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Analyzing Factors Influencing AI Adoption in Accounting Using TRAM Model

Suci Andayani Putri[1], Andrey Hasiholan Pulungan[2]*

[1]Accounting Study Program, Sekolah Tinggi Manajemen PPM, Jakarta, Indonesia
Email: suciandayaniputri@gmail.com
[2]Accounting Study Program, Sekolah Tinggi Manajemen PPM, Jakarta, Indonesia
Email: dre@ppm-manajemen.ac.id
**Corresponding Author*

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ABSTRACT

Although artificial intelligence (AI) is revolutionizing the accounting industry and increasing efficiency, many professionals are still reluctant to embrace it because of concerns about losing their jobs or having to learn new skills. This study explores how technological readiness influences AI acceptance among accountants and auditors by using the Technology Readiness and Acceptance Model (TRAM). Specifically, it examines the effects of optimism, innovativeness, discomfort, and insecurity on perceived ease of use and usefulness in shaping AI adoption decisions. Data were collected through purposive sampling and an online survey, yielding 225 responses, of which 202 were valid for analysis using SMART PLS 4.1.1.2. The results reveal that perceived ease of use and usefulness significantly drive AI adoption intentions. Optimism enhances perceived ease of use, while discomfort negatively affects perceived usefulness; innovativeness and insecurity show no significant impact. The findings validate TRAM's applicability in Indonesia and highlight practical implications for developing training programs that reduce discomfort, foster optimism, and strengthen user confidence to promote effective AI integration in the accounting profession.

***Keywords**: Artificial Intelligence, Accounting Profession, Indonesia Technology Readiness and Acceptance Model.*

ABSTRAK

Meskipun kecerdasan buatan (*Artificial Intelligence*/AI) sedang merevolusi industri akuntansi dan meningkatkan efisiensi, banyak profesional masih enggan untuk mengadopsinya karena kekhawatiran akan kehilangan pekerjaan atau keharusan untuk mempelajari keterampilan baru. Penelitian ini mengeksplorasi bagaimana kesiapan teknologi memengaruhi penerimaan AI di kalangan akuntan dan auditor dengan menggunakan *Technology Readiness and Acceptance Model* (TRAM). Secara khusus, penelitian ini menguji pengaruh optimisme, keinovatifan, ketidaknyamanan, dan ketidakamanan terhadap persepsi kemudahan penggunaan dan persepsi kebermanfaatan dalam membentuk keputusan adopsi AI. Data dikumpulkan melalui metode *purposive sampling* dan survei daring, yang menghasilkan 225 responden, dengan 202 responden yang dinyatakan valid untuk dianalisis menggunakan SMART PLS 4.1.1.2. Hasil penelitian menunjukkan bahwa persepsi kemudahan penggunaan dan persepsi kebermanfaatan secara signifikan mendorong niat untuk mengadopsi AI. Optimisme meningkatkan persepsi kemudahan penggunaan, sementara ketidaknyamanan berpengaruh negatif terhadap persepsi kebermanfaatan; sedangkan keinovatifan dan ketidakamanan tidak menunjukkan pengaruh yang

signifikan. Temuan penelitian ini memvalidasi penerapan TRAM dalam konteks Indonesia serta menyoroti implikasi praktis dalam pengembangan program pelatihan yang dapat mengurangi ketidaknyamanan, menumbuhkan optimisme, dan memperkuat kepercayaan pengguna untuk mendorong integrasi AI yang efektif dalam profesi akuntansi.
Kata Kunci: *Artificial Intelligence, Accounting Profession, Indonesia Technology Readiness and Acceptance Model.*

Introduction

Artificial intelligence (AI) can be defined as the optimal capability of an artificial system to effectively accomplish novel objectives via computational algorithms [1]. AI is rapidly evolving as a transformative technology with broad applications. Today, AI encompasses a range of techniques, including machine learning, natural language processing, and computer vision, enabling systems to learn from data, understand and generate human language, and interpret visual information.

Accounting provides a compelling context for examining the integration of AI-based technologies into modern knowledge work. AI is increasingly replacing human involvement in routine tasks—for example, through software robots that automate data recording and collection [2]—while also supporting processes such as reconciliations and valuations, thereby shifting accountants' focus toward ensuring statement accuracy and effective communication. In auditing, AI tools such as ChatGPT enable faster tax law research, allowing auditors to concentrate on higher-value activities [3]. [4] states that accountants play a key role in turning sustainability commitments into action, making the urgent adoption of AI and automation essential to improve transparency, credibility, and governance.

Nevertheless, Global AI Index in 2024 reports that Indonesia's 49th-place ranking out of 83 countries, indicating a moderate position that is still below the global average [5]. Figure 1 also indicates that AI adoption in finance in Indonesia remains low. This may raise issues whether professionals still hesitant to adopt AI due to job security fears or a reluctance to acquire new skills [6]. Consequently, investigating the factors that influence AI adoption within accounting remains relevant.

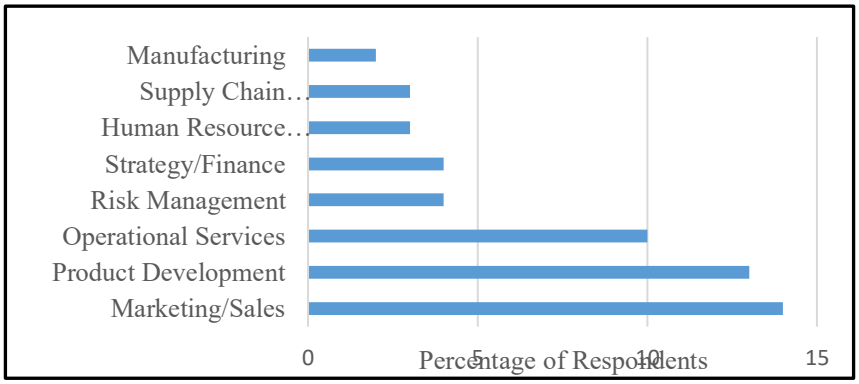

Figure 1. The Implementation of AI across sectors
Source: Ahdiat (2024)

Numerous studies have extensively utilized the Technology Readiness and Acceptance Model (TRAM) to understand technology adoption across diverse fields. Their findings, however, suggest various results, which depend on the type of technology being implemented. The study by [7], for example, shows that three out of the four aspects of Technology Readiness (TR)—optimism, innovativeness, and discomfort—have a positive impact on how useful and easy people think technology is, which affects their intention to use Quick Response Code Indonesian Standard (QRIS) as a digital payment system. In contrast, the research by [8] on Self Check-in Technology (SCT) used in Indonesian cabin hotels shows that only optimism has a strong positive effect on how useful and easy to use people think the technology is, while innovativeness, discomfort, and insecurity do not have significant effects. [9] found that optimism and innovativeness positively affect perceived usefulness and ease of use, while discomfort and insecurity negatively impact these factors in airline mobile apps. These different determinants for each technology may lead to different impacts on practical application, which imply that research on factors of specific technologies like AI can help identify potential barriers (e.g., discomfort or insecurity with new technologies) and facilitators (e.g., optimism or innovativeness) of AI adoption, thereby informing strategies to optimize AI's integration into accounting profession.

Furthermore, earlier research conducted in Indonesia does not focus on the effect of TRAM of artificial intelligence application in accounting field. While some studies in Indonesia have examined TRAM in connection to technology, they did not concentrate on AI nor on the accounting and auditing professions [7], [8]. Research on TRAM within the framework of artificial intelligence in the accounting and auditing professions usually take place overseas [10]. Thus, this study aims to evaluate the factors of AI adoption in the accounting profession by employing TRAM.

This study enhances both academic literature and practical application. It expands existing knowledge on AI acceptance among accounting professionals, particularly in developing nations like Indonesia, where research is limited. The study provides empirical evidence supporting the Technology Readiness and Acceptance Model's role in accountants' and auditors' AI adoption decisions. For companies, the study offers insights into encouraging AI acceptance. Results suggest that targeted training to reduce discomfort and build confidence can increase willingness to embrace new technologies. Furthermore, improving user experience and highlighting AI's tangible benefits can increase its perceived value and ease of use, thereby promoting greater acceptance in the accounting profession.

Accountants' Acceptance of Artificial Intelligence

Accounting is among the professions significantly reshaped by technological change. Ongoing digitalization and automation have already shifted the field toward a data-driven discipline, transforming how information is measured, processed, and managed, while increasing reliance on large and complex datasets. Within this context, AI has proven particularly effective in automating routine and well-defined tasks. It can perform activities such as inventory counting, contract review, and invoice processing with greater speed and accuracy than human workers [12]. AI systems also support financial reconciliation, detect inconsistencies, and identify duplicate transactions in

accounts payable [13] Using image recognition, they can extract key details from scanned documents and ensure that payments correspond to valid invoices. Additionally, by analyzing transaction patterns, AI can flag anomalies—such as suspicious insurance claims—enabling firms to focus on higher-risk areas. Beyond automation, AI increasingly contributes to decision-making through predictive models. These tools improve estimates of bad debt and allowance calculations, enhance loan payment predictions [14], and support auditing processes by assessing going concern assumptions, identifying irregularities, and evaluating overall audit risk [15]

However, AI implementation also raises important challenges, including regulatory compliance, ethical responsibility for algorithmic decisions, data security, and the need for accountants to strengthen their technological skills [16], [17]. The accountants also emphasized the necessity to assess, oversee, and verify the system operations to gain direct insight into its reliability [11]. Furthermore, its growing presence has introduced unease across the accounting profession. Concerns are especially pronounced among early-career practitioners, who often worry that rapid technological change could diminish the relevance of their roles. This apprehension largely revolves around job security and the need to continuously adapt to shifting competency requirements [18]. Harnessing AI benefits depends on prior acceptance; without it, adoption remains limited and potential gains are missed [19].

Technology Readiness and Acceptance Model (TRAM)

TRAM consists of the Technology Acceptance Model (TAM) developed by [20] and the Technology Readiness Index (TRI) developed by [21]. Technology Readiness is a metric designed to quantify an individual's overall confidence in technology, encompassing four key aspects: optimism, innovativeness, discomfort, and insecurity. TRI assesses the extent to which individuals are prepared to adopt and feel at ease with new technologies. It summarizes an individual’s attitudes toward using technology across many areas.

Personality and prior technology experience are key to technology readiness [22]. Positive experiences boost optimism and innovativeness, as seen with well-implemented mobile learning systems and effective training, fostering trust and exploration [23]. Conversely, negative experiences increase discomfort and insecurity, reducing readiness [24]. Poor user experiences with digital services, like in university libraries, can lead to frustration and disengagement, reducing the adoption of digital services [25]. This underscores the importance of assessing technology readiness.

Unlike technology readiness, TAM stresses how an individual's choice to adopt a given technology system depends on its efficiency and user-friendliness [20], [26]. TAM is a system particular model that emphasizes users' opinions about a given technological application instead of their general attitude toward technology. It reveals two main beliefs that influence a person's perspective on system use: perceived simplicity of use and perceived usefulness.

The degree to which one believes that using technology will improve their job performance defines perceived usefulness [20], [26]. Based on this definition, for example, students are more likely to use mobile learning platforms if they see them as helpful for acquiring instructional resources and interacting with peers [23]. A student could find that the features of a platform—such as interactive quizzes and on-demand

video lectures—help them to better understand the topic and improve their test results [23]. This concept of utility will then improve their attitude and, finally, their actual use of the m-learning system.

Perceived ease of use can be defined as the degree to which a person believes that using the technology will be free of effort [20], [26]. These perceptions directly impact the user's attitude toward the technology, which in turn influences their behavioral intention to use it and ultimately their actual usage behavior. For example, if tax professionals encounter a new digital tax platform that is cumbersome, with an ambiguous interface, and provides insufficient assistance [27], they will likely regard it as lacking user-friendliness [20], [26]. This perception may foster a negative disposition toward the platform, diminishing their willingness to dedicate the time and effort required to grasp it. As a result, they may oppose the use of the new platform, as noted in the editorial document, and continue utilizing familiar, though less efficient, tax preparation procedures [27]. Thus, TAM provides a structured framework for understanding how perceived characteristics of a system drive technology adoption decisions.

In the TRAM model, the relationship between TR and TAM is established, as TR serves as a critical factor that shapes and influences individuals' perceptions of the usefulness and ease of use of technology within the TAM framework. This relationship provides a conceptual basis for understanding how an individual's readiness for technology adoption can influence their acceptance of technological innovations. Next sections explains the impact of TR dimensions (optimism, innovativeness, discomfort, and insecurity) on TAM dimensions (Perceived Usefulness and Perceived Ease of Use).

Research by [9] supports the adaptability of TRAM by means of brand application in the airline sector. The results show that opinions of the simplicity and usefulness of the application are much influenced by dimensions of technological readiness, such as optimism and innovation, which then determines satisfaction and the intention to keep using it. The study shows that TRAM is useful in clarifying technology adoption behavior in many spheres, thus it is also relevant for use in the framework of artificial intelligence application in auditing and accounting. Consistently, TRAM has also been widely used in fields including health and health technologies [28], and financial systems and financial technology [7]. Verifying its general relevance in comprehending technological preparedness and acceptance in many different environments.

Technology Readiness (TR), Perceived Usefulness (PU), and Perceived Eased of Use

Technology Readiness has been described as the inclination of people to embrace and use new technologies in an attempt to reach goals in their life and job [21]. Technology Readiness comprises psychological motivators like optimism and innovativeness as well as challenges like discomfort and insecurity that together affect a person's inclination to embrace new technologies [21]. The technology readiness aspects consists of optimism, innovativeness, discomfort, insecurity.

Across a wide range of studies, technological readiness has also been a strong predictor of technology-related behavioral intentions [7], [9], [28]. The assertion is also consistent with [21] assertion that adoption of leading-edge technology is correlated

with a greater degree of technological readiness. Technology readiness is a fundamental component in influencing an invidual' confidence in the integration of AI in their work since artificial intelligence represents a part of the technological usefulness. While a person with skepticism and fear is probably less ready to use AI, someone with great degrees of optimism and creativity will probably see AI as a useful and basic tool to use [9].

TRAM suggests that a person's perceived value of a given technology can vary depending on their degree of technological readiness. The degree to which someone feels they should be using a given system is known as perceived usefulness [20]. It is a key determinant of technological acceptability and represents a cognitive evaluation of the benefits given by a system. Meanwhile, Perceived Ease of Use (PEOU) denotes the extent to which an individual believes that utilising a specific system would require minimal effort [20]. It signifies a cognitive assessment of the ease provided by a system and is a crucial factor in technological acceptability. The TRAM theoretical framework holds that people's perceptions of the utility and the ease of use of a technology depend much on their technological readiness (TR). As such, it is required to investigate how each dimension of TR—optimism, creativity, discomfort, and insecurity—reflects a person's psychological tendency to embrace new technology. The subsequent sections focus on how each dimension of technology readiness influences individuals' perceived of usefulness.

a. Optimism

Within TRAM, optimism is recognized as a basic psychological motivator influencing a person's technological employability [21]. Optimism is a personality feature marked by the expectation of positive events for oneself [29]. This inclination is a broad quality not limited to a particular field of work, hobby, or event that combines several life events. Generally, optimistic people show more capacity to overcome challenges and approach problems with more efficiency. Optimism is connected with someone since their activities reflect their aspirtions and their belief that they can reach their goals. In the framework of technology readiness, optimism is defined as a good attitude toward technology since it is seen as a means of improving individual control, flexibility, and efficacy in life [21].

This positive view is supposed to affect people's confidence in using technology, especially in terms of their assessment of its applicability. This is so related with the definition of perceived usefulness as the conviction that a system improves performance since optimistic people are inclined to expect that new technologies would generate favorable results [20]. Therefore, optimism can affect a person's view of the usefulness of the system by affecting their view of its possible advantages even before it is really used. Optimism has been linked, according earlier studies, to perceived usefulness [7], [8], [23].

Similarly, TRAM posits that the optimism factor affects perceived ease of use [21]. When an individual perceives that a technology offers control and significant flexibility, it influences their assessment of the technology's ease of use. An optimistic individual is likely to be more "diligent" in seeking methods to leverage technology for optimal outcomes. Such individuals will create an impression of ease in utilizing technology

within their job process. This favorable correlation is further corroborated by a prior study conducted by [7], [8]. [23].

H1a: Optimism positively influences the Perceived Usefulness of AI
H1b: Optimism positively influences the Perceived Ease of Use of AI

b. Innovativeness

Innovativeness is identified by TRAM as a psychological motivator influencing an individual's readiness to accept technology [21]. Consumers' propensity to be the first group to test new products upon their market introduction defines innovativeness [30]. Having a positive attitude toward technology within the context of technological readiness indicates a desire to be a thought leader and pioneer in the field, thus defining innovativeness [21].

Individuals who are highly innovative tend to adopt new technologies and demonstrate a willingness to experiment with them. These characteristics encourage others to perceive technology as beneficial, as these innovators show a keen interest in understanding its potential advantages and possess confidence in its applications. This point of view fits the concept of perceived usefulness—that is, the belief that a system enhances performance [20]. Innovative individuals may perceive advanced technologies as instrumental instruments that enhance productivity, streamline operations, or expeditiously resolve issues. Their proactive approach of investigating emerging systems helps them to identify potential advantages before these systems are implemented. This view is supported by [6], who demonstrated how innovation-oriented behaviors in major corporations reflect the characteristics of technology pioneers. This viewpoint is further substantiated by TRAM. Their proactive use of cutting-edge technologies shows how creatively both personally and professionally early recognition of the possible advantages of technology fosters. Earlier studies have indicated that innovation increases perceived usefulness [9], [10].

Additionally, innovativenes which closely resembles optimism, affects the perceived ease of use in technology utilization. According to the notion of innovativeness within the context of technology readiness, an innovative individual endeavors to be a trailblazer in the realm of technology. Such an individual will foster a profound curiosity in researching technology, resulting in a familiarity with its utilization. Consequently, these traits will enable the user to acclimate more rapidly to a technology, partly due to their confidence in utilizing it [9], [10]. Numerous prior investigations further corroborate this positive relationship [9], [10].

H2a: Innovativeness positively influences the Perceived Usefulness of AI
H2b: Innovativeness positively influences the Perceived Ease of Use of AI

c. Discomfort

TRAM acknowledges discomfort as a psychological component affecting a person's readiness to embrace technology [21]. According to [31], discomfort is a subjective reaction to the surroundings influenced by several physical, psychological, and physiological elements. The interaction of a person's internal wants and expectations with their subjective interpretation of outside events causes discomfort. This makes discomfort a personal feeling influenced by complex events. Within the framework of

technology readiness, discomfort is defined by a positive attitude toward manifesting as a sense of being overwhelmed by it and a felt lack of control over it [21].

Often linked with uncertainty, a main barrier to the acceptance of new technologies, discomfort is Technologies lacking user-friendliness could cause uncertainty, so reducing their apparent value [7]. This uncertainty resulting from a poor understanding of technology could prevent its efficient application and erode consumers' confidence in its possible benefits. Previous studies show that discomfort reduces perceived usefulness since people experiencing overwhelm or uncertainty might overlook or reject the possible use of the technology [9], [23].

The discomfort experienced by individuals when utilizing technology can also influence the perceived ease of use. When individuals experience discomfort with technology, they often regard it as challenging to utilize. Despite attempting it, they will continue to feel the same way. This may stem from an aversion to technology due to unease.This adverse correlation is further supported by prior studies [9], [23].

H3a: Discomfort negatively influences the Perceived Usefulness of AI
H3b: Discomfort negatively influences the Perceived Ease of Use of AI

d. Insecurity

TRAM acknowledges psychological elements affecting a person's inclination to embrace technology including insecurity [21]. Insecurity can be defined as a feeling of uncertainty, inadequacy, and anxiety about ourselves, our performance, our relationships, our qualities with respect to others, our society, and finally, our very life [32]. In terms of technological readiness, uncertainty is mistrust of technology and mistrust of its capacity to function as intended [21].

Concerns often arise on how technology should be used in the workplace regarding the effective functioning of technology and data security. These concerns stem from a skeptical perspective about the technology being utilized. According to the TRAM theory, uncertainty among individuals generates fear related to the technologies they employ [7]. Insecurity among consumers influences their perception of technology applications prior to use. Individuals who feel apprehensive about integrating technology into their daily operations tend to develop a negative outlook on its value and view it as less beneficial for their jobs. Preliminary studies by [9] indicate that perceived usefulness is negatively impacted by insecurity.

The relationship between feelings of insecurity and perceived ease of use is similar to the relationship between discomfort and perceived ease of use. Individuals often exhibit reluctance to utilize technology in their work when they experience insecurity [7]. This perspective suggests that the notion would emerge that technology is challenging to utilize, even during its application, in an effort to "liberate" oneself from its dependence.This adverse correlation aligns with prior findings [9], [33].

H4a: Insecurity negatively influences the Perceived Usefulness of AI
H4b: Insecurity negatively influences the Perceived Ease of Use of AI

Technology Acceptance Model (TAM) and AI Implementation

Under the TRAM model, the relationship between TAM and technology usage is established whereby TAM—which consists of Perceived Usefulness and Perceived

Ease of Use—serves as a fundamental determinant of people's intention to use technology. People's intention to use a technology grows more strong as their belief in its usefulness and simplicity of use rises. Thus, TAM offers a generally applicable theoretical framework for comprehending the psychological mechanisms underlying technology adoption across many contexts.

Technology describes the instruments, methods, or tools used to solve problems or improve operational effectiveness [34]. revious studies in a variety of sectors, including healthcare, education, and financial, show that when users view a technology as useful (PU) and easy to use (PEOU), the adoption rate of the technology increases significantly [7], [23], [28], [35].

Artificial intelligence (AI) has become a strategic innovation as technology develops that provides maximum capacity of an artificial system to effectively reach a fresh goal by computational algorithms [1]. Adoption of artificial intelligence (AI) is mostly dependent on users' perceptions of its usefulness (PU) and ease of use (PEOU), same as other forms of technologies. Users who think AI can greatly improve their work performance and who find AI systems to be simple to operate are more likely to use AI in their regular activities.

According to the explanation, someone who recognizes the benefits of integrating artificial intelligence into their activities, such as high efficiency and flexibility, for instance, will be more likely to integrate AI in their activities. Nevertheless, the integration of AI will increase once it is feasible to do so without having to undergo complex and time-consuming training that becomes a burden in their work processes. Research conducted in previous years has shown that the acceptance of artificial intelligence is directly associated with perceived ease of use and perceived usefulness [10], [36].

H5: Perceived Usefulness of AI positively influences AI Implementation
H6: Perceived Ease of Use of AI positively influences AI Implementation

Research Method

Data Samples

Our research applies non-probability sampling, particularly purposive sampling. This method guarantees that the selected sample is representative of the research question—that is, it would look at how artificial intelligence (AI) can be applied in auditing and accounting. Therefore, the sample population for this study is accountants and external auditors (public accountants) in private sectors who are likely experienced or acquainted with the integration of artificial intelligence into audit and accounting work. This survey is intended to gather more precise and detailed information on the impact of artificial intelligence on working life, issues encountered, and advantages reaped in the workplace.

The survey was distributed from March 2024 to May 2024 using google forms. This led to the collection of a total of 225 responses. However, a thorough analysis reduced the final data set to 202 valid responses, representing 89.78% of the total. This was after. responses were excluded on the basis of incompleteness. The validated responses provide integrity and validity to the research findings, which lay the basis for subsequent statistical analysis.

Variable measurement and technical analysis

The questionnaire is designed to gather measurable and statistical information from the respondents, thus rendering the information uniform and reliable. The scenario and questionnaire are based on [37] and [38]. The questionnaire has two sections. In the first section, focused on demographic details of the respondents, such as their age, gender, educational level, profession, position, and work experience. In the first section we also asked open ended questions on what type of AI used by the participants and how they use the AI in their works. In the second section, closed-ended statements are used to identify the attitude and perception of individuals in regards to the implementation of artificial intelligence (AI). The psychological characteristics that underlie the use of AI, including optimism towards technology, innovation, discomfort, and insecurity in using it, are quantified in this section in the format of statements. In addition, perceived usefulness and ease of use of AI are measured in this study. Then, in the second part, this survey assesses the extent to which the use of AI has been achieved in the respondents' workplaces. All items in this survey were measured using the Likert scale with the five-point range of values between 1 (strongly disagree) and 5 (strongly agree). Figure 2 illustrates the proposed research model, while Table 1 provides operational definitions of this research.

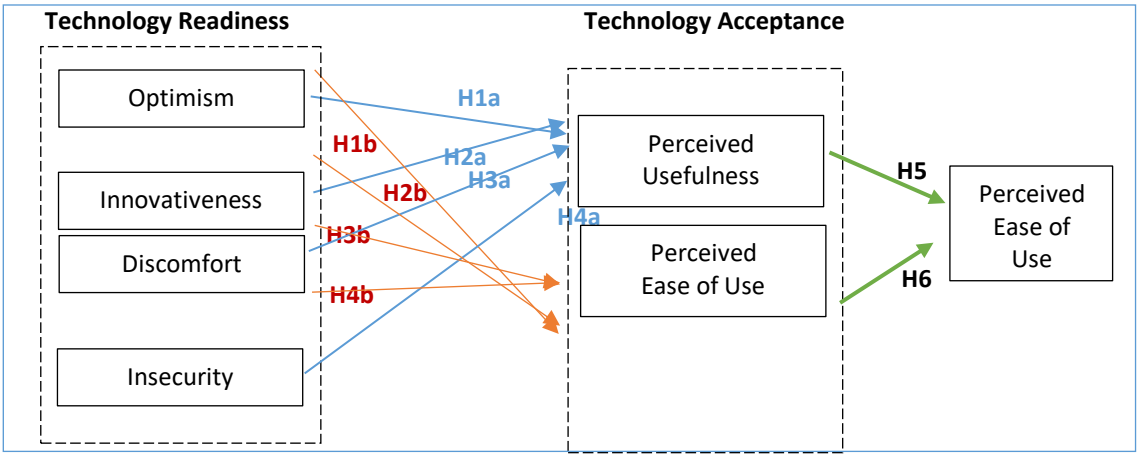

Figure 2. Conceptual Framework

Table 1. Operational Definition of Variables

Variable	Operational Definition	Indicators
AI Implementation (AII)	AI adoption is the process of integrating new and diverse knowledge through the development of new capabilities, technologies, and training programs [39]	Four measurement items used from [38].
Perceived of Usefulness (PU)	The extent to which an individual thinks that utilizing a specific method would improve their effectiveness at work [20].	Three measurement items used from [38].
Perceived Ease of Use (PEOU)	The degree to which one anticipates that employing a specific system will be effortless [20].	Three measurement items used from [38].

Optimism (O)	A positive perspective on technology and the conviction that it provides individuals with enhanced control, flexibility, and efficiency in their daily lives [21]	Four measurement items used from [37]
Innovativeness (Inn)	The capacity to be a technology pioneer and thought leader [21]	Four measurement items used from [37]
Discomfort (D)	A sense of being overpowered by technology and a perceived absence of control over it [21]	Four measurement items used from [37]
Insecurity (Ins)	Skepticism regarding the functionality of technology and distrust of its efficacy [21]	Four measurement items used from [37]

Results And Discussion

Demographic Information

Table 2 indicates that a significant majority of respondents, comprising 65.3%, were female, while male participants accounted for 34.7%. The demographic distribution suggests a potential inclination for female representation in the outcomes. A substantial segment of the respondents, approximately 42.1%, were aged 31 or older, and 57.9% were below the age of 31.

Concerning educational qualifications, over half of the participants (78%) were engaged in a bachelor's degree or a four-year certificate program, with a notable 54.5% of this group employed as accountants. The data indicates that the predominant respondents are young professionals, primarily those under the age of 31, with 1–6 years of work experience. This indicates a respondent pool that is likely still in the early stages of their career, which could influence their perspectives on technological adoption or professional development within the accounting and auditing field.

A significant percentage of the participants (57.9%) hold entry- to mid-level employment. Subsequently, those at the supervisor or assistant management level constitute 27.2%, although a minor percentage occupies senior executive roles, including manager/senior manager (10.4%), and director/vice president (4.5%). This distribution corresponds with the previous observation of a younger responder demography, further substantiating the premise that the data predominantly represents the perspectives of early- to mid-career professionals.

Finally, an analysis of professional experience reveals that 77.7% of respondents have up to six years of experience, with 41.1% in the one- to three-year category and 36.6% in the four- to six-year category. Only 16.9% of respondents have over seven years of experience. This may indicate that the study's findings more accurately represent growing trends and perceptions among the younger generation of accounting and auditing professionals.

Table 2. Demographic Information

Characteristics	Frequency	%
Total respondent	202	100%
Gender		
Male	70	34.7%
Female	132	65.3%
Age		
≤ 30 years old	117	57.9%
31 – 40 years old	58	28.7%
41 – 50 years old	23	11.4%
> 50 years old	4	2.0%
Degree		
Diploma (D3)	44	22%
Bachelor/ Diploma (S1/D4)	131	65%
Master (S2)	24	12%
Doctor (S3)	3	1%
Profession		
Accountant	110	54.5%
Auditor	92	45.5%
Position		
Staff / Junior Auditor / Associate Senior / Senior Audit	117	57.9%
Supervisor / Assistant Manager	55	27.2%
Manager / Senior Manager	21	10.4%
Director / Vice Director / Vice President	9	4.5%
Working Experience		
< 1 year	11	5.4%
1 – 3 years	83	41.1%
4 – 6 years	74	36.6%
7 – 10 years	26	12.9%
>10 years	8	4.0%

Source: Generated from field survey data utilizing Microsoft Excel (primary data)

Measurement Model

We evaluated the degree to which the scale items reflect their related components using an item-level measurement model. Six latent constructs, which are AI Implementation (AII), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Optimism (O), Innovativeness (INN), Discomfort (D), and Insecurity (INS), were identified in the model. We measured convergent validity using factor loadings and the average variance extracted (AVE). S presented in Table 3, all items met the established criteria. Specifically, the average variance extracted values for each construct consistently exceeded the 0.5 threshold, thus demonstrating adequate convergent validity and the constructs' ability to effectively represent the measured variables [40]. Moreover, as shown in Table 3, Cronbach's alpha and composite reliability (CR) were computed for internal consistency. The Cronbach's alpha and composite reliability (CR) values of all constructions exceeded 0.7, so confirming the dependability of the items used in this study.

Table 3. Convergent Validity and Reliability Test Result

Construct	Items	Factor Loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
AI Implementation			0.851	0.863	0.693
	AII1	0.910			
	AII2	0.856			
	AII3	0.807			
	AII4	0.749			
Perceived Usefulness			0.858	0.889	0.776
	PU1	0.857			
	PU2	0.889			
	PU3	0.897			
Perceived Ease of Use			0.819	0.834	0.734
	PEOU1	0.848			
	PEOU2	0.821			
	PEOU3	0.900			
Optimism			0.857	0.910	0.697
	O1	0.891			
	O2	0.844			
	O3	0.810			
	O4	0.790			
Innovativeness			0.848	0.872	0.685
	INN1	0.879			
	INN2	0.837			
	INN3	0.811			
	INN4	0.782			
Discomfort			0.865	0.897	0.708
	D1	0.853			
	D2	0.811			
	D3	0.809			
	D4	0.890			
Insecurity			0.836	0.883	0.663
	INS1	0.890			
	INS2	0.795			
	INS3	0.737			
	INS4	0.828			

Source: SmartPLS version 4.1.1.2

Additionally, we evaluated discriminant validity to determine whether each concept explains its indicators' variation more successfully than that of other constructs [41]. Table 4 shows, using the Fornell-Lacker Criterion, that the square root of the Average Variance Extracted (AVE) for each concept, listed along the diagonal, is greater than the values in the other rows and columns. Thus, our data strongly confirm the discriminant validity of all components in the proposed model.

Table 4. Discriminant Validity (Fornell-Lacker Criterion)

Constructs	All	PU	PEOU	O	INN	D	INS
All	**0.833**						
PU	0.305	**0.881**					
PEOU	0.271	0.210	**0.857**				
O	0.148	0.102	0.348	**0.835**			
INN	0.156	0.120	0.119	0.180	**0.828**		
D	-0.274	-0.227	-0.102	-0.130	-0.032	**0.841**	
INS	-0.158	-0.146	-0.170	-0.175	-0.239	0.099	**0.814**

Source: SmartPLS version 4.1.1.2

We assessed convergent validity by analyzing the factor loadings and cross-loadings of all indicator items about their corresponding latent constructs. Table 5 illustrates that the cross-loadings of each item exhibit robust correlations with their corresponding components and negligible correlations with other constructs. The findings demonstrated that all items had loadings ranging from 0.748 to 0.910 on their corresponding structures. Consequently, it may be inferred that these measurement items precisely embody their corresponding latent conceptions.

Table 5. Discriminant Validity (Cross Loading Result)

Items \ Constructs	All	PU	PEOU	O	INN	D	INS
All1	**0.910**	0.284	0.236	0.134	0.138	-0.182	-0.168
All2	**0.856**	0.249	0.264	0.161	0.129	-0.212	-0.111
All3	**0.807**	0.189	0.166	0.048	0.178	-0.234	-0.118
All4	**0.749**	0.274	0.218	0.129	0.088	-0.291	-0.126
PU1	0.215	**0.857**	0.161	0.029	0.088	-0.134	-0.152
PU2	0.261	**0.889**	0.183	0.116	0.094	-0.198	-0.100
PU3	0.312	**0.897**	0.204	0.110	0.126	-0.248	-0.136
PEOU1	0.313	0.225	**0.848**	0.245	0.154	-0.143	-0.141
PEOU2	0.099	0.116	**0.821**	0.334	0.070	-0.006	-0.132
PEOU3	0.257	0.187	**0.900**	0.324	0.077	-0.096	-0.163
O1	0.185	0.091	0.392	**0.891**	0.138	-0.086	-0.100
O2	0.082	0.072	0.230	**0.844**	0.110	-0.070	-0.094
O3	0.133	0.107	0.210	**0.810**	0.182	-0.100	-0.251
O4	0.067	0.075	0.270	**0.790**	0.180	-0.182	-0.173
INN1	0.173	0.121	0.123	0.133	**0.879**	-0.081	-0.213
INN2	0.162	0.091	0.097	0.129	**0.837**	-0.066	-0.223
INN3	0.109	0.072	0.081	0.185	**0.811**	0.021	-0.144
INN4	0.057	0.103	0.084	0.163	**0.782**	0.045	-0.201
D1	-0.351	-0.209	-0.151	-0.122	-0.044	**0.853**	0.067
D2	-0.159	-0.141	-0.067	-0.124	0.014	**0.811**	0.106
D3	-0.110	-0.166	-0.029	-0.053	0.030	**0.809**	0.041
D4	-0.238	-0.227	-0.068	-0.126	-0.075	**0.890**	0.117
INS1	-0.140	-0.156	-0.174	-0.206	-0.207	0.039	**0.890**
INS2	-0.083	-0.089	-0.173	-0.085	-0.200	-0.002	**0.795**
INS3	-0.104	-0.070	-0.069	-0.061	-0.129	0.107	**0.737**
INS4	-0.190	-0.136	-0.099	-0.176	-0.223	0.226	**0.828**

Source: SmartPLS version 4.1.1.2

Structural Model

The evaluation results comprised comprehensive analyses of the standardized structural coefficients, specifically the beta values and their corresponding t-values,

utilizing the bootstrapping approach established by [42]. This methodology was highly rigorous, involving 5,000 resamples. Subsequently, we assessed the explanatory power, namely R^2 and effect size (f^2) for the model, as outlined in the framework by [42]. These measurements elucidate the robustness and importance of the interactions within the model, extending to a comprehension of the model's overall explanatory power.

Table 6 offers an analysis of the structural relationships among the variables to predict the adoption of AI in the accounting profession. The findings suggest that only some of the hypothesized relationships were statistically significant. Specifically, only hypotheses H3, H1b, H9, and H10 were supported, while H1a, H2, H4, H2b, and H3b were not supported. On the other hand, discomfort was found to significantly and negatively affect perceived usefulness (β = -0.216; t = 3.146; p = 0.002), hence supporting H3. This research indicates that persons with greater anxiety with technology are likely to view AI as less beneficial in their professional responsibilities. Similarly, optimism demonstrated a substantial positive impact on perceived ease of use (β = 0.320; t = 4.880; p = 0.000), supporting H1b and suggesting that a favorable disposition towards technology enhances the perceived usability of AI. Moreover, both perceived usefulness and perceived ease of use strongly forecasted AI implementation (β = 0.256; p = 0.002 and β = 0.224; p = 0.004, respectively), supporting for H9 and H10. These findings highlight the critical importance of perceived of use and ease of use in influencing accountants' and auditors' intention to incorporate AI into their job processes. Conversely, characteristics such as innovativeness, insecurity, and discomfort do not have significant effects on perceived ease of use, and both innovativeness and insecurity do not significantly predict perceived usefulness. The results indicate that although individual characteristics such as optimism and perceived discomfort significantly affect technology perception and adoption, not all personality aspects equally influence professionals' acceptance of AI technologies in accounting and auditing.

Table 6. Structural Model Test of Hypotheses

Hypotheses	Beta	t-value	p-values*	f^2
O → PU	0.040	0.558	0.577	0.002
INN → PU	0.087	1.079	0.281	0.007
D → PU	-0.216	3.146	**0.002**	0.046[1]
INS → PU	-0.106	1.398	0.162	0.010
O → PEOU	0.320	4.880	**0.000**	0.109[1]
INN → PEOU	0.043	0.510	0.610	0.001
D → PEOU	-0.059	0.658	0.511	0.003
INS → PEOU	-0.108	1.198	0.231	0.011
PU → AII	0.256	3.100	**0.002**	0.075[1]
PEOU → AII	0.224	2.891	**0.004**	0.052[1]

*p < 0.05

[1]Small effect size; [2]Medium effect size; [3]Large effect size

Source: SmartPLS version 4.1.1.2

Table 6 shows that, although discomfort affects perceived usefulness, optimism influences perceived ease of use, and both perceived usefulness and perceived ease of use impact AI implementation, their effect sizes are small (Cohen, 1988 as cited in [43]). For instance, just 0.046 is the effect size of discomfort on perceived usefulness. This suggests that even if these components have some influence, their practical relevance

may be limited and other factors could take a more central part in shaping opinions and hence influencing the use of AI. The modest effect sizes underscore the intricate nature of technological acceptability, suggesting the necessity of incorporating a broader range of factors beyond the confines of the present model.

Figure 3 shows the structural model of the study, so providing a knowledge of the elements influencing the use of artificial intelligence (AI) among accountants and auditors in their professional life. With an adjusted R-squared value of 0.076, optimism, innovativeness, discomfort, and insecurity taken together account just 7.6% of the variance in perceived usefulness. Likewise, an adjusted R-squared value of 0.137 implies that these same variables account for 13.7% of the variance in perceived ease of use. These results demonstrate the significance of personal attitudes and behaviors toward technology in shaping perceptions of artificial intelligence. However, they also imply that additional factors, not incorporated into the current model, substantially impact the variance, accounting for 92.4% of perceived usefulness and 86.3% of perceived ease of use.

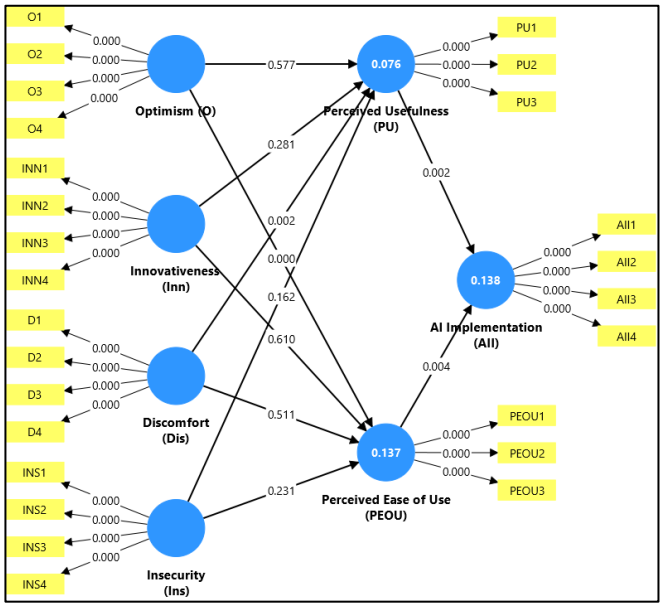

Figure 3. Structural Path Results

Together, perceived usefulness and perceived ease of use also explain 13.8% of the variance in the actual application of artificial intelligence in accounting and auditing procedures. This result emphasizes the predictive power of perception in influencing behavior; nevertheless, the rather low adjusted R-squared value also shows that other factors outside of these two perceptual models drive 86.2% of the variance in AI application. Taken together, these findings imply that, although optimism, innovativeness, discomfort, insecurity, and technology perceptions play a role, a more general set of contextual, organizational, or technological factors most certainly influences AI adoption decisions in professional accounting environments.

Discussion

Our analysis highlights several important findings. First, consistent with TAM, the study confirmed that both perceived ease of use and perceived usefulness significantly contributed to AI implementation among accountants and auditors. If perceived usefulness significantly and positively influences AI implementation, it reinforces the core tenet of TRAM and TAM: that individuals are more likely to adopt a technology if they believe it will improve their performance or productivity [44]. Likewise, a significant positive relationship between perceived ease of use and AI implementation would suggest that if accountants and auditors find AI systems easy to learn and use, they are more likely to implement them. This is in line with TAM and numerous empirical studies, which emphasize the importance of user-friendliness in technology adoption. If a system is easy for users to operate, it lowers adoption barriers (time, effort, frustration), and if it is useful, it provides a compelling reason to change existing work processes [45], [46], [47], [48].

In other words, when accountants and auditors perceive AI as a tool that can automate routine tasks, reduce errors, and provide better insights, they will be more inclined to implement it in their work. As they grow more acquainted with artificial intelligence tools, they could identify creative ways to improve their processes even more, so raising general production levels. This is in line with studies in different professions that show a positive attitude toward artificial intelligence could ultimately help to build an adaptive and always improving culture [49], [50], [51], [52].

Secondly, our study reveals that the measurement model exhibits a lack of statistical significance concerning the influence of Technology Readiness (TR) inhibitors—specifically innovativeness and insecurity—on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Insecurity does not significantly affect accountants' perceptions of artificial intelligence, particularly their evaluations of perceived usefulness and perceived ease of use. This finding is consistent with [54]. This implies that hesitation toward AI among accountants may not always stem from insecurity as a psychological barrier. Consequently, insecurity should be understood as a factor that directly determine how accountants assess AI. This result contributes to a more nuanced understanding of technology readiness in accounting, because it shows that not every negative feeling toward technology translates into a meaningful perception of AI itself.

The finding that innovativeness does not significantly influence perceived usefulness and perceived ease of use of artificial intelligence can be justified by considering how innovativeness operates within the technology readiness framework. Empirical evidence from the attached studies indicates that cognitive beliefs about AI are more strongly shaped by experience and system-related factors [54]. In other words, innovativeness may encourage initial curiosity or trial but does not directly determine how accountants cognitively evaluate AI systems in terms of usefulness and ease of use [55]. For instance, prior AI experience has been shown to positively influence both perceived usefulness and ease of use, suggesting that familiarity and exposure are more critical than inherent innovativeness in forming these perceptions. This implies that even individuals who are highly innovative may not perceive AI as useful or easy to use unless they have sufficient practical experience or clear evidence of its benefits.

Our results shows that only optimism and discomfort that partially affect perceived usefulness or perceived eased of use. Specifically, individual's perceived usefulness of artificial intelligence decreases with discomfort, or when technology makes one feel uncomfortable or out of control. This aligns with the limiting aspect of technological readiness related to feeling overwhelmed or threatened by new technologies [21]. Increased discomfort with artificial intelligence makes accountants and auditors less likely to see its advantages, hence reducing their perceived value. Professionals worried about the complexity or dependability of artificial intelligence start to doubt its usefulness for their jobs. This finding aligns with previous research indicating that discomfort can undermine confidence in the benefits of technology.If accountants and auditors are uncomfortable with AI, they may not trust it to deliver accurate or compliant results [9], [23]. When uneasy, individuals may focus on risks, hindering appreciation of the technology's potential. For instance, an auditor feeling overwhelmed by AI analytics may doubt its outputs and value, diminishing their perception of its usefulness.

Interestingly, discomfort does not significantly affect their perceived ease of use. This suggests that even users who are not completely comfortable with AI may not necessarily consider it difficult to use. One reason for insignificant influence on the perceived ease of use is modern AI tools (like audit data analytics platforms) often have intuitive designs or templates, and users can rely on instructions or teamwork to operate them effectively. They also might find the interfaces or tools easy to navigate, possibly because of user-friendly designs or good training provided by their companies.

Another reason could be the collaborative work culture in Indonesia [53], where people often work in teams to complete tasks. Training sessions, peer mentoring, and collective problem-solving are common in firms adapting to new regulations or tools. This collectivism environment can help mitigate individual feelings of discomfort regarding ease of use; colleagues assist each other in learning and using new systems, ensuring that even those initially uneasy can get up to speed with the tool's operation. Thus, an accountant might acknowledge that an AI software's interface is straightforward (no effect on PEOU) because training and peer support have made it manageable, yet still feel uneasy about the technology's outcomes or trustworthiness – which manifests as a lower sense of usefulness. This dynamic explains why discomfort impacts PU (belief in the technology's value) more directly than it impacts ease-of-use perceptions.

In regards to optimism, our research indicates that optimism substantially affects perceived ease of use, but does not impact perceived usefulness. This conclusion contradicts [54], which discovered that optimism affects accountants' perception of utility rather than perceived ease of use. Within the framework of technological readiness, optimism denotes a favorable disposition towards technology, prompting people to perceive AI solutions as more accessible. This approach diminishes anxiety, hence greatly enhancing favorable attitudes towards technology adoption [54]. Conversely, the mentality cultivates confidence, enabling accountants to interact with AI systems without trepidation. An optimistic auditor utilizing AI-based auditing tools anticipates ease of use, hence enhancing their experience while navigating the system.

Finally, our results on the function of discomfort and optimism should be seen in light of Indonesia's accounting and auditing context, which is undergoing digital transformation but still struggles with AI adoption. Indonesia has been pushing sectors to modernize; for example, the government started a digital transformation initiative meant to make Indonesia a top digital economy [56]. Companies and public accountants are realizing how artificial intelligence could increase analytics and efficiency. However, adoption among Indonesian accountants and auditors is still uneven and cautious [57]. This may cause auditors and accountants' attitudes towards AI are shaped in great part by discomfort and optimism. Professional culture values accuracy, compliance, and risk reducing among Indonesian accountants. They might be naturally dubious of untested technologies, which would aggravate anxiety and discomfort with artificial intelligence. Auditors, for example, are taught to exercise professional skepticism; those with less tech confidence may worry about data security (insecurity) or fear that AI could create errors they do not understand (discomfort). This can lead them to doubt AI's ability to satisfy high client expectations and regulatory requirements.

Therefore, in Indonesia's high-context culture [53], success stories from peer companies and endorsements from corporate leaders can also help to persuade practitioners about value, so progressively transforming skeptics. Showing the specific benefits of artificial intelligence by means of case studies and pilot projects helps to inspire acceptance and confidence. Furthermore, emphasizing that AI aligns with Indonesian cultural values, such as collectivism and community, may increase its appeal and acceptance. This strategy places artificial intelligence not as a replacement for human labor but rather as a tool to increase cooperation and support general production, so fostering a feeling of group advancement.

CONCLUSION

This study aims to evaluate the factors of AI adoption in the accounting profession by employing TRAM. This research utilized TRAM to evaluate the impact of four dimensions of technology readiness—optimism, innovativeness, discomfort, and insecurity—on perceptions of usefulness and ease of use, and how these perceptions subsequently affect AI adoption in the professional domains of accounting and auditing. The study shows that AI adoption among accountants and auditors is primarily driven by core beliefs from the Technology Acceptance Model—perceived usefulness and perceived ease of use—while elements of Technology Readiness play a more selective and indirect role. Specifically, optimism and discomfort shape perceptions differently, whereas innovativeness and insecurity do not significantly influence how AI is evaluated, suggesting that practical experience and system characteristics matter more than inherent traits. Particularly optimism affects perceived ease of use, implying that professionals who view technology favorably usually find artificial intelligence systems more understandable and controllable. Conversely, discomfort indicates that emotions of technological overload or unease may prevent professionals from appreciating the advantages of artificial intelligence, so affecting perceived usefulness.

The results contribute theoretically and practically. It theoretically increases the body of knowledge on artificial intelligence adoption among accounting professionals,

especially in Indonesia where study in this field is rare. The evidence demonstrates that the dimensions of TR exert asymmetric effects across professional subgroups, challenging the common assumption of uniform TR dimensionality in prior TRAM research. Moreover, it suggests that TRAM's explanatory power in the context of AI adoption within professional accounting services is considerably more limited than in consumer technology settings.

The study offers organizations trying to encourage artificial intelligence adoption important new perspectives. Specific training courses that alleviate users' discomfort and enhance confidence, thereby better preparing accountants and auditor to adopt AI. Furthermore, improving user experience and highlighting the specific benefits of artificial intelligence will help to increase perceived usefulness and ease of use, so encouraging more general acceptance.

The study has several limitations that may open opportunities for future studies. The study's findings are constrained by several methodological limitations that affect both validity and generalisability. The sample is heavily skewed toward early-career respondents, with most participants having limited professional experience and occupying junior roles, which may not reflect the perspectives of senior decision-makers responsible for AI adoption. This demographic imbalance raises concerns about the construct validity of the AI implementation measure and limits its applicability to the broader accounting profession. Additionally, the relatively small sample size reduces the ability to capture the diversity and complexity of accounting and auditing practices across Indonesia. The reliance on self-reported survey data introduces potential response biases, including social desirability bias, while the low R-squared values suggest that the model may omit other influential factors such as organisational support, regulatory pressure, and perceived risk.

Future research may include a more balanced and representative sample by incorporating senior professionals, such as managers and partners, to better capture organisational decision-making dynamics. Increasing the sample size and ensuring broader geographic and organisational coverage would enhance generalisability. Researchers are also encouraged to complement self-reported data with objective or mixed-method approaches to reduce bias. Finally, expanding the research model to include additional variables—such as organisational readiness, regulatory environment, and risk perception—would provide a more comprehensive understanding of AI adoption in the accounting profession.

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