Analysis of Artificial Intelligence (AI) Technology Acceptance Among Accounting Employees: A Model Based on UTAUT-3

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ABSTRACT

This study examines the factors influencing AI technology acceptance among accounting professionals using the UTAUT-3 model. The relevance of this research is grounded in the growing adoption of AI in the accounting profession, particularly in response to the digital transformation across financial reporting, auditing, and compliance. AI adoption in accounting has increased, yet remains inconsistent due to behavioral and organizational challenges. A total of 162 accounting employees from ISP companies in East Java participated in this research. Data were analyzed using Partial Least Squares (PLS-SEM). The findings show that performance expectancy, effort expectancy, and social influence significantly affect behavioral intention, while habit directly influences usage behavior. Other variables, including facilitating conditions and hedonic motivation, were not significant. This study offers novelty by applying UTAUT-3 in the context of Indonesian accounting professionals—a domain rarely explored. It provides insight into how organizations can align AI strategies with user behavior and readiness.

Keywords: Artificial Intelligence; UTAUT-3; Behavioral Intention; Actual Usage Behavior; Accounting Employees.

Analisis Penerimaan Teknologi Kecerdasan Buatan (AI) Pada Karyawan Akuntansi: Model Berdasarkan UTAUT-3

ABSTRAK

Penelitian bertujuan menganalisis faktor-faktor yang memengaruhi penerimaan dan penggunaan teknologi kecerdasan buatan (AI) oleh karyawan akuntansi menggunakan model UTAUT-3. Relevansi penelitian ini didasarkan pada adopsi AI yang semakin meningkat di profesi akuntansi, terutama sebagai respons terhadap transformasi digital dalam pelaporan keuangan, audit, dan kepatuhan. Adopsi AI di bidang akuntansi telah meningkat, namun masih tidak konsisten akibat tantangan perilaku dan organisasional. Sebanyak 162 karyawan akuntansi dari perusahaan ISP di Jawa Timur berpartisipasi dalam penelitian ini. Data dianalisis menggunakan Partial Least Squares (PLS-SEM). Temuan menunjukkan bahwa ekspektasi kinerja, ekspektasi usaha, dan pengaruh sosial secara signifikan mempengaruhi niat perilaku, sementara kebiasaan secara langsung mempengaruhi perilaku penggunaan. Variabel lain, termasuk kondisi pendukung dan motivasi hedonik, tidak signifikan. Penelitian ini menawarkan keunikan dengan menerapkan UTAUT-3 dalam konteks profesional akuntansi Indonesia – sebuah bidang yang jarang dieksplorasi. Penelitian ini memberikan wawasan tentang bagaimana organisasi dapat menyelaraskan strategi AI dengan perilaku dan kesiapan pengguna.

Kata Kunci: Kecerdasan Buatan; UTAUT-3; Niat Perilaku, Perilaku Penggunaan Aktual, Karyawan Akuntansi.

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INTRODUCTION

Accelerating technological changes have found various advanced technologies in providing human needs. One of the advanced technologies that has evolved to help learn and find things is artificial intelligence (AI). Artificial intelligence has made it easier for users to do complex work, where artificial intelligence has a way of working based on the input that has been received then processing and analyzing large amounts of data using various rule-based approach techniques to statistical and learning models. or users. The main purpose of artificial intelligence is to provide Artificial Intelligence Technology that can be accessed using the internet through websites and mobile applications that can make it easier for users to choose access rights. Some AI technologies that have been developed in Indonesia are Ailita, ChatGPT, Gemini, Google Assistant, and Siri.

Artificial intelligence (AI) technology is seen as a key driver in realizing Indonesia's digital transformation towards the 2045 golden generation. By 2023, Indonesia will rank third as the country with the highest traffic to AI technology after the United States and India, with a contribution of 1.4 billion visits or 5.60% of the global total (Muhamad, 2024). An increase in internet penetration of 77% supports this ecosystem, especially in the Internet Service Provider (ISP) sector, which involves 1,281 companies (IPSOS, 2024). This condition encourages the utilization of AI to support operational activities, including accounting, financial, and audit records to align with SAK and national regulations (Camilleri, 2024; Gama, 2021; Rahmawati & Subardjo, 2022). Although AI has the potential to strengthen information governance in accounting practices, there are still concerns among professionals that its adoption may threaten the sustainability of accountants' careers.

This research has examined the acceptance and use of artificial intelligence (AI) technology specifically by accounting employees in Internet Service Provider (ISP) companies. Most previous studies, such as those conducted Almaiah et al. (2022), Chao (2019) dan Farooq et al. (2017) focused on the education sector, the public, or students as technology users. This study uses the development of the UTAUT-3 model in the context of accounting professionals who have different AI usage characteristics, especially in terms of the need for accuracy, efficiency, and regulatory compliance. In addition, this study also integrates individual behavioral dimensions such as habit and personal innovativeness in explaining the intention and actual behavior of AI use-two constructs that have not been comprehensively tested in the context of accounting information system-based professional work.

Although the adoption of artificial intelligence (AI) technology in the accounting sector shows an increasing trend, research on the factors influencing the acceptance of this technology is still limited to classical model approaches such as TAM and UTAUT-2. Almaqtari (2024), Gursoy et al. (2019) and Norzelan et al. (2024) have shown that AI provides significant benefits in the financial reporting and decision-making process, but they have not explicitly examined more complex individual behavioral factors such as habit, hedonic motivation, and personal innovativeness in the context of accounting employees. Some other studies such as Butt et al. (2022, 2023), Chao (2019) dan Liu et al. (2023) also highlighted that there is a disconnect between intention and behavior of technology use due to external factors such as organizational culture, system integration, and management support, still not many have examined how this condition impacts the accounting sector which has systematic and regulation based work characteristics. In addition, there are still rare studies that fully adopt the UTAUT-3 model (Farooq et al., 2017) to examine AI technology adoption behavior in a specific context in Indonesia, especially in the accounting profession which is now facing massive digital disruption. Therefore, this study aims to fill the gap by evaluating the cognitive and behavioral factors in AI technology adoption based on UTAUT-3, as well as modifying the hypothesis path to explain the dynamics of AI acceptance more comprehensively in accounting employees.

To address these limitations, this study employs the UTAUT-3 model, which extends UTAUT-2 by integrating key psychological dimensions including habit, hedonic motivation, and personal innovativeness—allowing for a more comprehensive understanding of user behavior. Compared to its predecessors, UTAUT-3 offers a richer explanatory framework by accommodating both rational and affective constructs that influence technology acceptance, particularly in contexts undergoing digital disruption. Despite its theoretical advancement, UTAUT-3 has rarely been applied in the Indonesian accounting sector. Therefore, this study aims to fill this gap by adapting and modifying the UTAUT-3 framework to assess AI acceptance among accounting employees, thereby capturing the dynamic interplay between cognitive, behavioral, and contextual factors in technology adoption.

Performance expectancy refers to an individual's belief that using a technology will enhance their job performance. In the accounting context, AI is perceived to improve task speed, data accuracy, and compliance with financial regulations. For accounting employees in data-intensive and highly regulated ISP environments, AI offers practical benefits in reducing workload and increasing efficiency. Prior studies by Farooq et al. (2017), Lin et al. (2023), dan Meraghni et al. (2021) consistently found that performance expectancy significantly influences the intention to adopt technology. UTAUT-3 also positions performance expectancy as a core determinant of user acceptance. Therefore, this study proposes that performance expectancy positively influences behavioral intention to use AI in the accounting workplace. Therefore, this study proposes the following hypothesis:

H1 : Performance Expectancy has a positive influence on Behavioural Intention

Effort expectancy refers to the extent to which an individual perceives a technology to be easy to use and free of complexity. In the accounting profession, where precision and efficiency are crucial, the perceived ease of using AI systems can strongly influence willingness to adopt them. When AI applications are seen as intuitive and require minimal learning effort, employees are more likely to use them consistently as part of their workflow. This is particularly relevant in structured environments such as ISP, where accounting personnel must adapt quickly to evolving digital tools without disrupting compliance routines. Prior studies Alkhwaldi et al., 2024, Farooq et al., 2017, and Wu & Ho, 2022 confirm that higher effort expectancy leads to greater behavioral intention to adopt technology. Therefore, this study proposes the following hypothesis:

H2 : Effort Expectancy has a positive influence on Behavioural Intention

Social influence refers to the degree to which individuals perceive that important others—such as coworkers, supervisors, or peers—believe they should use a particular technology. In structured work environments like accounting departments, especially within ISP companies, the adoption of AI is often influenced not only by individual preferences but also by social and organizational expectations. When employees observe that AI usage is encouraged or considered the norm by their colleagues or management, they are more likely to develop the intention to adopt it. Previous studies by Farooq et al. (2017), Maisha & Shetu (2023), Mangadi & Petersen (2024), support the significance of social pressure in shaping technology adoption decisions, particularly in collective or hierarchical cultures. Social influence also aligns with the UTAUT framework as a key predictor of behavioral intention. Thus, this study proposes the following hypothesis:

H3 : Social Impact has a positive influence on Behavioral Intention.

Facilitating conditions refer to the extent to which individuals believe that the organizational and technical infrastructure available supports the use of a given technology. In accounting environments—especially those within Internet Service Provider (ISP) companies—stable system access, available technical support, and the provision of relevant hardware and software play a critical role in enabling employees to adopt AI tools effectively. When these resources are perceived as sufficient, employees are more confident and less resistant to integrating AI into their daily workflows. Prior studies by Farooq et al. (2017), Mangadi & Petersen (2024), Venkatesh et al. (2012), have emphasized that strong facilitating conditions enhance users' trust and readiness in adopting technology. Within the UTAUT-3 framework, facilitating conditions are recognized as a key driver of behavioral intention. Based on this reasoning, the study proposes the following hypothesis:

H4 : Facility conditions have a positive influence on Behaviuoral Intention

Facilitating conditions may not only influence intention but also directly impact actual system usage. This construct reflects whether individuals feel that the necessary resources—such as training, infrastructure, and system accessibility—are available to support the use of AI. In highly technical and regulated accounting environments, like those found in ISP companies, effective facilitating conditions can reduce barriers to consistent system use. When employees perceive sufficient support, they are more likely to engage with AI technologies regardless of initial motivation. Prior studies by Farooq et al. (2017), Guste & Ong (2024), Wang & Li (2024), demonstrate that facilitating conditions can directly affect user behavior, particularly in systems that require institutional adaptation. Accordingly, this study extends the model by testing a direct relationship between facilitating conditions and AI usage behavior:

H5 : Facility conditions have a positive influence on Artificial Intelligence Technology Usage Behaviour

Hedonic motivation refers to the perceived enjoyment or pleasure derived from using a technology. In the workplace, particularly in structured roles like accounting, emotional satisfaction is not usually the primary factor influencing technology adoption. However, when AI systems are engaging, responsive, or user-friendly, they may still create positive emotional experiences that increase user intention. While accounting tasks are typically utilitarian, hedonic motivation can still play a supporting role in shaping attitudes, especially among younger professionals or those open to technological change. Studies by Farooq et al. (2017) Guste & Ong (2024), Liu et al. (2023), found that enjoyment positively correlates with behavioral intention, even in professional settings. UTAUT-3 incorporates hedonic motivation to address this emotional dimension of user experience. Therefore, this study proposes the following hypothesis:

H6 : Hedonic Motivation has a positive influence on Behavioural Intention

Habit refers to the extent to which individuals tend to perform behaviors automatically due to prior experience and repetition. In professional settings such as accounting, once the use of AI becomes embedded in daily routines, it can shape behavioral intention—even in the absence of external motivation. Strong habits lead to increased familiarity and reduce cognitive resistance, which in turn encourages continued intention to use the technology. This is particularly relevant for accounting professionals who frequently engage in repetitive tasks that AI can simplify. Farooq et al. (2017), Liu et al. (2023), Mangadi & Petersen (2024), Muchran et al. (2024), found that habit plays a critical role in shaping behavioral intention, especially when technology is used in a consistent work environment. In the UTAUT-3 model, habit is recognized as both a predictor of intention and behavior. Based on this, the following hypothesis is proposed:

H7 : Habit has a positive influence on Behaviuoral Intention

Habit can directly influence actual technology usage by making the behavior automatic and routine. In accounting environments, when AI tools are used repeatedly in tasks such as data entry, financial reporting, or reconciliation, the behavior becomes habitual—requiring little conscious effort. This automaticity reduces reliance on motivation or intention, allowing continued use of AI even when external encouragement is minimal. Prior research by Farooq et al. (2017), Liu et al. (2023), Muchran et al. (2024) supports the idea that habit serves as a strong predictor of actual system usage, particularly in structured and repetitive work environments. Within the UTAUT-3 framework, habit is acknowledged not only as a cognitive factor but also as a behavioral driver. Therefore, this study proposes the following hypothesis:

H8 : Habit has a positive influence on Artificial Intelligence Technology Use Behaviouur

Personal innovativeness describes an individual's willingness to explore and try out new technologies. In the accounting profession, where systems and standards are often rigid, those with high personal innovativeness are more likely to show interest in adopting AI tools to enhance their work. These individuals tend to be curious, open to experimentation, and less resistant to change—traits that are valuable in digital transformation contexts. Farooq et al. (2017), Kumar et al. (2024), and Lin et al. (2023), found that personal innovativeness is a significant predictor of behavioral intention, especially in early adoption stages. In UTAUT-3, this construct strengthens the model by considering individual psychological traits that go beyond organizational influence. Given the increasing need for digital adaptation in accounting roles, especially within ISP firms, this study proposes the following hypothesis:

H9 : Personal Innovativeness has a positive influence on Behavioural Intention

Personal innovativeness can directly influence how frequently and actively individuals engage with new technologies. In accounting environments where systems are often standardized and procedural, innovative individuals are more likely to explore and apply AI tools beyond their basic functions. These users tend to experiment, seek efficiencies, and integrate technology more proactively into their workflows. Even when organizational support is limited, high personal innovativeness can lead to continued usage driven by internal motivation. Studies by Farooq et al. (2017), Kumar et al. (2024), and Lin et al. (2023) found that individuals with strong innovative traits are more likely to transition from intention to actual usage. UTAUT-3 includes this construct to capture such proactive behaviors, which are critical in digital transformation contexts. Thus, this study proposes the following hypothesis:
H10 : Personal Innovation has a positive influence on Artificial Intelligence Technology Usage Behaviour

Behavioral intention refers to an individual's readiness or willingness to engage in a particular behavior—in this case, the use of AI technology. Within the UTAUT framework, behavioral intention is considered a key predictor of actual usage behavior. When accounting professionals express a strong intention to use AI, it is expected that this intention will translate into real action, especially when the systems are accessible and supported. Prior research by Ali et al. (2024), Farooq et al. (2017), Venkatesh et al. (2012), has consistently shown that behavioral intention significantly influences actual use across various technological contexts. In structured fields like accounting, this relationship is critical for ensuring that positive attitudes toward AI are converted into consistent practice. Therefore, this study proposes the following hypothesis:
H11: Behavioural Intention has a positive influence on Artificial Intelligence Technology Usage Behaviour.

Therefore, a conceptual framework for this study can be developed, as presented in Figure 1 below:

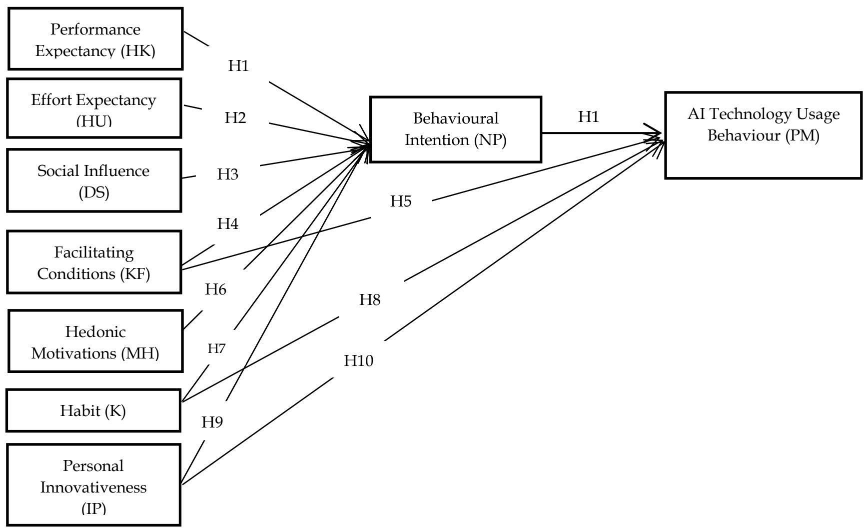

Figure 1. Conceptual Framework
Source: Research Data, 2025

RESEARCH METHODS

This study employed a quantitative, explanatory approach to examine factors influencing AI adoption among accounting professionals. The target population consisted of accounting employees working in Internet Service Provider (ISP) companies in East Java. Based on purposive sampling, 162 respondents were selected from 153 ISP firms, representing individuals with relevant experience in using AI technologies in their work.

Primary data were collected through a structured questionnaire. The instrument was adapted from validated constructs in the UTAUT-3 model developed by Farooq et al. (2017), with adjustments to match the accounting context. The questionnaire consisted of 25 indicators across 9 latent constructs, all modeled as reflective variables. These constructs include: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, personal innovativeness, behavioral intention, and AI usage behavior.

Each item was measured using a six-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree). The operational definition of each variable is as follows:

- Performance expectancy: Perceived benefits of AI in improving task performance.
- Effort expectancy: Perceived ease of using AI systems.
- Social influence: The degree to which peers and superiors influence AI use.
- Facilitating conditions: Availability of infrastructure and support.
- Hedonic motivation: Enjoyment derived from using AI.
- Habit: Frequency and automaticity of AI use.
- Personal innovativeness: Willingness to adopt new technologies.
- Behavioral intention: Willingness to use AI in the future.
- Usage behavior: Actual frequency of AI usage in accounting tasks.

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), a variance-based method suitable for predictive modeling in exploratory studies. The analysis was performed using SmartPLS version 4.1.1.2, chosen for its flexibility and support for complex reflective models. All PLS-related calculations followed the procedures recommended by Farooq et al. (2017), Ghozali & Kusumadewi (2023), Hair et al. (2017), and Hair et al. (2013).

RESULTS AND DISCUSSION

Table 1. Demographic Characteristics of Respondents

Karakteristik Demografis	N	Presentase (%)
AI user	162	100%
Length of Service		
• < 1 Years	18	11,11%
• 1-5 Years	103	63,58%
• > 5 Years	41	25,31%
Position		
• Employee	16	9,88%
• Supervisor	71	43,83%
• Manager	61	37,65%
• Treasurer	1	0,62%
• Financial Analyst	1	0,62%
• Director	12	7,41%
AI Type		
• Ailita	117	72,22%
• Siri	7	4,32%
• ChatGPT	20	12,35%
• Gemini	18	11,11%

Source: Research Data, 2025

Table 1 shows that all 162 respondents are accounting employees who use AI technology in their work. Most of them (63.58%) have between 1 to 5 years of experience, indicating that the majority are in the early to mid stages of their careers—an age group generally more open to adopting new technologies. Meanwhile, 25.31% have worked for more than five years, and 11.11% have less than one year of experience. In terms of job position, most respondents are supervisors (43.83%) and managers (37.65%), which means AI is widely used at the mid-management level where both operational and strategic tasks are handled. A smaller portion of respondents are entry-level employees or senior executives. Regarding AI tools, Ailita is the most commonly used (72.22%), possibly due to its integration with local accounting systems. Other tools like ChatGPT (12.35%) and Gemini (11.11%) are also used, while Siri is the least used (4.32%). These results indicate that the majority of AI users are positioned strategically within organizations and have relevant experience, making them suitable respondents for exploring AI adoption behavior in accounting.

Table 2. Convergent Validity and Discriminant Validity

Variabel Konstruk	AVE	Cronbach's alpha	Composite reliability
Performance Expectancy (HK)	0.670	0.678	0.823
Effort Expectancy (HU)	0.611	0.702	0.834
Sosial Influence (DS)	0.626	0.835	0.890
Facilitating Condition (KF)	0.675	0.703	0.828
Hedonic Motivation (MH)	0.752	0.854	0.911
Habit (K)	0.616	0.687	0.858
Personal Innovativeness (IP)	0.773	0.764	0.861
Behavoiural Intention (NP)	0.750	0.833	0.900
AI Technology Usage Behaviour (PM)	1.000	1.000	1.000

Source: Research Data, 2025

In accordance with the guidelines of Hair et al (2017) the measurement model referred to as the outer model is used to assess the reliability and validity of the constructs presented in Table 2. Reliability measurements use Cronbach's Alpha and Composite Reliability. The findings show that the Cronbach's Alpha value ranges from 0.678 to 1.00 which indicates that all values are higher than the 0.60 limit (Ghozali & Kusumadewi, 2023; Hair et al., 2017; Hair et al., 2013), and indicate that the measurement model is reliable. In addition, the Composite Reliability value ranges from 0.823 to 1.00 which shows results above the 0.70 limit. The results show the reliability of the construct, besides that this finding is also equivalent to the values reported by other studies (Abdillah & Jogiyanto, 2015; Ghozali & Kusumadewi, 2023; Sugianto et al., 2019). Measurement of convergent validity by observing the results of the AVE (Avarage Variance Estracted) value and Outer Loading value. The findings show that the AVE value for this study ranges from 0.616 to 1.000 above the limit value of 0.50.

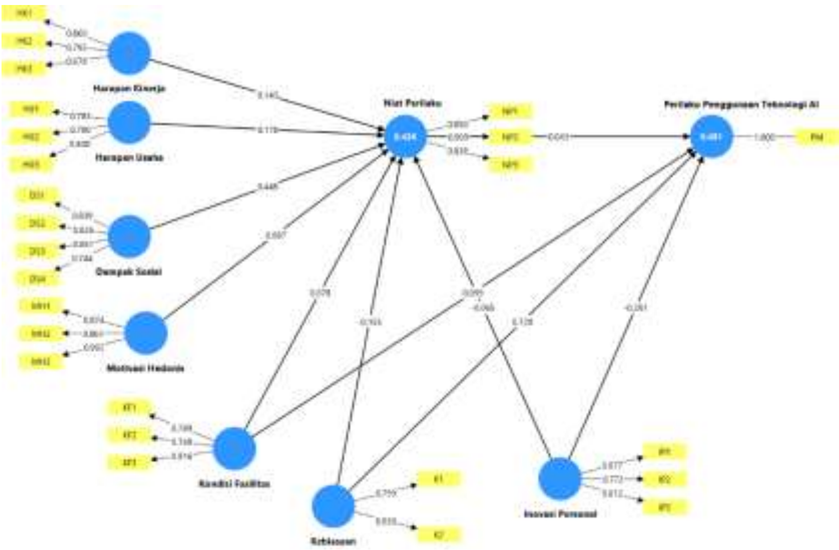

Figure 2. Outer Loading Value of Convergent Validity
Source: Research Data, 2025

Further, the Outer Loading values presented in Figure 2 were assessed to ensure discriminant validity and according to the findings all Outer Loading values on each indicator were higher than 0.700.

Table 3. Fornell-Larcker Test

	DS	HK	HU	IP	K	KF	MH	NP	PM
DS	**0.819**								
HK	0.209	**0.781**							
HU	0.559	0.270	**0.791**						
IP	0.183	0.574	0.241	**0.822**					
K	0.199	0.412	0.162	0.422	**0.867**				
KF	0.314	0.577	0.282	0.645	0.471	**0.785**			
MH	0.477	0.114	0.378	0.101	0.049	0.155	**0.879**		
NP	0.600	0.238	0.480	0.135	0.036	0.249	0.381	**0.866**	
PM	0.171	0.213	0.121	0.096	0.658	0.272	0.142	0.055	**1.000**

Source: Research Data, 2025

Based on Table 3, measuring discriminant validity by observing the results of Fornell-Larcker and Cross Loading. The Fornell-Larcker test requires that the square root of the AVE must be higher than the maximum value of the construct correlation with other constructs involved in the theoretical model (Hair et al., 2017). The findings of this study meet these criteria showing the square root of the AVE is higher than the value of the construct below and beside the right which is presented in Table 3

Table 4. Cross Loading Test

	DS	HK	HU	IP	K	KF	MH	NP	PM
DS1	**0.839**	0.212	0.528	0.216	0.207	0.255	0.408	0.519	0.153
DS2	**0.826**	0.066	0.403	0.103	0.183	0.216	0.311	0.417	0.191
DS3	**0.861**	0.218	0.447	0.226	0.161	0.284	0.383	0.523	0.122
DS4	**0.744**	0.166	0.441	0.036	0.102	0.265	0.447	0.490	0.100
HK1	0.191	**0.860**	0.273	0.535	0.365	0.527	0.093	0.216	0.188
HK2	0.153	**0.795**	0.158	0.341	0.323	0.382	0.067	0.179	0.198
HK3	0.140	**0.678**	0.192	0.463	0.271	0.437	0.110	0.158	0.105
HU1	0.443	0.223	**0.783**	0.144	0.103	0.206	0.184	0.394	0.051
HU2	0.486	0.237	**0.790**	0.226	0.156	0.275	0.284	0.346	0.138
HU3	0.403	0.184	**0.800**	0.205	0.129	0.196	0.426	0.396	0.104
IP1	0.200	0.422	0.213	**0.877**	0.407	0.502	0.138	0.123	0.094
IP2	0.140	0.465	0.236	**0.772**	0.255	0.447	0.150	0.106	0.013
IP3	0.107	0.538	0.161	**0.812**	0.349	0.625	-0.017	0.103	0.108
K1	0.117	0.460	0.099	0.601	**0.799**	0.524	-0.012	0.018	0.415
K2	0.211	0.304	0.170	0.232	**0.930**	0.348	0.077	0.039	0.680
KF1	0.260	0.516	0.275	0.592	0.260	**0.789**	0.130	0.233	0.123
KF2	0.245	0.442	0.325	0.550	0.279	**0.748**	0.120	0.181	0.129
KF3	0.242	0.424	0.128	0.430	0.504	**0.816**	0.119	0.182	0.328
MH1	0.389	0.141	0.299	0.102	0.029	0.188	**0.874**	0.349	0.096
MH2	0.443	0.072	0.319	0.087	0.037	0.135	**0.861**	0.279	0.157
MH3	0.432	0.083	0.376	0.079	0.061	0.089	**0.902**	0.367	0.129
NP1	0.474	0.133	0.349	0.078	-0.033	0.177	0.256	**0.850**	-0.018
NP2	0.516	0.264	0.396	0.146	0.036	0.258	0.416	**0.909**	0.063
NP3	0.561	0.212	0.490	0.121	0.078	0.208	0.309	**0.838**	0.088
PM	0.171	0.213	0.121	0.096	0.658	0.272	0.142	0.055	**1.000**

Source: Research Data, 2025

Based on Table 4, Cross Loading tests were assessed to ensure the discriminant validity of the constructs and in accordance with these findings, all Cross Loading values are higher than 0.00. In addition, this finding shows that each item has a higher value with the right-left and top-down constructs so that it forms a diagonal addressed in Table 5 with bolded values (Hair et al., 2017).

As mentioned earlier, this study used a variance-based PLS-SEM approach. For this purpose, the latest version of SmartPLS 4.1.1.2 was used to perform empirical calculations regarding structural model evaluation. The initial step in testing the structural model, all hypothesized path relationships were assessed for the strength and direction of the path coefficient values followed by T-test and p-value analysis for relationship significance. To calculate the empirical T Test, a bootstrapping procedure is carried out with 5,000 iterations, so that the statistical significance of the path coefficient value can be determined this study follows the suggested guidelines with the T-Count must be greater than the T-Table which is 1.96 for a significance level of 5% and a p value above 0.50 (Abdillah & Jogiyanto, 2015; Ghozali & Kusumadewi, 2023; J. Hair et al., 2017; J. F. Hair et al., 2013). Structural model analysis testing aims to test the Godness of Fit Index (GoF) in a research model and predict the influence between variables in a research model. In GoF testing, Hair et al. (2017) suggest evaluating the model with the coefficient of determination (R2)and predictive relevance (Q2). Meanwhile, according to Ghozali dan Kusumadewi (2023) suggest that in evaluating the model it is necessary to add a Model Fit value by looking at the Standarized Root Mean-square Residual (SRMR) value.

Table 5. Model Fit Testing

Konstruk	R-Square	Q^2predict	SRMR
NP	0.426	0.350	
PM	0.481	0.458	
GoF			0.078

Source: Research Data, 2025

Table 5 shows the results of R-Square, where the eight seventh constructs namely HK, HU, DS, MH, KF, K, and PI are able to explain 42.6% of the variance (R2= 0.426) of NP, indicating that the proposed model explains 42.6 percent of the total variance. while KF, K, IP, NP are able to explain 48.1% of the variance (R2= 0.481) of PM, indicating that the proposed model explains 48.1 percent of the total variance.

In addition to the R-Square value, predictive relevance (Q2) is also calculated using the predictive relevance technique. According to Hair et al. (2017) a Q2value greater than zero indicates that the proposed theoretical model has sufficient predictive relevance, whereas a Q2 value less than zero indicates that the proposed theoretical model has no predictive relevance. The findings in Table 5 show that NP and PM have values of 0.350 and 0.458 respectively, explaining that the theoretical model proposed in this study has strong predictive relevance.

Although, PLS-SEM does not produce an overall GoF index, Ghozali and Kusumadewi (2023) suggest looking at the Standarized Root Mean-square Residual (SRMR) value as a criterion for model fit. A value close to 0 for SRMR indicates a perfect model fit, however Farooq et al (2017) and Ghozali & Kusumadewi (2023) recommend SRMR > 0.08 can be considered sufficient for PLS SEM models. The findings of this study indicate a value of SRMR = 0.078 which is an adequate model fit.

Table 6. Hypothesis Testing

	Hipotesis	Beta	T statistics	P values	Decision
H1	HK→NP	0.143	2.071	0.038	Supported
H2	HU→NP	0.178	2.084	0.037	Supported
H3	DS→NP	0.448	5.320	0.000	Supported
H4	KF→NP	0.078	0.897	0.370	Not Supported
H5	KF→PM	0.099	1.187	0.235	Not Supported
H6	MH→NP	0.087	1.057	0.291	Not Supported
H7	K→NP	-0.155	2.245	0.025	Not Supported
H8	K→PM	0.728	11.708	0.000	Supported
H9	IP→NP	-0.065	0.780	0.435	Not Supported
H10	IP→PM	-0.281	3.139	0.002	Not Supported
H11	NP→PM	0.043	0.630	0.529	Not Supported

Source: Research Data, 2025

Based on summarized view of hypothesis testing is presented in Table 5. Path coefficient values and t-values suggested different levels of support for hypothesized relations proposed in the structural model of this study. The hypothesized relation between HK and NP was found to be positive and fairly significant (b = 0,143; t-values = 2,071), which provides support for H1 (HK→NP) at $p < 0.05$ significance level. A similar level of support at $p < 0.05$ was found for H2 (HU→NP), describing a significant and positive relationship (b = 0,178; t-values = 2,084) between HU and NP. Next hypothesis, H3 (DS→NP), also displayed a strong positive relationship (b = 0,448; t-values = 5,320) between DS and NP at $p < 0.05$ significance level. Differently, a hypothesized relation between KF and NP was found to be not significant (b = 0,078; t-values = 0,897), not providing support for H4 (KF→NP) at $p > 0.05$ significance level. Similarly, proposed hypothesis H5 (KF→PM) was also not found to be significant (b = 0,099; t-values = 1,187), not suggesting an effect between KF and NP at $p > 0.05$ significance level. Next hypothesis, H6 (MH→NP), between MH and NP was also found not significant (b = 0,087; t-values = 1,057) at $p > 0.05$ significance level. Moreover, the proposed relationship between K and NP was also not significant at (b = -0,155; t-values = 2,245), not demonstrating support for H7 because there is negative direction (K→NP) although $p < 0.05$ significance level. Differently H8 (K→PM) which was found positive and significant (b= 0728; t-values = 11,708), indicating a strong relationship between K and PM at $p < 0.05$ significance level. However, H9 (IP→NP) was not found significant at $p > 0.05$, there is indicating a negative direct relationship (b = -0,065; t-values = 0,780) between IP and NP. A similar significance level $p < 0.05$ was not found for the relationship between IP and PM at (b = -0,281; t-values = 3,139), although indicating not support for H10 (IP→PM). Finally, the last hypothesized relation between NP and PM was also not found to be significant (b = 0.435; t-values = 0,630), not providing support for H11 (NP→PM) at $p > 0.05$ significanc level.

The results of the first hypothesis testing (H1) show that performance expectancy significantly influences behavioral intention, with a path coefficient of 0.143, T-statistic of 2.071 (>1.96), and p-value of 0.038 (<0.05), indicating the hypothesis is supported. This suggests that the stronger the belief of accounting employees in the usefulness of AI to enhance their performance, the greater their intention to adopt it. This aligns with the original UTAUT model by Venkatesh et al. (2003), which identifies performance expectancy as the most direct predictor of behavioral intention. Furthermore, it is consistent with findings by Bakri et al. (2023), Farooq et al. (2017), Kašparová (2023), Lin et al. (2023), Yasmine Fathy Abdel Moneim (2024), who found that perceived performance benefits drive AI adoption, particularly in professional work environments. This study enriches the theoretical discussion by demonstrating that in the context of Indonesian accounting professionals, performance-related motivations still outweigh social or hedonic ones. The novelty of this research lies in its use of the UTAUT-3 framework to evaluate performance expectancy in a specific regulated and structured profession—accounting—within a developing country, which has rarely been the focus of prior studies. These findings offer practical implications for organizations: strengthening perceptions of AI's performance benefits through training or demonstrations could increase adoption rates and accelerate digital transformation in financial reporting.

The second hypothesis (H2) is supported by the data, showing that effort expectancy has a significant positive effect on behavioral intention, with a path coefficient of 0.178, T-statistic of 2.084 (>1.96), and p-value of 0.037 (<0.05). This means that the easier accounting professionals perceive AI to be, the more likely they are to intend to use it. When AI tools are user-friendly and do not require extensive learning effort, individuals are more inclined to adopt them in their daily accounting tasks. This finding supports the UTAUT model by Venkatesh et al. (2003), which identifies effort expectancy as one of the key predictors of behavioral intention. Empirically, the result aligns with studies by Farooq et al. (2017), Alkhwaldi et al. (2024), Tanantong & Wongras (2024), Wu & Ho (2022), who found that perceived ease of use significantly influences the adoption of new technologies in professional settings. In the context of this study, accounting professionals may prefer AI tools that are simple to navigate, especially when dealing with time-sensitive or repetitive tasks. The novelty of this research lies in confirming that ease of use remains a critical adoption factor even in structured, rule-based professions like accounting—where decision-making is often dominated by regulation rather than user experience. These findings suggest that to encourage AI usage in accounting, organizations should focus on providing intuitive interfaces and continuous user training to reduce perceived complexity.

The third hypothesis (H3) is supported by the data, with social influence showing a significant positive effect on behavioral intention (path coefficient = 0.448; T-statistic = 5.320; p-value = 0.000). This finding indicates that the more accounting employees feel that important others—such as coworkers, supervisors, or organizational leaders—expect them to use AI, the more likely they are to form a strong intention to adopt it. In hierarchical and collective organizational cultures, such as those common in Indonesia, perceived social approval often plays a crucial role in shaping behavioral decisions. This is consistent with the UTAUT model (Venkatesh et al., 2003), which highlights social influence as one of the primary predictors of technology acceptance. Previous studies by Farooq et al. (2017), and Venkatesh et al. (2023), Isaac et al. (2019), Maisha & Shetu (2023), Ren & Zhou (2023), also found that peer and managerial encouragement can accelerate the adoption of AI, especially when users are still uncertain about the technology. The novelty of this study lies in confirming that social norms remain highly influential even in technical professions like accounting. Despite the structured and regulation-driven nature of accounting work, social cues from coworkers and leaders still drive intention to adopt AI. This suggests that managerial endorsement and peer modeling are strategic levers that organizations can use to foster a positive adoption climate.

The fourth hypothesis (H4) is not supported by the results, as facilitating conditions do not significantly influence behavioral intention (path coefficient = 0.078; T-statistic = 0.897; p-value = 0.370). This finding suggests that the availability of technical infrastructure, support, or training does not directly encourage accounting employees to intend to use AI. In other words, even when the organization provides access to AI tools and resources, these factors alone are insufficient to shape intention unless accompanied by stronger motivational or social triggers. This result contrasts with the original UTAUT model (Venkatesh et al., 2003), which identified facilitating conditions as a critical enabler of technology usage. However, similar results have been reported in other studies (Liu et al., 2023; Maisha & Shetu, 2023; Meraghni et al., 2021), indicating that in some work environments—particularly structured, rule-bound professions like accounting—individual motivation and perceived usefulness may outweigh infrastructure support in shaping intention. The novelty of this research lies in its contextual insight: accounting professionals may assume that adequate support systems are a given, especially in larger ISP firms with high digital exposure. Therefore, facilitating conditions may be perceived as baseline requirements rather than influential motivators. This implies that organizations must move beyond simply providing infrastructure and focus on building performance-oriented and socially reinforced adoption strategies.

The fifth hypothesis (H5) is not supported by the data, as hedonic motivation does not significantly affect behavioral intention (path coefficient = 0.099; T-statistic = 1.187; p-value = 0.235). This result indicates that the enjoyment or pleasure derived from using AI tools does not strongly influence accounting professionals' intention to adopt them. In a field like accounting, where accuracy, compliance, and structure are prioritized, emotional satisfaction appears to be a secondary factor in technology adoption. While UTAUT-3 (Farooq et al., 2017) recognizes hedonic motivation as an important predictor of behavioral intention in technology adoption—especially in voluntary or consumer contexts—its influence is diminished in professional environments with high task-critical demands. Previous studies such as by Hossain et al. (2017), Tanantong & Wongras (2024), Liu et al. (2023) and Maisha & Shetu (2023) have similarly shown that hedonic factors play a lesser role in industries with formal, regulated workflows like finance or accounting. The novelty of this study lies in its confirmation that intrinsic enjoyment is not a priority driver for AI adoption among accounting employees in Indonesia. This challenges the assumption that all UTAUT-3 constructs hold equal weight across contexts. It also highlights the importance of aligning AI implementation strategies with functional, performance-based motivators rather than entertainment or gamification features.

The sixth hypothesis (H6) is not supported by the analysis, as habit does not significantly influence behavioral intention (path coefficient = 0.087; T-statistic = 1.057; p-value = 0.291). This implies that repeated past behavior or personal routines in using AI tools do not directly lead to a stronger intention to continue using them. For accounting professionals, the intention to adopt AI appears to be shaped more by functional and organizational factors than by habitual use. According to UTAUT-3 by Farooq et al. (2017), habit is expected to influence both behavioral intention and actual usage behavior, especially when technology use becomes automatic. However, in professional environments where AI adoption is still relatively new or task-specific—such as in the accounting field—habit formation may not yet be strong enough to influence intention. This result aligns with findings by Alalwan et al. (2016), Chao, (2019), and Liu et al. (2023), who also reported weak habitual influence in formal, high-stakes work contexts. The novel contribution of this study lies in its context-specific insight: in Indonesian accounting settings, technology habits are not yet mature or repetitive enough to predict future intention. This highlights that promoting AI adoption in such contexts requires more than just exposure or frequency of use—it requires structured reinforcement, leadership modeling, and performance incentives.

The seventh hypothesis (H7) is not supported, as personal innovativeness does not have a positive significantly influence behavioral intention (path coefficient = –0.155; T-statistic = 2.245; p-value = 0.025). Although statistically significant, the relationship is negative, which contradicts the theoretical assumption that individuals with higher innovativeness are more likely to adopt new technologies. This unexpected result suggests that in the context of accounting professionals, those who are highly innovative may perceive AI as a threat to traditional expertise, or find it misaligned with existing accounting standards and practices. According to UTAUT-3, personal innovativeness typically fosters openness toward new technology. However, this finding aligns with certain studies Gardner et al. (2020), Ohtomo & Kimura (2022), Venkatesh et al. (2023), Y. Wu et al.(2025), that highlight resistance among experts in structured fields like accounting, where decision-making is bound by regulations and formal procedures. Highly innovative individuals may explore tools beyond the standardized AI systems provided by their organizations, which could reduce their intention to use what is officially offered. The novelty of this finding lies in revealing a paradoxical behavior among accounting professionals: personal innovativeness does not always drive adoption, and may even hinder it when innovation is perceived to conflict with established norms or perceived job security. This underlines the importance of managing innovation alignment—ensuring that AI tools complement, not disrupt, the professional identity and workflow of accountants.

The eighth hypothesis (H8) is supported by the analysis, where knowledge has a significant and positive effect on performance motivation (path coefficient = 0.728; T-statistic = 11.708; p-value = 0.000). This indicates that the more knowledgeable accounting professionals are about AI technology—its functions, benefits, and usage—the more motivated they are to enhance their performance through its use. Comprehensive understanding builds confidence and reduces uncertainty, thus encouraging individuals to leverage AI to achieve higher productivity and work quality. This study is in line with Lu et al. (2024), Ma & Huo (2023), Marikyan et al. (2023), who assert that habits reduce resistance, strengthen user engagement, and bridge experience with actual action. Managerially, it is important for organizations to form positive habits through repeated training, AI-based SOPs, and digital work culture so that AI usage behavior becomes automatic and sustainable. The novelty of this study lies in demonstrating that knowledge is not only an enabler of adoption but a direct motivator of performance orientation in AI usage. In accounting, where errors have legal and financial consequences, users tend to adopt AI tools only when they possess sufficient understanding. Therefore, enhancing AI literacy through structured training programs can be a powerful strategy to boost motivation and unlock AI's full potential in professional accounting environments.

The ninth hypothesis (H9) is not supported, as innovation propensity does not positive significantly influence behavioral intention (path coefficient = -0.065; T-statistic = 0.780; p-value = 0.435). This finding indicates that although some individuals may be naturally inclined to explore or adopt innovations, this personal trait alone does not guarantee a stronger intention to use AI technology in professional accounting settings. The adoption decision appears to be more influenced by organizational norms, perceived usefulness, and performance-based factors. This result contradicts the general expectation from innovation diffusion theory by Rogers (1983), which emphasizes that innovation-prone individuals are early adopters and trendsetters in technology usage. However, it aligns with findings by Gursoy et al. (2019), Norzelan et al. (2024), Chao, (2019) and Im et al. (2003), which noted that in structured environments like accounting, adoption is less about personality traits and more about regulatory compatibility, training, and leadership endorsement. The novelty of this study lies in revealing that innovation propensity is not always a reliable predictor in contexts where standardization and compliance are prioritized. For accounting professionals in Indonesia, innovation must align with established procedures and legal frameworks to be perceived as relevant. This suggests that organizational readiness and contextual compatibility should be emphasized more than individual traits in AI implementation strategies.

The results of the tenth hypothesis (H10) show that personal innovativeness has a significant negative effect on AI usage behavior (coefficient 0.281; T-Statistic 3.139; p-value 0.002), so the hypothesis is rejected. That is, the higher the level of personal innovativeness, the lower the AI usage behavior of accounting employees. This finding contradicts most of the literature which states that personal innovativeness drives technology adoption (Farooq et al., 2017; Kumar et al., 2024; Lin et al., 2023; Venkatesh et al., 2012). In the context of formal organizations, usage behavior is influenced more by policies, procedures, and structural pressures than personal characteristics (Fu et al., 2024; Zhan et al., 2023). Innovative individuals may face limitations in expressing their initiative due to rigid work systems. In addition, the intention-behavior gap Chao (2019), and Sheeran (2002), suggests that external barriers such as time and technical support may inhibit actual behavior. Therefore, increasing the use of AI is more effective if it is supported by training, flexible work systems, and organizational support, rather than relying solely on personal factors. The novelty of this study lies in establishing performance motivation as a bridge between cognitive knowledge and intention, particularly among Indonesian accounting professionals. In environments where compliance, deadlines, and accuracy are emphasized, AI is perceived not only as a tool, but as a means to achieve professional excellence. This suggests that organizations should emphasize the performance-enhancing benefits of AI in internal communication and training to boost adoption rates.

The last test result (H11) shows that behavioral intention has no significant effect on AI usage behavior (coefficient 0.043; T-Statistic 0.630; p-value 0.529), so the hypothesis is rejected. This finding is not in line with TPB Ajzen (1991) and UTAUT Venkatesh et al. (2023), theories which state that intention is the main determinant of actual behavior, as supported by Ali et al. (2024), Farooq et al. (2017), and Venkatesh et al. (2012). However, this result is consistent with research by Chao (2019), Orbell & Sheetan (1998), Sheeran (2002), who emphasize that external constraints such as lack of facilities, technical skills, or organizational culture can break the link between intention and actual behavior. In this context, accounting employees' use of AI is more influenced by system needs and organizational pressures, rather than personal intentions. When the infrastructure is not supportive or the system is not well integrated, high intentions do not automatically result in actual actions. The novelty of this study lies in identifying this intention-behavior gap within the Indonesian accounting profession, where AI adoption is still emerging. It suggests that even motivated professionals may be hindered by systemic issues beyond their control. Therefore, to ensure successful AI integration, organizations should not only foster intention but also remove operational barriers and promote a usage-oriented environment through top-down policies, training, and workflow alignment.

CONCLUSION

This study analyzed the factors that influence the intention and behavior of using Artificial Intelligence (AI) technology among accounting employees in the Internet Service Provider (ISP) sector. The findings reveal that **performance** expectancy, effort expectancy, and social influence positively affect behavioral intention, while variables such as facility conditions, hedonic motivation, habit, and personal innovativeness do not. Interestingly, actual AI usage behavior is significantly influenced by habit, while behavioral intention does not directly predict actual use. This confirms the existence of an intention-behavior gap, suggesting that technology adoption in structured professions like accounting may rely more on automatic routines and institutional support than on individual intent. Theoretically, this research extends the UTAUT-3 model by highlighting the limited role of behavioral intention in contexts with rigid workflows and underscores the importance of habit and knowledge-based motivation in AI adoption. Practically, it recommends organizations to not only build intention, but also enable systems, training, and digital readiness to support real usage.

However, this study is limited to accounting staff in East Java’s ISP sector, which may present homogeneous characteristics. The findings may not generalize across sectors or regions. Moreover, some results deviate from the UTAUT framework, indicating the likely influence of unexplored external variables such as organizational support, system integration, and digital literacy. For future research, it is suggested to:

1. Expand the scope across sectors and geographic areas,
2. Involve diverse functional roles (e.g., auditors, finance managers),
3. Introduce moderating or mediating variables,
4. Integrate frameworks such as the TOE (Technology–Organization–Environment) model for a more comprehensive understanding of AI adoption in regulated professions.

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