefined tasks. Multiple disciplines, including engineering, accounting, information technology, marketing, and bioinformatics, have acknowledged and embraced the far-reaching implications of ML. ML harnesses the power of AI to acquire knowledge and engage in logical reasoning, addressing complex problems. Through statistical methodologies and sophisticated algorithms, ML learns from extensive datasets, autonomously enhancing the accuracy and precision of information. With the proliferation of web-based data, ML adeptly utilises it to organise patterns and develop predictive models efficiently (Kommunuri, 2022). ML significantly enhances the accuracy of loss estimations within accounting, surpassing traditional accountant capabilities, thus improving forecast reliability and consistency. Recognised as one of the most advanced technologies, ML excels in evaluating complex accounting estimates during audit engagements (KPMG, 2016). With its empirical methodologies, it discerns patterns of consistent misstatements through meticulous evaluation of the informational content inherent in financial statement analyses. This approach involves a detailed examination of historical and forthcoming entries, the projection of cash flows without reliance on spreadsheets, the identification of nascent trends, and notably enhanced decision-making processes by deploying sophisticated cognitive functions (Stafie & Grosu, 2022).

Next, AI-driven robotic process automation (RPA) has seamlessly integrated into IT infrastructures, significantly bolstering efficiency by automating tedious and repetitive tasks. This technology adeptly executes foundational operations, including invoice processing, document finalisation, report generation, and data validation, alleviating the burden of repetitive tasks on employees. The adoption of RPA in accounting significantly improves operational efficiency, precision, and cost-effectiveness. This technology simulates human actions to execute repetitive tasks based on established protocols, thereby facilitating rapid decision-making and extensive transaction processing (Razak & Ismail, 2022). Despite its proficiency, RPA may be perceived as a system with limited intelligence due to its inability to adapt to alterations or make intricate decisions (Stafie & Grosu, 2022). The apprehension that the functions of RPA may lead to the displacement of human workers by robots is unsubstantiated. On the contrary, RPA reorients the focus of accountants towards analysis and forecasting, thus relieving them of mundane tasks (Cooper et al., 2019). RPA has emerged as a prominent tool in accounting, particularly in taxation, enabling professionals to effectively manage a greater volume of tasks and empirical work, as well as facilitate improved planning and analysis processes (Deloitte, 2023).

Artificial neural networks (ANNs) possess the capacity to process intricate information qualitatively, emulating the neural networks of the human brain within computational frameworks. This facilitates their ability to train and adjudicate with a semblance of human cognition. ANNs, by replicating the synaptic connections of human cerebral cells, are esteemed for their superior intelligence compared to traditional linear-logic computational systems (Zhang et al., 2020). In accounting, where meticulous analysis of multifaceted data and its myriad interrelations are crucial, ANNs are indispensable. They adeptly manage risk assessments and algorithmic categorisations in various tasks, such as market forecasting, analysis of financial statements, and analytical review procedures, thus fulfilling the exigencies of analytic proficiency (Kommunuri, 2022).

Natural language processing (NLP) stands as an essential subset of AI focused on the intersection of computer systems and human language. It facilitates machine comprehension, interpretation, and generation of human language in a contextually meaningful and valuable manner. The accounting field leverages sophisticated computational methodologies to analyse extensive sets of natural language data. Jurafsky and Martin (2014) noted that NLP encompasses critical tasks such as machine translation, sentiment analysis, speech recognition, and information retrieval, all of which are pivotal for interpreting unstructured textual data. The profound significance of NLP is underscored by its extensive application across a variety of sectors. It is indispensable in healthcare for the analysis of clinical documentation and serves as a fundamental component in customer service, providing immediate support through chatbots and virtual assistants (Chowdhury, 2003). Advancements in NLP technology can significantly enhance the efficiency of human-computer interactions, consequently making technology more accessible and intuitive (Manning et al., 2008).

In accounting, the integration of AI has been steadily gaining traction despite being in its initial developmental phase. The industry is well-positioned to harness AI's diverse benefits, actively integrating these technologies to fortify and enhance its fundamental processes. Among the Big Four Accounting Firms, PricewaterhouseCoopers (PwC) distinguishes itself with its adoption of RPA for tasks such as data collection, determination of entity filing status, trial balance sheet assessments, and tax basis data conversion. PwC's application of RPA has notably advanced its taxation procedures, streamlining the preparation and revision of tax returns and executing tax payments (Pricewaterhouse Coopers, 2017).

Further exemplifying its commitment to AI, PwC has made substantial investments in an audit laboratory to enhance audit quality, efficiency, data accuracy, and information acquisition. Notably, a strategic collaboration with H2O.ai from Silicon Valley resulted in the creation of GL.ai, an innovative robot that utilises ML to replicate the decision-making processes of professional auditors (Pricewaterhouse Coopers, 2018). Similarly, Ernst & Young (EY) has effectively integrated ML techniques in fraud detection, achieving a 97% accuracy rate in invoice identification while developing an intelligent tax classifier for categorising taxable transactions (Ernst & Young, 2017). KPMG, through its specialised division 'KPMG Ignite', is actively exploring the application of AI to address complex challenges (KPMG, 2018). On the other hand, Deloitte employs RPA within its tax division to deploy automated 'bots' that manage routine tasks, such as document uploads to tax regulatory portals (Deloitte, 2023).

The exploration of AI strategies within the Big Four accounting firms delineates a discernible pattern of the deliberate integration of AI into the fundamental operations of the accounting profession. Collectively, these prominent firms underscore that AI surpasses its traditional designation as a contemporary tool and manifests as an indispensable component for the prospective triumph of the accounting industry (Zhang et al., 2020).

2.2.1 Artificial Intelligence in Modern Accounting Disciplines

2.2.1.1 Artificial Intelligence's Impact on Financial Accounting

Financial accounting constitutes a methodical approach to documenting, encapsulating, and disseminating an organisation's financial transactions via standardised reports, notably balance sheets, income statements, and cash flow statements. These documents furnish external stakeholders, encompassing investors, creditors, and regulatory bodies, with an exhaustive perspective on the financial stability of a corporation (Kimmel et al., 2012). The incorporation of AI into financial accounting has markedly revolutionised the field, augmenting efficiency, precision, and the capacity for informed decision-making processes.

The historical challenge of manual transaction recording has been a labour-intensive process susceptible to human error, potentially leading to significant inaccuracies in financial statements. The advent of AI-driven tools, such as RPA, has effectively mitigated these challenges by automating data entry procedures. RPA, with its capacity to accurately extract information from financial documents and input it into accounting systems, has significantly reduced errors and enhanced operational efficiency (Harrast, 2020). This automated process guarantees the precise and timely recording of transactions, thus upholding the integrity of financial data.

Integration of NLP and ML plays a pivotal role in augmenting the field of financial accounting through the automation of data extraction, analysis, and anomaly detection. NLP methodologies facilitate the automated extraction and analysis of financial data from unstructured sources, thereby diminishing manual effort and reporting errors (Adedoyin Tolulope et al., 2024). Additionally, ML models, encompassing supervised and unsupervised approaches such as deep learning and isolation forests, proficiently discern irregularities within general ledger data, streamline data summarisation, and reduce errors, thus ensuring heightened accuracy and dependability of financial statements (Bakumenko & Elragal, 2022).

The maintenance of compliance with regulatory standards poses a significant and continuous challenge in the field of financial accounting. The dynamic nature of regulations necessitates continual monitoring and updates to ensure adherence. AI tools play a crucial role in this process by continuously monitoring compliance issues and ensuring financial reports adhere to the latest regulatory standards. ML automates the detection of non-compliant behaviour and anomalies by learning from historical data, enhancing accuracy without the need for human intervention (Jain et al., 2024). NLP scrutinises communications, such as emails, chats, and documents, to ensure they comply with regulatory standards, thus strengthening surveillance capabilities and pre-empting potential violations (Zhang & El-Gohary, 2022). Predictive analytics utilise historical data and AI algorithms to forecast potential compliance breaches, enabling proactive risk mitigation and reducing the likelihood of regulatory penalties (Bandari, 2021).

In essence, AI technologies have revolutionised financial accounting by automating repetitive tasks, improving data accuracy and analysis, and enforcing stringent regulatory adherence. These innovations offer a dynamic and all-encompassing approach to contemporary financial accounting challenges, underscoring the pivotal role of AI in advancing the field's efficiency and reliability.

2.2.1.2 Artificial Intelligence's Impact on Management Accounting

The field of management accounting is committed to providing crucial financial information and analysis to organisational managers, aiding them in decision-making, planning, and control. This involves the utilisation of both financial and non-financial data to derive insights that steer business strategy and enhance operational efficiency (Kaplan, 1992). The recent advancements in AI tools have substantially revolutionised management accounting by automating and improving various functions.

The application of ML models significantly enhances financial planning and budgeting processes by analysing historical financial data to forecast future trends with greater precision. These models employ a wide range of methodologies, including supervised and unsupervised learning algorithms, as well as complex ensemble and time series analysis techniques. Researchers have found these approaches to be critical in improving the accuracy of financial predictions, particularly in forecasting stock prices and addressing classification issues within the financial sector (Sonkavde et al., 2023). For instance, neural networks are adept at processing extensive historical financial data to recognise patterns and correlations, which are then leveraged to forecast revenue and costs with exceptional precision (Loo, 1994).

AI tools significantly enhance manufacturing cost analysis and allocation by rapidly and accurately processing large datasets. ML algorithms detect cost patterns and trends, enabling precise forecasting and proactive cost management, such as timely bulk purchases, to avoid price hikes (Shi et al., 2015). Predictive analytics allow AI to identify key cost drivers, offering insights to optimise production processes for efficiency. This leads to streamlined workflows and better resource allocation, minimising waste and inefficiencies (Shedrack et al., 2024).

AI-powered analytics offers in-depth insights into financial and operational metrics, leading to a significant enhancement in performance analysis. AI algorithms, such as support vector machines and random forests, are utilised to scrutinise financial statements and other data, uncovering key performance indicators (KPIs) and trends. This comprehensive analysis reveals the underlying drivers of performance, supports well-informed decision-making, and enables managers to optimise strategies effectively. Support vector machines excel in identifying intricate patterns and relationships within financial data (Rainarli, 2019), while random forests enhance prediction accuracy by amalgamating the results of multiple decision trees (Kostopoulos et al., 2017). These powerful analytical tools facilitate the identification of non-linear correlations within accounting data, providing deeper insights into market valuation and performance metrics (Kureljusic & Karger, 2023).

Additionally, AI enhances customised reporting by generating reports tailored to the specific requirements of various stakeholders. Natural language generation (NLG) technologies enhance the accessibility and understanding of intricate financial data by automatically transforming it into clear and understandable narratives. This process assists stakeholders in interpreting financial forecasts and insights more efficiently. For instance, NLG tools can generate comprehensive reports that elucidate budget projections, emphasise significant trends, and identify potential issues, thus facilitating well-informed decision-making among managers and executives (Yagamurthy et al., 2023).

In summary, AI tools have fundamentally reshaped the field of management accounting by augmenting capacities in planning and budgeting, cost analysis and allocation, continuous monitoring and control, and performance analysis. These technological advancements facilitate precise, real-time data processing, integration of intricate datasets, and the derivation of actionable insights, thereby profoundly enhancing the efficiency and effectiveness of financial management methodologies.

2.2.1.3 Artificial Intelligence's Impact on Taxation

The domain of tax accounting encompasses the meticulous preparation and examination of tax returns and payments to ensure adherence to pertinent laws and regulations. The integration of AI tools has significantly transformed this field by automating repetitive tasks, increasing precision, and providing comprehensive analytical insights. This advancement assists tax professionals in efficiently navigating intricate processes. The traditional method of tax preparation, entailing manual data input and scrutiny, is both time-consuming and susceptible to errors (Stein Smith, 2018). AI-driven automation revolutionises the processing of tax returns through the classification and reconciliation of financial data, thus ensuring accuracy and compliance with tax legislation.

A primary application of AI in tax accounting lies in its capacity for data analysis and real-time processing. AI systems excel at handling extensive volumes of tax-related data, swiftly analysing it to uncover patterns and trends that may elude human accountants. This capability enables more precise forecasting of tax liabilities and better preparation for future tax scenarios (Belahouaoui & Attak, 2024). Notably, ML models play a pivotal role in augmenting tax compliance by foreseeing potential issues before they manifest. These models draw on historical tax data to predict compliance risks, empowering businesses to proactively address these risks and circumvent penalties. Through continuous learning from new data, AI systems can vigilantly monitor and adapt to changes in tax regulations and economic conditions, upholding stringent compliance standards (Sedlacek, 2024).

In tax controversy matters, generative AI aids tax professionals by anticipating the requirements of tax authorities and compiling pertinent information. Notably, it is adept at identifying and referencing relevant laws and rulings for technical submissions and forecasting potential inquiries from tax authorities. These predictive capabilities are based on available data and serve to optimise the efficiency and effectiveness of the preparation process (KPMG, 2023). Furthermore, AI technology possesses the ability to identify tax loopholes and enhance tax planning strategies while adhering to legal regulations. This proactive approach effectively mitigates various risks, including taxpayer insolvency, tax avoidance, and non-compliance, consequently presenting opportunities for tax savings and operational efficiency (Rahimikia et al., 2017). AI-driven tools also rapidly detect anomalies and irregular patterns indicative of fraudulent activities or errors, safeguarding the integrity of financial reporting.

Generative AI with NLP capabilities revolutionises tax accounting by serving as an advanced virtual assistant. This technology efficiently handles routine tax queries, significantly reducing response times for tax professionals. It swiftly processes and drafts accurate and consistent responses to tax-related inquiries (KPMG, 2023). AI tools analyse complex tax scenarios, optimise tax structures, and provide insights for effective tax planning, including personalised strategies tailored to individual or business needs. Integrating generative AI enhances efficiency, allowing tax professionals to focus on strategic decisions and risk management with precise, real-time insights. As an advanced application of generative AI, AI chatbots offer extensive functionality that surpasses traditional chat systems. These sophisticated tools meticulously analyse regulatory documents and consultative resources to deliver precise recommendations and actionable strategies tailored to specific tax scenarios (Zadorozhnyi et al., 2023).

In summary, AI is reshaping the landscape of tax accounting through the automation of processes, bolstering compliance measures, and offering customised tax planning. These technologies contribute to heightened precision and productivity, empowering tax professionals to allocate their focus towards strategic responsibilities such as risk management and decision-making. Consequently, this translates to improved financial outcomes and refined tax strategies for businesses and individuals.

2.2.1.4 Artificial Intelligence's Impact on Auditing

The implementation of AI is revolutionising the field of auditing through the automation of labour-intensive tasks, heightened precision, and the provision of comprehensive analytical insights. Consequently, this advancement significantly enhances the efficiency and effectiveness of audit processes, empowering auditors to redirect their focus towards higher-value activities and deliver more profound conclusions (Abdullah & Almaqtari, 2024). In the preliminary phase, AI systems aggregate and scrutinise extensive data relating to market trends, industry developments, regulatory updates, and financial news. This endeavours to furnish auditors with an exhaustive comprehension of the client's industry and organisation, thus facilitating a more informed initial risk assessment. Subsequently, AI harnesses these insights to ascertain audit hours, compute fees, and generate personalised engagement letters by means of historical data and prior contract analysis. This process substantiates resource allocation, establishes practical timelines, and augments documentation, demonstrably amplifying the efficiency and accuracy of the audit process (Issa et al., 2016). AI tools exponentially augment risk assessment processes through meticulous analysis of extensive data derived from diverse sources to discern and appraise potential risks with heightened precision. By leveraging predictive analytics, these systems utilise historical data and trends to prognosticate future risks, enabling auditors to systematically prioritise high-risk areas and allocate resources more effectively (Dhamija & Bag, 2020).

AI tools markedly advance auditing by optimising data analysis, supplanting traditional, labour-intensive, and error-susceptible manual sampling and transaction testing methods (Vărzaru, 2022). AI algorithms, particularly those leveraging ML, have the ability to comprehensively analyse datasets to identify anomalies and patterns indicative of discrepancies or fraudulent activities (Brown-Liburd & Vasarhelyi, 2015). ML tools, such as neural networks and clustering algorithms, excel at pinpointing atypical patterns that warrant further scrutiny. For instance, these methods can identify nonstandard leases with substantial implications, such as those involving unconventional asset retirement obligations (Dickey et al., 2019).

Moreover, AI tools contribute significantly to continuous auditing by leveraging automated software and advanced technologies to monitor, collect, and analyse audit evidence in real time. These tools encompass embedded audit modules, integrated test facilities, concurrent audit techniques, and data warehouses, all of which facilitate the continuous gathering and assessment of electronic data. AI-driven analytics, including digital analysis and data mining, are employed to detect anomalies and exceptions in transactions, empowering auditors to deliver immediate and ongoing assurance regarding the accuracy and reliability of financial information (Rezaee et al., 2018). In addition, the application of AI in continuous auditing allows for the production of dynamic audit reports that are graded on a scale, as opposed to relying on static assessments. This methodology offers a more comprehensive evaluation of the financial integrity and performance of the audited entity. Through continuous updating of the audit score using real-time data analysis, auditors are capable of furnishing a current and accurate portrayal of the entity's compliance and risk status. This fosters transparency and enables proactive management of potential issues (Issa et al., 2016).

By redefining various stages of the auditing process, AI not only enhances the efficiency and accuracy of audits but also empowers auditors to offer in-depth insights and robust assurances. This technological progress influences the auditing landscape, leading to more dynamic and effective audit practices.

2.2.2 Information Technology Integration in Malaysian Higher Education Accounting Curriculum

The incorporation of Information Technology (IT) into the accounting curriculum of Malaysian higher education plays a pivotal role in equipping graduates with the necessary skills to meet the contemporary demands of the accounting profession. However, a discernible disparity exists between the IT competencies offered in academic programs and those requisite in the professional sphere, particularly in advanced data analytics and AI applications (Kwarteng & Mensah, 2022). Despite concerted efforts, a striking deficiency in advanced IT competencies among graduates persists, underscoring the pressing need for curriculum reform (Albrecht & Sack, 2000; Ballantine et al., 2024; Chang & Hwang, 2003; Tandiono, 2023).

The present curriculum is designed to strengthen students' technical competencies and prepare them for a digitalised business environment. This encompasses a thorough education on enterprise resource planning (ERP) systems such as SAP, which amalgamate diverse business functions—such as finance, HR, procurement, and supply chain management—into a unified system (Blount et al., 2016). Proficiency in ERP systems provides students with a holistic understanding of business operations, equipping them to navigate intricate organisational processes and enhancing their employability in large corporations (Faccia & Petratos, 2021). Furthermore, the courses regularly incorporate spreadsheets for financial analysis and reporting, employing tools such as Microsoft Excel. Mastery of Excel empowers students to execute a broad spectrum of tasks, spanning from fundamental data input to intricate financial analysis. This specialised skill, highly coveted by potential employers, amplifies the capacity of graduates to scrutinise financial information, generate comprehensive reports, and render well-grounded decisions (Ramachandran Rackliffe & Ragland, 2016).

Accounting information systems (AIS) play a crucial role by facilitating the collection, storage, and processing of financial and accounting data, thus supporting organisational decision-making processes. These systems streamline routine tasks, minimise the potential for human error, and guarantee adherence to regulatory standards. A comprehensive understanding of AIS is fundamental for students as it forms the bedrock of financial reporting and data management, both essential for fortifying organisational integrity and underpinning strategic decision-making (Kearns, 2014). However, to adequately bridge the identified gap, the curriculum should emphasise advanced data analytics and AI applications. By integrating these sophisticated IT skills into the curriculum, students can better align themselves with professional expectations, thus catering to the demands of the contemporary business landscape more adeptly (Faccia & Petratos, 2021).

AI is an emerging area within the accounting curriculum, albeit at the nascent stage of integration. As per a study conducted by the Malaysian Institute of Accountants (MIA), the inclusion of AI and other emerging technologies is progressively gaining significance for the future of accounting education (Malaysian Institute of Accountants, 2021). AI topics are incrementally integrated via workshops and supplemental modules rather than being offered as standalone courses. This phased approach ensures that students establish a solid foundation in essential IT competencies before immersing themselves in more advanced AI applications.

The MIA's Digital Technology Blueprint, unveiled in 2018, encompasses a three-year operational plan (2019-2022) that laid the foundation for the subsequent two-year digital economy plan (2022-2024). This blueprint offers insights into the integration of digital technologies, notably AI, into accounting education, emphasising the imperative for future accountants to possess proficiency in AI and other digital skills to maintain competitiveness (Malaysian Institute of Accountants, 2021, 2023). Furthermore, the

Malaysian Qualifications Agency (MQA) has played a pivotal role in propelling these transformations by establishing standards and conferring accreditation for programs encompassing advanced IT and AI elements. The MQA has delineated prerequisites for higher education institutions to incorporate digital competencies in their accounting curricula, ensuring that graduates are adept at addressing contemporary technological challenges in the accounting realm (Malaysian Qualifications Agency, 2014).

Despite advancements, the incorporation of AI within the accounting curricula remains limited in scope. Research conducted by the Malaysian Institute of Accountants (2021) uncovered that a mere fraction of universities have initiated the inclusion of AI in their academic programs. In instances where AI has been introduced, it is primarily at the preliminary or intermediate stages, with the inclusion of advanced AI concepts being notably infrequent (Malaysian Institute of Accountants, 2021). Therefore, this study intends to furnish distinct guidelines for universities to adeptly assimilate AI into their curricula, thus addressing the prevailing ambiguity.

By broadening AI-related course offerings, embedding them within core accounting subjects, providing continuous training for educators, and forging collaborations with industry partners to introduce practical AI applications and case studies into the curriculum, Malaysian higher education institutions can more effectively prepare accounting graduates for the future. This holistic approach ensures that students attain proficiency in AI and advanced technologies, preparing them for successful careers. Continuously updating their knowledge and skills through ongoing courses ensures that graduates remain abreast of advancements, enabling them to fulfil current accounting requirements and adapt to forthcoming innovations.

2.3 Behavioural Intention to Use Artificial Intelligence

Behavioural intention (BI), a fundamental construct in the exploration of individual behaviour, denotes the likelihood of an individual partaking in a specific future behaviour. Historically recognised as a potent predictor of subsequent behaviour, BI encapsulates the level of resolve and commitment an individual is prepared to dedicate to the execution of a particular action or sequence of actions (Fishbein & Ajzen, 1975). In the context of technology integration, particularly with advancements such as AI, the relevance of BI is accentuated. It embodies the amalgamation of cognitive and practical endeavours an individual anticipates in assimilating such innovations.

The prominence of BI in models related to technology acceptance and integration is a testament to its relevance. The TAM postulates BI as a direct offshoot of an individual's attitude towards using technology and its perceived usefulness (Davis et al., 1989). Further amplifying this conceptualisation, Davis et al. (1992) assert that the strength of BI is a reflective measure of an individual's intrinsic motivation, signalling the effort one is prepared to exert in the enactment of the behaviour. Concurrently, Ajzen (2012) reinforces this perspective, underscoring BI's role as a formidable motivational element, offering a calibrated projection of the energy, attention, and devotion an individual is likely to allocate to the initiation and maintenance of behaviour.

When delineated within the spectrum of AI, BI becomes instrumental in gauging the level of acceptance, readiness, and potential resistance among users, offering crucial insights into facilitating smoother integration trajectories (Venkatesh & Bala, 2008). The nuances of BI, particularly in contexts rife with rapid technological advancements, serve as an invaluable guide for researchers, practitioners, and policymakers to comprehend and navigate the evolving landscape of human-technology interactions.

2.3.1 Foundational Development of Behavioural Intention

The exploration of behavioural intention (BI) as a construct is deeply embedded in social psychology. It has evolved significantly over time, adapting to the intricacies of human behaviour and decision-making. This development originated from the imperative to more accurately comprehend and anticipate human actions across diverse contexts, with a particular emphasis on technology usage. The Theory of Reasoned Action (TRA), pioneered by Fishbein and Ajzen (1975), stands as a cornerstone and highly influential model in the exploration of the determinants of human behaviour within this domain. TRA posits that an individual's intention to engage in a behaviour is dictated by two principal elements: their attitude towards the behaviour (an individual's positive or negative evaluations of performing the behaviour) and the subjective norms surrounding it (the perceived social pressures to engage or not engage in the behaviour). These components highlight the dual influence of personal assessments and societal pressures in shaping one's intentions and subsequent actions.

Delving deeper into the contextual aspects of behaviour, Ajzen (1985) introduced the Theory of Planned Behaviour (TPB), an augmentation of TRA. TPB incorporated an additional construct - perceived behavioural control (PBC), predicated on the degree to which individuals perceive their capability to perform a behaviour, factoring in both internal (self-efficacy) and external (controllability) elements. The integration of PBC into TPB was a seminal enhancement, effectively bridging the interspace between intention and actual behaviour, particularly in contexts where external factors might constrain an individual's ability to act (Ajzen, 2002).

The progression did not halt with these models. As technology increasingly intertwined with daily life, scholars began to recognise that traditional frameworks might not entirely encompass the intricacies of behaviour in a technological context. The TAM, introduced by Davis (1989), streamlined the constructs of TRA and TPB to address technology utilisation specifically. TAM highlighted perceived usefulness and perceived ease of use as primary determinants of BI in technological contexts, emphasising the role of utility and simplicity in influencing technology adoption behaviours. Subsequent research and models, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), further diversified and enriched the understanding of BI by introducing constructs like 'social influence' and 'facilitating conditions', reflecting the multifaceted nature of technology engagement in diverse environments.

In sum, the journey of understanding BI has been marked by continuous evolution, integrating multi-disciplinary perspectives and accommodating the dynamic nature of human-technology interactions. The various models and theories, supported by a plethora of empirical studies, offer a comprehensive lens to decipher the myriad factors influencing an individual's intention to act, especially within the technological realm.

2.3.2 The Role of Attitude in Behavioural Intention

In the complex landscape of technology integration dynamics, the concept of 'attitude', as delineated by the TRA, holds a pivotal position. It encapsulates an individual's beliefs, evaluations, and anticipated outcomes, painting a comprehensive picture of one's stance towards a particular technology or behaviour. Focused on accounting students assessing the potential infusion of AI into their curriculum, this essence becomes vivid. The overarching sentiments spanning from enthusiasm to ambivalence and scepticism towards technology mirror the quintessence of attitude. Factors such as prior experiences with similar technologies, evaluations of AI's capacity to enhance academic pursuits, and the promise of AI in future professional landscapes shape this disposition (Compeau & Higgins, 1995; Davis, 1989; Venkatesh et al., 2003; Venkatesh & Bala, 2008; Venkatesh et al., 2016).

Moreover, elements like perceived usefulness (PU), superior functionality (SF), job relevance (JR), and technology readiness (TR) are prominent. These factors, intrinsically linked to a person's evaluative criteria, offer a critical understanding of students' predispositions regarding the intention to utilise AI. Collectively, these elements echo the core facets of attitude, having a significant impact on BI, and underscore the interaction of perceptions, evaluations, and intentions (Legris et al., 2003; Venkatesh & Davis, 2000).

JR assesses the alignment between AI and a student's envisioned professional trajectory. When AI strongly correlates with career ambitions, it solidifies its perceived significance, reflecting a positive attitude towards the technology (Lai, 2017; Venkatesh et al., 2003). Empirical evidence repeatedly underscores the centrality of JR in shaping BI. For instance, Venkatesh et al. (2003) determined that the congruence of technology with occupational roles directly influences usage intentions. This sentiment resonates in diverse sectors: cloud computing adoption in IT departments (Opitz et al., 2012) and public-sector technology integration (Chu et al., 2009). More recent analyses, such as those on the Industrial Internet of Things and Big Data tools (Okcu et al., 2019), reiterate that professionals' perception of technology's relevance to their roles amplifies their intention to embrace it. Consequently, JR remains instrumental in modulating perceived utility and the impetus to integrate technologies.

Defined by Parasuraman (2000), TR encapsulates an individual's mental receptiveness towards innovative technologies. Key facets of this readiness, namely optimism and innovativeness, signify a positive disposition towards technology utilisation. Conversely, dimensions like discomfort and insecurity can lead to a more sceptical or reserved attitude. Flavián et al. (2021) confirmed that pronounced optimism and innovativeness correlate with enhanced attitudes, influencing BI towards AI. Yusuf et al. (2021) observed similar trends in adopting learning management systems, and Kuo et al. (2013) witnessed it within healthcare settings. Furthermore, Buyle et al. (2018) showcased how citizens'

TR steered their attitudes and subsequent embrace of smart city technologies. Collectively, these findings underscore that TR, both positive and negative aspects, intricately shapes attitudes and intentions across diverse sectors.

Rooted in the TAM, PU probes into one's belief in a technology's capability to amplify performance. An affirmative belief in a technology's utility aligns with a positive attitude towards its incorporation (Davis, 1989). Venkatesh and Davis (2000) highlighted PU's role in influencing intentions across various contexts. Luarn and Lin (2005) reaffirmed it in mobile banking, indicating that recognising a technology's utility directly steers the willingness to integrate and use it. Jackson et al. (1997) and Chau and Hu (2002) found similar relationships in information systems and IT professional settings, respectively. Meanwhile, studies like Wu and Wang (2005) on mobile commerce and Gefen et al. (2003) on online shopping further emphasises PU's pivotal role. Collectively, these works underscore that PU profoundly impacts BI across different technology domains, channelling through attitudes.

SF, rooted in the unique benefits of technology, significantly drives attitudes and decision-making intentions. Stemming from the Diffusion of Innovations (DOI) theory, SF shapes both evaluative judgments and tendencies towards embracing and integrating new technologies (Rogers, 2003). Roy et al. (2018) pinpointed that discerning a technology's exceptional features crucially steered customer acceptance. This aligns with Tao (2011), who found that distinct advantages of mobile internet had a direct bearing on user inclinations. Further exploration by Moore and Benbasat (1991), Tornatzky and Klein (1982), and Ferreira et al. (2014) all underscored its relative advantage — akin to SF — as a key factor influencing IT usage intentions. To elucidate, 'relative advantage' refers to the technology's inherent benefits compared to previous or alternative solutions, mirroring the concept of SF. These collective insights emphasise the pivotal role of SF in guiding BI across varied technological contexts.

Constructs such as PU, SF, JR, and TR inherently encompass elements traditionally classified under 'attitude' within TRA and TAM frameworks. By virtue of their design, they capture an individual's personal evaluations, beliefs, and anticipated outcomes from technology engagement. Hence, in modelling the influence of these constructs on BI, the subtle nuances of attitude are inherently accounted for. The sway these constructs hold over BI intrinsically imbibes the evaluative essence of attitude, providing a nuanced exploration of determinants influencing BI.

2.3.3 Reassessing Subjective Norms in Voluntary Technology Adoption

Within the established framework of technology integration, subjective norms have conventionally been posited as central influencers, as evidenced by their prominence within the TRA and TPB. These norms reflect an individual's perceptions of societal expectations and pressures regarding the execution of specific behaviours or technologies, often shaped by anticipations of how significant others might perceive their actions. However, the terrain of voluntary technology utilisation demands a recalibration of this emphasis. In such settings, the impetus for engagement is less about societal alignment and more rooted in individualised evaluations and contextual relevance. Taking the example of Malaysian accounting students' voluntary engagement with AI, the decision-making process transcends mere societal validation but is anchored in a nuanced matrix of personal assessments. The calculus of an accounting student's decision to embrace AI revolves around its perceived potential to enhance their academic prowess and future professional prospects. This involves gauging the technological benefits, assessing its alignment with their academic discipline, and their personal readiness to navigate novel technological landscapes. Their cumulative attitude towards AI, moulded by these determinants, becomes the linchpin influencing their BI—either driving them towards AI usage or dissuading them from it.

Given these dynamics, the traditional emphasis on subjective norms demands reconsideration. In scenarios of voluntary technology utilisation, as exemplified in this study, the gravitas shifts from societal pressures to individualised evaluations and contextual alignment. Venkatesh and Davis (2000), in their extension of the TAM, have emphasised the reduced role of external factors in favour of intrinsic evaluations in specific contexts. Similarly, Gefen et al. (2003) observed in the context of online shopping that while subjective norms played a role, the primary drivers were individual trust and PU. Wu and Wang (2005) and Jackson et al. (1997) echoed this sentiment, highlighting how individual personal evaluations and perceptions dominate over societal influences in determining intentions related to information system usage. This understanding provides the impetus for deemphasising subjective norms in this study, prioritising instead the facets that intimately resonate with an individual's internal evaluations. Consequently, within such voluntary contexts, attitude — enriched by TR, JR, PU, and SF — emerges as the pivotal determinant shaping BI, underscoring its centrality in the intention to use AI among Malaysian accounting students.

To encapsulate, BI stands as a crucial concept in deciphering individual behaviour, especially in the context of technology integration, including AI, profoundly influenced by factors such as TR, JR, PU, and SF. These elements collectively mould and guide BI, yielding invaluable insights for the successful integration of AI and other advanced technologies.

2.4 Technology Readiness

Technology readiness (TR) emerges as a pivotal concept in academic discussions due to its ability to clarify an individual's propensity to adopt and harness emerging technologies in both personal and professional spheres. Rooted in the psychological state of an individual, TR integrates cognitive beliefs, emotional reactions, and behavioural tendencies, affecting the reception and productive use of technological advancements. The overarching essence of TR addresses its role in spanning the human spectrum of sentiments and beliefs about technology, ranging from deep optimism and propensity for innovation to marked apprehension and unease (Parasuraman, 2000).

Historical analyses underscore detailed scrutiny of technology integration dynamics, with the progression of telecommunication innovations serving as a notable illustration. This is exemplified by the remarkable achievement wherein telephones attained a 25% market penetration within a mere 13-year span, a stark contrast to the 55 years required for automobiles to reach a similar level of acceptance (Berry, 1999; Parasuraman, 2000). As technological developments advance swiftly, an increased level of consumer discontent becomes evident. The apparent paradox between rapid technological advancement and increasing user discontent can be attributed to various factors. For certain individuals, the challenge is magnified by a lack of technical expertise, the increasing complexity of modern product updates, coupled with unclear user guides and diminished support from developers. Such impediments have driven investigations into the concept of TR, establishing it as a vital predictor of an individual's intention towards technology utilisation (Parasuraman, 2000). This perspective gains heightened significance in modern innovations, especially regarding behavioural intention linked to the reception and use of AI.

Parasuraman's (2000) study serves as a cornerstone in this domain, with the introduction of the Technology Readiness Index (TRI) as an evaluative instrument that is particularly pivotal in delineating TR through various interlinked dimensions. Primary among these is optimism, indicating an overarching affirmative outlook and faith in technology, accompanied by the conviction of its tangible advantages. Concurrently, the dimension of innovativeness reflects an individual's disposition towards new technologies, discerning whether early adoption or caution characterises their approach. Contrarily, discomfort illuminates sensations of being beleaguered, proposing that technology could, for certain individuals, introduce complications instead of simplifications. Insecurity, in contrast, delves into scepticism, encapsulating those who might regard technology with apprehension due to potential unreliability concerns.

2.4.1 Origins and Advancement of Technology Readiness

The emergence of technology readiness (TR) as a pivotal academic concept in the late 20th century mirrored societal transitions towards escalating technological innovation. Central to this discourse was Parasuraman's (2000) introduction of the TRI, which marked a significant advancement in the field. The foundation of this initiative traces back to the seminal work by Mick and Fournier (1998), which expounded on eight technology paradoxes that explicate the intricate and often conflicting emotions and attitudes of individuals towards technology. Parasuraman's (2000) TRI provided a nuanced framework that not only augmented these early insights but also deepened the comprehension previously established by scholars such as Eastlick (1996) and Davis et al. (1989). It offers a holistic approach to examining the adoption and implementation of technology in various contexts.

Subsequent to Parasuraman's (2000) seminal work, various studies have sought to both reference and expand upon the original insights provided by the TRI. For instance, Chen et al. (2013) integrated the concept of TR into the expectation–confirmation model, specifically exploring user continuance of mobile services. Their approach underlined the importance of TR in influencing user behaviours in the realm of mobile technologies. On the other hand, Walczuch et al. (2007) delved into the relationship between service employees' TR and their technology acceptance. Their research illuminated how personal readiness levels can influence the broader acceptance and utilisation of technological tools, especially in professional settings. The refinement of the TRI by Parasuraman and Colby (2015) represents a significant advancement in the conceptualisation of TR. The update streamlined the TRI into a more succinct 16-item scale, adeptly incorporating dimensions that more accurately mirror the evolving technological landscape, addressing contemporary concerns such as digital dependency and privacy. This enhancement of the TRI is instrumental in providing a more sophisticated understanding of individual interactions with and adaptations to technological innovations. It ensured that the TRI remained an applicable and relevant tool in the context of the rapidly changing technological environment, thereby broadening the conceptual and practical utility of the TR construct.

In summation, the evolution of TR as a scholarly concept is firmly rooted in global trajectories of technological advancements and societal evolutions. As the modern era grappled with profound technological shifts, academic exploration intensified to decode the multitudinous ways individuals navigated, embraced, or challenged these innovations. Through these continuations and expansions of Parasuraman's (2000) foundational work, the comprehensive understanding of TR has become both richer and more contextually diverse.

2.4.2 Influence of Technology Readiness on User Intentions

Empirical research has shed light on the nuances of technology readiness (TR) and its significant impact on behavioural intention (BI) to use cutting-edge technologies. The literature meticulously unravels the diverse elements of TR, situating its importance amid rapid technological advancements. At the heart of this discussion lies the influence of TR in determining an individual's disposition towards novel innovations, including AI. A clear link between TR and the intention to use AI has emerged, emphasising the need to comprehend user perspectives on emerging technology. Yap et al. (2023) delved into the association between farmers' TR and their inclination to engage with the e-Agri Finance app. The findings indicated that positive attitudes towards technology amplified users' inclination to engage, while reservations yielded the contrary effect. This accentuates the central role of TR in steering users' usage intentions.

The research conducted by Lin and Hsieh (2007) focused on assessing the influence of consumers' TR on their satisfaction and BI regarding self-service technologies (SSTs). Their findings revealed a significant correlation: enhanced TR is associated with increased customer satisfaction and more favourable BI towards SSTs. This study highlights the critical role of TR in forming positive attitudes and behaviours towards SSTs in consumers. In a similar vein, Flavián et al. (2021) analysed the interplay between TR, service awareness, and the intention to use analytical AI services, spotlighting robo-advisors. The research highlighted that robust technological optimism bolstered usage intentions, while apprehensions served as deterrents.

Interestingly, the study unveiled that technological discomfort may, in fact, promote the intention to use, presenting a departure from traditional notions within the technology adoption literature. While the studies mentioned above might not exclusively focus on AI, the insights extrapolated bear significant relevance to AI usage patterns. Such revelations underscore the argument that TR is pivotal in cultivating a welcoming stance towards AI.

In the scholarly discourse on TR, the nexus with BI is frequently mediated by elements such as SF and, more notably, PU. This nuanced interplay is exemplified in a range of sector-specific investigations. For instance, Kampa's (2023) study within the educational sphere illustrates how TR influences engagement with mobile learning platforms, significantly channelled through the lens of PU. This pattern is mirrored in the industrial sector, as emphasised by Abu Bakar et al. (2021), and similarly in healthcare, according to Kuo et al. (2013). These studies collectively suggest an interdependent relationship as these factors mutually reinforce utilising such technologies across different sectors. Thus, PU emerges as a key element that bolsters the connection between TR and BI, reinforcing individuals' acknowledgement of the practicality and efficiency of technology, which in turn boosts their willingness to integrate and effectively employ technological innovations.

Expanding upon existing knowledge, the research conducted by Roy et al. (2018) in the retail context articulately demonstrates that PU and SF serve as mediators in the TR-BI relationship. This research accentuates the intricate nature of TR's impact, emphasising the importance of technology's perceived value and supremacy. It indicates that a diverse and multifaceted array of variables mediates TR's influence, highlighting the indispensability of considering elements such as PU and SF to grasp the full spectrum of TR's effect on technology use. Consequently, the study posits that TR, while pivotal, frequently operates in conjunction with these mediators, yielding a more intricate understanding of behavioural intentions towards technology.

2.4.3 Technology Readiness Dimensions

2.4.3.1 Optimism

The concept of optimism (OP) in the context of technology, as initially formulated by Parasuraman (2000), posits that technology notably enhances control, flexibility, and efficiency in daily activities, affirming a positive outlook towards technological advancements. This perspective underscores the empowering and facilitating role of technology. Building on this, Parasuraman and Colby (2015) further expounded on OP as a vital component of TR, emphasising its proactive, optimistic stance towards technological innovations and their role as catalysts for progress at individual and organisational levels. Rooted in psychological constructs, OP is recognised for promoting resilience and adaptive behaviours (Scheier & Carver, 1985).

Within the sphere of technology utilisation, OP acts as a guiding framework shaping how individuals perceive and engage with technological advancements. Those with pronounced OP perceive technology beyond its functional attributes, envisioning it as a key driver of transformative change. This perspective extends beyond mere utility, considering technology as an instigator for creativity, efficiency, and innovative solutions, in line with broader insights into technological optimism. Technology, thus, is portrayed not only as a facilitator but also as an essential driver of evolutionary and revolutionary progress (Røpke, 1996). The nexus between OP and TR becomes even more palpable in the context of groundbreaking innovations like AI. As elucidated by Haenlein and Kaplan (2019), OP can elicit divergent perspectives on AI, portraying it either as a herald of unparalleled progress or as a potential disruptor with ambiguous ramifications. In this context, an individual's inclination towards one side of this dichotomy is primarily shaped by their inherent level of OP.

In a recent study examining the acceptance of connected and autonomous vehicles (CAVs) among Finnish residents, O'Hern and St. Louis (2023) identified OP significantly influenced user intentions, particularly among individuals with higher levels of technological OP, who showed greater inclinations to use conditionally automated vehicles. This highlights the substantial impact of OP towards technology on driving user intentions in emerging technological domains. In a similar vein, Hsieh (2023) explored the relationship between physicians' OP and their inclination to utilise AI-assisted diagnosis in medical imaging. The results established a positive correlation, demonstrating that increased levels of OP were associated with a greater propensity to adopt this advanced technological tool. This finding underscores the crucial role of a positive attitude towards technology in integrating innovative solutions within the medical field, particularly in enhancing diagnostic accuracy and efficiency through AI.

Furthermore, OP's influence on perceived barriers within the realm of technological innovation is noteworthy. Optimistic individuals tend to minimise potential challenges posed by new technologies, focusing on harnessing the opportunities presented (Son & Han, 2011). This aligns with the findings of Walczuch et al. (2007), suggesting that optimists are not only more open to new technologies but also more adept at navigating associated challenges, rendering them more effective and reliable users.

Given the rapid proliferation of AI across various industries, the significance of OP is increasingly evident. In areas such as AI-enhanced healthcare diagnostics and finance data analytics, individuals with a high degree of OP are poised to engage with and leverage these technological advancements effectively. Thus, the integration of OP into educational curricula, particularly in fields such as accounting, holds paramount importance. This initiative aims to equip students with both the necessary technical skills and a mindset geared towards positively embracing and applying AI in their academic pursuits and future professional environments.

2.4.3.2 Innovativeness

Innovativeness (IN) emerges as a paramount dimension of TR, epitomising an individual's proclivity towards pioneering novel technological advancements. Parasuraman and Colby (2015) articulated that this dimension accentuates an affinity for emerging technologies, potentially elevating one's stature in technological arenas. Such predispositions manifest not merely as a heightened interest in new technologies but also as an intrinsic motivation to be among the early adopters (Oliveira et al., 2016). In the detailed analysis of the DOI theory, Rogers (2003) underscores the critical role of innovativeness. This attribute, defined as the degree to which an individual or organisation is among the first to embrace new ideas within a system, significantly enhances the understanding and participation in the essential behaviours of the innovation-decision process. Braak (2001) discerns IN as a characteristic marked by relative constancy, influenced by societal factors, and manifesting variability across distinct innovations, highlighting an entity's inclination towards deviation from established norms.

The association between IN and BI, particularly in the context of AI, is intricate. Karahanna et al. (2002) have posited that IN fosters favourable perceptions and inclinations towards technology, even in the absence of immediate and tangible benefits. This influence is notably pronounced among individuals distinguished by their proclivity for embracing risks and novel experiences, coupled with their capacity to discern the potential value of contemporary technologies. In the healthcare sector, Hsieh (2023) discovered that professionals inclined towards early technology integration generally hold a favourable view of AI-assisted diagnosis, acknowledging its potential to enhance work efficiency, elevate professional status, and create new experiences.

Complementing this, Yi et al. (2006) emphasise the importance of mediation in this context. The study identified that the influence of individual IN on technology integration could be partially explained by the ability to foresee the benefits of innovation, thereby enhancing receptivity to the practical advantages provided. Agarwal and Prasad (1998) underscore a critical aspect of IN, highlighting that individuals inclined towards innovation encounter a range of opportunities and challenges. Advocacy exists for a balanced approach to embracing technological advancements, with an awareness of the accompanying ethical complexities. This balanced perspective proves particularly pertinent in rapidly evolving technological environments, underlining the necessity for responsible technology integration.

The increasing prominence of AI across diverse industries underscores its burgeoning significance within accounting. For accounting students, cultivating innovativeness is imperative to swiftly adapt to AI-induced transformations in accounting practices and to judiciously assimilate and innovatively utilise AI technologies in both their academic and future professional contexts.

2.4.3.3 Discomfort

Discomfort (DS) represents a significant facet of TR, primarily as it pertains to individuals' hesitations or anxieties concerning the intention to use new technological innovations. Often rooted in past adverse experiences or perceived intricacies of technological interfaces, DS can be a salient barrier to harnessing the potential of evolving technologies like AI. According to Parasuraman and Colby (2015), the sensation of DS arises from an individual's perceived lack of control over or feeling overwhelmed by new technologies. It reflects the extent to which individuals harbour apprehensions about technology-driven services and products, feeling that these offerings may cater to a select few rather than being universally accessible (Parasuraman, 2000). Cenfetelli and Schwarz (2011) illuminated in their research that specific beliefs, categorised as 'inhibitors', serve to dissuade individuals from engaging with technology. These inhibitors are not merely the antithesis of 'enablers' or facilitative elements of technology usage. Rather, inhibitors comprise a distinct set of factors that exert significant influence on individuals' intentions and perceptions regarding technological interaction.

Further expanding upon the theme of DS, Tarafdar et al. (2007) introduce the concept of 'technostress' – the stress induced by the unrelenting pace of technological change. This stress is posited to precipitate feelings of inadequacy among users, a notion consonant with the inhibitor framework delineated by Cenfetelli and Schwarz (2011). Such sentiments of inadequacy, or DS, underscore the difficulties individuals encounter when faced with the integration of modern technologies, thereby emphasising the pivotal role of the DS dimension in TR. Highlighting the repercussions of DS, Venkatesh et al. (2012) argue that the rapid pace of technological advancements sometimes surpasses users' adaptability rates. This incongruity can lead to users perceiving a disparity between their competencies and the requisites of advanced technologies, impacting their intention to use. Bhattacherjee and Premkumar (2004) noted that positive or negative past experiences substantially influence subsequent technology integration. Consequently, interventions such as comprehensive training, user-friendly designs, and feedback mechanisms demonstrate the capacity to mitigate digital scepticism and foster a positive orientation towards modern technologies.

DS may initially impede the inclination to engage with emergent technologies; however, a meticulously crafted curriculum and judicious interventions have the capacity to substantially reshape these perceptions. Through proactive mitigation of these apprehensions, educational initiatives can foster a more receptive milieu for embracing innovations such as AI, thereby facilitating a seamless transition for students into contemporary technologically-driven professional milieus.

2.4.3.4 Insecurity

The insecurity (IS) dimension within the TR framework adeptly encompasses the significant apprehensions that individuals commonly harbour concerning emerging technological systems. These apprehensions transcend mere unfamiliarity and instead stem from a fundamental lack of confidence in the reliability and potential adverse impacts of new technologies. (Parasuraman & Colby, 2015). This aspect holds particular relevance in sensitive sectors such as financial data analysis and management, where the repercussions of technological malfunctions can be substantial. Corroborating this interpretation, Hemdi et al. (2016) assert that individuals often steer clear of technologies perceived as unreliable or potentially harmful, a situation further exacerbated by negative perceptions of technological advancements.

The rapid proliferation of AI in accounting serves to exacerbate these apprehensions. AI, owing to its unparalleled capacity for data analysis, introduces operational intricacies that may not always be immediately apparent. The inherent opaqueness surrounding AI's functionalities can prompt uncertainty among users, particularly accounting students who place a premium on accuracy. Concerns regarding AI's precision in financial analysis, compounded by potential predispositions and inaccuracies, become more conspicuous due to the absence of operational transparency, potentially leading to reservations among students regarding the reliability of AI (Haenlein & Kaplan, 2019).

Historical events, notably data breaches, profoundly impact the domain of Information Systems (IS). Smith et al. (2011) emphasise that such breaches, especially in critical sectors such as finance, extend beyond mere data compromise to unveil technological vulnerabilities. The advent and increased integration of emerging technologies, notably AI, exacerbate concerns and elevate the level of scrutiny applied to its deployment. Li et al. (2018) suggest that a pervasive lack of understanding concerning these new technologies significantly amplifies perceived risks, thus engendering a sense of IS among prospective users, including accounting students.

The influence of prior technological failures, particularly those that result in financial discrepancies, is paramount in the establishment of trust (Bélanger & Crossler, 2011). Within precision-oriented disciplines such as accounting, there is an elevated requirement for technological transparency and reliability. Zhang (2008) posits that the perceived transparency of Information and Communication Technology (ICT) systems directly impacts their utilisation. In areas such as accounting, any semblance of doubt can notably deter the integration of new technologies. Furthering this narrative, Blut and Wang (2019) delve into the psychological dimensions of technology adoption, highlighting that individuals uncertain about technology tend to accentuate its potential risks, thus disproportionately diminishing its perceived advantages. This aversion to risk can consequentially depreciate the perceived utility and practical application of the technology.

Additionally, the existing curriculum in numerous accounting programs may inadvertently contribute to widening the trust gap. The potential lack of comprehensive coverage of emerging technologies can exacerbate the scepticism among students. In conclusion, as AI continues to integrate into the accounting realm, it is evident that the IS dimension of TR holds significant relevance. To cultivate a positive viewpoint regarding AI and its capabilities, it is imperative to address these concerns, ensuring that accounting students discern the genuine potential of AI in reshaping their field.

2.5 Job Relevance

The rapid pace of technological evolution is redefining numerous industries, with AI spearheading this transformative journey. Among the myriad sectors experiencing the ripple effects of AI's advancement, accounting stands out as a particularly intriguing field of interest (Krishna et al., 2022). Traditionally rooted in detailed calculations and analyses, accounting is at the precipice of a monumental shift, largely attributable to AI's capabilities. The promise of AI's integration into a plethora of accounting functions—from automated data entries to intricate predictive analytics—is increasingly becoming tangible (Kommunuri, 2022). However, as the discipline gravitates towards this new technological paradigm, it is imperative to probe deeper into certain pivotal determinants influencing its integration. One such determinant is job relevance (JR), which looms large in discussions around BI to incorporate technology (Venkatesh & Davis, 2000). Especially pertinent to accounting students gearing up to navigate a dynamically evolving profession, the perceived JR of AI is considered of paramount significance.

In the scholarly discourse pertaining to the assimilation of technology, JR implies the significance of individual perception regarding the seamless alignment of technological innovations with anticipated career requisites (Venkatesh & Davis, 2000). Kieras and Polson (1985), alongside Polson (1987), asserted that individuals possess distinct knowledge linked to their professional domains. This expertise facilitates their ability to effectively determine which tasks can be efficiently executed via a particular system. The reshaping of the accounting milieu, driven by AI's innovative prowess, necessitates an acute understanding of how JR acts as a linchpin in shaping the inclinations of tomorrow's accountants. Venkatesh and Davis (2000) elucidated that JR serves as a foundational cognitive component, playing a pivotal role in shaping an individual's perceived utility of a specific technological instrument, distinctly apart from external social influence mechanisms. This standpoint is further substantiated by Chong and Chan (2012), who emphasised the centrality of JR in shaping perceptions of a technology's intrinsic worth and potential benefits. Expanding on this notion, Sohn (2017) contends that such perceptions are deeply rooted in an individual's innate comprehension of the congruence between a technological tool and the nuances of one's professional tasks. The interplay between JR and PU is pivotal in technology utilisation. Numerous studies highlight the significant influence of user experience on individuals' perceptions of technology. The degree to which a technology's efficiency in executing professional tasks augments its perceived value, subsequently influencing an individual's usage intentions. In light of this, the present research endeavours to unravel this intricate nexus, spotlighting how perceptions of JR can potentially steer the intentions of budding accountants to integrate AI into their future practices.

2.5.1 Foundational Developments of Job Relevance

Exploring the intersection of technology with its relevance to professional tasks unfolds through several theoretical frameworks. At the forefront, the Cognitive Fit Theory, introduced by Vessey (1991), posits that alignment between technology and an individual's tasks enhances task performance and augments their problem-solving prowess. Leonard-Barton and Deschamps (1988) highlighted the concept of 'job-determined importance', indicating that the significance users attribute to their roles profoundly impacts their engagement with technology, particularly when it directly relates to their responsibilities. Building on this concept, Hartwick and Barki (1994) introduced the 'involvement' aspect, suggesting that a deeper connection between a user and a system, driven by personal importance and relevance, increases the likelihood of its effective utilisation. Advancing this notion, Goodhue (1995) developed the 'task-technology fit' construct, proposing that a harmonious relationship between the capabilities of a technology and the demands of a task fosters its successful integration.

Extending this idea further, Venkatesh and Davis (2000) argued that the alignment between what technology provides and an individual's professional expectations plays a crucial role in shaping the intention to integrate that technology into their workflow.

Within the broader discourse on technology engagement, the TAM, introduced by Davis (1989), occupies a critical position as an instrumental theoretical framework. The TAM provides a systematic approach to understanding the intention behind and actual use of technological systems, focusing on key constructs such as PU and PEOU. Furthermore, the perceived JR emerges as a critical external influence that shapes individuals' perceptions of a technology's potential usefulness. TAM asserts that JR is not merely a supplementary concept but a fundamental cognitive determinant that impacts how potential users evaluate the relevance and suitability of a technology. This becomes particularly apparent when a technology seamlessly aligns with professional responsibilities, ultimately enhancing its PU.

The synthesis of perspectives elucidates the pivotal role of JR in sculpting the narrative surrounding technology integration. When applied to the context of accounting education, it is evident that if AI systems align with the anticipated responsibilities of accounting students, their perceptions of JR are positively influenced. This congruence strengthens their propensity to employ AI tools in their forthcoming professional activities.

2.5.2 Scholarly Inquiries and Retrospective Insights

Empirical literature, fortified by rigorous methodologies, has long been providing compelling insights into the pivotal role of JR in shaping BI towards technology utilisation. The landscape of research suggests that irrespective of the technological domain under scrutiny, JR remains a persistent determinant. In Izuagbe et al. (2022), the intricate relationship between JR and behavioural motivation was explored in the context of e-databases. Faculty members, positioned at the nexus of academic rigour and practical implications, represented a valuable demographic for this study. The definitive findings highlighted that perceptions of relevance functioned as a pivotal catalyst, propelling faculty members to engage more intensely in research upon recognising the e-database as an indispensable resource for their scholarly pursuits. The implications of these findings for AI in the field of accounting cannot be overstated. It provides a perspective for anticipating an increase in BI to utilise AI tools among accounting students, provided these tools are perceived as congruent with their future professional responsibilities.

Saroia and Gao (2018) undertook a detailed exploration of the interplay between mobile learning management systems and students' BI, elucidating the variable of academic relevance. Analogous to the concept of JR, academic relevance contemplates the degree to which a technological system's attributes align with an individual's scholastic objectives. The research results demonstrate that students exhibit a greater propensity to employ such systems when there is a notable alignment between the system's features and academic goals. This empirical evidence corroborates the hypotheses posited by Izuagbe et al. (2022) and enriches understanding by underscoring the crucial role of technology in the current educational milieu. Consequently, this study stands as an instrumental reference, drawing parallels between academic and occupational relevance.

The work of Hart and Porter (2004) provided another cornerstone in this tapestry of empirical evidence. Their investigation into Online Analytical Processing (OLAP) systems, a relatively niche but potent domain, revolved around unravelling the interdependencies between cognitive perceptions, JR, and PU. The findings revealed a compelling narrative where the perception of OLAP systems as relevant to job roles directly correlated with an increased rating of their utility. Subsequently, this enhanced perception led to a heightened intention among users to integrate OLAP systems into their professional workflow. In light of the fast-paced advancements in the Industrial Internet of Things (IIoT) and related digital technologies, Kar et al. (2021) analysed professionals' learning behaviours towards these innovations. Their comprehensive study highlighted JR as a pivotal factor influencing professionals' intentions to acquire new technological skills. Essentially, as technologies evolve, professionals perceive the need to learn aligned skills to remain pertinent in their roles. This finding underscores the importance of JR in shaping professionals' responses to technological shifts.

Recent investigations provide corroborative evidence on the influential role of JR in the integration and utilisation of technology. For instance, the research conducted by Dhiman et al. (2023) investigated the application of HR analytics within the framework of the TAM. The findings indicate a significant linkage between JR and the PU of HR analytics. Specifically, when HR analytics align well with assigned tasks, there is a notable increase in the belief in their utility. The aforementioned observation reinforces the notion that technology, considered pivotal for the efficient execution of tasks within stipulated timeframes, can exert a positive influence on the inclination to employ it (Okcu et al., 2019). Reflecting on these insights, it is evident that while JR can directly foster intentions to use technology, as evidenced in the study, the role of PU is also crucial, albeit partial. PU acts to amplify and accelerate the process of technology integration and utilisation.

The intricate weave of historical contexts, theoretical frameworks, and empirical studies underscores the central role of JR in determining BI towards technological integration. Across various domains, from e-databases to the burgeoning field of AI in accounting, the significance of technology aligning with users' professional aspirations remains vital. In essence, for AI to gain traction among future accountants, it is imperative that it be perceived not merely as an advanced instrument but one intrinsically tied to their professional future. The overarching message, echoing through ages and studies, is clear: at the juncture of technological innovation and professional endeavour, maintaining relevance is of utmost importance.

2.6 Superior Functionality

The notion of superior functionality (SF) is a critical concept in the analysis of technology integration, recognised for its indispensable mediation in evaluating new technological advancements. The essence of SF lies in its provision of considerable enhancements in features and performance, distinguishing itself not merely by the technology's novelty but by substantially improving the user experience over existing alternatives. This principle aligns with the insights of Rogers (2003), highlighting the significance of technological progress that moves beyond a simple innovation.

Rieger et al. (2022) argue that mere innovativeness alone is insufficient; the focal point should be directed towards realising tangible enhancements in efficiency, functionality, and user experience. SF necessitates a meticulous examination of technology, emphasising its capacity to deliver substantial enhancements that align with the evolving needs and expectations of users. This perspective differentiates SF from PU by entailing a comprehensive evaluation of the tangible superiority of technological advancements over existing options, as opposed to a purely subjective assessment of their perceived efficacy. AI emerges as a paragon in this analytical discourse, with its rapid engagement across a myriad of sectors—ranging from the precision-driven world of healthcare to the data-intensive realm of finance—a testament to its unparalleled capabilities. However, it is crucial to recognise that the allure of AI is not restricted to its sheer computational power. Instead, the essence of its appeal lies in its suite of intrinsic attributes. The adaptability of AI systems, their continuous learning algorithms, and their uncanny predictive capabilities coalesce to define the archetype of SF in the modern technological era (Pabby & Kumar, 2017).

The trajectory of AI, akin to any significant technological advancement, is fraught with complexities. The discourse is interspersed with ethical dilemmas and considerations, notably regarding transparency, fairness, and potential misuse. Such concerns necessitate thorough scrutiny and careful deliberation, especially in light of their significant societal implications (Dignum, 2018). However, when juxtaposed with the empirical benefits that AI affords—ranging from aiding in prompt and accurate diagnoses of diseases to enabling sophisticated predictions in financial markets forecasts—the scales often tilt in favour of its integration, albeit with necessary safeguards (Jordan & Mitchell, 2015).

To encapsulate, as technological innovations continue their inexorable march, integrating seamlessly into myriad facets of human existence, the doctrine of SF remains an anchor. It serves as both a beacon and a yardstick, guiding stakeholders in the evaluation, endorsement, and judicious assimilation of these technologies, ensuring that they resonate with the evolving needs and aspirations of society.

2.6.1 Artificial Intelligence Superiority in Modernizing Traditional Systems

AI has been heralded as a groundbreaking force in computational abilities, making traditional systems seem almost archaic in comparison. Particularly in sectors such as healthcare, finance, and, notably, accounting, the potential of AI is highly promising and resonates strongly (Pabby & Kumar, 2017). Traditional accounting processes, once regarded as the epitome of managing financial data, now grapple with the increasing onslaught of data in terms of volume, complexity, and velocity (Sun et al., 2020). AI, equipped with dynamic algorithms, offers robust solutions to conventional challenges, effectively addressing the growing demands in accounting. Unlike static systems, AI's ability to evolve its analytical parameters based on emerging data is anticipated to provide unparalleled accuracy in financial forecasting and risk assessment (KPMG, 2016). This adaptability is not merely a technological feature but a critical asset, particularly in navigating real-world financial uncertainties.

Deep learning, a cornerstone of AI, efficiently processes extensive datasets via neural networks, uncovering complex patterns beyond the reach of conventional methods. These advancements extend past the theoretical knowledge familiar to accounting students, offering avenues for the refinement of fiscal strategies and the augmentation of sophisticated decision-making processes within their imminent professional roles (Schmidhuber, 2015). The automation capabilities of AI are a compelling aspect that captures the interest of accounting students. In contrast to traditional tools, which have limited automation for routine tasks, AI adeptly handles intricate functions such as audits and the amalgamation of data from various sources, marking a pivotal advancement (Kokina & Davenport, 2017). In the sphere of fraud detection, which presents an ever-evolving challenge, the adaptive pattern recognition capabilities of AI are perceived as a revolutionary development. In comparison to rule-based traditional systems, AI offers the promise of bolstered defences against deceptive financial tactics (West & Bhattacharya, 2016). The ascendance of AI in accounting is defined not solely by its technological innovations but also by the expectations and aspirations of the upcoming generation of accountants. The advanced capabilities of AI are perceived to be a critical element that markedly affects their envisaged career trajectories within the accounting field.

2.6.2 Theoretical Underpinning of Superior Functionality

Superior functionality (SF), essential for grasping the intention to use technology, can be traced back to Rogers's (1962) Diffusion of Innovations (DOI) theory. This theory introduces ‘relative advantage’ as the perceived superiority of an innovation compared to its predecessors. Aligning with the concept of SF, the theory underscores notable advancements in features, performance, and operational capabilities introduced by new technologies (Roy et al., 2018). SF embodies tangible, concrete benefits of technology, transcending mere perceptual aspects. Such enhancements, when authentically present, naturally amplify the perceived relative advantage of the technology, influencing the propensity towards its usage. This significance becomes markedly evident in accounting, where traditional systems often fall short in addressing modern financial complexities. Equipped with the capability to process extensive datasets, identify patterns, and deliver predictive insights, AI asserts undeniable superiority.

Transitioning to a more intricate facet of technology engagement, it is imperative to distinguish between SF and PU. SF delves into the inherent technical strengths of a technology, offering an objective framework for evaluating its features and capabilities. It revolves around the substantial enhancements and technical merits a technology introduces relative to its forerunners (Roy et al., 2018). In contrast, PU presents a more subjective evaluation rooted in the perspectives of individual users. It assesses how the features of a technology could improve performance or streamline operations. SF delineates the "what" – the intrinsic attributes a technology offers – while PU explores the "why", elucidating the reasons users might find these features advantageous (Davis, 1989; Venkatesh & Bala, 2008). Recognising this distinction is paramount, as well as elucidating the dynamic between a technology's innate characteristics and its perceived value in specific contexts.

In conclusion, the interplay between Rogers's (1962) DOI and Davis's (1989) TAM underscores the pivotal role of SF in technology integration dynamics, particularly in evolving fields such as accounting. The cohesion of SF with relative advantage offers profound insights, solidifying its significance in understanding technology utilisation nuances.

2.6.3 Operationalisation of Superior Functionality in Prior Research

The construct of superior functionality (SF) has prominently featured in research endeavours examining the nuances of intention to use technological innovations. The differential in capability and supremacy stands as a significant influencer of user perceptions and subsequent behaviours. Roy et al. (2018) elucidated that when individuals identify a technological platform as possessing advanced features that surpass conventional alternatives, a favourable disposition towards the technology arises, particularly from the dimensions of TR. In parallel, the concept of 'relative advantage', closely associated with SF, has received scholarly attention. This concept, often perceived as synonymous with SF, concerns the extent to which an innovation is seen as superior to the product or service it aims to replace. Studies by Agarwal and Prasad (1998) and Moore and Benbasat (1991) emphasised the significance of relative advantage in the context of intention to use technology, drawing analogies with SF. Research conducted by Zhou et al. (2010) focusing on mobile banking revealed that certain elements of SF, particularly attributes including advanced features and discernible advantages, significantly influenced BI. Users exhibited a higher propensity to incorporate mobile banking into daily routines upon recognising its functional superiority over traditional banking mechanisms.

In the realm of technological advancements, SF plays a pivotal role in shaping user experiences across various domains. Despite the diversity in its manifestations, SF consistently exerts a significant influence on the PU of technological systems, as evidenced by scholarly research. In this context, the study by Ferreira et al. (2014) in the digital reading domain provides critical insights. This research focuses on the transition from traditional printed books to e-books, highlighting how the SF of e-books, which includes features such as searchability, portability, and font customisation, is instrumental in shaping users' PU. Likewise, Lu et al. (2014) conducted a study in the domain of mobile banking services, revealing a parallel trend. The study identifies specific superior features, such as real-time transaction updates and instantaneous bill payments, as key factors enhancing the perceived value of the service for users. In both cases, the acknowledgement of SF contributes to an elevated perception of the service's usefulness, thus underlining the direct and substantial impact of SF on PU across diverse technological platforms.

In scholarly discussions centred around the intention to utilise AI, SF emerges as a central mediating variable. AI's appeal rests not merely on its novelty but predominantly on the tangible enhancements and benefits it presents. User propensity to integrate AI increases with the recognition of its functional superiority over extant technologies. Although AI's dynamic nature is captivating, its broader acceptance leans heavily on tangible advantages alongside ethical considerations. In summary, SF serves as a linchpin in charting the course of AI's integration, highlighting its centrality in user acceptance models.

2.7 Perceived Usefulness

Perceived usefulness (PU), as a principal construct derived from research in technology integration, has been pivotal in understanding user's attitudes and behaviours towards emerging technologies. At the core of this concept lies the notion that individuals evaluate the value of a technology based on its ability to improve their job performance or aid in their professional roles. PU, therefore, acts as a bridge connecting cognitive evaluations of technology with the external factors that affect its use, enabling an assessment of how users perceive a technology's capacity to enhance their tasks and responsibilities.

With the rapid advancement of technology and the seamless incorporation of new solutions across various industries, the significance of PU in predicting BI to use technology has become increasingly pronounced. The criticality of this subject is underscored in foundational research, notably by Venkatesh et al. (2003) and Davis (1989), highlighting PU's role as a subjective measure of technology's effectiveness and as a crucial element in the decision-making process regarding technology acceptance and integration. PU, therefore, plays an essential role in shaping how technology is used across various sectors, reflecting its importance in the evolving landscape of technological utilisation. In essence, the concept of PU extends beyond subjective impressions, emerging as a significant determinant that profoundly shapes the future pathways of technology deployment and application across various industries.

2.7.1 Origins and Development of Perceived Usefulness

The inception of the perceived usefulness (PU) construct is attributed to the foundational research conducted by Davis (1989), which introduced the Technology Acceptance Model (TAM). Within this framework, PU emerges as a critical determinant shaping users' intentions and subsequent interactions with technology. Over the years, TAM emerged as a touchstone in the field, spawning myriad research endeavours and conceptual extensions, primarily focusing on elucidating the determinants and outcomes of BI to use. Delving deeper into the conceptual roots, the foundational elements of PU draw significant inspiration from the TRA crafted by Fishbein and Ajzen (1975). The TRA, a groundbreaking theoretical framework in the social psychology arena, articulates the relationship between an individual's beliefs, attitudes, and behaviours. The central tenet of TRA is the emphasis it places on BI. In this schema, attitudes and subjective norms collectively form an individual's BI, thus predicting their actual behaviours.

Drawing parallels between TAM and TRA, Davis's (1989) conceptualisation of PU echoes the attitude construct in TRA. In the context of TAM, PU pertains to the potential user's assessment of the benefits of employing a specific technology, reflecting how they anticipate it would aid or enhance their tasks. This evaluation process, albeit influenced by external and intrinsic factors, is pivotal in shaping their BI to use the said technology. Successive research endeavours further enriched this conceptual framework. For instance, the Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. (2003), synthesised elements from multiple acceptance models, including TAM. In this expanded framework, the principle of PU from the TAM is adeptly reincorporated as performance expectancy that mirrors the fundamental notion of PU, concentrating on the extent to which individuals perceive that using technology will improve their job performance. UTAUT, while expanding the parameters of technology usage studies, retains the essential role of PU, albeit under the label of performance expectancy. This retention underscores the continual relevance of PU's foundational concepts in understanding technology integration and utilisation. The historical trajectory of the PU construct, from its origins in TAM and TRA principles to its refined forms in models like UTAUT, illuminates its crucial role in academic discourse on technology engagement and its persistent significance for forecasting user behaviour and preferences in a progressively digitalised landscape.

2.7.2 The Primacy of Perceived Usefulness in Technology Acceptance Model

In accordance with the Technology Acceptance Model (TAM) conceptualised by Davis (1989), perceived usefulness (PU) is identified as a crucial determinant. The TAM posits that an individual's inclination to use technology is influenced by two primary factors: PU and perceived ease of use (PEOU). The model places an elevated emphasis on PU, particularly in its interplay with PEOU, signifying the criticality of this interaction in understanding user acceptance and adoption of technology. PU pertains to the user's belief in the extent to which a particular technology will enhance their job performance. The emphasis on the utility of technology for performance enhancement underscores the pivotal role of PU in the model. The underlying rationale emphasises that individuals' propensity to utilise technology is heavily predicated on their view of technology as a catalyst for improved performance and increased efficiency in tasks.

PEOU, on the other hand, pertains to the expected ease associated with using the technology. The TAM model initially proposed that PU and PEOU held equivalent levels of influence. Nevertheless, with the progression of technology and the diversification of user experiences, contemporary research has highlighted a more significant role of PU in shaping user behaviour. Esteemed studies conducted by Mathieson (1991), Keil et al. (1995), and Adams et al. (1992) have robustly evidenced the paramount influence of PU, relegating PEOU to a secondary position. The transition towards prioritising PU signifies a recognition that the efficacy of technology in enhancing task performance frequently presents a more persuasive argument to users than mere ease of use. This shift is underscored by the swift progress and complexity of contemporary technology, further cementing the pre-eminence of PU (Venkatesh & Davis, 2000). As users navigate an expanding spectrum of technological tools, their evaluation of a technology's potential to improve and facilitate their work or tasks becomes an essential determinant of their engagement choices.

In summary, PU is recognised as a cornerstone within the TAM model, garnering heightened focus for its pivotal role in the broader context of technology engagement and adaptation processes. PU emphasises the criticality of users' assessments regarding technology as an essential instrument for enhancing task performance and efficiency. This perspective elucidates its emergence as a central theme in the ongoing development and refinement of the TAM framework. This evolution marks a theoretical pivot and a pragmatic adaptation to the evolving dynamics of technology utilisations and the expectations of users in the modern digital landscape.

2.7.3 Mediating Role of Perceived Usefulness

In technology engagement research, perceived usefulness (PU) serves as a crucial intermediary that facilitates the connection between external variables and BI when interacting with specific technological systems. This concept transcends mere objective evaluation, embodying a subjective appraisal that encapsulates the perceived value from the user's perspective. The facets of Technology Readiness (TR) are critical in assessing technological intentions, with their impact significantly mediated by PU. In this context, PU plays an integral role, skilfully bridging the gap between the dimensions of TR and the intention to use technology. The importance of this mediating role is underlined through the research conducted by Barua and Urme (2023), which emphasises PU's contribution to mediating the propensity to adopt online teaching platforms. Furthermore, this mediating function of PU is supported by additional empirical evidence, as seen in the work of Mufidah et al. (2022) on Learning Management Systems (LMS) and Nugroho and Fajar (2017) on Web-Based Attendance Systems. Collectively, these studies affirm the lasting impact of TR on shaping utilitarian intentions and underscore the crucial function of PU in enabling this process.

The academic research, focusing on its engagement with PU, is marked by a dynamic and responsive approach to the evolving technological milieu. Contemporary research efforts are directed towards exploring the complex interplay between JR and the propensity to employ AI, positioning PU as a critical intermediary variable. In this arena, the study conducted by Alharbi and Drew (2014) delves into the engagement of academics with learning management systems and the investigation by Rui-Hsin and Lin (2018) into the use of e-learning applications by police officers are both subjects of considerable interest. Both these studies unveil a positive linkage between JR and PU, which in turn significantly influences BI to employ technology. Essentially, an amalgamation of seminal research initiatives by Davis (1989), Venkatesh and Davis (2000), and Venkatesh et al. (2012) underscores the pivotal role of PU in mediating the relationship between external motivators, such as TR and JR, and end-user behaviours and intentions. Its undeniable prominence in the technology engagement landscape accentuates the pressing need to grasp its intricacies, offering invaluable insights to both researchers and practitioners seeking to harness the optimal potential of technological interventions.

This profound influence of PU, established by Davis (1989) as a key driver of user intentions to employ technology, provides a foundation for further exploration. This foundational concept has stood the test of time and has been echoed and substantiated in varied technological contexts. Delving into the intricacies of early information technology adopters, Karahanna and Straub (1999) underscored how PU significantly sways both user behaviours and overarching attitudes. Similarly, in the dynamic world of mobile commerce, Tao (2011) reemphasised the pivotal role of PU, arguing that its influence is paramount in determining users' BI to use mobile commerce platforms. Expanding on this idea, Gefen et al. (2003) provided a nuanced perspective, articulating how individual perceptions intertwined with trust concerns could reshape the contours of PU. This, in turn, has a cascading effect, influencing users' intentions to interact with specific technologies. E-learning, another rapidly evolving sector, has also been influenced by this trend, with Sánchez and Hueros (2010) noting that the dynamics of PU in e-learning environments mirror those in other domains, directly impacting users' intentions to use e-learning platforms. A similar sentiment is evident in the healthcare sector, as demonstrated by Yi et al. (2006), which revealed that healthcare professionals significantly weigh the PU when confronted with new technologies, influencing their BI to integrate these tools into their practice.

Tracing the trajectory of technology acceptance research, PU emerges not merely as a peripheral element but rather as a cornerstone underpinning the framework. Its significance transcends the realm of understanding perceived technological value. At its core, PU acts as a vital mediator, orchestrating the interplay between external variables such as JR and TR and culminating in the BI to employ a particular technology. The crux lies not solely in the apparent value of the technology but in how this perceived utility shapes an individual's determination to employ it. Given this intricate role, a thorough comprehension of PU is imperative. It serves as the fulcrum upon which decisions regarding technology utilisation pivot. Ignoring the nuances of PU would sideline a crucial determinant bridging external evaluations with internal intentions. In a rapidly advancing technological world, understanding PU is paramount to fostering an informed and intentional approach to technology utilisation rather than mere acceptance or passive adoption.

CHAPTER 3: THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

3.1 Introduction

Existing literature in the Information Systems discipline has offered numerous theories to elucidate the relationship between factors that influence technology adoption, acceptance, and intended usage. Such influencing elements typically encompass perceptions, user attitudes, experiences, and beliefs. Although well-known models such as the Theory of Planned Behaviour (TPB) (Fishbein & Ajzen, 1975), the Diffusion of Innovation Theory (DOI) (Rogers, 1995), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003; Venkatesh et al., 2012) are often utilised, they generally emphasise technical aspects. In contrast, the Technology Acceptance Model (TAM) (Davis, 1989) is frequently applied due to its superior validity (Adams et al., 1992; Chau, 1996) and adaptability to include additional variables, as observed in past empirical studies (Abu Bakar et al., 2021; Alharbi & Drew, 2014; Moon & Kim, 2001; Stern et al., 2008; Venkatesh et al., 2003; Venkatesh & Davis, 2000).

This investigation utilises the theoretical foundations of TAM, as proposed by Davis (1989), and the TR dimensions formulated by Parasuraman (2000). The study aims to uncover novel perspectives on the behavioural intention (BI) to use AI, especially within educational environments. By including TR and JR as independent variables, along with integrating SF and PU as mediating variables, it seeks to augment the TAM's theoretical robustness and empirical applicability. TAM, a fundamental model in technology acceptance research, has a storied history of modifications and expansions. The proposed extension further broadens TAM's scope by merging it with TR dimensions, underscoring TR and JR in the context of the specific technology (Abu Bakar et al., 2021; Alharbi &

Drew, 2014). This combination seeks to provide a more comprehensive insight into the BI towards the usage of AI, a domain yet to be fully investigated.

In summary, the TAM, augmented by the strategic alignment of independent, mediating, and dependent variables, provides a nuanced methodology for evaluating BI towards AI utilisation. This investigation seeks to shed light on less explored aspects in technology engagement research, thereby contributing significantly to the advancement of understanding within this domain. The focus is on expanding the scope of inquiry and enriching the existing body of knowledge, with an emphasis on the intricate dynamics of technology integration and utilisation in various contexts.

3.2 Technology Acceptance Model

The Technology Acceptance Model (TAM), conceptualised by Davis (1989), represents a refinement of the Theory of Reasoned Action (TRA), a psychological framework designed to predict and elucidate BI. This model has garnered substantial application across varied research paradigms owing to its efficacy in pinpointing determinants that influence technology adoption. Central to the TAM are the constructs of perceived usefulness (PU) and perceived ease of use (PEOU), which furnish pivotal insights into accountants' behavioural intentions towards AI, a critical aspect for understanding technology integration dynamics within the accounting sector. The prolific deployment of this model across diverse studies (Ha & Stoel, 2009; Rafique et al., 2020; Stylios et al., 2022; Yousafzai et al., 2010) underscores its pertinence and utility in examining technology interactions. Hence, it serves as an exemplary theoretical framework for the present study, particularly in scrutinising the interplay between accounting students and AI technologies.

The TAM has established its predictive validity across a multitude of business domains. With the passage of time, this model has been subject to substantive refinements, culminating in an enriched framework through the incorporation of several explanatory constructs. These enhancements include perceived enjoyment (Alalwan et al., 2017; Davis et al., 1992; Pantano et al., 2017), perceived mobility value (Huang et al., 2007), subjective usage norms (Al-Nawafleh et al., 2019; Venkatesh & Davis, 2000), perceived self-efficacy (Altin Gumussoy et al., 2017), social influence (Hsu & Lu, 2004; Karahanna & Straub, 1999; Patel & Patel, 2018) and perceived playfulness (Moon & Kim, 2001). These advancements have significantly broadened the applicability of TAM, enhancing its relevance within a wide array of technological environments.

Integrating the Technology Readiness Index 2.0 (TRI 2.0) with the TAM significantly enhances the understanding of intentions to utilise AI. TRI 2.0, accentuating individual technological inclinations, synergises with TAM by offering a refined gauge of TR, particularly pertinent in AI utilisation (Parasuraman, 2000; Parasuraman & Colby, 2015). Additionally, incorporating JR and SF into TAM enables a focused examination of facets directly related to the pragmatic deployment of AI within educational environments. JR underscores the importance of AI's applicability in future careers (Alharbi & Drew, 2014; Okcu et al., 2019; Venkatesh & Davis, 2000), while SF emphasises the advanced capabilities of AI over conventional methods (Hong et al., 2002; Roy et al., 2018).

This integration of TRI 2.0 and TAM, with emphasis on JR and SF, overcomes several shortcomings identified in alternative theoretical models such as DOI, UTAUT, TAM2, and TAM3, particularly in AI incorporation within academic environments. Despite the significant contributions of these frameworks to the broader understanding of technology acceptance, their applicability to the intricacies of this specific analysis remains limited. For instance, the DOI (Rogers, 1995) predominantly explores the dynamics of innovation dissemination within social systems, placing diminished emphasis on the influence of individual characteristics or the specific features of technology that may impact its adoption and utilisation. Similarly, the UTAUT (Venkatesh et al., 2003; Venkatesh et al., 2012), despite offering a comprehensive perspective of user acceptance by amalgamating eight models, including TAM, encounters limitations due to the intricacy and context-specific characteristics of its constructs, potentially restricting its applicability. Specifically, within an academic framework, not all components of UTAUT, such as social influence and facilitating conditions, would be pertinent (Dwivedi et al., 2017).

TAM2 and TAM3, while serving as significant extensions of the original TAM, focus predominantly on PU (Venkatesh et al., 2003; Venkatesh & Davis, 2000). TAM2 further incorporates social influence and cognitive instrumental processes as pivotal determinants of PU, whereas TAM3 enriches the model by adding constructs such as PEOU and computer self-efficacy. Despite their contributions towards enhancing the understanding of general technology acceptance factors, these models may fall short in addressing the nuanced and distinct challenges associated with AI in educational contexts. These challenges include but are not limited to, the dynamic technical evolutions of AI technologies, their alignment with educational goals, and their advanced functionalities. The rapid progression and innovation within the AI landscape, marked by novel applications and continual improvements, necessitate a more flexible and context-specific framework. Consequently, the applicability of TAM2 and TAM3 for a comprehensive exploration of AI utilisation and its intricacies within educational environments could be limited.

In summary, the adapted framework combining TRI 2.0 with the extended TAM provides a refined approach for examining AI utilisation in academic contexts. This tailored framework effectively overcomes the limitations of broader models like DOI, UTAUT, TAM2, and TAM3, ensuring a more context-specific and comprehensive analysis of AI engagement in the educational domain.

3.2.1 External Factors

Davis (1989) developed TAM, a robust framework that has been extensively applied across various technological scenarios to predict and clarify user interaction and utilisation of information technology. Despite its widespread application, critiques have emerged pointing out the framework's insufficient engagement with the user's perspective towards technologies and systems. (Moon & Kim, 2001; Patel & Patel, 2018). To rectify this oversight, Moon and Kim (2001) proposed a refinement of TAM by introducing additional variables designed to better reflect the context of the specific technology, its primary users, and the setting. Building on existing literature, these enhancements can be classified into two main groups: individual differences and system characteristics. The revised research model effectively integrates these aspects, including the TR Dimensions within individual differences and introducing two system characteristics: JR and SF.

3.2.1.1 Individual Differences

The significance of individual differences in technology engagement forms a central theme in TAM research. Notable scholars such as Venkatesh and Davis (2000), Venkatesh et al. (2003), and Agarwal and Prasad (1999) have underscored the far-reaching influence of these differences. Factors such as age, gender, cognitive style, prior experience, personality traits, and attitudes towards technology have been acknowledged for their substantial impact on PEOU, PU, and the intention to engage with technology. These elements, which are external to the technology itself, reflect the diverse characteristics of the user population and their effect on technology utilisation. Demographic factors, specifically age and gender, though external to an individual's belief system, play a pivotal role in shaping intentions to use technology (Gefen et al., 2003; Venkatesh et al., 2003). Furthermore, personality traits, such as computer self-efficacy and personal innovativeness, are considered external factors within the TAM framework. These pre-existing traits, not acquired through interaction with the specific technology, significantly impact both PEOU and PU.

The TRI, originally conceptualised by Parasuraman (2000), contributes to the discourse by offering a comprehensive analysis of individual variances in technology engagement. Integrating the dimensions of TRI into the TAM, forming the Technology Readiness and Acceptance Model (TRAM), as demonstrated by Lin et al. (2007), reveals the significant influence of personal characteristics on technology usage intentions. This integration shows that optimism and innovativeness, positive aspects of TRI, increase the intent to use technology, while discomfort and insecurity, its negative aspects, diminish such intent. The application of TRI within TAM, reinforced by research from Lin et al. (2007) and Parasuraman (2000), underscores the crucial role of personal distinctions in shaping individuals' propensity to engage with emerging technologies, such as AI.

Lin et al. (2007) elucidated that within e-service systems, both PEOU and PU serve as mediators that modify the impact of the TRI on the intentions to engage with technology. This augmented framework, termed the TRAM, enhances the original TAM by broadening its scope and increasing its explanatory power, especially in contexts where technology integration is driven by individual choice rather than organisational directives. Yusuf et al. (2021) explore the influence of TRI and TAM in the context of learning management systems (LMS) for online learning, and Kampa (2023) further validates the application of TRAM in appraising students' readiness for engaging in mobile learning within open and distance learning settings. These findings underscore the utility of the model in educational environments, specifically for predicting the extent of students' engagement with emerging digital learning instruments.

In summary, the integration of TR into TAM enhances the model, equipping it to predict and explain intentions to use technologies, especially AI, more accurately. The inclusion of TRI dimensions as markers of individual differences significantly amplifies the TAM framework's ability to assess intentions for technology usage.

3.2.1.2 System Characteristics

In the refined TAM, the influence of system characteristics on user interactions and attitudes towards technological systems is substantially acknowledged. These characteristics, which include specific attributes and features of the technology, play a crucial role in shaping user perceptions and intentions towards system use. Davis et al. (1989) posited that the objective design characteristics of a system have a direct impact on PU, a fundamental construct in TAM. This assertion is supported by subsequent research conducted by Igbaria et al. (1995), Venkatesh and Davis (1996) and Hong et al. (2002), who collectively found a significant correlation between system characteristics and the intention to use information systems. Furthermore, Venkatesh and Davis (2000) articulated that the extended TAM model transcends mere individual perceptions, such as PU and PEOU, to incorporate external factors into the assessment of technology engagement. This enhancement of the framework is essential for the comprehensive integration of system characteristics within the TAM. As such, this study encapsulates both the inherent attributes of the technology, as epitomised by SF and its congruence with the user's professional requirements, as exemplified by JR.

Rogers (2003) posits that SF underscores technological excellence characterised by exceptional capabilities and performance inherent to the technology and independent of subjective user assessments. This dimension frequently influences users' perceptions of a technology's utility in a positive manner (Lee et al., 2003). Thompson et al. (1991) define JR as the extent to which users perceive technology as pertinent to their professional tasks. Operating as an external factor, JR zeroes in on the alignment between the technology and the user's professional milieu, thereby potentially augmenting PU and the propensity towards utilising technology that seamlessly integrates with job demands (Venkatesh & Davis, 2000).

By integrating both SF and JR, the extended TAM effectively underscores the impact of these external system attributes on perceptions and intentions related to technology usage. This approach offers a thorough insight into the determinants propelling the BI to utilise technology, particularly AI, by assessing its inherent properties and pertinence to the user's professional milieu.

3.2.2 Internal Factor

The heart of the TAM, as outlined by Davis (1989), centres on the constructs of PU and PEOU. Within this framework, PU is underscored as a mediating factor, reflecting the internal assessment process of technology users. Both PU and PEOU collectively evaluate a user's perception of technology as beneficial and user-friendly, with PU focusing primarily on its utility. PU represents an internal factor encompassing an individual's internal belief or perception regarding how the use of specific technology will enhance their job performance. It constitutes a psychological and cognitive assessment internal to the individual, shaped by their experiences, expectations, and needs. The original TAM posits a substantial interrelationship between PU, PEOU, and BI to use technology.

Various empirical studies consistently emphasise the strong association between PU and BI, in contrast to the more variable link between PEOU and BI (Davis et al., 1992; Gefen et al., 2003; Karahanna & Straub, 1999; Venkatesh & Davis, 1996, 2000). Such findings underscore the critical role of PU as an internal driver of technology integration. Despite occasional discrepancies in TAM's constructs, the model has garnered extensive support across diverse technologies. This support underscores a fundamental principle: prioritising enabling users to achieve meaningful and beneficial outcomes with technology rather than solely ensuring the technology's ease of use (Keil et al., 1995). This principle highlights the centrality of PU, aligning the capabilities of technology with the user's objectives and tasks based on their internal value perception. PU is identified as an internal element within the TAM, originating from a user's personal beliefs and perceptions regarding the utility of technology. These subjective perceptions, as opposed to objective assessments of technological functionality, are pivotal in influencing a user's inclination to engage with the technology.

In conclusion, the present research enriches the TAM by integrating external factors—TR, JR and SF—with the internal element of PU. This holistic model provides insightful revelations concerning the modalities of AI usage intentions among Malaysian accounting students. Consequently, it substantially advances the scholarly discourse on technological assimilation within the realm of accounting education.

3.3 Conceptual Framework

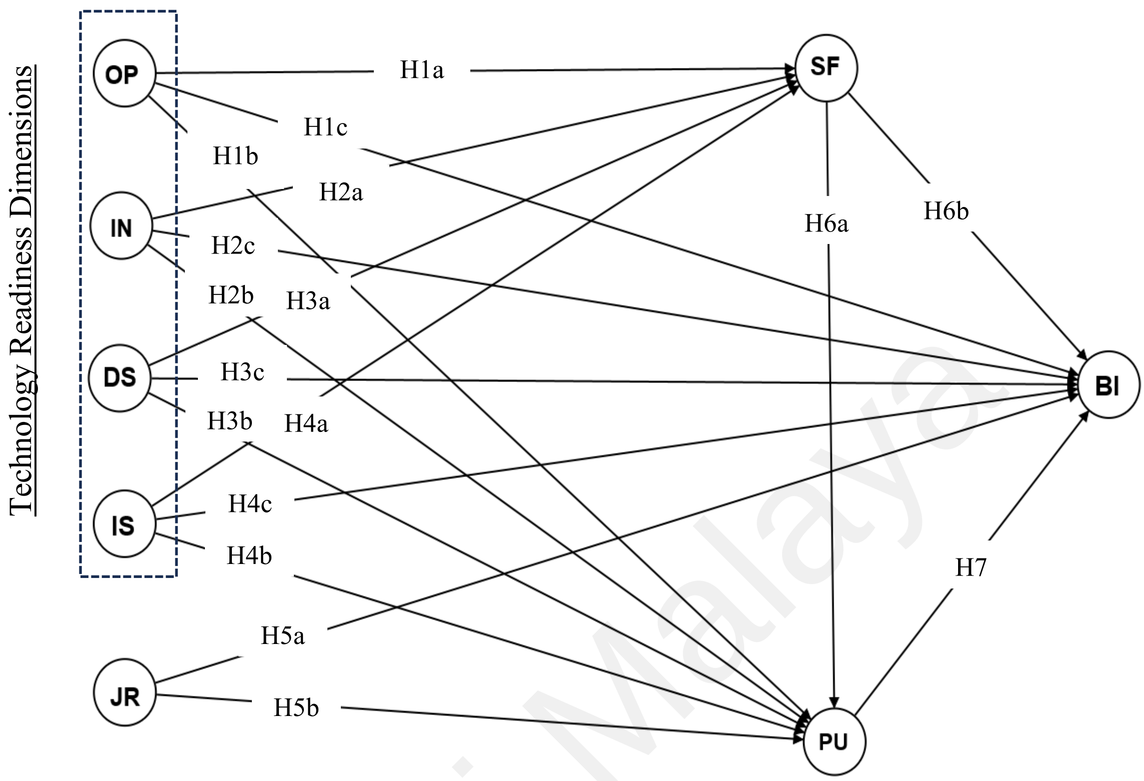

Figure 3.1: Conceptual Model of Behavioural Intention to Use AI

Notes. OP= Optimism, IN= Innovativeness, DS= Discomfort, IS= Insecurity, JR= Job Relevance, SF= Superior Functionality, PU= Perceived Usefulness, BI= Behavioural Intention

Table 3.1: Definitions and Sources of Key Variables

Variable	Abbreviations	Definition	Main Sources
DEPENDENT VARIABLE			
Behavioural Intention	BI	The degree to which an individual has formulated conscious plans to perform or not perform a specified future behaviour.	Davis (1989)
INDEPENDENT VARIABLES			
Dimensions of Technology Readiness	TR	Technology Readiness Index (TRI) dimensions measure individual predispositions towards technology adoption.	Parasuraman and Colby (2015)
Optimism	OP	A positive perspective towards technology, believing it offers increased control, flexibility, and efficiency.	Parasuraman and Colby (2015)
Innovativeness	IN	The tendency to be an early adopter and pioneer in the use of new technologies.	Parasuraman and Colby (2015)
Discomfort	DS	A sense of unease and lack of control when interacting with technology.	Parasuraman and Colby (2015)
Insecurity	IS	Distrust and scepticism regarding the reliability and functionality of technology.	Parasuraman and Colby (2015)
Job Relevance	JR	The extent to which an individual perceives technology as relevant to their job responsibilities.	Venkatesh and Davis (2000)
MEDIATING VARIABLES			
Perceived Usefulness	PU	The belief of using a particular system will enhance one's job performance.	Davis (1989)
Superior Functionality	SF	The extent to which a system or technology offers superior features and advanced functions over existing technologies.	Orel and Kara (2014); Wünderlich et al. (2013)

3.4 Hypotheses Development

The pervasive influence of AI across a multitude of sectors underscores its significant transformative capacity. Within the ambit of this transformation, a critical consideration is the manner in which professionals in sectors profoundly impacted by AI are adjusting and aligning with these technological advancements. In this regard, the field of accounting stands out as a particularly salient example. Given its inherent reliance on precision, the potential and actual integration of AI tools within accounting practices accentuates the urgency of gauging the BI of accounting students to embrace AI. This cohort's inclinations offer invaluable foresight into the prospective orientation of the accounting profession.

Historically, TR research approached this construct as a consolidated entity. However, recent academic discourse underscores TR's multifaceted nature, advocating that elements like optimism, innovativeness, discomfort, and insecurity individually shape the BI (Abu Bakar et al., 2021; Buyle et al., 2018; Faizal et al., 2022; Flavián et al., 2021; Kampa, 2023; Kuo et al., 2013; Walczuch et al., 2007; Yusuf et al., 2021). Examining these dimensions distinctly clarifies how specific attitudes towards technology influence perceptions of AI's functionality and its inherent value, subsequently driving its intended utilisation. Such interpretations accentuate the importance of interpreting TR as a composite of diverse elements rather than a singular monolith (Parasuraman & Colby, 2015).

The study, guided by Baron and Kenny's (1986) framework, conducts a detailed analysis of variable interactions in research, uncovering the mechanisms of their direct and indirect influences. Building on this solid theoretical base, the study hypothesises that SF and PU are key mediators in linking various aspects of TR with the intent to use AI technologies. Additionally, PU is posited as a mediator in the link between JR and the BI to use AI, aligning with Davis's (1989) TAM, which accentuates PU as a primary predictor of users'

BI, thereby reinforcing its pertinence in the AI discourse. Integrating these constructs within the framework established by Baron and Kenny (1986), the study meticulously delineates the complex causal relationships and underlying mechanisms that govern these interactions. This comprehensive approach not only adheres to stringent academic standards but also provides a holistic understanding of the determinants shaping the intention to incorporate AI within the accounting field.

Subsequent sections will present a slew of hypotheses grounded in prior research, elucidating the direct and mediated relationships between TR dimensions, JR, SF, PU, and the BI to use AI among accounting students. These hypotheses collectively carve out a robust theoretical foundation, paving the way for a comprehensive empirical exploration.

3.4.1 Optimism

In the realm of technology intentions, the psychological inclinations of individuals significantly influence their response to innovative advancements. Parasuraman and Colby (2015) elucidate how individuals with an optimistic orientation not only exhibit a higher receptiveness to state-of-the-art technologies like AI but also actively advocate for their superior merits. Optimism (OP) is rooted in cognitive psychology and engenders a viewpoint that perceives technology as beneficial in the present and potent with future possibilities. Such a bias towards technology propels individuals to acknowledge and champion the transformative capabilities of AI, recognising it as a superior alternative to traditional functionalities (Roy et al., 2018).

Blut and Wang (2019) support the view that optimists see innovative technologies as catalysts for paradigm shifts, aligning with the notion of optimists as technological visionaries. Their evaluation extends beyond immediate functionality, embracing the broad spectrum of transformative possibilities such technologies herald. Specifically, in the context of AI, an optimistic focus on its role in the industry revolution, resource optimisation, and the development of novel methods highlights the far-reaching impact of these advancements (Hecht, 2013).

Therefore, the trait of OP, notably prevalent among accounting students, inclines them to acknowledge the favourable aspects and prospective advancements intrinsic to AI technologies. This viewpoint, stemming from an optimistic disposition, empowers these students to envisage AI's broad and revolutionary impact within the accounting sector, especially in comparison to traditional accounting methods. Considering these theoretical foundations and empirical findings, the study proposes the following hypothesis:

H1 (a): Optimism exerts a direct, positive effect on the superior functionality of AI.

Optimism (OP) plays a crucial role in shaping perceptions of technology, particularly advanced systems like AI. OP induces a pivotal shift in the cognitive framework, moving beyond viewing technology as a mere operational tool. As Thompson et al. (1991) highlighted that this shift entails considering technology as an essential component of achieving strategic objectives. This reorientation enhances the perceived utility of technology, elevating its role in personal and professional settings.

Expanding on this perspective, Kampa (2023) illustrates that OP drives engagement and fosters a more nuanced and comprehensive exploration of technology's practicality. In contexts like mobile learning and by extrapolation in AI, an optimistic mindset propels users to delve into the effectiveness and potential applications of the technology with greater depth. This depth of engagement is crucial for unlocking and exploiting the full potential of technological systems. The focus is not merely on frequent utilisation but on a thorough understanding and mastery of what the technology can offer (Blut & Wang, 2019). An outlook inspired by OP is essential for leveraging the myriad benefits of modern technological systems like AI, enabling users to navigate and utilise these complex systems to their utmost capacity.

OP profoundly impacts how accounting students view and utilise AI, shifting their perspective from seeing it as a simple tool to a critical resource for success. This positive mindset encourages a more profound engagement with AI, deepening their understanding and skill in its application in both their academic journey and future career paths. Hence, OP is essential for students to fully leverage AI's value, leading to the hypothesis:

H1 (b): Optimism directly and positively influences the perceived usefulness of AI.

The TRA, proposed by Fishbein and Ajzen (1975), articulates a fundamental connection between individual attitudes towards technology and their subsequent BI. This principle posits that an optimistic mindset likely cultivates favourable beliefs of AI. Extending this notion, Taylor and Todd's (1995) Decomposed Theory of Planned Behaviour demonstrates how OP positively influences intentions to utilise technology. This is achieved by nurturing positive attitudes, enhancing motivation, and strengthening resilience during technological interactions.

Complementing these viewpoints, Walczuch et al. (2007) observe that individuals endowed with optimistic traits — notable for their adaptability and minimised avoidance behaviours — display consistently strong intentions towards engaging with technology. This inclination is maintained even when faced with adverse information and markedly increases their propensity to utilise technology in conjunction with a reduced tendency for risk aversion (Hwang & Good, 2014).

Within the specific domain of accounting education and the shift to AI-enhanced professional settings, the innate OP of students emerges as a crucial factor influencing their intention to integrate AI into their academic and career-oriented activities. This tendency is not merely a recognition of AI's capabilities but is deeply anchored in their optimistic disposition, naturally guiding them towards incorporating AI into their professional practices. Therefore, in light of these insights, the study proposes:

H1 (c): Optimism has a direct positive effect on the behavioural intention to use AI.

The predisposition towards technological advancements, particularly AI, entails more than mere faith in their potential; it necessitates an acknowledgement of their distinct advantages over existing solutions. Moore and Benbasat (1991) elucidated the concept of relative advantage', a notion akin to SF, which emerges as critically significant for optimistic individuals. This concept serves as a pivotal empirical foundation, transforming their optimistic predisposition into explicit intentions towards technology integration. When individuals discern an innovative technology as offering superior features, capabilities, performance, and unique attributes vis-à-vis existing alternatives, their propensity to use such technology increases. This perception serves as a conduit, facilitating the connection between their optimistic perspective and the intention to engage with AI.

Orlikowski and Gash (1994) highlighted the role of technological frames—mental structures that influence individuals' perceptions and interactions with technologies. Optimistic individuals, guided by these frames, are more inclined to recognise the potential of AI, reinforcing their intention to integrate it into their workflows. Building on this, Low et al. (2011) noted that these viewpoints encompass individuals' favourable appraisals of the enhanced capabilities of new technology, informed by their past IT experiences and assessments of the new technology's merits. This sense of superiority is pivotal, converting a general interest in AI into a definitive dedication to its application.

The positive disposition of these students regarding AI is projected to augment their comprehension of its sophisticated technical attributes and unparalleled excellence. This enhanced cognisance of AI's distinctive capabilities is presumed to significantly influence their aspirations to integrate AI into their scholarly and subsequent professional endeavours. The hypothesis, therefore, tailored to this context, is:

H1 (d): Optimism exerts an indirect positive influence on the behavioural intention to use AI, mediated by the superior functionality of AI.

In the pursuit of integrating technological innovations, personal attitudes, notably optimism (OP), are crucial. OP establishes a foundation for receptiveness towards contemporary technologies like AI; however, its effect on the genuine intention to utilise these technologies is channelled through more sophisticated mechanisms, primarily PU, as delineated in the TAM. TAM accentuates the primacy of PU in shaping BI towards technology use, underscoring its critical rather than peripheral role. Building upon this framework, individuals with an optimistic perspective tend to minimise their focus on negative aspects, fostering a more favourable attitude towards technology. This disposition results in a perception of technology as practical and effective, attributed to reduced concerns about potential drawbacks, thereby promoting a greater willingness to utilise it (Nugroho & Fajar, 2017). In academic settings, this tendency is particularly conspicuous among students who harbour an optimistic perspective. Their confidence in the utility of technology profoundly influences their PU of advanced technological tools like AI, framing these tools as vital for academic and professional progression. Research by Yusuf et al. (2021) and Blut and Wang (2019) corroborate this, revealing that such perceptions are consistently mirrored in their positively oriented intentions.

Overall, by nurturing a belief in the effectiveness and value of AI, OP results in a positive evaluation of its utility for enhancing professional skills and practices. This perception of AI's usefulness serves as a key intermediary, transforming their OP into a concrete intention to incorporate AI into their academic pursuits and future career paths. Therefore, the proposed hypothesis is:

H1 (e): Optimism positively influences the behavioural intention to use AI, mediated by the perception of AI's usefulness.

3.4.2 Innovativeness

In his influential work, Rogers (2003) delineates the attributes of early adopters, highlighting their cosmopolitan outlook, cognitive sophistication, and propensity for embracing new risks. These traits are particularly evident in their engagement with advanced technologies like AI. Far from being casual users, these individuals delve deeply into AI, exploring its expansive capabilities. This profound engagement resonates with Deci's (1975) Intrinsic Motivation Theory posits that internal motivations often outweigh external incentives. In the context of AI, this theory suggests that those driven by inherent curiosity are more likely to gain a comprehensive understanding of the technology, appreciating both its complexity and transformative power. Expanding on this idea, Midgley and Dowling (1978) note that individuals with a natural proclivity for innovation are especially adept at recognising and valuing the advanced functionalities of modern technologies like AI. This inclination towards innovation is pivotal in fostering a nuanced appreciation of AI's supremacy and understanding how these advancements augment the technology’s overall performance. Aligning with this perspective, Rogers's (2003) theory, 'relative advantage' refers to the degree to which an innovation like AI is seen as surpassing previous solutions. Thus, AI is regarded as a considerable evolutionary progress rather than merely a slight enhancement.

Students with a strong inclination towards innovation, coupled with intrinsic motivation and technical proficiency, are well-positioned to recognise and appreciate the advanced functionalities of AI. Their innovative mindset aligns with an understanding of AI's technical sophistication and its transformative potential in accounting practices. Based on the understanding of the relationship, the following hypothesis is proposed:

H2 (a): Innovativeness exerts a direct and positive influence on the superior functionality of AI.

In the evolving landscape of technology, particularly with advancements like AI, the role of individual psychological dispositions, especially innovativeness (IN) inclination, is crucial in shaping PU (Agarwal & Prasad, 1998). This inclination towards innovation transcends a mere affinity for newness; it entails a profound intellectual commitment. Their engagement with technological progress is rooted in a thorough understanding of how such innovations can address challenges and enhance processes (Lu et al., 2005b).

These individuals are distinguished by their readiness to embrace novel technologies, coupled with a propensity towards risk-taking and diligent pursuit of knowledge regarding the potential applications of these advancements. The comprehensive approach profoundly influences their perception of the technologies, particularly in assessing their practical utility. It positions them as pioneers in adoption and astute evaluators of technological capabilities (Chung et al. (2015).

Students with a strong inclination towards innovation are likely to perceive AI not merely as a novel technological tool but as a practical solution poised to enrich their educational experience and future professional practice significantly. Their propensity for innovation inclines them to view AI as a technology driven by utility, offering substantial value in augmenting their accounting skills and proficiency. In light of this, the study proposes the following hypothesis, acknowledging the distinctive role of accounting students in this technological evolution:

H2 (b): Innovativeness positively and directly influences the perceived usefulness of AI.

Rogers (2003) delineates innovativeness (IN) as the readiness to engage with emerging technologies at an initial stage, correlating this characteristic with an augmented likelihood of forming positive dispositions towards technology engagement. Lu et al. (2005a) further investigate the characteristics of individuals with high IN levels, observing that attributes such as audacity and inquisitiveness not only propel them towards active engagement with emerging technologies but also stimulate an innate motivation derived from the excitement of exploring technological novelties (Hemdi et al., 2016). This proclivity for innovation is fundamental for the dedicated exploration and experimentation with novel technological offerings, resulting in enhanced comprehension and integration of technologies such as AI (Simarmata & Hia, 2020). Such dedication cultivates an extensive mastery of these innovations, thereby positioning individuals not merely as adept connoisseurs but also as guiding figures in the evolution of AI-related domains (Pham et al., 2018).

In accounting education, students exhibiting a higher level of innovative traits, such as robust technological competence and an inquisitive mindset, are more likely to engage effectively with AI in their studies and subsequent professional pursuits. These attributes, indicative of an innovative temperament, amplify their eagerness to actively seek and utilise AI applications, driven by knowledge and passion. This positions them as potential trailblazers in their academic endeavours and professional pursuits. Based on these insights, the study posits the following hypothesis:

H2 (c): Innovativeness exerts a direct positive influence on behavioural intention to use AI.

From a conceptual standpoint, it is embedded in human nature for individuals to instinctively be drawn to the distinct aspects of innovation. This inherent predisposition towards innovation is commonly identified as 'inherent innovativeness'. As noted by Morton et al. (2016), this instinctive attraction to innovation is not merely about favouring newness; it involves a deep recognition and appreciation of the enhanced capabilities and superior functions of new technologies over existing ones. It reflects a profound understanding of the transformative impact these technologies can exert, compelling individuals to aspire to utilise them. Yi et al. (2006) highlight that this enhanced understanding is developed through active engagement and hands-on exploration, which sharpens the ability to discern the benefits of modern technologies compared to traditional ones. Consequently, this prompts a strategic choice to incorporate advanced technologies across various operational contexts. Agarwal and Prasad (1998) argue that individuals possessing high Innovativeness (IN), by virtue of their cognisance of recent technological advancements and ability to swiftly acquaint themselves with such innovations, are more inclined to regard innovative technologies as notably effective and superior. This discernment, in turn, strengthens their intent to utilise these technologies due to an appreciation of their advanced features and supremacy.

AI features like enhanced data analytics, automated financial reporting, and fraud detection algorithms are particularly attractive to students inclined towards innovation. This interest goes beyond a basic preference, playing a vital role in motivating the integration of AI into various accounting applications. The awareness and rapid adaptation to AI's functionalities among accounting students foster a firm intention to employ AI, leveraging its superior benefits in their academic and professional endeavours. Given these insights, the study proposes the following hypothesis:

H2 (d): Innovativeness positively influences the behavioural intention to use AI, mediated by the perception of AI's superior functionality.

Davis's (1989) TAM highlights perceived usefulness (PU) as a key driver in technology integration, with individual IN influencing the intention to use technologies like AI. This analysis is further validated by Fan and Wang (2023), highlighting that PU plays a critical role in shaping students' perspectives concerning the role of AI in fostering learning, productivity, and career potential, thereby affirming its integral role in the framework of BI. Lin et al. (2007) provide a significant contribution to the discourse by illustrating that individuals possessing high levels of inherent innovativeness engage in a rigorous evaluation of technology's utility, particularly in sectors prioritising efficiency, such as accounting.

This evaluation process encompasses a cognitive routine wherein users critically assess the potential of AI to enhance their operational efficiency, prioritising practicality and effectiveness. Additionally, Blut and Wang (2019) highlight that individuals with an innovative orientation do not merely recognise the capacity of technology to solve specific problems; they also strategically integrate technology use with their personal and professional aspirations. This strategic alignment fosters a more deliberate intention towards effective technology adoption and utilisation.

The inherent predisposition of accounting students towards innovation, coupled with a judicious evaluation of AI's utility, ideally situates them to utilise AI to its fullest potential. This amalgamation of IN and perceived utility engenders a more intensive interaction with AI. Such an integration is poised to revolutionise accounting methodologies and establish a new paradigm of educational and professional excellence. Therefore, the study proposes the following hypothesis:

H2 (e): Innovativeness is posited to have a positive indirect effect on the behavioural intention to utilise AI, with perceived usefulness acting as the mediating factor.

3.4.3 Discomfort

Within the TR framework, as delineated by Parasuraman (2000), discomfort (DS) with technology emerges as a pivotal psychological state adversely impacting users' perceptions and engagements with contemporary technological systems. This specific state triggers a range of emotional and psychological responses, including unease, anxiety, or apprehension among individuals. Such reactions can consequently cloud the effective recognition and valuation of the technology's SF. Expanding upon this model, Moore and Benbasat (1991) emphasised that an individual's comfort level with technology significantly influences their perception of SF. Individuals more at ease with technology are generally more inclined to acknowledge its superiority, while those less comfortable tend to concentrate on potential obstacles and challenges disproportionately. Additionally, studies conducted by Ferreira et al. (2014) and Roy et al. (2018) substantiate this view, indicating that individuals possessing elevated levels of DS are likely to perceive innovative technology as less effective in comparison to current methods or technologies. This phenomenon is attributed to DS fostering a negative bias, which results in individuals underestimating or disregarding the advanced features of the new technology.

Within the domain of AI, especially considering its advanced capabilities in machine learning and the processing of large data sets, accounting students who possess minimal technical knowledge could potentially face heightened levels of DS. This may inhibit their complete grasp and appreciation of the cutting-edge functionalities presented by AI within the accounting discipline. Consequently, the refined hypothesis can be stated thus:

H3 (a): Discomfort exerts a direct and negative influence on the superior functionality of AI.

Within the context of technology engagement, discomfort (DS) stands as a significant psychological barrier that markedly affects an individual's assessment of a technology's utility. According to Blut and Wang (2019) DS may lead individuals to focus disproportionately on the perceived complexities and challenges associated with technology, diminishing its potential value and utility. This adverse psychological and emotional reaction can significantly reduce the perceived value of the technology, ultimately influencing its overall PU. Bhattacherjee and Hikmet (2007) delineate three primary determinants of technology-induced anxiety: perceived threat, resistance to change, and compatibility with extant work processes. These elements collectively cover apprehensions such as dread of relinquishing control, reluctance towards adopting novel systems, and a sensed discordance with established protocols, frequently causing individuals to perceive technology as inefficient.

Given this context, computer anxiety warrants special attention. This form of distress, intricately linked to computer usage, exerts a considerable influence on technological perceptions. Elevated levels of computer anxiety are commonly correlated with negative sentiments towards computers and technological advancements, thus influencing the PU of these systems. Furthermore, computer anxiety can undermine an individual's self-efficacy and mastery over technology, negatively affecting their perception of technology's utility (Igbaria et al., 1994).

For accounting students, DS may stem from being overwhelmed by AI's intricate nature or anxiety about integrating it into established methodologies. This may lead to an excessive emphasis on the perceived obstacles, thereby overshadowing AI's potential to streamline accounting tasks and improve data analysis. This skewed perception could hinder their ability to acknowledge the full spectrum of AI's applicability, causing them to underestimate its value. Consequently, the proposed hypothesis is:

H3 (b): Discomfort has a direct negative effect on the perceived usefulness of AI.

Discomfort (DS), defined as apprehension towards modern technologies, significantly impedes technology integration efforts. This psychological state, as elucidated by Ramírez-Correa et al. (2019) leads to perceptions of technological complexity, which erodes user confidence and hinders engagement. Prodanova et al. (2018) and Ismail and Wahid (2020) extend this notion, arguing that DS contributes not only to a daunting perception of technology but also to avoidance behaviours and heightened anxiety regarding innovative technological advancements. This results in altered engagement patterns, marked by excessive caution, negative perceptions towards technology innovation, a preference for minimal interaction, and, at times, proactive avoidance of technology (Doronina, 1995). Users affected by DS or related anxiety often require more support to navigate these technologies or, alternatively, may lean towards simpler solutions, thereby decreasing the probability of adopting advanced technologies like AI (Martens et al., 2017).

In the context of accounting academia, DS among students, attributed to perceived AI complexity and related anxieties, can critically deter their propensity to utilise such technologies. This aversion can lead to a decline in their confidence to apply AI tools, significantly influencing their intention to integrate AI into their academic and professional pursuits. Consequently, the proposed hypothesis is:

H3 (c): Discomfort directly and negatively influences the behavioural intention to use AI.

The mediation of superior functionality (SF) in the relationship between discomfort (DS) and the intention to use technology is critically shaped by users' perceptions and interactions with technological attributes. Chen et al. (2019) highlight that frustration emerges from the technology's inherent intricacies and concerns regarding users' abilities to effectively utilise these advanced capabilities. Additionally, Schuh et al. (2019) underscored that the escalation in technological sophistication accompanying advanced functionalities may foster a perception that these tools are primarily designed for individuals with considerable technical expertise rather than the average user. Hence, the prevailing belief that effective use of such technology demands frequent communication with technical support or comprehensive knowledge of detailed service manuals further solidifies this hesitance. Consequently, these aspects contribute to a sense of insufficient technical proficiency, which can obstruct users' proficient employment of AI services (Carsten et al., 2018). Moreover, users often assess advanced functionalities against the effort and resources needed for adaptation. Lu et al. (2012) note that this evaluation can heighten reluctance to engage, particularly when the perceived effort or complexity is deemed to outweigh the benefits, resulting in an exaggerated perception of the challenges and nuances associated with technological attributes and functionalities.

While AI offers superiority over conventional accounting methods, its perceived complexity can induce unease among students, especially when they anticipate the need for additional effort and support. The advanced nature of AI, while beneficial, can become a barrier if perceived as overly challenging, affecting students' willingness to integrate it into their academic and professional endeavours and influencing their engagement with the technology. The hypothesis, therefore, considers these nuanced interactions:

H3 (d): Discomfort indirectly and negatively influences the behavioural intention to use AI, mediated by its superior functionality.

Discomfort (DS) with technology, characterised by feeling overwhelmed or intimidated, profoundly influences users' perceptions of its practical utility and their inclination to interact with it. This phenomenon is particularly evident when users face intricate interfaces or lack sufficient training, leading to challenges in effective system use. Godoe and Johansen (2012) highlight that this struggle can significantly diminish the perceived practical value of the technology. Unfamiliarity with emerging technologies may engender a sense of DS, consequently diverting individuals' attention from evaluating the utility of these innovations, which in turn negatively impacts their perceived value. This inclination towards the familiar fosters a predilection for existing or simpler technologies, ultimately manifesting a subconscious resistance to utilising advanced or novel technological solutions (Kuo et al., 2013). Extending this idea, Chen and Lin (2018) and Walczuch et al. (2007) demonstrate that DS with technology, arising from feelings of being disempowered, significantly affects users' perception of the technology and their intention to engage with it. Thus, DS often leads to technology being perceived as convoluted, which can result in its undervaluation and subsequently diminish its PU.

Accounting students' DS with AI, stemming from being overwhelmed and lacking mastery, can negatively influence their PU and, subsequently, their willingness to engage with it. DS might stem from the hurdles in adapting to AI technology and a lack of belief in its practical value for accounting tasks, impacting their intention to utilise AI in their studies and future careers. Thus, synthesising these insights, the proposed hypothesis is:

H3 (e): Discomfort negatively influences behavioural intention to use AI, mediated by the perception of AI's usefulness.

3.4.4 Insecurity

Insecurity (IS) towards technology, as conceptualised by Parasuraman and Colby (2015), is characterised by a lack of trust in its reliability and apprehensions regarding potential negative repercussions. This viewpoint significantly amplifies concerns over security threats such as unauthorised access, data breaches, and the misuse of information. Concentrating on these detrimental aspects may result in an undervaluation or oversight of the security features inherent in contemporary technologies (Walczuch et al., 2007). In pivotal sectors such as accounting, where the handling of confidential financial information is paramount, this form of scepticism could prompt students to prefer traditional methods over the adoption of technological advancements.

This scepticism often revolves around the advanced and complex features of technology, which play a pivotal role in enhancing its functionality and supremacy. Roberts et al. (2021) highlight that scepticism concerning the efficiency and necessity of these features, particularly in contrast with existing technologies, can lead to a diminished perception of their significance. This altered perception, exacerbated by apprehensions regarding the long-term reliability and consistency of these complex features, poses a significant obstacle to fully appreciating the core capabilities of technologies such as AI (Kesharwani & Singh Bisht, 2012).

Inevitably, accounting students may not fully comprehend the transformative effects of AI, influenced by prevailing concerns about the system’s vulnerabilities and dependability. This results in a diminished acknowledgement of AI’s distinct and superior capabilities (Reepu & Arora, 2022). Therefore, the hypothesis to be investigated is:

H4 (a): Insecurity has a direct negative effect on the recognition of superior functionality of AI.

The notable hesitance in relying on technology, particularly when it is viewed as unreliable, indicates a deep-seated reluctance among users. This hesitancy extends beyond a mere temporary reaction, fundamentally shifting the perceived efficacy of technology in everyday tasks and strategic objectives (Ayyagari et al., 2011). Such a perspective markedly changes the perceived value of technological solutions.

This feeling of IS often manifests as a resistance to integrating technology smoothly into established routines. Users exhibit concerns about excessive reliance on systems that lack their complete trust or comprehension, especially when there is uncertainty regarding these systems' ability to meet expectations (Cecutti et al., 2021; Larasati et al., 2017). This concern plays a pivotal role in impeding the effective assimilation of new technological tools into established frameworks, thereby influencing their perceived efficacy. Moreover, the assessment of perceived risks versus benefits plays a crucial role in shaping the overall perception of technology's effectiveness. Johnson et al. (2008) note that when perceived risks of technology exceed its practical value, it reduces confidence in its value, resulting in a more cautious approach to its use.

In the field of accounting, student concerns regarding AI, especially those related to its reliability and complexity, significantly impact their PU. Such concerns often result in a biased evaluation, where the perceived risks of AI overshadow its potential benefits, like enhanced data processing efficiency and analytical precision. This leads to a reduced perception of AI's practical value in accounting tasks, underscoring the importance of transparent communication and stringent security measures to address and alleviate these concerns. Thus, the following hypothesis is proposed:

H4 (b): Insecurity has a direct negative effect on the perceived usefulness of AI.

Technological insecurity (IS) significantly impacts user willingness to engage with AI in accounting, a notable trend in advanced technology usage. Concerns about security and data fraud, as highlighted in the studies by Blut and Wang (2019) and Oliveira et al. (2016), constitute substantial obstacles to the utilisation of these technologies, particularly in the field of accounting, where handling sensitive financial information is paramount. These fears, rooted in a lack of trust and the perception of heightened risks, notably impact the decision to employ AI-driven systems. Moreover, in financial sectors like accounting, characterised by direct, trust-based client relationships and the need for effective communication of complex financial matters, additional concerns may arise. Flavián et al. (2021) note that fears related to technology dependence and a potential reduction in the quality of personal interactions are especially pronounced. Such concerns can deter professionals from fully embracing AI, as it is perceived as a threat to the vital personal engagement and tailored service that are foundational in the field.

Concerns about data security, the reliability of AI systems, and their impact on traditional accounting practices could lead to reluctance by accounting students to integrate AI into accounting functions and decision-making. Addressing this, Haenlein and Kaplan (2019) suggest that building a foundational understanding of AI is key in mitigating these IS. By demystifying AI and educating users in accounting about its core functionalities, these fears can be alleviated. Therefore, the hypothesis stands as follows:

H4 (c): Insecurity has a direct negative effect on the behavioural intention to use AI.

In the technological landscape, insecurity (IS) significantly influences user intentions, particularly when confronted with the SF of innovative technologies. As Moore and Benbasat (1991) note, the perception of new technology as markedly superior to existing methods can create a sense of pressure, especially if current practices are viewed as less effective. However, this scenario is further complicated by the uncertainty associated with the utilisation of contemporary technology. An overemphasis on its SF can exacerbate these IS, leading to increased resistance or reluctance, as users may feel overwhelmed by the perceived technological leap. Roy et al. (2018) and Lam et al. (2008) reinforce this concept, illustrating how chronic IS can distort perceptions of modern technologies' SF, especially under perceived risks. This IS can cause users to misjudge the advanced capabilities and efficiencies of these technologies. Similarly, Yen (2005) observed that consumer perceptions of IS regarding a service can lead to diminished capability or reliability, adversely affecting their overall satisfaction with the service offering.

For accounting students encountering AI, these insights imply that IS about the technology, particularly regarding its sophisticated capabilities, can negatively impact their intention to engage with it. When students encounter AI as significantly more advanced yet feel IS about their ability to use it effectively, this can lead to a reluctance to engage with AI despite acknowledging its SF. Addressing these insecurities and providing a better understanding of AI's functionalities is crucial in encouraging its use in accounting practices. To encapsulate these interrelations and the discussion, the following hypothesis is proposed:

H4 (d): Insecurity negatively influences behavioural intention to use AI through the mediator, superior functionality.

The perception of insecurity (IS) that users experience during their interactions with technology, particularly AI, significantly influences their perceptions regarding the technology's PU and their BI to utilise it. IS, defined by diminished trust in the technology's reliability, generally originates from uncertainties pertaining to its effectiveness. Tsikriktsis (2004), Parasuraman (2000), and Panday (2018) have highlighted that such perceptions of IS frequently correlate with lower usage of technology. This is attributed to the reservations it engenders regarding the technology's efficiency, which, in turn, diminishes the users' intention to employ it.

The insights from Lu et al. (2005a) and Walczuch et al. (2007) are crucial in understanding the impact of user apprehensions on the PU of technologies like AI. They draw attention to the fact that specific concerns, such as potential biases, issues with transparency, and fears of AI supplanting human skills, can adversely affect users' perceptions of AI's usefulness. These concerns are often seen as inherent risks associated with using AI. Particularly, trepidation regarding AI's safety, security or reliability can provoke doubts about its effectiveness. Such doubts can lead to diminished confidence in AI's utility, influencing users' willingness to utilise the technology. Addressing these concerns is, therefore, vital to improving the PU of AI and promoting its application.

The correlation between IS regarding AI and the inclination to interact with it holds particular significance for accounting students. IS, arising from perceived risks, security concerns, or uncertainties related to AI, has the potential to mould their perception of AI as less valuable in both their academic pursuits and future professional engagements. This altered perception of the utility of AI can, in turn, impact their readiness to utilise AI technologies. Therefore, the following hypothesis is posited:

H4 (e): Insecurity negatively influences behavioural intention to use AI through the mediator, perceived usefulness.

3.4.5 Job Relevance

The correlation between job relevance (JR) and perceived usefulness (PU) holds significant importance in technology utilisation, particularly within specialised domains such as accounting. JR pertains to the extent to which a technological tool aligns with an individual's professional objectives and responsibilities. Venkatesh and Davis (2000) underscore the necessity for users to perceive the clear benefits of technology in their current or future professional duties for successful integration into work processes. Students' assessment of AI technology goes beyond academic curiosity to include its practical relevance for their future professional roles, particularly focusing on how well AI aligns with the demands of these roles (Alharbi & Drew, 2014).

Similarly, Thompson et al. (1991) define 'perceived job fit' as the belief in technology's ability to improve job performance, specifically through enhanced information accessibility, decision-making, and task efficiency. A strong alignment between technology and job requirements generally leads to a higher PU, especially if the technology aids key job functions and improves productivity and work quality (Goodhue, 1988; Rui-Hsin & Lin, 2018).

Applying these insights to AI-based robotics, it is evident that finely tuned systems to meet specific job task requirements can significantly improve learning and operational processes. The degree of alignment between such technology and the anticipated job tasks of students in fields like accounting directly correlates with its PU. From these insights, the following hypothesis is formulated:

H5 (a): Job relevance has a direct positive effect on the perceived usefulness of AI.

The nexus between job relevance (JR) and behavioural intention (BI) to engage with technology is a focal point in the study of technological integration among students. It is postulated that students' determination of technology's alignment with future career enhancement engenders a robust propensity to utilise said technology. The imperative of aligning academic endeavours with occupational aspirations is emphasised as non-negotiable, with Smit et al. (2020) noting that a significant share of student engagement in specific subjects or technologies is contingent on their perceived alignment with future career paths. With the advent of AI across multiple sectors, from healthcare to finance, and its ensuing redefinition of professional landscapes, students — especially those in tertiary education — are compelled to acknowledge the criticality of AI proficiency. Davis et al. (1989) corroborate this stance, positing that students' recognition of a technology's relevance to their future roles incites an intensified intent to use it. Kar et al. (2021) contribute to this discourse by asserting that appreciating the relevance of these technologies to professional objectives is essential for driving mastery and enhancing employability and skill sets within chosen career fields.

Consequently, this collective body of research illustrates the fundamental role of JR in influencing students' BI towards specific technologies. For instance, students who recognise the escalating significance of AI in fields like accounting tend to be more inclined to interact with these technologies during their academic pursuits and subsequent professional endeavours. This recognition of AI's relevance reflects an understanding of the evolving demands of the profession and the necessity to integrate such technologies into their skillset. Thus validating the hypothesis:

H5 (b): Job relevance has a direct positive effect on the behavioural intention to use AI.

The interrelationship between job relevance (JR) and behavioural intention (BI) to use technology, as analysed through a mediating framework, is intricately linked to an individual's perception of the technology's utility. In their expansion of the TAM, Venkatesh and Bala (2008) argue that foundational beliefs about a technology's relevance to job tasks initiated the evaluative process. Nonetheless, the individual's perception of the technology's utility steered it towards a more definitive impact on their BI. This concept is further supported by the work of Venkatesh et al. (2003) in the UTAUT. Their findings reveal a significant relationship between expectancy—which encapsulates performance and effort expectancy—and BI, highlighting that a technology's PU in fulfilling professional duties enhances the intention to utilise it.

In a related vein, Mathieson (1991) suggested that when individuals perceive technology as useful, particularly due to its relevance to their jobs, it creates a cascading effect on the usage intentions. Son et al. (2012) further contextualise this relationship, suggesting that PU acts as the bridge or conduit, amplifying the effects of foundational beliefs like JR. This mediating role suggests that when technology is both relevant to an individual's job and perceived as useful, the intention to use it is significantly bolstered. Accounting students, navigating a landscape increasingly influenced by AI, assess technology on its inherent value and how it aligns with and enhances their future professional roles. Their perception of AI's usefulness, informed by its relevance to accounting tasks and functions, directly influences their intention to engage with AI tools. Thus, the hypothesis tailored for this context is as follows:

H5 (c): Job relevance indirectly influences the behavioural intention to use AI through the mediator, perceived usefulness.

3.4.6 Superior Functionality

Rogers (2003) articulates that superior functionality (SF) is determined through an assessment of a technology's comparative advantages and sophisticated features. These elements are crucial in moulding users' perceptions of its value and its potential advantages. This critical evaluation significantly impacts users' perceptions of the technology's utility, relating to its practical benefits and applications (Davis, 1989). Recognition of a technology's superior functionality in comparison to existing alternatives heightens the probability of users perceiving it as advantageous, especially in terms of enhancing productivity and performance outcomes (Ferreira et al., 2014; Wünderlich et al., 2013).

The SF of AI in tackling challenges related to data management, regulatory compliance, and fraud prevention within the accounting sector enhances its perceived utility among practitioners (Garaus et al., 2016). Thus, recognising AI's advanced capabilities in these critical domains prompts accounting students to acknowledge its substantial value. This appreciation derives from the insight that AI not only aligns with the stringent standards of the accounting profession but offers significant practical merits that enhance operational and academic endeavours. Significantly, the link between AI's advanced functionalities and practical applicability is vital in accounting—a discipline where precision and operational efficiency are paramount. Therefore, based on this discussion, the following hypothesis is proposed:

H6 (a): Superior functionality exerts a direct positive effect on the perceived usefulness of AI.

Superior functionality (SF), characterised by advanced features, cutting-edge capabilities, and technological innovation, significantly influences users' attitudes towards innovative technologies. The allure of SF lies in its dominance and pre-eminence, motivating users to integrate these advancements into their educational or professional environments. The correlation between the technology's SF and the greater likelihood of its early utilisation is well-recognised (Eastlick & Lotz, 1999). Users often exhibit a preference for technologies that offer a higher level of functionality, which includes enhanced features and capabilities. This predilection transcends the mere practical applications of the technology, extending to an appreciation of its inherent advanced characteristics (Lee et al., 2003).

In the context of AI technologies, the assessment of SF involves a comparative analysis, where users evaluate new technologies against traditional methods or existing solutions (Riquelme & Rios, 2010). Features such as predictive analytics, sophisticated fraud detection capabilities, and real-time financial reporting are particularly valued in AI technologies. This evaluation process, focusing on the specific attributes of the technology, underscores the importance of SF in influencing students' engagement and the decision to utilise AI in their academic and professional endeavours. In light of this, the detailed hypothesis is formulated as follows:

H6 (b): Superior functionality has a direct positive effect on the behavioural intentions to employ AI.

3.4.7 Perceived Usefulness

Perceived usefulness (PU) emerges as a central construct in the TAM, indicative of the belief that employing a specific technology will elevate job performance (Davis, 1989). This concept posits that individuals are inclined to utilise a technology if they perceive it as instrumental in augmenting their job performance, thereby streamlining processes and optimising task outcomes (Davis et al., 1992). PU has been identified as a potent predictor of BI to use technology (Chang & Tung, 2007; Liu & Huang, 2015; Poong et al., 2016; Venkatesh & Bala, 2008; Verkijika, 2019), with its influence spanning across diverse environmental and technological paradigms (Buyle et al., 2018; Chin & Todd, 1995; Sun & Zhang, 2006).

Within the academic sphere, especially in accounting education, assessing the efficacy of AI in augmenting performance is pivotal to its PU. When accounting students evaluate AI, their focus centres on its potential to refine accounting procedures and augment the precision and efficiency of financial tasks, thereby enhancing their educational and professional skill sets. The perception of AI's utility in these aspects is expected to be a crucial factor in determining their BI to integrate AI into their academic and professional repertoire. Hence, the hypothesis can be formulated as follows:

H7: Perceived usefulness exerts a direct positive effect on the behavioural intentions to use AI.

CHAPTER 4: METHODOLOGY

4.1 Introduction

The research framework for this study is conceptualised as a cross-sectional, cause-and-effect analysis executed within a defined timeframe utilising a survey methodology for primary data collection. The underlying philosophy aligns with a positivist stance, emphasising an objective representation of reality and adhering to rigorous scientific research methodologies for reliable, systematic responses to posed inquiries (Davis & Fisher, 2018). In alignment with this positivist ethos, a quantitative research methodology is utilised, aimed at the measurement, quantification, and statistical evaluation of the phenomenon under study, distinguishing itself from qualitative methodologies that concentrate on comprehensive descriptions and nuanced interpretations (Coolican, 2009). The study's structure is inherently deductive, orchestrating the research trajectory in accordance with hypothesis generation rooted in established theoretical constructs, thus ensuring a systematic approach where all facets of the investigation are meticulously predefined prior to the commencement of data gathering (Kumar, 2014). Given the theoretical backdrop of this investigation, the selection of a quantitative methodology is adjudged to be the most apt.

The research scope encapsulates third and fourth-year undergraduate accounting students from four distinct institutions: University of Malaya (UM), University Kebangsaan Malaysia (UKM), Sunway University (SU), and Multimedia University (MMU). Selection criteria for these universities are primarily based on their pertinence to the research subject as well as geographical accessibility for the investigator. The target population for the study encompasses approximately 1,244 accounting students across these chosen universities to achieve a sample size of 294 students. Despite diligent efforts, the data collection process via a computer-administered survey resulted in a limited participation of 136 students, equating to a response rate of approximately 46.26%. The implications of this participation rate will be extensively discussed and analysed in the following sections.

4.2 Questionnaire Development

In this scholarly inquiry, meticulous care was devoted to ensuring the validity and reliability of the quantitative survey instrument, with constructs being scrupulously derived from pertinent academic literature. The development of the questionnaire involved a comprehensive review of existing research studies to identify relevant constructs and measurement scales. Subsequently, these identified constructs were adapted to align with the specific focus of this study, ensuring accurate capture of the intended dimensions. Additionally, the research supervisor critically reviewed the preliminary version of the questionnaire to ascertain its appropriateness and relevance to the study's objectives.

The questionnaire was bifurcated into two principal sections: demographic information and specific constructs. The demographic segment encompassed data such as academic year, ethnicity, university affiliation, nationality status, and gender. For assessing the dimensions of technology readiness (TR), including optimism, innovativeness, discomfort, and insecurity, the 16-item scale from the TRI 2.0, developed by Parasuraman and Colby (2015), was employed. Job relevance (JR) was gauged using two items derived from the work of Venkatesh and Davis (2000), and the construct of superior functionality (SF) incorporated four items, drawing upon the research of Orel and Kara (2014) and Wünderlich et al. (2013). The assessment of perceived usefulness (PU) entailed six items adapted from Davis (1989), and the final segment, focusing on the behavioural intention (BI) to use AI, was constructed with three items based on the framework established by Davis (1989). Responses were solicited using a 7-point Likert scale, ranging from strong disagreement (1) to strong agreement (7), enabling respondents to precisely indicate their level of agreement with each statement. Table 4.1, provided below, summarises the measurement sources for these variables, delineating the academic grounding of each construct within the survey.

Table 4.1: Measurement of Variables

Variables	Main Sources
Technology Readiness Dimensions (Optimism, Innovativeness, Discomfort, Insecurity)	Parasuraman and Colby (2015)
Job Relevance	Venkatesh and Davis (2000)
Superior Functionality	Orel and Kara (2014) Wünderlich et al. (2013)
Perceived Usefulness	Davis (1989)
Behavioural Intention to Use	Davis (1989)

4.3 Population and Sample

4.3.1 Respondents

This research will focus on third and fourth-year undergraduate accounting students from four distinguished Malaysian universities: University Malaya, University Kebangsaan Malaysia, Sunway University, and Multimedia University. The rationale for selecting these students hinges on their advanced academic progression, which ensures a profound understanding of their curriculum, a more nuanced awareness of industry requisites, and the alignment of their academic endeavours with the professional landscape. In contrast, students in the initial stages of their undergraduate journey might lack a comprehensive grasp of accounting principles and the industry's anticipations. Such a deficiency could compromise the precision and trustworthiness of their feedback. Hence, focusing on third and fourth-year students becomes pivotal for eliciting data that mirrors genuine and informed perspectives on the incorporation of AI within their discipline.

4.3.2 Universities Selection Rationale

The selection of University Malaya, University Kebangsaan Malaysia, Sunway University, and Multimedia University for this study was based on a balanced consideration of their geographical location, alignment with the study's emphasis on AI in accounting, and overall institutional prestige.

The University Malaya (UM) in Kuala Lumpur is an esteemed institution renowned for its rigorous accounting program. The integration of technology is prominently displayed through a range of research initiatives conducted at UM, focusing on the role of technology in the accounting field. These initiatives exemplify UM's unwavering commitment to remaining at the forefront of advancements in accounting practices. The diverse perspectives of UM's student body further enhance the value of the research, providing valuable insights into the utilisation of AI in accounting.

University Kebangsaan Malaysia (UKM), located in Bangi, Selangor, is a premier public university renowned for its exceptional accounting program. The program is celebrated for its extensive curriculum, accredited by leading accounting organisations and meets global standards. It offers a range of specialisations and practical experiences across various tracks, ensuring that students are thoroughly equipped to engage with complex concepts, including AI. UKM exhibits a strong commitment to technological advancement by purposefully integrating AI and other advanced technologies in its research endeavours, especially within the Graduate School of Business. This emphasis on embedding state-of-the-art technologies in their research projects, prominently featured in the Bangi Management Review, highlights UKM's dedication to maintaining a leading position in innovation and development within the accounting sector. This commitment fosters a rigorous academic environment, priming students with the necessary knowledge and perspective to effectively integrate AI into their future professional endeavours.

Sunway University (SU), a beacon in Malaysian education, boasts a robust and attuned curriculum to the fluidity of the global business domain. Its collaborations with esteemed institutions like Lancaster University elevate its global standing and interweave global educational standards and practices. Moreover, its affiliations with preeminent accounting bodies, such as the Association of Chartered Certified Accountants (ACCA), the Chartered Institute of Management Accountants (CIMA), the Certified Public Accountant (CPA), and the Institute of Chartered Accountants in England and Wales (ICAEW), underscore its dedication to shaping students to meet the exacting demands of the accounting world. Situated in the heart of the technologically advanced Sunway City township, SU seamlessly integrates technological proficiency into its academic ethos. Given this comprehensive academic and technological framework, SU's undergraduate accounting students present a prime cohort for this study, ensuring a nuanced understanding of the research objectives.

Multimedia University (MMU) is distinguished for its technology-centric curriculum and robust emphasis on research excellence. The university's steadfast dedication to the incorporation of avant-garde technology within its academic framework positions its students at the forefront of technological innovation. Awarded the Premier Digital Tech University Status in 2017, MMU exemplifies its commitment to harmonising academic pursuits with the dynamic requirements of the industry. The curricula, guided by industry insights, ensure the educational content is contemporary, pertinent, and resilient to future changes. Notably, half of MMU's programs, including accounting, are meticulously designed to align with the burgeoning sectors, mirroring the institution's progressive approach to education.

The inclusion of various institutions in this research is designed to capture a wide array of perspectives on the role of AI in accounting. This approach facilitates a thorough understanding of the behavioural intentions of accounting students from diverse university environments. The findings from this study are poised to inform the integration of AI into accounting curricula and assist policymakers and educators in augmenting the role of AI within the field of accounting.

4.3.3 Public and Private Universities

To attain a comprehensive understanding of accounting students' perceptions regarding AI, this study meticulously examines groups from both public and private universities. This approach is grounded in the recognition that students hailing from these distinct types of institutions often possess dissimilar experiences and expectations, thus affording a varied range of perspectives. Through the incorporation of both public and private universities, the research achieves a broader spectrum of viewpoints and augments the depth of analysis regarding the intention to utilise AI in accounting.

4.3.4 Sample Size

The research team meticulously calibrated the sampling methodology to achieve an optimal balance between ensuring adequate representation of the target population and maintaining the practicality and efficiency of data collection processes. The primary objective of this study is to rigorously test the postulated hypotheses concerning the behavioural intent of accounting students to utilise AI. Additionally, a secondary analytical examination will be conducted to contrast the average perceptions of AI among accounting students at public and private universities. Participants' responses will be collectively analysed at a group level, with the intent to uncover significant trends or patterns in their perceptions and intentions regarding AI.

Convenience sampling was employed as the methodological strategy, recognised for its pragmatic and efficient nature in securing a sample of accessible and willing participants (Saunders et al., 2019). This approach has proven advantageous in scenarios constrained by limited resources and time (Bryman & Bell, 2015). The researcher meticulously determined the population size of the targeted student group through proactive engagement with the respective academic institutions, specifically by contacting university representatives to ascertain the accurate population size. The aggregate population of third and fourth-year undergraduate accounting students across the selected universities is approximately 1,244. The distribution encompasses 132 third-year and 161 fourth-year students at UM, 136 third-year and 162 fourth-year students at UKM, 403 third-year students at Sunway University, and an estimated 250 combined third and fourth-year students at MMU. The research entailed a precise calculation to establish a sample size of 294 students, designed to achieve a 95% confidence level and a 5% margin of error. This approach adheres to the established social science research standards (Bryman & Bell, 2015; Saunders et al., 2019), thus ensuring the representativeness and reliability of the research findings.

Despite the inherent limitations of convenience sampling in terms of generalisability, the incorporation of multiple academic institutions into the study is intended to augment the representativeness of the sample, consequently enhancing the study's overall reliability (Saunders et al., 2019). The chosen confidence level of 95%, combined with a 5% margin of error, strikes a deliberate balance between precision and resource management. This parameter suggests that the findings of the study are projected to reside within the stipulated margin of error for 95 out of every 100 analogous samples, thus imparting a commendable degree of confidence in the outcomes (Bryman & Bell, 2015; Singh & Masuku, 2014). This methodological approach ensures that the study is conducted with rigour and feasibility without compromising its representativeness and integrity (Saunders et al., 2019).

4.4 Data Collection

Prior to distributing the questionnaire, an application for ethics clearance was submitted to and approved by the University of Malaya Research Ethics Committee (UMREC). UMREC is tasked with reviewing the ethical aspects of all non-medical research involving human participants, regardless of funding status. The committee examines several ethical dimensions, including the robustness of the methodology, potential risks and benefits to participants, recruitment methods, informed consent, confidentiality, data management, and feedback mechanisms. The review process may take up to 60 days, depending on the complexity of the research.

The participant recruitment process entailed selective engagement of individuals demonstrating both accessibility and willingness to participate. The primary modality of data collection implemented consisted of an online survey using Google Forms, systematically disseminated to eligible undergraduate accounting students in their penultimate and final academic years at the selected institutions. Accompanied by comprehensive explanatory emails, the surveys were distributed to students via their official university email addresses. These communications elucidated the objectives of the study, the survey's expected duration, participation prerequisites, and assurances of confidentiality. It emphasised the voluntary nature of participation and the participants' autonomy to withdraw from the process at any point.

Confronted with a suboptimal response rate, the researcher undertook several proactive measures to enhance participation rates. These measures included dispatching reminder emails and obtaining approvals for faculty endorsements. Lecturers of core courses were solicited to endorse and disseminate the survey among their third and fourth-year accounting cohorts. Additionally, the survey link was circulated through accounting clubs and societies within the universities, expanding its reach while minimising classroom disruptions and aiming to augment the response rate.

In the event of persistently low response rates, the researcher contemplated directly engaging eligible students as a contingency. This direct interaction aimed to underscore the significance of their contributions to the research and encourage survey completion. However, it is pertinent to note that this direct approach to student engagement was ultimately not implemented. All aforementioned measures were executed in strict compliance with the ethical standards and protocols of the participating institutions, ensuring the protection of participants' rights and welfare.

To uphold participant anonymity, the study protocol assured respondents that their inputs would be treated confidentially, with only aggregated results being reported. This strategy was designed to create an environment conducive to genuine and precise responses. Prior to survey participation, respondents were presented with an electronic consent form at the onset of the online survey, typically positioned as the initial segment of the Google Form. Participants were required to express their informed consent by selecting an 'Agree' option. Additionally, an overview of the study's objectives and a concise introduction to AI were provided to ensure participants' comprehensive understanding, thus facilitating informed feedback.

4.5 Participant Engagement and Research Integrity

In an endeavour to evaluate the behavioural intention to use AI among accounting students, this research sought participation from both public and private universities, specifically targeting third—and fourth-year undergraduates from institutions such as UM, UKM, SU, and MMU. The research successfully garnered participation from 136 students, equating to 46.26% of the predetermined sample size. This figure may initially appear to fall short of the expected threshold; however, it is imperative to recognise the deeper statistical and practical implications. Bhattacherjee (2012) elucidates that in quantitative studies, especially those investigating niche domains, achieving absolute response rates are often elusive, predominantly due to the particularities inherent in the topic or the intricacies of the survey mechanism. Given the research's focus on the nuanced interplay between AI and accounting—a distinctly specialised area—the prospect of achieving 100% participation might be formidable.

Vasileiou et al. (2018) assert that in academic inquiries, the richness and calibre of the data often outweigh mere numerical abundance. This investigation, probing into less charted territories like TR and JR, aims to evaluate their influence on the intention to use AI amongst accounting students. The comparative analysis between public and private universities further amplifies the study's value. The data, derived from a thoroughly engaged participant group, promises to yield substantial and insightful conclusions. Bartlett et al. (2001) observe that response rates in social science research typically range between 30% and 50%, and such metrics are generally deemed adequate for drawing reliable conclusions, particularly when the data is rigorously examined and contextualised. Adhering to the guidelines set forth by Hair et al. (2016) notably, the 'ten-times rule', which prescribes a minimum of ten responses for each construct, suggests a baseline sample size of 80. This study considerably surpasses that benchmark with 136 participants, thus augmenting the statistical validity of its findings.

In summation, the participation rate, albeit not fully aligned with the initial estimate, firmly situates itself within scholarly acceptable parameters. The essence of this research is poised not just in its numerical representation but predominantly in the depth and rigour of the insights it is set to unveil about the future accountants' disposition towards AI.

CHAPTER 5: FINDINGS

5.1 Descriptive Statistics

Leveraging the capabilities of IBM SPSS for descriptive analysis enables a deeper exploration into the nuances of the dataset, providing a holistic view of the patterns and characteristics present. This analytical exposition primarily centres attention on the demographic profile of the participating students, as depicted in Table 5.1. Additionally, the demographic delineation contributes to robust statistical interpretation and establishes a solid foundation for contrasting mean values, particularly in differentiating between students from public and private academic backgrounds, as illustrated in Table 5.2 below.

Table 5.1: Demographic Profile of Respondents

Personal Information		Number	Percentage (%)
Academic Year	Year 3	84	61.8
	Year 4	52	38.2
University	University Malaya (UM)	40	29.4
	University Kebangsaan Malaysia (UKM)	33	24.3
	Sunway University (SU)	25	18.4
	Multimedia University (MMU)	38	27.9
Ethnicity	Malay	34	25
	Chinese	79	58.1
	Indian	23	16.9
Nationality	Malaysian	134	98.5
	Other	2	1.5
Gender	Male	103	75.7
	Female	33	24.3
Total Number of Respondents (N)		136	100

In an academic context, it is noteworthy that third-year students represent a substantial majority, accounting for 61.8% of the total cohort, compared to their fourth-year counterparts, who constitute merely 38.2%. It can be postulated that fourth-year students engaged in advanced coursework, comprehensive examinations, and critical projects at the peak of their academic journey have constrained opportunities to participate in additional research activities. The inclusion of internships in their final year, a standard element of accounting programs, likely reduces their campus presence, further contributing to their minimal participation. It is crucial to note that the accounting program at SU spans only three years, designating the third year as the concluding year of the curriculum. This structural difference in program duration could be a contributing factor to the observed disparities in participation rates between the third and fourth-year cohorts.

Examining university affiliations, UM emerges as the predominant institution, with 29.4% of participants, marginally surpassing MMU at 27.9%. The participation rates of students from the UKM and SU are significant, constituting 24.3% and 18.4%, respectively. It is imperative to emphasise the equitable distribution of the survey across these academic institutions, adhering to the principle of impartiality and ensuring equal participation for every student. In a composite view, the participation from private entities, namely MMU and SU, accumulates to 46.3%, while public institutions, UM and UKM, collectively contribute 53.7%. This symmetrical distribution facilitates a well-rounded insight into the research topic.

The dataset reveals a notable prevalence of Chinese students, constituting 58.1% of the sample, followed by Malay and Indian students, comprising 25% and 16.9%, respectively. This demographic trend could be indicative of the intrinsic student composition at the chosen institutions, or it might suggest a particular inclination among Chinese students towards disciplines that intertwine accounting with technology. Suhaili et al. (2019) highlight the multicultural dynamic prevalent in Malaysian public universities, while Leung et al. (2011) note that Chinese culture and parental expectations significantly influence the career choices of Chinese university students. The perception of accounting as a prestigious field, renowned for its educational value and potential for career success, could elucidate the heightened representation of Chinese students in accounting programs.

The study's data is chiefly domestic, with 98.5% of respondents being Malaysian. This underscores the study's pertinence within the Malaysian academic context and reflects a pronounced local interest in AI-related subjects. Conversely, only 1.5% of participants are from international backgrounds, indicating a primary focus on the Malaysian perspective. However, the low international representation may indicate underrepresentation or limited engagement of this group in the study. This is particularly noteworthy in light of ICEF Monitor's (2023) report on the rising trend in international student applications in Malaysia for 2022, suggesting a growing international presence in the educational sector.

Lastly, the analysis of gender distribution within the dataset reveals a tangible skew. Female participants are in a clear majority, constituting 75.7% of the sample, whereas male participants constitute only 24.3%. Such a pronounced disparity warrants contemplation. It may suggest an amplified fervour for AI among female accounting students, or it could reflect the gender composition within the accounting departments of the selected universities. This observed pattern aligns with broader educational observations, wherein certain academic domains witness a female-dominated student populace, a phenomenon affirmed by Wan (2017).

The descriptive analysis, leveraging the robust capabilities of IBM SPSS, provides a comprehensive understanding of the multifaceted attributes within the dataset. This analysis serves as a foundational basis for subsequent inferential analyses and sheds light on pivotal patterns that can inform future research endeavours.

5.2 Comparative Analysis of University Groups

The investigation into the perceptions of students from public and private institutions regarding AI offers a nuanced understanding of their behavioural intention (BI) to engage with this technology. A detailed analysis of the data presented in Table 5.2 reveals several significant insights. This comparative analysis was conducted based on institutional type rather than gender or socio-economic background to examine how varying environments and resources influence students' attitudes towards AI. This decision was informed by the premise that variables such as technological access, funding levels, and the focus of the curriculum have a more pronounced effect on student engagement with AI, as opposed to individual demographic traits (Ayanwale & Molefi, 2024; Lin & Yu, 2023). Focusing on these institutional differences, the analysis provides detailed and actionable insights into the effects of educational environments on students' behavioural intentions towards AI usage. These findings have profound implications for the development of policies and the enhancement of educational strategies.

Table 5.2: Mean Comparison of Groups (Public and Private Universities)

Constructs	Group 1 Public Universities (UM, UKM)	Group 2 Private Universities (SU, MMU)
	Mean	
OP	5.85	5.74
IN	4.82	4.66
DS	3.00	3.61
IS	4.95	5.13
JR	6.12	5.95
PU	5.99	5.99
SF	5.81	5.57
BI	6.32	5.98

The comparative analysis of mean scores between the two cohorts reveals a complex spectrum of attitudes and readiness towards AI. Both cohorts exhibit considerable alignment in their viewpoints, albeit with slight divergences in specific domains. Notably, the most significant discrepancy emerged in the technology readiness (TR) dimensions of discomfort (DS) and insecurity (IS), indicating nuanced differences in their respective perceptions of AI. Students from private institutions (SU, MMU) demonstrated a higher mean in the DS dimension, recording a mean of 3.61, compared to their counterparts from public universities (UM, UKM), with a lower mean of 3. This indicates an increased level of unease or potential challenges associated with AI technology among private institution students. Furthermore, the IS dimension, while displaying a narrower gap, still noted a marginally higher mean for students from private universities at 5.13, in contrast to a mean of 4.95 for students from public institutions. This modest difference reinforces the notion that students from private universities may possess more reservations concerning the potential risks associated with AI technology.

In contrast to the pronounced apprehensions observed in the TR dimensions among students from private institutions, the mean values for constructs such as optimism (OP) and innovativeness (IN) exhibit relative parity between the two groups. This equivalence suggests that, regardless of the heightened concerns regarding AI prevalent among students from private institutions, their general disposition towards technology remains neither pessimistic nor less innovative. Specifically, the OP construct yielded means of 5.85 and 5.74 for public and private institutions, respectively, and the IN construct followed a similar trend with means of 4.82 and 4.66.

Furthermore, constructs integral to the core of the study, including behavioural intention (BI) and job relevance (JR), reveal that differences, though existent, are not as highly pronounced. The BI construct exhibited mean values of 6.32 for public universities and 5.98 for private institutions. The JR construct displayed a similar pattern, with public universities showing a mean of 6.12 compared to 5.95 for private institutions. These findings indicate that irrespective of university affiliation, students perceive AI as highly relevant to their future careers and possess a relatively strong intent to utilise it.

Perceived usefulness (PU) is uniformly acknowledged by both groups, each with an identical mean of 5.99, underscoring a shared recognition of AI's benefits in their academic and professional endeavours. The superior functionality (SF) construct echoed mean values of 5.81 for public institutions and 5.57 for private institutions, thus reinforcing the previously observed pattern indicating that public university students are slightly more inclined to perceive AI as superior in its capabilities.

In summation, the comparative analysis offers a comprehensive depiction of the complexities and varied dimensions of student perceptions. Albeit certain apprehensions and hesitations are evident, particularly among private university attendees, the overarching narrative underscores a burgeoning enthusiasm and readiness to embrace AI across both institution types. The findings emphasise the importance of fostering a robust understanding of AI and addressing prevalent concerns to facilitate a smooth transition for students into professional realms that increasingly integrate AI applications.

5.3 Reliability and validity

5.3.1 Data Cleaning

The data cleaning process for the Google survey, which initially garnered a total of 138 responses, was conducted with meticulous precision to ensure the accuracy and integrity of the data. The identification and elimination of duplicate entries were central to this process, as these duplicates were presumably caused by respondents inadvertently refreshing the page post-submission. Such duplications could distort the analysis by disproportionately amplifying certain responses. Following a detailed examination of response timestamps and cross-referencing of answers provided, it was determined that two entries were duplicates. The elimination of these entries was imperative to uphold the integrity of the dataset, consequently revising the total count of unique responses to 136.

The analysis of survey responses involved a comprehensive review of both duplicate entries and instances of straight-line answering patterns. This examination was essential in identifying potential issues of respondent disengagement or response bias, particularly reflected in participants consistently selecting identical answers across multiple survey questions. Additionally, the mandatory requirement for respondents to answer all questions prior to submitting the survey significantly reduced the occurrence of incomplete or partial responses, thereby enhancing the overall quality and reliability of the dataset.

Another key aspect of the data-cleaning process was the careful evaluation of outliers (Kwak & Kim, 2017). Recognising the potential value of outliers in representing unique, albeit genuine, perspectives, each outlier was assessed on its own merit. This strategy aimed to eliminate data anomalies emanating from errors or misconceptions whilst ensuring the inclusion of responses encapsulating rare yet legitimate viewpoints (Duraj

& Szczepaniak, 2021). Such a balanced treatment of outliers was crucial in preserving the diversity of viewpoints and enriching the insights derived from the survey.

In summary, the data cleaning process, encompassing the removal of duplicate entries, straight-lining analysis, and a nuanced approach to outliers, was instrumental in refining the dataset to 136 unique and representative responses. This rigorous approach laid a robust foundation for the subsequent data analysis, ensuring that the findings drawn from the survey were both credible and comprehensive.

5.3.2 Evaluation of Measurement Model

In the PLS-SEM methodology, the initial and critical stage involves evaluating the measurement model for reliability and validity, which precedes the examination of the structural model. This step is crucial for ensuring data reliability, leading to consistent outcomes, and affirming the validity and accuracy of the findings (Altheide & Johnson, 1994; Mohajan, 2017). The evaluation process begins with a thorough analysis of the measurement model to ascertain the degree to which the survey items accurately represent the theoretical constructs. This includes a detailed examination of the predictive correlations between each latent construct and its associated observed indicators. The evaluation of the reflective model in this study is based on the fundamental concept that latent constructs are the primary influencers of the observed variables.

This analysis includes a thorough examination of construct validity, which involves assessing convergent validity through the Average Variance Extracted (AVE) and factor loadings and establishing discriminant validity using the HTMT criterion, the Fornell-Larcker criterion, and cross-loadings (Ab Hamid et al., 2017; Hair et al., 2022). The study also rigorously measures internal consistency reliability, employing Cronbach's alpha and composite reliability metrics rho_a and rho_c. Collinearity issues are meticulously assessed using the Variance Inflation Factor (VIF) to ensure the robustness of the model.

5.3.2.1 Convergent Validity

Convergent validity in the study is determined by the correlation among indicators within the same construct, ascertained using the Average Variance Extracted (AVE). According to Bagozzi and Yi (1988) and Hair et al. (2013), convergent validity is established once the AVE exceeds 0.5. This threshold signifies that, on average, the construct explains more than half of the variance of its indicators. In other words, an AVE value above 0.5 indicates that a majority of the variance in the indicators can be attributed to the underlying construct, demonstrating a strong convergence among the indicators towards the same construct. In this study, as presented in Table 5.4, the AVE values surpass the 0.5 benchmark, confirming that the constructs possess a high level of convergent validity. This suggests that the indicators used in the study are consistent and reliable in representing their respective constructs.

Outer loading values are critical in evaluating the strength of the association between indicators and their corresponding constructs. An indicator is considered to have a strong association if its outer loading value is above 0.70. When outer loading values are between 0.4 and 0.7, they indicate a moderate association, and the removal of such an indicator may be considered if it contributes to an improvement in the construct's composite reliability and AVE (Hair et al., 2014). Indicators with outer loading values below 0.4 typically reflect a weak association with the construct and are generally recommended for exclusion from further analysis (Hair et al., 2011). In this research, the IS4 item from the insecurity dimension was removed, as its outer loading value of 0.179 fell well below the minimum required threshold, as shown in Table 5.3, indicating a weak relationship with its respective construct.

Table 5.3: Outer Loadings (Mean, Standard Deviation, T-Values)

Items	Original sample	Sample mean (M)	Standard deviation	T statistics
OP1	0.832	0.825	0.043	19.395
OP2	0.827	0.819	0.044	18.914
OP3	0.731	0.734	0.048	15.128
OP4	0.804	0.804	0.036	22.116
IN1	0.771	0.766	0.056	13.789
IN2	0.803	0.801	0.041	19.588
IN3	0.783	0.78	0.05	15.782
IN4	0.834	0.836	0.032	26.025
DS1	0.826	0.815	0.072	11.455
DS2	0.846	0.838	0.069	12.297
DS3	0.889	0.881	0.050	17.852
DS4	0.930	0.925	0.039	23.874
IS1	0.855	0.826	0.102	8.337
IS2	0.828	0.817	0.092	9.006
IS3	0.775	0.747	0.107	7.217
IS4	0.179	0.153	0.217	0.824
JR1	0.948	0.945	0.024	39.882
JR2	0.955	0.954	0.017	55.527
SF1	0.822	0.820	0.046	17.961
SF2	0.808	0.808	0.032	25.438
SF3	0.838	0.839	0.038	22.026
SF4	0.804	0.802	0.043	18.766
PU1	0.860	0.858	0.029	30.136
PU2	0.908	0.906	0.021	43.066
PU3	0.903	0.903	0.017	52.129
PU4	0.910	0.910	0.02	44.696
PU5	0.894	0.895	0.023	39.496
PU6	0.869	0.867	0.030	29.342
BI1	0.945	0.945	0.013	70.372
BI2	0.953	0.953	0.009	105.733
BI3	0.902	0.902	0.027	33.985

Table 5.4: Cronbach's Alpha, Composite Reliability and AVE

Constructs	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted
OP	0.811	0.816	0.876	0.876
IN	0.814	0.845	0.875	0.875
DS	0.898	0.967	0.928	0.928
IS	0.772	0.810	0.863	0.863
JR	0.895	0.898	0.950	0.950
SF	0.835	0.838	0.958	0.890
PU	0.948	0.948	0.890	0.958
BI	0.926	0.929	0.953	0.953

5.3.2.2 Internal Consistency Reliability

Internal consistency reliability in this study is assessed using Cronbach's alpha and composite reliability. Both metrics evaluate the coherence among items within a construct, with scores ranging from 0 to 1, where higher values signify more robust reliability. Following Nunnally's (1978) guideline, a Cronbach's alpha of 0.7 or above indicates high reliability; as evidenced in Table 5.4, all constructs in this study satisfy this criterion. Furthermore, composite reliability, encompassing rho_a and rho_c, offers a more refined measure of reliability by accounting for the varying contributions of individual indicators to their respective constructs. Considering the differential loadings of indicators, this approach more accurately reflects the latent variable's reliability significantly as indicators vary in importance. In this research, both Cronbach's alpha and composite reliability values surpass the 0.7 threshold, indicating robust internal consistency across constructs. This reinforces the measurement model's reliability and the validity of the constructs in the PLS-SEM analysis.

5.3.2.3 Discriminant Validity

Discriminant validity signifies the measure to which distinct constructs are separate and not intercorrelated. Methods such as examining cross-loading indicators, applying the Fornell & Larcker criterion, and the computation of the Heterotrait-Monotrait (HTMT) ratio are commonly employed to assess this validity. Commencing with the assessment of cross-loading, it is paramount that the factor loading values for a designated construct surpass those affiliated with other constructs, with a minimum benchmark of 0.7 (Hair et al., 2011; Hair et al., 2014). In this study, all items exhibited higher loadings within their respective constructs in comparison to other constructs, surpassing the requisite threshold, as reflected in Table 5.5.

Table 5.5: Cross Loadings

Items	BI	JR	PU	SF	DS	IN	OP	IS
BI1	0.945	0.491	0.489	0.644	-0.198	0.364	0.453	0.332
BI2	0.953	0.478	0.513	0.663	-0.196	0.408	0.51	0.309
BI3	0.902	0.518	0.493	0.537	-0.24	0.307	0.384	0.198
JR1	0.492	0.948	0.427	0.413	0.028	0.228	0.271	0.443
JR2	0.515	0.955	0.469	0.407	-0.004	0.253	0.322	0.324
PU1	0.505	0.445	0.86	0.552	-0.189	0.256	0.422	0.153
PU2	0.458	0.417	0.908	0.586	-0.092	0.339	0.47	0.26
PU3	0.429	0.405	0.903	0.594	-0.12	0.315	0.452	0.31
PU4	0.45	0.437	0.91	0.57	-0.091	0.32	0.435	0.213
PU5	0.511	0.432	0.894	0.601	-0.089	0.327	0.43	0.261
PU6	0.494	0.383	0.869	0.577	-0.096	0.301	0.491	0.292
SF1	0.597	0.429	0.566	0.822	-0.031	0.463	0.461	0.276
SF2	0.556	0.358	0.54	0.808	-0.08	0.442	0.459	0.271
SF3	0.512	0.33	0.439	0.838	-0.081	0.382	0.393	0.318
SF4	0.485	0.28	0.576	0.804	-0.108	0.372	0.344	0.269
DS1	-0.189	0.03	-0.049	-0.12	0.826	-0.059	-0.17	-0.039
DS2	-0.125	0.043	-0.094	-0.019	0.846	-0.053	-0.093	0.109
DS3	-0.155	0.009	-0.15	-0.04	0.889	0.013	-0.157	0.186
DS4	-0.269	-0.018	-0.138	-0.105	0.93	-0.025	-0.133	0.089
IN1	0.215	0.204	0.231	0.331	0.023	0.771	0.395	0.186
IN2	0.287	0.177	0.106	0.392	0.057	0.803	0.383	0.151
IN3	0.255	0.14	0.282	0.414	0.078	0.783	0.216	0.201
IN4	0.424	0.266	0.415	0.465	-0.188	0.834	0.552	0.415
OP1	0.458	0.285	0.424	0.433	-0.057	0.299	0.832	0.417
OP2	0.385	0.249	0.352	0.399	-0.167	0.358	0.827	0.347
OP3	0.298	0.199	0.433	0.369	-0.153	0.451	0.731	0.282
OP4	0.39	0.259	0.406	0.425	-0.144	0.499	0.804	0.271
IS1	0.266	0.432	0.34	0.31	0.089	0.297	0.421	0.857
IS2	0.265	0.207	0.207	0.31	0.039	0.23	0.318	0.826
IS3	0.196	0.352	0.061	0.203	0.128	0.276	0.238	0.785

The Fornell-Larcker criterion entails a methodological comparison between the latent variable correlations and the square root of the AVE construct (Fornell & Larcker, 1981). It is a prerequisite for the value of each AVE construct to exceed the correlations of other constructs. This validates that a latent construct explicates its individual items rather than explaining the variance of alternate latent constructs. The data in Table 5.6 reflects that the square roots of the AVE constructs supersede the corresponding correlation values, affirming that the constructs measured in this research possess valid measurements.

Table 5.6: Fornell–Larcker criterion

Constructs	BI	DS	IN	IS	JR	OP	PU	SF
BI	0.934							
DS	-0.225	0.874						
IN	0.387	-0.033	0.798					
IS	0.302	0.095	0.323	0.823				
JR	0.53	0.012	0.253	0.401	0.951			
OP	0.483	-0.159	0.499	0.415	0.313	0.799		
PU	0.534	-0.127	0.348	0.278	0.472	0.505	0.891	
SF	0.66	-0.09	0.51	0.346	0.431	0.51	0.651	0.818

According to the research conducted by Henseler et al. (2014), the application of the Heterotrait-Monotrait (HTMT) ratio has been proven to exhibit unparalleled efficacy in specificity and sensitivity rates in comparison to both cross-loadings and the Fornell-Larcker criteria. A value of HTMT approaching 1 indicates a lack of discriminant validity, with a threshold set at 0.85 (Henseler et al., 2014; Kline, 2011). The recorded HTMT values in the table are all under this threshold, as depicted in Table 5.7, thus affirming that discriminant validity is established in this research.

Table 5.7: Heterotrait-Monotrait (HTMT) ratio

Constructs	BI	DS	IN	IS	JR	OP	PU	SF
BI								
DS	0.232							
IN	0.423	0.147						
IS	0.344	0.155	0.375					
JR	0.583	0.049	0.287	0.482				
OP	0.551	0.189	0.598	0.496	0.364			
PU	0.569	0.133	0.367	0.294	0.511	0.577		
SF	0.744	0.103	0.601	0.414	0.494	0.614	0.728	

5.3.2.4 Collinearity Analysis

The detection of collinearity, indicated by significant correlations among indicators, complicates interpretation by masking the effects of individual indicators in the model. The Variance Inflation Factor (VIF) is critical in assessing collinearity, with values over 5 indicating notable distortion in coefficient variance and adversely affecting the model's validity (Hair et al., 2021). To safeguard the model's integrity and ensure accurate conclusions, constructs with high VIF values, like BI2 and PU2 noted in Table 5.8, have been excluded from the analysis. This step is crucial to prevent interpretative errors and ensure analytical rigour.

Table 5.8: Collinearity Statistics (VIF)

Constructs	VIF
BI1	4.741
BI2	5.117
BI3	2.721
JR1	2.911
JR2	2.911
PU1	3.485
PU2	5.102
PU3	4.354
PU4	4.222
PU5	4.189
PU6	3.076
SF1	1.739
SF2	1.759
SF3	2.118
SF4	1.847
DS1	2.097
DS2	2.611
DS3	3.069
DS4	3.662
IN1	1.835
IN2	1.961
IN3	1.578
IN4	1.584
OP1	2.381
OP2	2.39
OP3	1.595
OP4	1.793
IS1	1.521
IS2	1.555
IS3	1.72

5.3.3 Structural Model

In the presented model, R-square values illuminate the degree to which exogenous constructs explain variance in endogenous constructs. Falk and Miller (1992) have posited that an R-square value above 0.10 is acceptable, a perspective in line with Cohen's (1988) classification of R-square values, categorising 0.26 as substantial, 0.13 as moderate, and 0.02 as weak explanatory power. Additionally, Chin (1998) delineates that figures of 0.67, 0.33, and 0.02 for an independent variable correspond to substantial, moderate, and weak influence, respectively.

In this context, the model's explanation of behavioural intention (BI) is particularly significant, with an R-square of 0.531, accounting for 53.1% of the variance in BI, thus signifying substantial to moderate explanatory power. Similarly, perceived usefulness (PU) with an R-square of 0.506 explains 50.6% of its variance, falling into the same category of explanatory power. Superior functionality (SF) also shows an R-square of 0.361, indicating that 36.1% of its variance is explained by the model, thereby aligning with substantial to moderate explanatory power.

Table 5.9: Structural Model (R-Square)

Constructs	R-square	Adjusted R-square
BI	0.531	0.506
PU	0.506	0.483
SF	0.361	0.341

The constructs of optimism (OP), innovativeness (IN), discomfort (DS), insecurity (IS), and job relevance (JR) are intricately linked to PU and SF, which subsequently exert influence on BI. These established connections, albeit significant, are not exhaustive in encompassing all potential influencing factors. The unexplained variability in BI, PU, and SF suggests the presence of other variables, thus indicating potential avenues for future research to elucidate the determinants of technology integration in greater depth.

5.4 Hypotheses Testing

5.4.1 Main Path Model

The application of the SmartPLS algorithm and bootstrapping with 5,000 subsamples, as suggested by Hair et al. (2011), facilitated a robust evaluation of the proposed hypotheses through p-values and β estimates. The outcomes detailed in Tables 5.10 and 5.11 provide a comprehensive overview of how various psychological constructs impact technological intentions, revealing both direct and indirect effects within the structural model.

In examining technology readiness (TR) among accounting students, optimism (OP) was found to positively influence both superior functionality (SF) ($\beta = 0.290$, $p < 0.01$) and perceived usefulness (PU) ($\beta = 0.227$, $p < 0.01$), corroborating hypotheses H1a and H1b. However, OP's direct effect on behavioural intention (BI) was not significant ($\beta = 0.093$, $p > 0.05$), leading to the rejection of H1c. This indicates that while OP enhances perceptions of technology's utility and functionality, it does not directly drive the intention to use technology among accounting students.

Innovativeness (IN) showed a positive impact on SF ($\beta = 0.324$, $p < 0.001$), affirming H2a, but did not significantly influence PU or BI ($\beta = -0.059$, $p > 0.05$; $\beta = 0.011$, $p > 0.05$), leading to the non-validation of H2b and H2c. Discomfort (DS) negatively influenced BI ($\beta = -0.177$, $p < 0.01$), endorsing H3c, yet had no significant effect on SF or PU ($\beta = -0.044$, $p > 0.05$; $\beta = -0.053$, $p > 0.05$), leading to the rejection of H3a and H3b. Insecurity (IS) did not exhibit substantial effects on any of the investigated constructs ($\beta = 0.125$, $p > 0.05$; $\beta = -0.053$, $p > 0.05$; $\beta = -0.020$, $p > 0.05$), culminating in the rejection of H4a, H4b, and H4c.

Job relevance (JR) was found to positively influence PU ($\beta = 0.232$, $p < 0.01$) and BI ($\beta = 0.320$, $p < 0.001$), substantiating H5a and H5b. Furthermore, SF emerged as a significant predictor of both PU (β = 0.478, $p < 0.001$) and BI (β = 0.400, $p < 0.001$), affirming H6a and H6b. However, the direct effect of PU on BI was not substantiated (β = 0.048, $p > 0.05$), necessitating the rejection of H7.

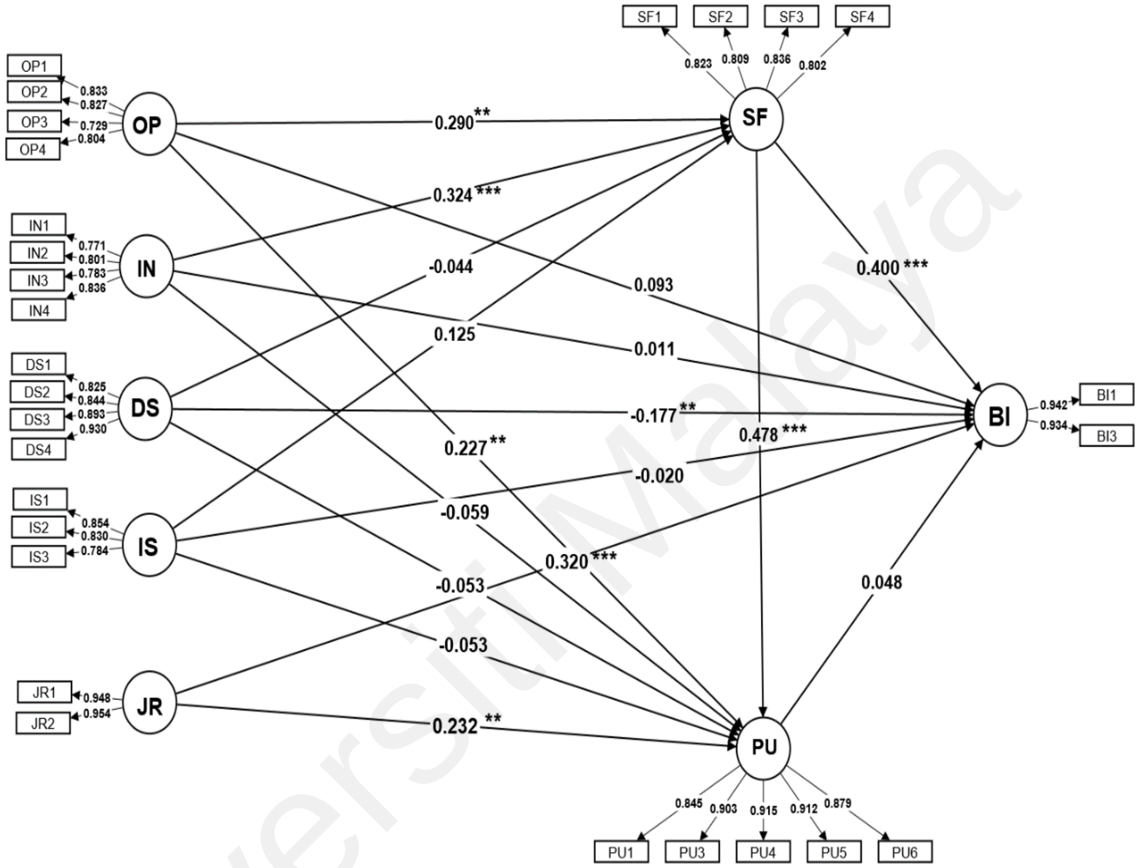

Figure 5.1: Structural Model

Notes. *, **, *** denotes significant at $p < 0.05$, $p < 0.01$, $p < 0.001$, respectively. OP= Optimism, IN= Innovativeness, DS= Discomfort, IS= Insecurity, JR= Job Relevance, SF= Superior Functionality, PU= Perceived Usefulness, BI= Behavioural Intention

Table 5.10: Results of Testing Hypotheses for Direct Effects

Hypotheses	Path	β	P- Values	Decision
H1a	OP → SF	0.290	0.004**	Supported
H1b	OP → PU	0.227	0.005**	Supported
H1c	OP → BI	0.093	0.212	Not Supported
H2a	IN → SF	0.324	0.000***	Supported
H2b	IN → PU	-0.059	0.365	Not Supported
H2c	IN → BI	0.011	0.887	Not Supported
H3a	DS → SF	-0.044	0.536	Not Supported
H3b	DS → PU	-0.053	0.482	Not Supported
H3c	DS → BI	-0.177	0.003**	Supported
H4a	IS → SF	0.125	0.139	Not Supported
H4b	IS → PU	-0.053	0.561	Not Supported
H4c	IS → BI	-0.020	0.809	Not Supported
H5a	JR → PU	0.232	0.004**	Supported
H5b	JR → BI	0.320	0.001***	Supported
H6a	SF → PU	0.478	0.000***	Supported
H6b	SF → BI	0.400	0.000***	Supported
H7	PU → BI	0.048	0.651	Not Supported

Table 5.11: Results of Testing Hypotheses for Indirect Effects

Hypotheses	Paths	β	P- Values	Indirect/ Mediation effect	Decision
H1d	OP → SF → BI	0.116	0.026*	Full	Supported
H1e	OP → PU → BI	0.011	0.677	No	Not Supported
H2d	IN → SF → BI	0.13	0.013*	Full	Supported
H2e	IN → PU → BI	-0.003	0.779	No	Not Supported
H3d	DS → SF → BI	-0.018	0.545	No	Not Supported
H3e	DS → PU → BI	-0.003	0.796	No	Not Supported
H4d	IS → SF → BI	0.05	0.157	No	Not Supported
H4e	IS → PU → BI	-0.003	0.824	No	Not Supported
H5c	JR → PU → BI	0.011	0.67	No	Not Supported

5.4.2 Mediating Effect

In examining the mediating effects on accounting students' technological intentions, the study adopted methodologies consistent with Baron and Kenny (1986) and further informed by the research approaches of Aris et al. (2022), Siu and Ismail (2022), Sin and Ismail (2021), and Kustono et al. (2023). Full mediation is characterised by an insubstantial direct path from the independent to the dependent variable, coupled with significant indirect paths via a mediator. In contrast, partial mediation arises when both direct and indirect paths show significance. No mediation is identified if there is a notable direct effect unaccompanied by substantial indirect effects.

The study found that superior functionality (SF) fully mediated the relationship between optimism (OP) and behavioural intention (BI) ($\beta = 0.116$, $p < 0.05$) and between innovativeness (IN) and BI ($\beta = 0.13$, $p < 0.05$), thus supporting hypotheses H1d and H2d. This suggests that in the context of accounting students, the influence of OP and IN on their intention to engage with technology operates through their perception of its SF. However, the anticipated mediating role of SF in the context of discomfort (DS) in Hypothesis 3d and insecurity (IS) in Hypothesis 4d were not supported, as indicated by non-significant beta values ($\beta = -0.018$, $p > 0.05$ for DS and $\beta = 0.05$, $p > 0.05$ for IS). This finding implies that DS and IS do not significantly influence accounting students' BI through SF.

The results of this research indicate a significant departure from extant literature concerning the role of perceived usefulness (PU). The analysis discerned that PU did not mediate the relationships between OP, IN, IS, and BI, as hypothesised in H1e, H2e, and H4e. This points to an absence of PU's mediating influence and a lack of direct effects on BI within these specific TR dimensions. Moreover, the mediation effect analysis in this study identified that PU did not function as a mediator between DS and BI ($\beta = -0.003$, $p > 0.05$), nor between Job Relevance (JR) and BI ($\beta = 0.011$, $p > 0.05$), leading to the rejection of hypotheses 3e and 5c. These findings, however, underscore a direct linkage between DS and JR with BI, bypassing the mediation of PU, particularly within the realm of accounting education. The study thus concludes that in these instances, PU did not act as a mediating variable.

CHAPTER 6: DISCUSSION

6.1 Introduction

This investigation rigorously examines the factors influencing accounting students' behavioural intention to engage with AI, utilising an expanded framework of the Technology Acceptance Model (TAM). The study's significance is anchored in its capacity to shape educational strategies that effectively address impediments and amplify enablers for AI integration within the domain of accounting education. This is pivotal for tailoring accounting curricula to the requisites of Industry 4.0, ensuring graduates are proficient in a technology-intensive professional landscape. The ensuing discussion is meticulously structured, focusing on each construct identified in the study. It will methodically analyse both the direct and indirect effects of these constructs on the students' intention to utilise AI, as comprehensively delineated in Tables 5.10 and 5.11. This systematic approach is designed to provide a profound understanding of the determinants influencing AI engagement in accounting education.

6.2 Analysis of Key Variables

6.2.1 Optimism

The exploration of the interrelationship between individual optimism (OP) and intentions to utilise AI in the realm of accounting education reveals a complex dynamic. The study underscores that OP among accounting students markedly improves their perception of AI's superior functionalities (SF), in line with Roy et al.'s (2018) findings and supporting H1a. This OP viewpoint plays a crucial role in enabling students to identify AI's advanced features as key to enhancing their professional skills and accuracy in the field. It leads to a more in-depth appreciation and understanding of AI's sophisticated capabilities, shifting their perception from viewing AI as a mere technological novelty to recognising it as a vital component for professional development and analytical precision.

The positive link between OP and perceived usefulness (PU) of AI, supporting Hypothesis 1b, resonates with findings from Kampa (2023) and Yusuf et al. (2021). This consistency highlights a broader trend in which OP tends to elevate the perceived value of emerging technologies, such as AI. The implication that students with an OP outlook are more inclined to perceive AI as beneficial is likely influenced by the growing relevance and application of AI in modern accounting practices, where its ability to enhance precision and streamline operational processes is highly esteemed.

However, it is noteworthy that OP does not significantly sway the behavioural intention (BI) to use AI, contrary to Hypothesis 1c. Despite the existence of a positive association, as noted in studies like Flavián et al. (2021) and Hwang and Good (2014), the lack of statistical significance in this relationship implies that OP alone may not be a decisive factor in students' intentions to use AI in accounting. This perspective is supported by Negm (2022), who implies that within the pragmatic and conservative sphere of accounting, students are likely to give precedence to concrete evidence of AI's effectiveness and its applicability to their academic and professional aspirations over a purely optimistic mindset.

Corroborating this viewpoint, the study further reveals that SF plays a critical full mediating role between OP and BI. This finding reinforces the idea, in line with Roy et al., 2018, that while technology is integral for data analysis and problem-solving in accounting education, students' intent to use AI is more strongly influenced by the technology's superiority over traditional systems (Inman & Nikolova, 2017). Thus, the perceived advanced capabilities of AI, rather than just a general positive attitude towards technology, appear to be a more significant determinant in influencing students' intentions in this field.

Additionally, the absence of a significant mediating effect of PU between OP and BI resonates with the findings of Buyle et al. (2018), Panday (2018) and Nugroho and Fajar (2017). The significant direct effect of OP on PU suggests that accounting students, driven by their optimistic outlook, generally acknowledge AI's potential benefits in theory. However, their perception of AI's usefulness remains constrained due to a lack of comprehensive understanding regarding how AI's specific tools can be practically applied in their field (Compeau et al., 1999). This disconnect between their theoretical belief in AI's advantages and the practical application of AI functionalities results in the insignificance of PU as a mediator. In contrast, SF represents a broader concept encompassing AI's intelligence and overall superiority, which aligns with their optimistic perspective. Students are more influenced by this overarching perception of AI's advanced capabilities, even though they may not possess an in-depth understanding of its specific applications in accounting (Hargittai, 2010). Consequently, SF serves as a significant mediator as it relates to their more generalised belief in AI's capabilities, fostering their intention to use it.

To support accounting students' OP in utilising AI, universities should emphasise the transformative impact of AI in enhancing accounting practices, aligning with students' positive perceptions of technology. Educational programs should include discussions on the evolving role of AI in accounting, highlighting how it enhances functionality and efficiency, thereby reinforcing the optimistic view of AI as a valuable tool. Additionally, integrating insights on how AI can shape future accounting practices could further inspire students by demonstrating its PU. This approach, focusing on the positive aspects of AI and its potential to innovate the accounting sector, can help cultivate an environment where OP about AI leads to a willingness to engage with and effectively use these technologies in their education and future careers.

6.2.2 Innovativeness

The study's exploration of innovativeness (IN) and its impact on AI usage intentions in accounting education reveals a meaningful interaction between individual traits and technology. The significant positive correlation between IN and SF, in line with Hypothesis 2a, corroborates with Agarwal and Karahanna (2000) and reflects the evolving nature of the accounting field. This domain, increasingly reliant on precision, efficiency, and data-driven methodologies, aligns well with the propensities of innovative students. These students, open to new ideas and technologies, are naturally inclined towards AI's advanced features, recognising their potential to revolutionise traditional accounting methods (Huang et al., 2007). Their forward-looking perspective drives an appreciation for AI's enhanced capabilities, demonstrating an understanding of how these sophisticated technologies can be integrated into and benefit accounting practices (Agarwal & Prasad, 1998).

The study identifies a negative correlation between IN and PU of AI in accounting education. This outcome, lacking statistical significance, deviates from the anticipated positive correlation described in Hypothesis 2b. This finding is in line with Chen and Lin (2018) and Khadka and Kohsuwan (2019) but contrasts with research like Kampa (2023) and Yusuf et al. (2021), Lewis et al. (2003), Lu et al. (2005b) that showed positive correlations. The unexpected negative correlation might be linked to the surveyed accounting students' moderate level of innovativeness, compounded by their limited understanding of AI's application in the field. This prudent approach indicates a balanced perspective towards innovation, prompting a discerning evaluation of AI's practicality in academic and professional spheres, shaped by prevailing uncertainties. Therefore, while acknowledging AI's capabilities, students might perceive its present applications as not entirely addressing their specific needs in accounting. This perspective represents a sophisticated balance, highlighting their excitement for technological advancements while realistically appraising its current applicability in accounting, tempered by their limited knowledge (Bhattacherjee & Hikmet, 2007).

The absence of a significant direct relationship between IN and BI to use AI is consistent with Flavián et al. (2021), Kang (2020), and Blut and Wang (2019), refuting Hypothesis 2c. IN, while a foundational element, may not solely suffice to foster the intention to utilise AI in accounting education (Lu et al., 2005b). Despite their openness to innovation, students engaged in accounting studies place considerable emphasis on a range of pragmatic considerations. These encompass the reliability and precision of AI in executing complex accounting operations, its seamless integration within the educational curriculum (Hwang & Chang, 2011), its pertinence to their immediate academic objectives and prospective professional endeavours (Sun et al., 2008; Venkatesh et al., 2003). This necessitates a deeper investigation into these aspects to understand their impact on AI in this field.

The study's findings highlight a nuanced approach by innovative accounting students towards AI integration, revealing a strong preference for AI's SF, which supports Hypothesis 2d over its immediate PU, leading to the rejection of Hypothesis 2e in line with Panday (2018). Acknowledging the significant positive correlation and full mediation by SF in the relationship between IN and BI to use AI aligns well with the research of Agarwal and Prasad (1998). This indicates that students are more motivated to engage with AI based on its exceptional capabilities and potential to meet the evolving demands of the accounting profession.

This enthusiasm, however, is counterbalanced by a critical appraisal of AI's present practical use in their specific academic and professional realms. The rejection of Hypothesis 2e implies that students might perceive AI's current applications as not fully meeting their immediate practical requirements in accounting, thereby influencing their reluctance to use it. This discerning stance may stem from their high expectations and the thorough evaluation of AI's pertinence and feasibility, mirroring the research dynamics highlighted in Moore and Benbasat's (1991) work on technology compatibility, Bhattacherjee (2001) Expectation-Confirmation Theory, and Chen et al. (2013) investigation into technology discontinuance. These insights reflect a multifaceted relationship between welcoming innovation and pragmatically evaluating its current effectiveness in the accounting sector.

To foster the innovative tendencies of accounting students towards AI, universities should focus on integrating AI's advanced functionalities and long-term potential into their curricula. Educational curricula can foster forward-thinking and adaptability through the elucidation of AI's advanced capabilities in revolutionising accounting practices and articulating its future prospects. Providing practical exposure through hands-on experiences with AI tools will help bridge the gap between theoretical knowledge and real-world applications. These strategies aim to align with students' innovative traits, encouraging a deeper understanding and engagement with AI beyond its immediate utility, thereby preparing them for the evolving technological landscape of the accounting profession.

6.2.3 Discomfort

The study delineates a multifaceted relationship between students' emotional responses and their analytical perceptions of AI in accounting education. The research indicates that students' discomfort (DS) with AI does not meaningfully affect their cognitive recognition of AI's SF or PU, evidenced by minimal negative correlations, thus not substantiating Hypotheses 3a and 3b. This observation aligns with Lin et al. (2022) and implies that DS does not significantly modify its assessments of technology's enhanced capabilities and functionalities. Concurrently, results pertaining to Hypothesis 3b resonate with the findings of Yusuf et al. (2021) and Nugroho and Fajar (2017), indicating students' mature ability to separate emotional influences from objective evaluations of technology (Lerner et al., 2015; Negahban & Chung, 2014), underscores a sophisticated approach in their technological interactions.

Contrastingly, the notable negative correlation between DS and BI to utilise AI, confirming Hypothesis 3c, underscores the significant role of emotional states in shaping students' intentions regarding technology utilisation consistent with the insights of Negm (2022) and Hallikainen et al. (2017). This interpretation is consistent with Rolls's (2014) framework, emphasising emotions like DS towards technology can independently influence usage intentions, distinct from cognitive evaluations or adaptation behaviours.

The results of this study indicate that neither SF nor PU serves as significant mediators in the relationship between DS and BI to utilise AI, necessitating the rejection of Hypotheses 3d and 3e. The findings suggest that the effect of DS on the intention to utilise AI in accounting education cannot be fully accounted for by perceptions of the technology's advanced capabilities or its practical benefits, a conclusion that aligns with the perspectives offered in Panday (2018) and contrasts with the observations by Blut and Wang (2019). Instead, the direct impact of DS among accounting students arises from anxieties and hesitations associated with engaging in new technology, potentially overwhelming their inclination to utilise AI in their educational and professional endeavours.

For the successful integration of AI into accounting education, it is imperative to mitigate the emotional barriers encountered by students. This necessitates the implementation of educational strategies that encompass resources for managing technology-related anxiety, embedding ethical considerations of AI within the curriculum, facilitating hands-on AI experiences to cultivate familiarity, and encouraging transparent dialogues about AI applications. These initiatives are designed to assuage student apprehension, augmenting their preparedness to interact effectively with AI technologies.

6.2.4 Insecurity

Based on the rejection of Hypothesis 4a, the study's findings reveal a positive and statistically insignificant correlation between insecurity (IS) and the perception of AI's SF, a contrast to the findings of Huang and Liu (2012) and Tarafdar et al. (2017). As posited by Mandel et al. (2016), this could indicate that individuals with IS might positively perceive AI's advanced functionalities as a way to compensate for their concerns or scepticism. Despite their IS, these individuals may recognise the potential benefits of AI's advanced capabilities, viewing them as tools that could enhance performance or mitigate risks associated with their IS. This implies a multifaceted relationship where IS does not exclusively lead to negative perceptions but might also coexist with recognition of the technology's superiority. Nevertheless, the lack of statistical significance in this correlation necessitates further research to explore this intricate relationship in greater depth, particularly focusing on how different levels of IS may variably affect perceptions of technology in diverse contexts.

The observed negative, yet not significant, correlation between IS and PU of AI in accounting education aligns with the findings of Kampa (2023) and Nugroho and Fajar (2017) and contrasts with the positive correlations reported by Yusuf et al. (2021). This pattern indicates a cautious or sceptical approach among accounting students influenced by IS when evaluating AI's immediate practical utility. This cautiousness could stem from varying levels of uncertainty regarding AI and its perceived utility in accounting (Taylor & Todd, 1995). Such underlying IS among students may result in a more guarded perception of AI's usefulness, reflecting a balance between acknowledging its technological potential and a pragmatic approach to its reliability and applicability.

The relationship between IS and BI to use AI in accounting education, despite not supporting Hypotheses 4c, 4d, and 4e, presents an interesting dynamic when considering the roles of SF and PU. The negative but non-significant correlation between IS and BI to use AI, aligning with the findings of Hsieh (2023) but contrasting with those of Negm (2022) and Flavián et al. (2021), suggests a nuanced relationship. This scenario implies that students possessing only a superficial understanding of AI may not fully grasp its potential risks or safety implications. Consequently, this limited depth in their understanding of AI likely results in a neutral or ambivalent stance towards its usage (Davies, 2011).

The observed positive, albeit non-significant, influence of IS on BI through SF presents a multifaceted narrative. This perception, while favourable, fails to manifest in a significant intent to utilise AI. It infers that students, aware of AI's overarching potential rather than its distinct applications in accounting, are navigating a delicate equilibrium between their constrained knowledge and an acknowledgement of AI's technological prowess (Brown & Duguid, 2000). This complexity is compounded by the negative but insignificant impact of IS on BI, mediated by PU, suggesting that students' IS might result in a lesser acknowledgement of AI's practical utility in accounting; such concerns do not significantly influence their intention to utilise the technology. This phenomenon could stem from a limited comprehension of AI's applications, indicating that the decision to use AI is not substantially influenced by these unresolved and weak IS.

The findings suggest that students' lack of awareness regarding AI's risks and safety significantly diminishes the importance of the IS dimension. Therefore, it is imperative to develop an educational strategy centred on a comprehensive curriculum encompassing AI's technical aspects, practical applications in accounting, and potential risks. This approach ensures that accounting students acquire the requisite technical proficiency and psychological preparedness for effective AI utilisation in their future professional pursuits. Addressing the knowledge and emotional facets associated with AI will enable universities to substantially enhance students' confidence and readiness, fostering a more informed and secure framework for AI usage within the dynamic accounting field.

6.2.5 Job Relevance

The positive and significant influence of job relevance (JR) on PU, as evidenced in supporting Hypothesis 5a, resonates with the findings from studies such as Okcu et al. (2019), Alharbi and Drew (2014), and Venkatesh and Davis (2000). In the accounting field, where precision and efficiency are paramount, students' perception of AI as useful is notably heightened when they discern its relevance to their future professional roles. The observed correlation between JR and PU indicates that students are aware of AI's substantial potential to augment critical facets of their prospective work. As students recognise AI's applicability in practical tasks such as data analysis and automation—integral components in accounting—their valuation of AI's utility increases. This shift in perspective transforms AI from a mere theoretical concept to a practical tool, anticipated to be pivotal in their forthcoming professional milieu.

Furthermore, JR also shows a direct positive impact on BI to use AI, confirming Hypothesis 5b in line with findings by Kar et al. (2021). This indicates that the perceived applicability of AI to job-related tasks is a crucial motivator for intending to use it. In accounting, AI plays a crucial role in enhancing various operational facets; the direct correlation between JR and intention to use AI underscores the practical considerations driving technology engagement.

The observed positive but statistically non-significant impact of JR on BI, mediated by PU, leading to the rejection of Hypothesis H5c, presents an intriguing observation. This implies that JR influences students' perceptions of AI's usefulness, yet this perception does not significantly mediate their intention to use AI. For accounting students, the direct correlation between AI and their projected job responsibilities and positions stands as a more critical determinant of their propensity to employ it, surpassing their general perception of the technology's usefulness. This conclusion implies that accounting students exhibit a pragmatic mindset, giving precedence to the tangible applicability of AI within their prospective job functions over abstract assessments of its usefulness.

Universities should emphasise JR to effectively nurture both the PU and BI to use AI among accounting students. While nurturing PU is important, it is crucial to recognise that it may not significantly mediate the intention to use AI. To foster AI integration, universities should blend AI applications into accounting curricula, establish industry partnerships for practical insights, conduct workshops on AI's career impact, and host guest speakers on AI's evolving role in accounting. These measures, aimed at demonstrating AI's direct relevance and practical utility in accounting, are vital in motivating students to incorporate AI into their future professional endeavours while enhancing their understanding of its usefulness.

6.2.6 Superior Functionality

The examination of superior functionality (SF) within the context of AI usage intentions, particularly among accounting students, presents compelling insights. The positive and significant correlation between SF and PU, supporting Hypothesis 6a, aligns with findings from Roy et al. (2018), Ferreira et al. (2014), and Riquelme and Rios (2010). The direct relevance of its superiority to accounting tasks, such as simplifying complex procedures, improving accuracy, and boosting productivity, renders it highly valuable in the perception of students. Given their emphasis on accuracy and productivity, accounting students are inclined to favour technologies that enhance these fundamental attributes in their educational and professional activities. The perception of AI's SF thus directly contributes to its perceived utility, as these advanced capabilities align with the practical needs and demands of accounting.

The significant impact of SF on BI resonates with the research of Lu et al. (2014) and Lee et al. (2003), indicates that AI's advanced capabilities play a vital role in shaping students' intentions to utilise it. This trend is observed particularly in accounting, where students are drawn to AI for its enhanced data analytics and sophisticated problem-solving abilities, viewing it as a superior alternative to traditional methods (Riquelme & Rios, 2010). This preference highlights the need for accounting education to emphasise AI's advanced functionalities, showcasing its superiority over conventional accounting practices. Such a focus is vital in motivating students to embrace AI in both their academic journey and future professional endeavours, recognising its transformative potential in the field of accounting.

To boost the intention to use AI among accounting students, universities should focus on illustrating AI's SF and its direct relevance to accounting careers. By embedding practical demonstrations into the curriculum, universities can effectively showcase the advanced features of AI that surpass traditional accounting methods. This approach will enhance students' comprehension of AI's advanced capabilities and clearly demonstrate how these capabilities can be applied in practical accounting scenarios. Such a strategy is pivotal in strengthening students' resolve to incorporate AI into their academic learning and future professional endeavours.

6.2.7 Perceived Usefulness

The research findings elucidate the intricate correlation between perceived usefulness (PU) and behavioural intention (BI) to employ AI among accounting students. These insights reveal that, despite acknowledging the utility of AI, students' recognition does not significantly translate into their inclination to utilise it. This statistical insignificance underscores a noteworthy dynamic within AI acceptance and usage among accounting students. This finding diverges from some research that indicates a strong positive correlation, aligning instead with studies like Lin et al. (2007) and Buyle et al. (2018). The rapid evolution of AI technology presents a significant factor in this outcome, posing a challenge for students in establishing a stable, long-term PU, thus affecting their willingness to engage with AI. Furthermore, gaps in the accounting curriculum regarding practical AI applications and limited hands-on experience with AI tools may hinder students from fully realising its practical benefits (Venkatesh et al., 2003). To strengthen the link between PU and BI, accounting education programs should aim to more effectively embed AI in both theory and practice, enabling students to grasp its value in enhancing their professional skills.

CHAPTER 7: CONCLUSION AND RECOMMENDATIONS

7.1 Conclusion

This comprehensive study, utilising an extended Technology Acceptance Model (TAM), provides an in-depth understanding of the factors influencing accounting students' intentions to use AI. Analysing responses from 136 third and fourth-year undergraduate students across universities of UM, UKM, SU, and MMU, the research identifies key variables - optimism, innovativeness, discomfort, job relevance, and superior functionality - as central to shaping students' AI engagement intentions. In light of these findings, universities are positioned to strategically enhance their curricula and educational approaches to better prepare students for an AI-centric professional landscape.

The study's findings highlight the need for universities to strategically emphasise AI's superior functionality and perceived usefulness within their accounting curricula to effectively cultivate optimism among students. This approach entails incorporating comprehensive case studies and practical simulations that vividly illustrate AI's advanced capabilities and their direct applicability in accounting tasks. By facilitating hands-on experiences with AI tools, students can better appreciate AI's sophisticated features and understand their utility in professional accounting contexts. This focus is particularly crucial given the study's revelation that superior functionality fully mediates the relationship between optimism and behavioural intention to use AI. Such an educational strategy is essential to foster a positive perception of AI among accounting students, thereby equipping them with the confidence and skills necessary to leverage AI technologies in their future professional endeavours. Although innovativeness does not directly impact the behavioural intention, it exerts a significant influence when mediated by superior functionality. To cultivate this, universities should provide opportunities for students to engage with innovative AI technologies. This includes creating innovation labs, organising tech competitions, and encouraging research projects that allow students to explore and experiment with AI functionalities, thereby connecting their innovative tendencies with advanced AI applications. The study shows that discomfort has a direct impact on the behavioural intention. Universities should address this by creating an inclusive and supportive learning environment where students can openly discuss and address their apprehensions about AI. This involves incorporating AI topics in a gradual and comprehensive manner, providing counselling services, and organising peer-to-peer mentoring sessions that help demystify AI and reduce associated discomfort. Job relevance directly influences both perceived usefulness and behavioural intention. Universities should emphasise the practical applicability of AI in accounting through industry collaborations, case studies, and guest lectures by accounting professionals using AI. This real-world exposure will help students understand how AI skills are directly transferable to their future job roles, thereby enhancing both their perceived usefulness of AI and their intention to use it.

Given superior functionality's direct effect on perceived usefulness and behavioural intention, it is crucial for universities to actively demonstrate how AI's advanced features can be leveraged in accounting. This can be achieved through advanced AI software training, workshops on AI-driven data analytics, and exposure to the latest AI tools and technologies. By doing so, students will gain firsthand experience of AI's capabilities, enhancing their understanding of its usefulness and influencing their intention to engage with AI. Through these targeted strategies, universities can effectively align their educational offerings with the evolving needs of the accounting profession. By focusing on these key areas, they can ensure that their accounting students are academically prepared and psychologically ready to embrace and excel with AI in their future careers.

7.2 Limitations and Future Research

This study, focusing on Malaysian undergraduate accounting students primarily in their third and fourth years, encounters limitations regarding its generalisability. The selection of universities was methodical, and various factors were considered, including geographical convenience, relevance to the study, and institutional reputation. Nevertheless, integrating data from multiple universities improves the sample's representativeness with respect to the studied population (Saunders et al., 2019). To further enhance the external validity of these findings, future research should replicate this study across diverse educational and cultural settings, including various universities and locations. This approach would broaden our understanding of student attitudes towards AI in accounting education.

Notwithstanding the adequacy of the current sample size, an expansion in future studies would contribute to increased statistical power and enhance the robustness of the findings. Variations in the structures of accounting programs across different universities, illustrated by examples like Sunway University, may skew comparisons and impede effective understanding. Future research endeavours should, therefore, consider these structural differences to enhance the accuracy and relevance of comparative analyses. Further exploration of variables such as individual experiences with AI, technological proficiency and industry exposure is crucial for deeper insights into the drivers of student engagement with AI in accounting. In summary, this study provides important insights into accounting students' intentions to use AI, but further research is needed to overcome current limitations. Future studies should deepen our understanding of AI in accounting education and inform the development of curriculum integration strategies, equipping students with the changing demands of the profession.

7.3 Implications

7.3.1 Theory Implications

The integration of external variables, such as individual differences and system characteristics, including technology readiness dimensions and job relevance, into the Technology Acceptance Model (TAM) significantly broadens and enhances its theoretical scope. This study rigorously addresses the limitations inherent in the traditional TAM by incorporating these critical elements, which are essential for understanding the behavioural intentions of students to utilise AI in accounting education. By including technology readiness and job relevance as independent variables, the study offers a more nuanced comprehension of technology integration, elucidating specific factors that influence students' attitudes and intentions towards AI. This enhancement of the TAM constitutes a substantial contribution to the theoretical framework, presenting a more robust model that accurately reflects the complexities of technology integration within educational contexts.

Moreover, this study establishes a pivotal foundation for future research on AI technology usage intentions in accounting education. The research challenges scholars to further refine the theoretical framework by identifying underexplored variables and their impacts. Advocacy for thorough investigations into previously neglected factors advances a more comprehensive understanding of students' attitudes and behaviours in relation to AI. This expanded theoretical framework augments the comprehension of technology usage intentions and provides a solid basis for subsequent empirical studies. Researchers are urged to examine additional factors that influence AI integration in education, engage in cross-disciplinary collaboration to ensure the practical applicability of findings and disseminate insights through academic publications, conferences, and workshops to effectively inform and shape educational policies and practices. The theoretical implications of this study extend beyond a mere call for further research, underscoring the imperative for a holistic and sophisticated approach to comprehending and enhancing AI integration in accounting education.

7.3.2 Practical Implications

The findings from this study carry profound practical implications for stakeholders in accounting education, encompassing universities, curriculum developers, and governmental entities. This study empowers academic institutions to strategically integrate AI-centric content and capabilities into accounting curricula by identifying key variables that influence students' behavioural intentions to engage with AI. Such strategic integration is crucial for ensuring proficiency in utilising AI technologies among students, producing well-prepared graduates to excel in the rapidly evolving accounting profession. This approach aligns with current industry paradigms, wherein AI technologies are increasingly employed to streamline processes and facilitate data-driven decision-making.

To accomplish these objectives, it is imperative for universities and curriculum developers to formulate and integrate AI-focused modules within accounting programs to ensure the acquisition of essential skills. Regular updates to the curriculum to reflect technological advancements and industry trends are vital for maintaining relevance and effectiveness. Providing hands-on training using AI tools and technologies is fundamental to bridging the gap between theoretical knowledge and practical application. Moreover, organising workshops and training sessions on AI applications in accounting will enhance practical skills and instil confidence in utilising AI tools. Additionally, the provision of counselling and support services will further aid students in comprehending the significance of AI in their future careers and support their learning process.

Furthermore, the study underscores the critical need for increased investment in AI by governmental entities. Such financial investments are essential for driving economic growth, strengthening competitive advantages, and positioning the accounting industry and the nation as leaders in technological innovation. To support these initiatives, governmental entities should allocate substantial funds towards AI research, development, and education, thus driving economic growth and maintaining a competitive edge.

In conclusion, integrating AI into accounting education is crucial for preparing students to meet the future demands of the profession. Aligning educational practices with industry trends and investing in AI will ensure that graduates are equipped with the necessary skills to thrive in a technologically advanced landscape. This comprehensive approach will ultimately contribute to broader economic growth and technological innovation, positioning both the accounting profession and the nation at the forefront of global advancements. Collective efforts of educational institutions and governmental bodies are essential for realising this vision and ensuring a robust, future-ready workforce.

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