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ANALYSIS OF INTENT TO USE ARTIFICIAL INTELLIGENCE IN TAX ASSISTANCE BASED ON THE MODIFIED UTAUT2 MODEL

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Abstract
This study aims to analyze the factors influencing taxpayers' intention to use artificial intelligence (AI) for tax assistance in Indonesia. The research design employed a quantitative approach with an explanatory survey method of 200 respondents who had used AI tools such as ChatGPT, Gemini, or similar tools for tax assistance. The UTAUT2 model was modified by adding the Trust in AI construct and removing the Use Behavior construct. Data analysis was performed using Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4. The results showed that habit, performance expectancy, price value, and trust in AI significantly influenced behavioral intention, while effort expectancy, facilitating conditions, social influence, and hedonic motivation were insignificant. These findings confirm that intention to use AI in taxation is more influenced by practical experience and perceived value than by convenience or social influence. A limitation of this study is that it did not measure actual behavior; therefore, further research is recommended to examine this aspect. This study provides theoretical contributions to the development of AI adoption models in taxation, as well as practical implications for tax authorities and technology providers.
Keywords: Artificial Intelligence; Intention to Use; Tax Assistance; Technology Adoption; UTAUT2 Model

INTRODUCTION

The rapid advancement of digital technology in recent years has significantly reshaped the landscape of public services, including tax administration. The Directorate General of Taxes (DGT) in Indonesia is actively modernizing its operations to enhance service quality and taxpayer compliance. Among its notable initiatives is the implementation of the Core Tax Administration System, which aims to offer a more integrated, efficient, and responsive approach to taxation services (Arianty, 2023; Murnidayanti & Putranti, 2023). However, despite these technological advancements, many taxpayers continue to encounter difficulties in understanding complex tax regulations, managing their tax obligations independently, and accessing accurate and reliable information (Mohammed et al., 2023).

In this context, the modernization of tax administration is crucial not only for increasing efficiency but also for fostering public trust. As highlighted by Arianty, modernizing tax administration systems encourages fairness and honesty among tax officials, which can subsequently enhance citizens' confidence in their tax obligations being managed appropriately (Arianty, 2023). Furthermore, digitizing tax administration aims to reduce compliance costs for Micro, Small, and Medium Enterprises (MSMEs), demonstrating the tangible benefits that technology can bring to both the government and taxpayers (Murnidayanti & Putranti, 2023).

The integration of artificial intelligence (AI) into tax administration is widely regarded as a continuation of broader tax-service digitalization, with the potential to strengthen tax assistance services. A literature study focusing on Indonesia concludes that AI has substantial potential to improve the efficiency, accuracy, and transparency of the tax system. In practical terms, AI can accelerate administrative processes, simplify tax reporting and payment, and support higher taxpayer compliance; it is also linked to core-system modernization initiatives such as updates to the Core Tax Administration System (CTAS) (Pramesti & Emalia, 2024). In addition, an evaluation of the Coretax Administration System as a technology-based breakthrough highlights the importance of technological readiness and stakeholder perceptions regarding Coretax's effectiveness in supporting tax-administration digitization(Yasar et al., 2025).

Functionally, AI can be utilized as a tax assistance channel through the automation of information services and calculation/analytical support. Studies on the use of AI in the tax domain show that tax authorities use AI to automate tasks such as answering taxpayer questions, risk profiling, and audit selection (Cotrina-Reyes et al., 2025). A study on virtual assistance confirms that the use of chatbots and digital channels can reduce waiting times and operational costs while improving the accessibility of tax services (Cotrina-Reyes et al., 2025). On the process and control side, studies of digital taxation tool trends link AI and Big Data to the automation of tax procedures and transaction monitoring to strengthen administrative interaction and effectiveness (Pramesti & Emalia, 2024), while another review emphasizes that AI improves the efficiency of compliance monitoring, fraud detection, and revenue forecasting (Yip & Fong, 2025). Additional evidence also shows that AI helps improve efficiency through analytical/statistical models for tax audits and simplified data processing (Yip & Fong, 2025).

However, the literature also emphasizes that the use of AI for tax assistance requires serious attention to governance, risk, and trust because it involves personal financial data. Studies on explainable AI confirm that automation (including answering taxpayer questions and risk modeling) raises taxpayer rights issues if AI is non-explainable, making the need for explainability an important prerequisite for the legitimate and acceptable use of (Cotrina-Reyes et al., 2025). In line with this, studies on the principle of transparency in AI for tax management emphasize the need for a legal framework that protects taxpayer rights so that transparency can be guaranteed, while studies on tax policy in the digital economy remind us that digitization brings risks that must be taken into account in policy design and service implementation Literature specific to LLM-based assistants in tax reporting also highlights ethical challenges such as the risk of misinformation and accountability, and encourages a responsible AI framework (transparency, user control, and regulatory alignment) to ensure safe implementation (Yip & Fong, 2025)

This study aims to analyze the factors that influence taxpayers' intention to use artificial intelligence (AI) as a tax assistance tool using a modified UTAUT2 model. The eight constructs tested in this study include performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, and trust in AI. This study is expected to contribute theoretically to the development of AI technology adoption studies in the taxation sector and practically to the DGT and policymakers in designing AI-based tax assistance services that are more accessible, secure, and effective for taxpayers.

LITERATURE REVIEW

UTAUT2 Theory

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), introduced by Venkatesh, Thong, and Xu (2012), represents a consumer-oriented extension of the original UTAUT model. While UTAUT was designed for organizational contexts, UTAUT2 incorporates three additional constructs, hedonic motivation, price value, and habit, to better capture individual-level drivers of voluntary technology adoption. The model posits that seven constructs, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit, directly influence behavioral intention, which in turn predicts actual use behavior. Relative to UTAUT, UTAUT2 demonstrates substantially greater explanatory power, accounting for up to 74% of the variance in behavioral intention among consumer technology users (Venkatesh et al., 2012). Given its comprehensive coverage of cognitive, affective, social, and economic adoption drivers, UTAUT2 has been widely applied in studies of digital government services, mobile applications, and emerging technologies including artificial intelligence.

Modification of UTAUT2 in This Study

This study applies a modified version of UTAUT2 adapted to the specific context of AI use in tax assistance. Two structural modifications were introduced. First, the Use Behavior construct was excluded from the model. This decision reflects the study's primary objective of identifying the antecedents of taxpayers' adoption intention, rather than measuring actual technology usage. This approach is consistent with prior adoption studies in the taxation and e-government domains that treat behavioral intention as the terminal endogenous variable when actual behavioral data are unavailable or secondary to the research focus(Meiranto et al., 2024; Murnidayanti & Putranti, 2023)

Second, the Trust in AI construct was added as an additional predictor. The inclusion of trust is theoretically justified by the sensitive nature of tax-related data: taxpayers interacting with AI systems must disclose personal and financial information, making perceived accuracy, data security, and system reliability critical preconditions for adoption(Choung et al., 2023). This addition is further supported by literature on AI adoption in public services, which consistently identifies trust as a central determinant of user acceptance, particularly when AI systems operate in regulatory or compliance-sensitive environments(Cotrina-Reyes et al., 2025; Yip & Fong, 2025). The modified model thus comprises eight constructs predicting behavioral intention: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, and trust in AI.

Construct Definitions and Hypothesis Development

Based on the modified UTAUT2 framework, the definitions of each construct in the context of AI-based tax assistance and the corresponding research hypotheses are elaborated as follows.

Performance Expectancy (PE) refers to the degree to which taxpayers believe that using AI enhances their effectiveness in fulfilling tax obligations, including accelerating task completion, improving comprehension of tax regulations, and supporting accurate tax calculations. Consistent with the broader UTAUT2 literature, in which performance expectancy is among the most robust predictors of adoption intention across technology contexts, AI tools that are perceived as functionally useful in the tax domain are expected to drive stronger intentions to use. In the Indonesian context, the capacity of AI to automate information retrieval and simplify compliance processes constitutes a direct performance benefit for taxpayers (Pramesti & Emalia, 2024).

H1: Performance Expectancy has a significant positive effect on Behavioral Intention to use AI for tax assistance.

Effort Expectancy (EE) refers to the perceived ease of using AI for tax purposes, encompassing ease of interaction, clarity of AI-generated responses, and simplicity of the overall process. Technologies that minimize cognitive load and interaction effort are generally associated with greater adoption intention. However, in the taxation context, the complexity of AI interfaces and the technical terminology involved in tax regulation may moderate this relationship.

H2: Effort Expectancy has a significant positive effect on Behavioral Intention to use AI for tax assistance.

Social Influence (SI) refers to the extent to which taxpayers perceive that significant others, including peers, colleagues, and their broader social environment, support and encourage the use of AI for tax assistance. Social endorsement from trusted individuals can reduce adoption uncertainty and legitimize the use of novel technologies, thereby strengthening behavioral intention.

H3: Social Influence has a significant positive effect on Behavioral Intention to use AI for tax assistance.

Facilitating Conditions (FC) refer to taxpayers' perceptions of the availability of necessary infrastructure, including devices, internet connectivity, and foundational digital and tax knowledge, to support effective AI use. In the Indonesian context, where digital literacy among taxpayers remains heterogeneous across regions and demographics, facilitating conditions represent a potentially significant enabler or barrier to AI adoption for tax purposes (Mohammed et al., 2023)

H4: Facilitating Conditions have a significant positive effect on Behavioral Intention to use AI for tax assistance.

Hedonic Motivation (HM) refers to the intrinsic enjoyment or pleasure derived from using AI for tax assistance, including comfort, engagement, and the perceived attractiveness of AI-mediated interaction relative to conventional tax consultation methods. While hedonic factors may be less salient in instrumental, compliance-driven contexts such as taxation, they may nonetheless contribute to sustained engagement with AI tools.

H5: Hedonic Motivation has a significant positive effect on Behavioral Intention to use AI for tax assistance.

Price Value (PV) reflects taxpayers' cognitive trade-off between the perceived benefits of using AI and its associated monetary or effort costs. Given that widely used AI tools such as ChatGPT and Gemini are accessible at no direct cost, the perceived economic value of AI-generated tax information, relative to traditional paid tax consultation services, constitutes a material adoption driver for taxpayers, particularly those from lower socio-economic strata or small business owners seeking cost-effective compliance support.

H6: Price Value has a significant positive effect on Behavioral Intention to use AI for tax assistance.

Habit (HB) refers to the degree to which AI use has become an automatic, internalized behavior in taxpayers' tax-related activities, shaped by accumulated prior experience. As Indonesia's tax administration progressively integrates digital platforms, from e-Filing to DJP Online and the Core Tax Administration System (Coretax), repeated exposure to digital tax services creates conditions for habit formation, which is expected to reinforce taxpayers' intention to continue using AI (Arianty, 2023; Meiranto et al., 2024).

H7: Habit has a significant positive effect on Behavioral Intention to use AI for tax assistance.

Trust in AI (TR) refers to taxpayers' confidence in the accuracy, reliability, and data-security properties of AI systems used for tax assistance. Given the regulatory complexity of Indonesian tax law, governed by Ministerial Regulations (PMK) and DJP Circulars (PER DJP), and the sensitivity of personal financial data involved, trust in AI's capacity to provide compliant and confidential assistance is posited as a critical precondition for adoption intention (Choung et al., 2023; Yip & Fong, 2025)

H8: Trust in AI has a significant positive effect on Behavioral Intention to use AI for tax assistance.

The conceptual framework of this study, depicting the eight hypothesized relationships between the predictor constructs and Behavioral Intention, is presented in Figure 1 below. The framework reflects the modified UTAUT2 model with the addition of Trust in AI and the exclusion of Use Behavior, serving as the structural basis for the PLS-SEM analysis conducted in this study.

METHODS

This study uses a quantitative design with an explanatory survey approach to examine the factors that influence the intention to use artificial intelligence (AI) in tax assistance based on the modified UTAUT2 model with the addition of the Trust in AI construct. Respondents were determined using purposive sampling with the following criteria: (1) they are individual taxpayers or parties who handle corporate/company tax obligations, and (2) they have used AI for tax assistance. Based on the screening process, 200 questionnaires were collected that were suitable for processing and met the minimum sample size requirements for PLS-SEM analysis.

Primary data were collected through an online questionnaire (Google Forms) with a 1–5 Likert scale to measure the nine latent constructs in the model. All 200 respondents were taxpayers who had an NPWP or were involved in corporate tax management and had used AI for tax assistance. The majority were of productive age (around 20–35 years old), with slightly more women than men, and a regional distribution dominated by provinces on the island of Java, but still covering Sumatra, Kalimantan, Sulawesi, Nusa Tenggara, Bali, and Papua. Most respondents worked full-time (contract or permanent), followed by freelancers and business owners/entrepreneurs, with varying socio-economic statuses from lower, middle, to upper, and the majority were individual taxpayers, while the rest represented corporate taxpayers.

Data analysis was conducted by testing the structural model using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the help of the SmartPLS 4 application. Evaluation of the measurement model (outer model) included testing convergent validity, discriminant validity, and reliability through loading factors, AVE, Cronbach's Alpha, and Composite Reliability. Furthermore, the structural model (inner model) was analyzed by looking at the R-Square value and testing the significance of the path coefficients using a one-tailed bootstrapping procedure at a 5% significance level to test the hypothesis of the relationship between constructs in the proposed Adoption Intention Framework.

RESULTS AND DISCUSSION

Sample measurements were conducted using a Likert scale (1-5) for several questions to produce scores representing each variable, as shown in the following table:

Table 1
Variable Measurement

Construct / Variable	Code	Statement
Performance Expectancy	PE1	AI helps me complete my tax obligations more quickly.
	PE2	AI improves my effectiveness in understanding tax regulations.
	PE3	AI is useful in the process of calculating and preparing my tax reports.
	PE4	AI assists me in making tax-related decisions.
Effort Expectancy	EE1	Using AI for tax assistance feels easy to me.
	EE2	Interacting with AI does not require a lot of effort.
	EE3	AI provides clear and easy-to-understand tax explanations.
	EE4	The process of obtaining tax information through AI is very simple.
Social Influence	SI1	People around me suggest using AI for tax assistance.
	SI2	My friends or colleagues encourage me to use AI to help with tax matters.
	SI3	Using AI for tax assistance is viewed positively by my social circle.
	SI4	My social environment considers AI as a trustworthy tax assistance tool.
Facilitating Conditions	FC1	I have the devices (laptop/smartphone) that support the use of AI.
	FC2	My internet connection is adequate to use AI.
	FC3	I have sufficient basic knowledge to use AI for tax assistance.
	FC4	I have sufficient basic tax knowledge to validate the answers from AI.
Hedonic Motivation	HM1	I feel comfortable when using AI for tax assistance.
	HM2	I enjoy the experience of using AI.
	HM3	AI is more interesting to use compared to other tax assistance methods.
	HM4	Interacting with AI makes the tax assistance process more enjoyable.
Price Value	PV1	Using AI saves me on tax assistance costs.
	PV2	The benefits I get from AI are worth the cost (if any).
	PV3	AI provides high economic value to me.
	PV4	Free tax information from AI is more valuable than other assistance services.
Habit	HB1	Using AI has become a habit for me in conducting tax assistance.
	HB2	I automatically choose AI when I need tax assistance.
	HB3	I routinely use AI to help with tax matters.
	HB4	I am used to using AI without thinking twice.
Trust in AI	TR1	I trust AI to provide accurate tax information in compliance with regulations.
	TR2	I feel secure when using AI for tax assistance.
	TR3	I believe AI maintains the privacy and confidentiality of my data.
	TR4	I am confident that AI can be trusted as a reliable source of tax assistance.
Behavioral Intention	BI1	I intend to continue using AI for tax assistance in the future.
	BI2	I will recommend AI to my peers or colleagues for tax assistance.
	BI3	I am likely to choose AI over other tax assistance services.
	BI4	I have a positive intention to keep using AI in tax activities.

Source: data processed by researchers, 2025

The above questions were shared with respondents, and the results were then subjected to a series of tests as described below.

Convergence Validity Test

Table 2
Outer Loading, Cronbach's alpha, dan Composite reliability (rho_c) Value

Indicator	Outer Loading	Cronbach's alpha	Composite reliability (rho_c)
Behavioral Intention (BI)		0.911	0.937
BI1	0.924		
BI2	0.897		
BI3	0.885		
BI4	0.846		
Effort Expectancy (EE)		0.836	0.89
EE1	0.864		
EE2	0.787		
EE3	0.776		
EE4	0.844		
Facilitating Conditions (FC)		0.869	0.91
FC1	0.841		
FC2	0.816		
FC3	0.878		
FC4	0.85		
Habit (HB)		0.924	0.946
HB1	0.906		
HB2	0.902		
HB3	0.915		
HB4	0.888		
Hedonic Motivation (HM)		0.894	0.927
HM1	0.887		
HM2	0.884		
HM3	0.87		
HM4	0.845		
Performance Expectancy (PE)		0.88	0.917
PE1	0.875		
PE2	0.867		
PE3	0.868		
PE4	0.817		
Price Value (PV)		0.863	0.907
PV1	0.788		
PV2	0.871		
PV3	0.879		
PV4	0.826		
Social Influence (SI)		0.922	0.945

Indicator	Outer Loading	Cronbach's alpha	Composite reliability (rho_c)
SI1	0.884		
SI2	0.904		
SI3	0.894		
SI4	0.92		
Trust in AI (TR)		0.921	0.944
TR1	0.872		
TR2	0.924		
TR3	0.895		
TR4	0.906		

Source: data processed by researchers, 2025

The first convergent validity test is to measure the outer loading (loading factor) value. A construct is considered valid if the outer loading value is above 0.7. Table 2 above shows that the construct has met the first convergent validity requirement, as the outer loading value of all indicators exceeds 0.7.

The second convergent validity test is to measure the Average Variance Extracted (AVE) value. A construct is considered valid if the AVE value is above 0.5. Based on Table 3 below, it shows that the construct has met the second convergent validity requirement, because the value is above 0.5. For example, the AVE value of the BI construct is 0.889, which means it meets the AVE criteria.

Discriminant Validity Test

Table 3
Discriminant Validity Test Results using the Fornell Larcker criteria

	BI	EE	FC	HB	HM	PE	PV	SI	TR
BI	**0.889**								
EE	0.685	**0.819**							
FC	0.662	0.837	**0.847**						
HB	0.883	0.656	0.632	**0.903**					
HM	0.846	0.794	0.751	0.826	**0.871**				
PE	0.742	0.816	0.761	0.69	0.797	**0.857**			
PV	0.820	0.739	0.719	0.772	0.837	0.723	**0.842**		
SI	0.797	0.703	0.65	0.772	0.805	0.734	0.736	**0.900**	
TR	0.888	0.659	0.666	0.889	0.827	0.701	0.791	0.815	**0.900**

Source: data processed by researchers, 2025

The first discriminant validity test used the Fornell-Larcker criteria, namely that the Average Variance Extracted (AVE) value of each construct is higher than the correlation between other constructs. Table 3 above shows that the AVE value is higher than each construct. For example, the BI construct shows an AVE root value of 0.889, which is higher than the correlations between other constructs (0.685, 0.662, 0.883, 0.846, 0.742, 0.82, 0.797, and 0.888). Similar results were found in testing the EE to TR constructs, where all variables were declared discriminant valid.

The second discriminant validity test used the cross-loading value criterion, whereby the loading factor value must be higher than the cross-loading value. For example, in the BI construct test in Table 4 below, the BI loading factor is 0.924, 0.897, 0.885, 0.846, while the cross loading is the value from other constructs, namely from EE1 with a value of 0.602 to TR4 with a value of 0.812. This shows that all variables are valid discriminants.

Table 4
Results of Discriminant Validity Test with Cross Loading Criteria

	BI	EE	FC	HB	HM	PE	PV	SI	TR
BI1	0.924	0.632	0.634	0.855	0.785	0.673	0.757	0.712	0.839
BI2	0.897	0.579	0.562	0.772	0.728	0.637	0.719	0.716	0.788
BI3	0.885	0.554	0.508	0.79	0.744	0.601	0.715	0.678	0.756
BI4	0.846	0.67	0.646	0.718	0.75	0.727	0.723	0.727	0.771
EE1	0.602	0.864	0.761	0.61	0.736	0.749	0.689	0.656	0.61
EE2	0.467	0.787	0.666	0.433	0.537	0.607	0.535	0.44	0.442
EE3	0.603	0.776	0.592	0.569	0.696	0.622	0.6	0.623	0.601
EE4	0.548	0.844	0.722	0.512	0.602	0.685	0.58	0.552	0.478
FC1	0.494	0.676	0.841	0.506	0.582	0.6	0.521	0.515	0.539
FC2	0.511	0.729	0.816	0.48	0.595	0.631	0.605	0.52	0.533
FC3	0.57	0.694	0.878	0.577	0.645	0.631	0.66	0.558	0.587
FC4	0.643	0.733	0.85	0.566	0.703	0.701	0.633	0.597	0.588
HB1	0.781	0.627	0.626	0.906	0.795	0.635	0.71	0.738	0.818
HB2	0.805	0.633	0.578	0.902	0.775	0.67	0.677	0.666	0.758
HB3	0.84	0.603	0.601	0.915	0.753	0.636	0.739	0.719	0.826
HB4	0.761	0.503	0.475	0.888	0.658	0.547	0.662	0.665	0.808
HM1	0.77	0.733	0.698	0.758	0.887	0.738	0.705	0.707	0.762
HM2	0.737	0.699	0.717	0.708	0.884	0.723	0.736	0.672	0.709
HM3	0.746	0.638	0.583	0.718	0.87	0.668	0.718	0.72	0.721
HM4	0.693	0.697	0.617	0.692	0.845	0.646	0.763	0.71	0.687
PE1	0.61	0.749	0.694	0.605	0.678	0.875	0.609	0.62	0.56
PE2	0.697	0.714	0.637	0.591	0.736	0.867	0.63	0.659	0.655
PE3	0.642	0.714	0.668	0.61	0.707	0.868	0.667	0.641	0.641
PE4	0.585	0.62	0.612	0.56	0.603	0.817	0.57	0.592	0.537
PV1	0.572	0.557	0.58	0.531	0.558	0.472	0.788	0.468	0.543
PV2	0.75	0.613	0.617	0.722	0.765	0.657	0.871	0.677	0.724
PV3	0.703	0.722	0.652	0.658	0.743	0.679	0.879	0.675	0.676
PV4	0.717	0.593	0.571	0.669	0.728	0.605	0.826	0.631	0.7
SI1	0.669	0.617	0.587	0.652	0.659	0.643	0.647	0.884	0.682
SI2	0.71	0.542	0.512	0.712	0.697	0.592	0.612	0.904	0.725
SI3	0.737	0.682	0.646	0.702	0.79	0.702	0.713	0.894	0.753
SI4	0.75	0.688	0.595	0.712	0.748	0.702	0.676	0.92	0.772
TR1	0.784	0.689	0.686	0.771	0.76	0.706	0.78	0.735	0.872
TR2	0.809	0.593	0.614	0.837	0.781	0.633	0.724	0.741	0.924
TR3	0.789	0.512	0.5	0.799	0.685	0.574	0.643	0.704	0.895
TR4	0.812	0.579	0.595	0.79	0.749	0.611	0.699	0.753	0.906

Source: data processed by researchers, 2025

Reliability Test

Reliability testing used Cronbach's Alpha and Composite Reliability, as presented in Table 2. All variables showed values above 0.7, so it can be stated that each construct has a good level of internal consistency and meets reliability standards.

Model Structure Test (Inner Model)

The structural model (inner model) evaluation focused on evaluating the relationships between latent variables to test the research hypothesis. The quality of the structural model was assessed using two main metrics: the coefficient of determination (R^2) for endogenous variables, which measures the predictive power of the model, and the t-statistic (t-value) or P-value from the bootstrapping results.

The higher the R^2 value, the more effective the independent variables are in predicting or explaining the dependent (bound) variables in the research model. Based on the test results, an R-square value of 0.863 was obtained, indicating that 86.3% of the variation in the bound variables can be explained by the independent variables in the structural model, meaning that the model's predictive ability is very strong.

Table 5 Inner Model VIF Values (Variance Inflation Factor)

Construct	H	VIF	Status
Performance Expectancy (PE)	H1	3.907	Acceptable
Effort Expectancy (EE)	H2	5.029	Moderate
Social Influence (SI)	H3	3.820	Acceptable
Facilitating Conditions (FC)	H4	3.823	Acceptable
Hedonic Motivation (HM)	H5	6.420	Moderate
Price Value (PV)	H6	4.019	Acceptable
Habit (HB)	H7	5.516	Moderate
Trust in AI (TR)	H8	6.539	Moderate

Source: data processed by researchers, 2025

Multicollinearity assessment for the inner model was conducted by examining the Variance Inflation Factor (VIF) of each predictor construct, as presented in Table 5. Following the guidelines of Hair et al. (2019) for PLS-SEM, a VIF value below 5.0 is considered acceptable, while values between 5.0 and 10.0 indicate moderate multicollinearity that warrants careful interpretation. The results show that four constructs fall within the moderate range: Effort Expectancy (VIF = 5.029), Habit (VIF = 5.516), Hedonic Motivation (VIF = 6.420), and Trust in AI (VIF = 6.539). The remaining four constructs, Performance Expectancy (3.907), Social Influence (3.820), Facilitating Conditions (3.823), and Price Value (4.019), are within the acceptable threshold. The moderate VIF values observed are consistent with the inherently high inter-construct correlations characteristic of UTAUT2-based models, where theoretically related constructs such as Habit, Hedonic Motivation, and Trust in AI are expected to share substantial common variance with Behavioral Intention. As all VIF values remain below the maximum threshold of 10.0 recommended for PLS-SEM contexts(Hair et al., 2019; Kock, 2015), the structural model is considered interpretable. Nevertheless, the moderate multicollinearity for Effort Expectancy and Habit should be acknowledged as a potential contributing factor to the negative path coefficients observed for Effort Expectancy ($\beta = -0.047$) and Facilitating Conditions ($\beta = -0.042$), and these non-significant results should be interpreted with appropriate caution.

Hypothesis Testing

In PLS-SEM analysis, the bootstrapping method is applied to evaluate the significance of each relationship between variables in the structural model. The assessment is based on the t-statistic or p-value generated. A relationship is considered significant if the t-statistic exceeds 1.96 or the p-value is below 0.05. The test results are presented as follows.

Table 6
Path Coefficients

Hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/ STDEV|)	P values
Performance Expectancy → Behavioral Intention	0.123	0.121	0.069	1.791	0.037
Effort Expectancy → Behavioral Intention	-0.047	-0.040	0.070	0.676	0.250
Social Influence → Behavioral Intention	0.056	0.061	0.075	0.755	0.225
Facilitating Conditions → Behavioral Intention	-0.042	-0.044	0.067	0.630	0.264
Hedonic Motivation → Behavioral Intention	0.117	0.123	0.086	1.358	0.087
Price Value → Behavioral Intention	0.180	0.188	0.087	2.073	0.019
Habit → Behavioral Intention	0.309	0.299	0.093	3.303	0.000
Trust in AI → Behavioral Intention	0.302	0.290	0.102	2.963	0.002

Source: data processed by researchers, 2025

The results of the hypothesis test are shown in the figure below.

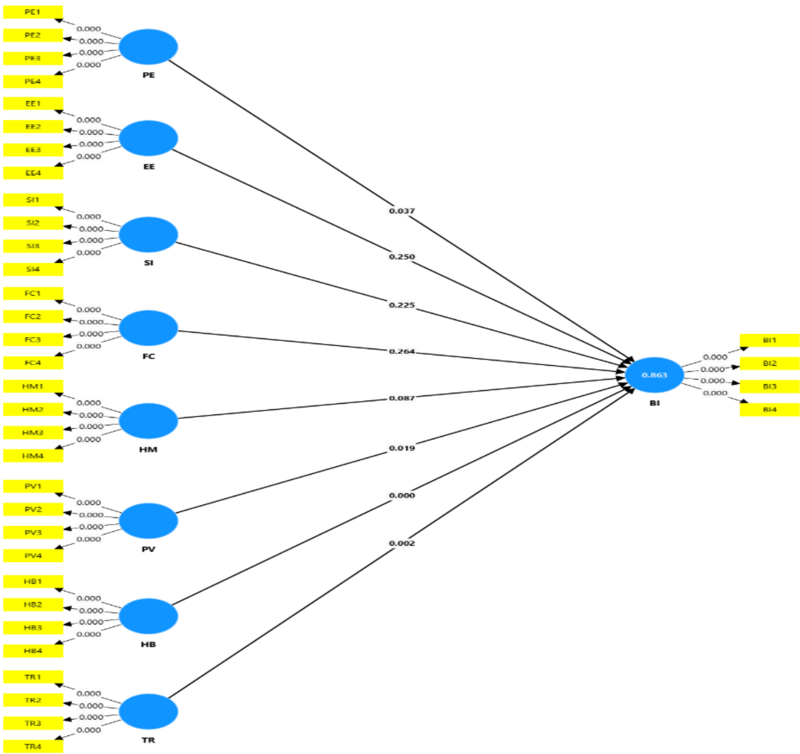

Figure 1. T-Statistic Test Results with P Value
(Source: Data processed by researcher, 2025)

Testing the structural model (inner model) showed that of the eight hypothesized causal relationships, four significantly influenced Behavioral Intention (AI usage intention). The coefficient of determination (R^2) of 0.863 indicates that 86.3% of the variability in usage intention can be explained by the independent variables in the model. This indicates the model's very strong predictive ability. The results of the path coefficient test are presented in Table 6, which summarizes the magnitude of the direct influence of each construct on usage intention and its significance. Overall, these findings provide a clear picture of the factors that most dominantly influence taxpayers' interest in adopting AI for tax assistance.

Habit is the strongest determinant of intention to use AI for tax assistance. Table 6 shows a path coefficient of habit of $\beta = 0.309$ with a significance level of $p < 0.001$. This means that the higher the habit or frequency of AI use by taxpayers, the stronger their intention to continue using it in the future. This finding is consistent with the trajectory of tax service digitalization in Indonesia, where repeated interaction with digital platforms, such as e-Filing and DJP Online, has been shown to gradually normalize technology use among taxpayers (Arianty, 2023; Murnidayanti & Putranti, 2023). As taxpayers accumulate positive experiences using AI for tax queries, habit formation reinforces their reliance on such tools, reducing cognitive effort in future interactions. This pattern is particularly relevant in the Indonesian context, where the progressive rollout of the Core Tax Administration System (Coretax) is expected to increase taxpayers' routine touchpoints with digital services (Yasar et al., 2025). Users who are already habituated to AI tools thus demonstrate stronger intentions to integrate them into their tax routines, suggesting that habit operates as a self-reinforcing adoption mechanism in the tax assistance context. This finding is consistent with evidence from government digital financial systems in Indonesia, where habit has been shown to significantly predict behavioral intention to use e-government applications (Meiranto et al., 2024).

The Trust in AI factor was also shown to play a significant role in driving intention to use. The trust path coefficient of $\beta = 0.302$ ($p = 0.002$) indicates that taxpayers' trust in AI (including perceived accuracy of answers, data security, and reliability of the AI system) has a strong positive influence on their intention to use AI as a tax assistance tool. These results confirm the importance of trust in technology acceptance, in line with previous literature highlighting trust as a key factor in AI adoption. For example, previous research conducted by Choung in 2022, using path analysis, confirmed that user trust significantly increases intention to use AI technology. In fact, the effect of trust can be both direct and indirect, through increased perceptions of the technology's usefulness (Choung et al., 2023). In the context of taxation, which is rife with sensitive information, trust is crucial, as taxpayers must be confident that AI can provide accurate tax information in accordance with applicable regulations and maintain the confidentiality of their personal data. With such confidence, users will be more willing to switch from conventional methods to AI for tax assistance.

The Performance Expectancy variable also significantly influenced AI adoption intention, albeit with a more moderate coefficient ($\beta = 0.123$, $p < 0.05$). These results indicate that users' perceptions of the benefits or performance of AI (such as helping them complete their tax obligations more quickly, improving their understanding of tax regulations, and effectiveness in tax calculations) drive their intention to use AI. These findings align with the UTAUT/UTAUT2 framework and technology adoption research in general, where performance expectancy or perceived usefulness is consistently the primary predictor of intention to use new technology. In the Indonesian taxation context, this is particularly relevant given that AI tools such as ChatGPT and Gemini have demonstrated practical utility in answering taxpayer queries, automating information retrieval, and supporting compliance processes (Cotrina-Reyes et al., 2025; Pramesti & Emalia, 2024). Furthermore, studies on AI applications in tax administration highlight that performance gains, including efficiency in compliance monitoring, accuracy in regulatory interpretation, and speed of administrative processing, are primary motivators for taxpayer engagement with AI-based services (Yip & Fong, 2025). The relatively moderate coefficient of Performance Expectancy compared to Habit and Trust in AI may reflect that while taxpayers acknowledge AI's functional utility, they still perceive limitations in AI's ability to handle the full complexity of Indonesian tax regulations, such as those governed by Ministerial Regulations (PMK) and DJP Circulars (PER DJP), which require contextual and up-to-date interpretation.

Price value (economic benefit value) was shown to have a significant positive effect on intention to use AI with a coefficient of $\beta = 0.180$ ($p = 0.019$). This indicates that economic considerations, for example, the perception that using AI can save costs or provide benefits commensurate with the cost/effort, are one of the drivers of taxpayers' intention to use AI. In the context of tax assistance, many respondents may feel that AI (such as ChatGPT and the like) can provide free or low-cost tax consultations or information, thereby reducing the need to spend money on traditional tax consultants.

CONCLUSION

This study aims to analyze the factors influencing taxpayers' intention to use artificial intelligence (AI) as a tax assistance tool using a modified UTAUT2 model. The results of the PLS-SEM analysis show that of the eight constructs tested, only four constructs significantly influence the intention to use: habit, performance expectancy, price value, and trust in AI. Habit is the most dominant construct, indicating the importance of habit in shaping the intention to reuse technology. Trust in AI also proved to be a strong influence, emphasizing the importance of user perceptions of the security, accuracy, and reliability of AI systems. In contrast, effort expectancy, facilitating conditions, social influence, and hedonic motivation did not have a significant influence, indicating that the intention to use AI in the tax context is more influenced by practical experience and perceived value than by convenience or social encouragement. The practical implication of these findings is the need for the Directorate General of Taxes (DGT) to encourage the habituation of AI use through integration into official services and increasing user technological literacy. AI technology providers are also expected to improve system functionality and security to build user trust. For future researchers, it is recommended to include actual use behavior variables and consider moderating factors such as job type and digital literacy to provide a more comprehensive picture. This research suggests that AI adoption strategies in the tax sector should focus on enhancing trust, user experience, and perceived value to strengthen future usage intentions.

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