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Taxpayers' awareness and perception of machine learning in enhancing tax compliance in Indonesia

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Abstract: This study explores taxpayers' awareness and perception of Machine Learning (ML) in the context of enhancing tax compliance in Indonesia. As the government advances digital tax systems, understanding how taxpayers respond to innovations becomes increasingly important. The research aims to identify whether familiarity, knowledge, and experience with ML influence users' perceptions of ease of use and usefulness, and ultimately, their willingness to comply with tax regulations. Using a quantitative approach, data were collected through a structured questionnaire distributed to individual taxpayers. A total of 306 responses were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS. The findings indicate that familiarity and experience positively affect perceived ease of use and usefulness, which in turn strongly influence tax compliance. Conversely, knowledge of ML does not show a significant impact. These results suggest that engagement with ML technologies is positively associated with tax compliance. This study provides valuable insights from the taxpayers' perspective on how Indonesian tax authorities could design a more digital, accessible, and user-centered tax system.

Keywords: *Machine learning, Tax compliance, Technology acceptance Model (TAM).*

1. Introduction

In recent years, rapid advancements in technological innovation have led to increased complexity and interconnectivity across various domains. These developments have significantly transformed numerous industries, with many sectors now extensively utilizing computer-based systems to enhance both efficiency and accuracy [1]. Recently, the taxation sector has also begun embracing technological integration as part of its efforts to achieve digital transformation and improve operational performance [2]. These advancements are primarily motivated by the growing demand for greater effectiveness, precision, transparency, and compliance in tax administration [3]. In response, the Indonesian government has recently introduced a comprehensive tax digitization initiative. However, the adoption of digital tax systems in Indonesia has not been without challenges, particularly in terms of user acceptance and overall system reliability. Such problems have negatively influenced taxpayers' perception of digital tax platforms, as many users report feeling overwhelmed and require additional time and resources to undergo training and adapt to the new system [4]. Consequently, rather than encouraging voluntary compliance, the system may unintentionally increase the administrative burden and discourage taxpayers' participation [5].

A case in point is the implementation of the Coretax Administration System, an integrated tax digitization initiative launched by the Directorate General of Taxes (DGT). This integrated system aims to streamline tax administration processes and offer benefits to various stakeholders, including taxpayers, the DGT itself, and other relevant institutions [6, 7]. Despite its intended advantages, the real implementation of the system has drawn considerable criticism from users. These criticisms largely were due to the system's complexity, lack of user-friendliness, and numerous technical issues such as

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software bugs and operational glitches [8, 9]. Such problems have negatively influenced taxpayers' perception of digital tax platforms, as many users report feeling overwhelmed and requiring additional time and resources to undergo training and adapt to the new system [4]. As a result, rather than encouraging voluntary compliance, the system may unintentionally increase the administrative burden and discourage taxpayers' participation [5]. These challenges highlight the importance of developing more adaptive, efficient, and user-oriented solutions within Indonesia's tax digitization initiatives.

One promising opportunity to address these challenges is the incorporation of machine learning (ML) technologies into the tax system [10]. Machine Learning offers the ability to process large volumes of taxpayers' data, identify anomalies, and detect behavioral patterns indicative of noncompliance [11]. Beyond enforcement, machine learning can also enhance tax services by automating tasks such as document classification, document matching, and transaction verification, thereby improving efficiency and minimizing the likelihood of human errors [6]. Although Machine Learning presents significant opportunities to enhance the tax system, it also poses certain challenges and limitations. The increasing reliance on Machine Learning also raises concerns regarding data quality and privacy [12]. The reliability of Machine Learning relies heavily on the quality and completeness of the taxpayers' data inputted, which means poor-quality data may result in flawed predictions and ineffective outcomes. Furthermore, the sensitive nature of taxpayers' data and information raises significant privacy and data security concerns, such as the risk of unauthorised access, data leaks, and potential misuse of personal information [13].

Nevertheless, the successful implementation of Machine Learning (ML) in Indonesia's tax system requires more than merely advanced technological infrastructure. While technology readiness is a critical fundamental base, the system's success also heavily depends on how it is perceived and accepted by its potential users [14]. In this context, taxpayers' perceptions and acceptance become key factors in determining whether a Machine Learning-based tax system will be embraced or resisted [15]. User acceptance is deeply influenced by individual perceptions, both positive and negative [16]. Positive perceptions could increase taxpayers' willingness to comply, especially if Machine Learning is seen as a fair, accurate, and efficient tool. Conversely, negative perceptions might lead to skepticism or even distrust toward the tax system, potentially reducing tax compliance [17]. Over and above these perceptions, some argue that Machine Learning may enhance compliance by simplifying procedures and making the tax process more accessible [18]. While others might argue that Machine Learning could encourage higher compliance rates, as taxpayers become more cautious and fearful of the potential consequences of noncompliance [19].

However, such expected outcomes are not guaranteed. Taxpayers' perceptions of machine learning-based tax systems can vary widely depending on their familiarity, knowledge, and previous experience with the technology itself [12]. Therefore, it is essential to understand and evaluate taxpayers' perceptions before full-scale implementation takes place. This is especially relevant in Indonesia, where the tax authority has begun modernizing its systems [8]. The most recent was through the Coretax System. Although Coretax shares similarities with the proposed machine learning-based tax system, its implementation has faced several challenges and has been criticized by its users, suggesting a need for a deeper understanding of public readiness [2].

By examining these perceptions, this research will evaluate whether Machine Learning would likely be accepted or resisted, and to what extent these attitudes might influence tax compliance behavior. This focus is motivated by the growing implementation of digital tax systems. Although the technical potential of Machine Learning is well-established, limited research has addressed how such innovations are perceived by end users, especially within the Indonesian tax environment. Hence, this study aims to explore how Indonesian taxpayers perceive the potential implementation of a Machine Learning-based tax system.

This study contributes both practically and theoretically to the field of tax administration. Practically, it offers valuable insights for policymakers and tax authorities on how Machine Learning may be received by taxpayers, supporting the development of user-centred, transparent, and effective digital tax systems that enhance compliance. Theoretically, it contributes to the literature on technology acceptance by examining the roles of familiarity, knowledge, and experience in shaping user perceptions of emerging technologies, particularly Machine Learning within the taxation domain.

2. Literature Review & Hypotheses Development

This study adopts the Technology Acceptance Model (TAM) as the theoretical foundation to evaluate taxpayers' awareness and perception of Machine Learning (ML) in enhancing tax compliance in Indonesia.

2.1. Familiarity with Machine Learning

Familiarity refers to the degree of recognition and prior exposure an individual has regarding a specific technology [20]. Prior studies indicated that familiarity encompasses knowledge and enhances a sense of confidence in the system's reliability and usability [21]. In the context of adopting a new system, newer users who are generally unfamiliar with the system might require more comprehension than experienced users who are more accustomed to using it [22]. As familiarity grows, users tend to perceive the system as easier to use and more useful, which makes familiarity an important factor influencing user acceptance [23]. To sum up, similar research has also shown that familiarity significantly influences individuals' willingness to adopt new technology by increasing their perceived ease of use and perceived usefulness [24].

Based on what the theories have discussed, we propose the first and second hypotheses as follows:

- Hypothesis 1 (H1): Familiarity with machine learning will affect taxpayers' perceived ease of use.
- Hypothesis 2 (H2): Familiarity with machine learning will affect taxpayers' perceived usefulness.

2.2. Knowledge of Machine Learning

According to Lewin and Grabbe [25], knowledge is one of the necessary components in fostering the acceptance of new values, working alongside emotional readiness, social influence, and active participation in the change process [25]. Prior research also stated that users' knowledge regarding information technology contributes to their confidence, attitude, and comfort towards using similar technology [26]. Moreover, knowledge plays a pivotal role in facilitating rational acceptance, as it enables individuals to form well-grounded reasoning, thereby reducing the risk of misconceptions and resistance to innovation [27].

According to the theories reviewed above, the third and fourth hypotheses were generated as follows:

- Hypothesis 3 (H3): Knowledge of machine learning will affect taxpayers' perceived ease of use.
- Hypothesis 4 (H4): Knowledge of machine learning will affect taxpayers' perceived usefulness.

2.3. Experience Using Machine Learning

Experience plays a crucial role in shaping user behaviour and perception [28]. Through experiential engagement with similar platforms, users develop a level of understanding of how a system works, often without conscious awareness [29]. Supported by previous research, it is stated that through different experiences, perception develops within a person over time, eventually leading to an attitude towards the use of a system [30, 31]. If users' experience is built positively towards a similar Machine Learning-based system, it would enhance their trust, satisfaction, and sense of value, hence strengthening users' willingness to adopt a similar Machine Learning-based system in new circumstances, such as taxation [32].

Referring to the discussed theories, the fifth and sixth hypotheses are framed:

- Hypothesis 5 (H5): Experience in using machine learning will affect taxpayers' perceived ease of use.

- Hypothesis 6 (H6): Experience in using machine learning will affect taxpayers' perceived usefulness.

2.4. Technology Acceptance Model (TAM)

Since its introduction by Davis [33], the Technology Acceptance Model (TAM) has been frequently utilized to describe how people begin to embrace new technology [33]. TAM is widely used for analyzing how users perceive the adoption of technology based on its analysis of testers' perceived ease of use and perceived usefulness [34]. In this context, perceived ease of use is defined as the extent to which an individual acknowledges that the new technology will be easy to use without significant effort or an extensive learning process [34, 35]. Perceived usefulness, on the other hand, is commonly stated as the degree to which a user believes that the technology used is capable of assisting them in successfully accomplishing their objectives more efficiently [34, 36].

Despite being a relatively aged model, the TAM remains one of the most commonly used frameworks for assessing technology acceptance due to its established effectiveness in predicting behavioral intentions [37]. Its versatility has allowed it to be used in various fields. In this context, the field of taxation has seen a growing interest in the use of advanced technologies, such as machine learning-based tax systems [38]. Several studies have stated that the complexity of the tax system will drag down taxpayers' compliance in paying taxes [39]. Given this concern, the implementation of user-friendly and effective technology becomes increasingly crucial in encouraging voluntary compliance [40].

According to these prior studies, the seventh and eighth hypotheses of this study are formulated as follows:

- Hypothesis 7 (H7): Perceived ease of use of machine learning will affect taxpayers' tax compliance.
- Hypothesis 8 (H8): Perceived usefulness of machine learning will affect taxpayers' tax compliance.

3. Research Methodology

This research follows an approach as described below to evaluate how Indonesian taxpayers perceive the potential implementation of a machine learning-based tax system.

3.1. Research Design & Approach

This research adopted a quantitative design with a survey approach to examine taxpayers' awareness and perception of the use of machine learning (ML) in enhancing tax compliance in Indonesia [41]. The survey aimed to gather information based on taxpayers' familiarity, knowledge, experience, and perception related to Machine Learning (ML) to assess its potential impact on enhancing taxpayers' compliance. Through the use of numerical data and statistical analyses, the quantitative method allows for the objective measurement of the variables.

3.2. Data Sources

The data used in this research is primary data, which was gathered directly from respondents through questionnaires via Google Forms [42]. The targeted respondents for this study were Indonesian taxpayers from a variety of backgrounds, including genders, age groups, and fields of work. This approach is outlined to capture a wider range of perceptions and guarantee that the results accurately represent the general taxpayers' opinions on the subject.

3.3. Data Collection & Analysis

The data was gathered using a closed-ended questionnaire on a Likert scale ranging from 1 to 5, where 1 indicates "Strongly Disagree" and 5 indicates "Strongly Agree." The questionnaire is divided into several segments. The first segment included general demographic questions such as the respondent's name, gender, age, and field of work. To evaluate the respondents' familiarity, knowledge, experience, perceived ease of use, and perceived usefulness of Machine Learning in encouraging tax compliance, the following segments included Likert-scale measures [43]. The variables, indicators, and corresponding research questions used in this study are listed and detailed in Appendix 1.

The data will be analyzed using SmartPLS, which is intended to examine the relationships between variables and assess both direct and indirect effects [44]. The use of SmartPLS is supported by various complex variables attached to the study. The analysis aimed to determine the magnitude of the influence and to test the hypotheses of the independent variables on the dependent variables.

3.4. Respondents & Sample Size Determination

As described in Section 3.2, the data used in this research were collected from Indonesian taxpayers with diverse demographic profiles. A total of 306 valid responses were obtained. The study applied a purposive sampling method to ensure that the participants were relevant to the research objectives. To determine the minimum number of respondents, the study employed the widely accepted rule for Partial Least Squares Structural Equation Modeling (PLS-SEM), which requires a sample size of at least 10 times the highest number of indicators used in a single latent variable [45]. In this study, the highest number of indicators for a construct is 15, resulting in a minimum requirement of 150 respondents.

The final sample size of 306 not only satisfies this requirement but also enhances the statistical power of the analysis. In addition to sample size sufficiency, the study also considered the demographic composition of respondents. The sample included individuals of varying age groups, genders, and fields of work, which contributes to the generalizability of the findings across different taxpayer segments. A detailed demographic summary is presented in Chapter 4.

3.5. Empirical Model

Based on the hypotheses formulated in the previous chapter, this study adopts the Technology Acceptance Model (TAM). The empirical model is constructed by integrating the key constructs of TAM with additional variables relevant to this research context, such as familiarity, knowledge, and experience with Machine Learning. These additional constructs are expected to influence users' perceptions of ease and usefulness when interacting with ML-based tax systems. The conceptual relationships between these variables are illustrated in a conceptual framework, which serves as the basis for hypothesis testing. The proposed model is presented graphically in Figure 1.

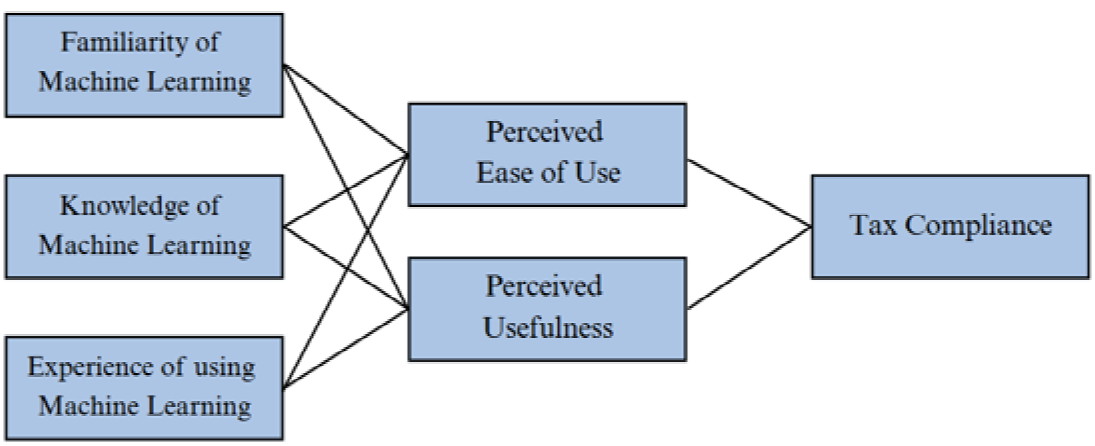

Figure 1.
Hypotheses-based TAM Model.

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4. Data Analysis & Findings

Data processing in this research utilizes a PLS-SEM (Partial Least Squares Structural Equation Modeling) approach with the help of SmartPLS software. This method is chosen for its suitability in handling complex models with multiple constructs and indicators. The analysis is carried out in two main stages: the measurement model evaluation, which assesses the reliability and validity of the outer model, and the structural model evaluation, which examines the inner model to test the hypothesized relationships among latent constructs.

4.1. Respondents' Demographic Profile

The questionnaire used in this study consisted of two main sections: demographic data and multiple construct measurements. In the demographic data, this research collected data about respondents' gender, age, and field of work. Respondents' fields of work were later grouped into broader categories for clarity, including professionals and office workers, business and industry, service and creative sectors, and the non-working population, such as students or retirees. This demographic composition supports the generalizability of findings and offers a relevant perspective on how different segments of the population perceive and respond to ML-based innovations in tax compliance. The detailed distribution of respondents based on age, gender, and field of work is presented in Table 1 below.

Table 1.
Details of Respondents.

Category	Sub-Category	Number of Respondents (n=306)	Percentage (%)
Gender	Male	104	34%
	Female	202	66%
Age	<20 years	10	3.3%
	20-29 years	205	67%
	30-39 years	36	11.8%
	40-49 years	21	6.9%
	50-59 years	30	9.8%
	>60 years	4	1.3%
Field of Work	Professionals and Office Workers	140	45.8%
	Business and Industry	48	15.7%
	Services and Creative Economy	66	21.6%
	Non-working / General Public	52	17%

4.2. Measurement Model Evaluation

The model measurement evaluation of this research was carried out by assessing the outer model through Cronbach's Alpha, Composite Reliability, Average Variance Extracted (AVE), and Discriminant Validity. This measurement is essential to ensure both the reliability and validity of the constructs used in this research.

Table 2.
Construct Reliability and Validity.

	Cronbach's Alpha	Composite Reliability (rho a)	Composite Reliability (rho c)	Average Variance Extracted (AVE)
Experience in Using ML	0.689	0.725	0.803	0.511
Familiarity with ML	0.816	0.831	0.879	0.645
Knowledge of ML	0.801	0.814	0.869	0.623
Perceived Ease of Use	0.847	0.855	0.887	0.569
Perceived Usefulness	0.840	0.842	0.882	0.555
Tax Compliance	0.874	0.876	0.905	0.614

According to the reliability thresholds proposed by Nunnally [46] and Chin [47], Cronbach's Alpha and Composite Reliability (CR) values above 0.70 are considered reliable. As presented in Table 2, the values of Cronbach's Alpha and Composite Reliability for each construct were above 0.7, which indicates reliability. Although Experience in using ML is slightly below 0.7 (0.689), it remains acceptable within the context of exploratory research, as supported by earlier literature [46]. Furthermore, both Composite Reliability Rho A and Rho C also indicate results above 0.7, which confirms adequate internal consistency reliability. In terms of convergent validity, all the AVE values show results above 0.5, which is the ideal result based on previous studies established by Fornell and Larcker [48]. Therefore, these AVE values indicate that the convergent validity was fulfilled, and the indicators are sufficiently representative to be considered both reliable and valid for further model analysis.

Next, discriminant validity was evaluated using the Heterotrait-Monotrait Ratio of Correlations (HTMT), which offers a more reliable assessment in evaluating whether each construct is sufficiently different from the others. Through the study from Henseler et al. [49], the value below 0.90 is generally accepted as evidence that constructs are sufficiently distinct from one another and do not exhibit problematic overlap. As presented in Table 3, all the construct values are below the 0.90 threshold, thereby indicating acceptable discriminant validity. Although the HTMT value between Perceived Ease of Use and Perceived Usefulness becomes the highest value observed (0.869), it is still within the acceptable limit. These results confirm that each latent construct is empirically distinguishable, allowing for valid interpretation in the structural model.

Table 3.
Discriminant validity.

	Experience in Using ML	**Familiarity with ML**	**Knowledge of ML**	**Perceived Ease of Use**	**Perceived Usefulness**	**Tax Compliance**
Experience in Using ML						
Familiarity with ML	0.783					
Knowledge of ML	0.763	0.850				
Perceived Ease of Use	0.683	0.614	0.559			
Perceived Usefulness	0.625	0.553	0.411	0.869		
Tax Compliance	0.547	0.508	0.498	0.834	0.782	

Furthermore, Figure 2 displays the graphical output generated by SmartPLS. Green-colored paths indicate a positive and statistically significant relationship between constructs, meaning the hypothesis is supported. Conversely, red-colored paths represent relationships that are not statistically significant, indicating that the hypothesis is not supported.

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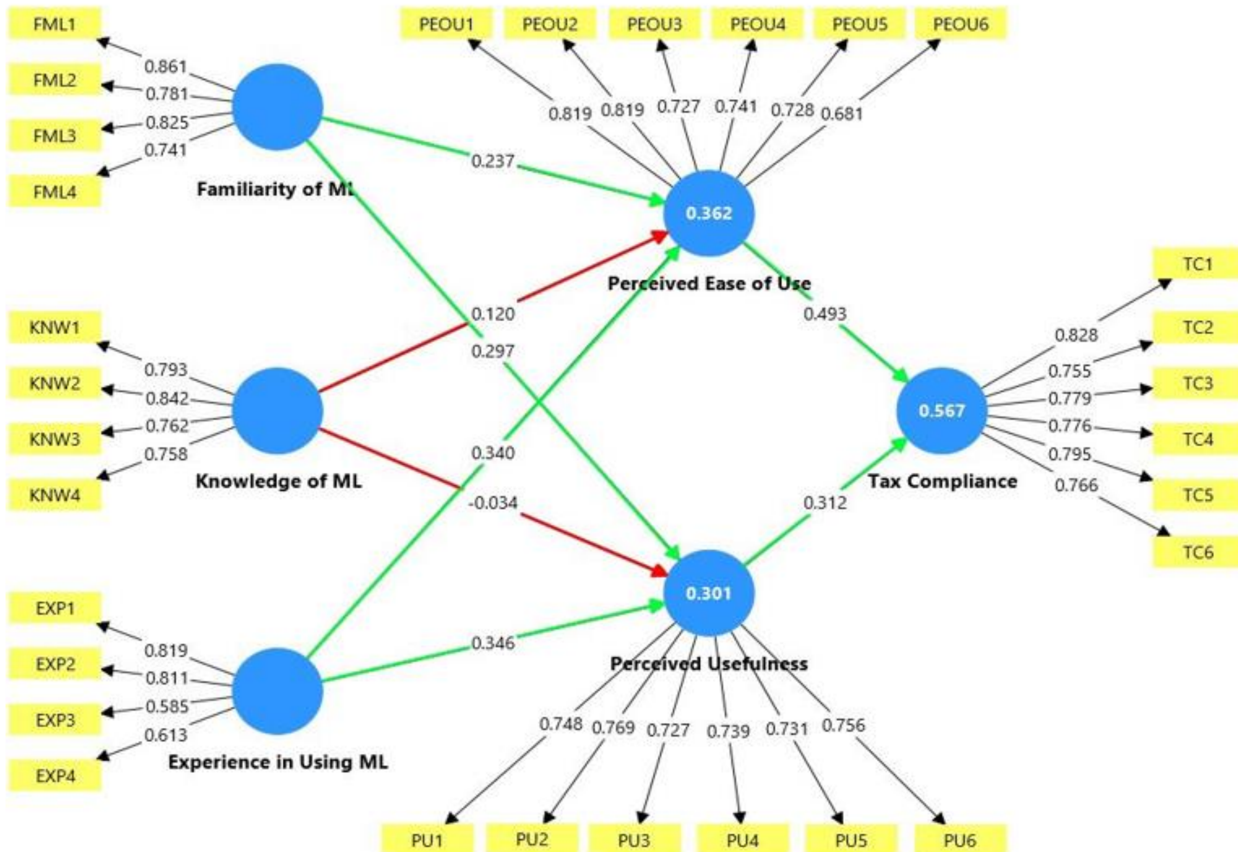

Figure 2.
Graphical PLS-SEM Output.

4.3. Structural Model Evaluation

Once the measurement model has been validated, the next step is to evaluate the structural model. This part of the analysis assesses the relationships between latent constructs based on the proposed hypotheses, utilizing the results of R-Square and path coefficients. R-Square, often referred to as the coefficient of determination, indicates the amount of variance in the endogenous variable that is explained by its predictors. According to Chin [47], the result of the R^2 value above 0.67 is considered substantial; between 0.33 and 0.67 is moderate; and between 0.19 and 0.33 is weak.

Table 4.
R-Square.

	R-Square	R-Square Adjusted
Perceived Ease of Use	0.362	0.356
Perceived Usefulness	0.301	0.294
Tax Compliance	0.567	0.565

As shown in the results, Perceived Ease of Use (R^2 = 0.362) and Perceived Usefulness (R^2 = 0.301) demonstrate a moderate level of explanatory power. This suggests that while prior exposure and understanding of ML technology play a notable role in shaping how taxpayers perceive its ease and usefulness, other external or contextual factors may also influence these perceptions [50]. Meanwhile, Tax Compliance (R^2 = 0.503) shows a higher level of explanatory power. Although the R^2 value of 0.503 is still considered moderate, it indicates a meaningful relationship according to Chin [47] it leans a bit towards being strong. This finding reflects that when taxpayers find ML systems intuitive and beneficial, they are more likely to comply with tax obligations.

Next, the analysis of path coefficients in this context represents the strength of the relationship between variables. By utilizing bootstrapping on SmartPLS, 5,000 subsamples were conducted to test the significance of the path coefficients. Based on Hair et al. [51], the result of a *t*-value above 1.96 and a *p*-value below 0.05 indicates statistical significance.

Table 5.
Path Coefficients and Proposed Hypotheses

Hypotheses	Path	Coefficient	*t*-value	*p*-value	Supported
H1	Familiarity to Perceived Ease of Use	0.237	3.293	0.001	Yes
H2	Familiarity to Perceived Usefulness	0.297	3.599	0.000	Yes
H3	Knowledge to Perceived Ease of Use	0.120	1.673	0.094	No
H4	Knowledge to Perceived Usefulness	-0.034	0.450	0.653	No
H5	Experience to Perceived Ease of Use	0.340	4.174	0.000	Yes
H6	Experience to Perceived Usefulness	0.346	4.295	0.000	Yes
H7	Perceived Ease of Use to Tax Compliance	0.493	7.883	0.000	Yes
H8	Perceived Usefulness to Tax Compliance	0.312	5.101	0.000	Yes

4.4. Discussions of Findings

Based on the results shown, familiarity positively influences perceived ease of use (β = 0.237, p = 0.001) and perceived usefulness (β = 0.297, p < 0.001). Therefore, Hypothesis 1 and Hypothesis 2 are supported. This demonstrates that even general exposure to ML reduces perceived complexity and enhances anticipated benefits. These results are consistent with previous study by Kegode et al. [52] which states that public technology adoption emphasizes the importance of exposure in creating initial comfort with innovation

Experience with ML applications also has a significant positive effect on perceived ease of use (β = 0.340, p < 0.001) and perceived usefulness (β = 0.346, p < 0.001). Therefore, Hypotheses 5 and 6 are supported. These results support the position that direct user experience plays a pivotal role in shaping perceptions, aligns with the findings from Zahra et al. [53] who argue that real-life experience with new technology boosts user confidence and expectations. Therefore, individuals who have interacted with ML-powered applications such as Shopee, Spotify, or TikTok are more likely to develop favorable perceptions about using similar systems in the context of taxation.

However, on the other hand, knowledge of ML does not significantly affect either perceived ease of use (β = 0.120, p = 0.094) or perceived usefulness (β = -0.034, p = 0.653). Therefore, Hypotheses 3 and 4 are rejected. This finding suggests that a theoretical or conceptual understanding of ML, without direct exposure or experience, is insufficient to alter perception. As Horowitz et al. [54] previously, it is argued that user acceptance is more strongly shaped by real-life engagement. These results indicate the necessity of promoting active interaction with ML rather than relying solely on educational content.

At last, both perceived ease of use (β = 0.493, p < 0.001) and perceived usefulness (β = 0.312, p < 0.001) significantly influence tax compliance. Therefore, Hypotheses 7 and 8 are supported. These findings align with the Technology Acceptance Model by Davis [33], which states that perceived ease of use and perceived usefulness are critical factors in user intention and behavior in adopting new technology.

5. Conclusion

This research aimed to examine and explore how Indonesian taxpayers' perception and awareness of the use of Machine Learning (ML) in enhancing tax compliance. Utilizing a quantitative approach with Partial Least Squares Structural Equation Modeling (PLS-SEM), the analysis was conducted on data obtained from 306 valid respondents with diverse age groups, genders, and fields of work. The research model consisted of six variables, such as familiarity, knowledge, and experience with Machine Learning (ML) as exogenous variables, perceived ease of use and perceived usefulness as mediating variables, and tax compliance as the endogenous variable.

The analysis found that familiarity and experience with Machine Learning (ML) positively impact perceived ease of use and perceived usefulness. In contrast, knowledge does not show any impact or influence on perceived ease of use and perceived usefulness. These findings suggest that actual interaction and hands-on experience with Machine Learning (ML) alter user perceptions more effectively than conceptual understanding. Furthermore, both perceived ease of use and perceived usefulness demonstrate a significant positive impact on tax compliance, especially perceived ease of use. This underscores the critical role of system usability and perceived benefits in encouraging compliance behaviors through the adoption of technology-based systems.

In conclusion, this study provides useful insights for policymakers and tax authorities, particularly the Directorate General of Taxes in Indonesia. The results show the importance of a dual approach, such as continuing to develop and implement ML-based tax systems while also ensuring these systems are easy to use and accessible for taxpayers. The findings suggest that improving familiarity and giving taxpayers the chance to actively use ML applications are more effective in encouraging tax compliance than only providing theoretical knowledge. Therefore, it is recommended that tax authorities design education and outreach programmes that include hands-on learning. Activities such as training workshops, interactive tutorials, and built-in help features in ML-based tax systems can help increase taxpayers' understanding and engagement. These efforts may lead to greater acceptance and use of ML-based tax services, which in turn can improve compliance levels.

For future studies, researchers are encouraged to examine long-term changes over time (longitudinal studies), expand the geographical scope, or explore qualitative perspectives. This would provide a deeper understanding of how machine learning affects taxpayers' behavior and support the development of more effective digital tax policies in the public sector.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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Appendix 1.

Operation of Variable.

Variable	Indicator	Question	Source
Familiarity with ML	1. Exposure	1. I am frequently exposed to the term "Machine Learning". 2. I am familiar with common Machine Learning terms such as "algorithm", "model", and "training data".	Sahari [55] and Schepman and Rodway [50]
	2. Awareness	3. I am aware that Machine Learning is applied in various aspects of daily life. 4. I am aware that Machine Learning has been implemented in several public service systems.	
Knowledge of ML	1. Understanding	1. I have a general understanding of how Machine Learning works. 2. I understand that Machine Learning can assist in automatically detecting potential tax noncompliance.	Horowitz et al. [54]
	2. Knowledge	3. I know that some countries have integrated Machine Learning into their tax examination procedures. 4. I am aware that the Directorate General of Taxes in Indonesia is planning to adopt Machine Learning technology.	
Experience of using ML	1. Incidental Use	1. I have used applications that incorporate Machine Learning (e.g., Shopee, TikTok, Spotify, etc). 2. I have utilized Machine Learning-based features within these applications (e.g., Shopee - Product recommendation systems, TikTok - Personalized For You Page based on user interactions, Spotify - Playlist generation according to users' listening patterns, etc).	Zahra et al. [53]
	2. Intentional Use	3. I have participated in courses, training sessions, or workshops related to Machine Learning. 4. I have experience in creating or implementing Machine Learning models, although only in basic forms.	
Perceived Ease of Use	1. User Comfort	1. If a Machine Learning-based tax system is implemented, I am confident that the system will be easy to use. 2. I believe that a machine-learning-based tax system would be more convenient to use compared to a manual tax system.	Van der Heijden [56] and Venkatesh et al. [57]
	2. Technical Barriers	3. I believe that I would not face major challenges in using a Machine Learning-based tax system. 4. I believe that operating the functions within a Machine Learning-based tax system will not cause confusion for the users.	
	3. Adaptability	5. I believe that taxpayers will easily adapt to a Machine Learning-based tax system.	

		6. If implemented, I am willing to learn the new features of the Machine Learning-based tax system.	
Perceived Usefulness	1. Tax Audit Effectiveness	1. I believe that a Machine Learning-based tax system will help improve the efficiency of tax examination. 2. I believe that a Machine Learning-based tax system will facilitate a quicker tax examination process.	Ciasullo et al. [58]
	2. Error Reduction	3. I believe that Machine Learning can minimize human errors in the tax reporting process. 4. I believe that Machine Learning can minimize human errors in the tax examination process.	
	3. Accuracy Improvement	5. I believe Machine Learning can help identify potential taxpayers' noncompliance more accurately. 6. I believe that a Machine Learning-based tax system provides higher accuracy than a manual tax system.	
Tax Compliance	1. Motivation	1. If a Machine Learning-based tax system is implemented, I would feel more motivated to comply with tax obligations. 2. I believe that a Machine Learning-based tax system will enhance taxpayers' sense of responsibility in fulfilling their tax obligations.	Iivari [59]
	2. Willingness	3. I believe that a Machine Learning-based tax system will enhance transparency, thereby increasing my motivation to comply with tax regulations. 4. I believe that the implementation of a Machine Learning-based tax system would encourage me to be more compliant with tax regulations compared to a manual system.	
	3. Confidence	5. 1. The presence of machine learning technology in the tax system increases my confidence in fulfilling my tax obligations on time. 6. I believe that a machine learning-based tax system will increase the risk of consequences for tax violators, thereby encouraging me to be more confident and transparent in reporting taxes.	