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Factors Influencing Cryptocurrency Adoption Using the Technology Acceptance Model

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Abstract
Cryptocurrency has become one of the most prominent financial technology innovations in the digital economy. Its adoption continues to increase globally due to the growing need for decentralized financial systems, digital investment instruments, and alternative payment technologies. However, cryptocurrency adoption is determined not only by the availability of the technology, but also by user perception, trust, perceived risk, technological awareness, and regulatory support. This study aims to analyze the factors influencing cryptocurrency adoption using the Technology Acceptance Model (TAM) approach. This model focused on perceived usefulness, perceived ease of use, trust, perceived risk, technological awareness, and behavioral intention. This study uses a quantitative explanatory approach through survey-based data collection from potential and actual cryptocurrency users. The proposed analysis method is Structural Equation Modeling–Partial Least Squares (SEM-PLS) to examine the relationships between variables. This study argues that perceived usefulness and perceived ease of use are the main predictors of behavioural intention, while trust and perceived risk are important external factors in shaping user acceptance. The findings of this study are expected to provide theoretical contributions to the development of TAM in the study of financial technology adoption as well as practical contributions for regulators, crypto platforms, and financial educators in increasing the safe and responsible adoption of cryptocurrency.

INTRODUCTION

The rapid development of financial technology has transformed the way individuals transact, invest, and manage digital assets (Arner et al., 2018; Ashta & Biot-Paquerot, 2018; Bok, 2023; George, 2024; Popescu, 2020). One of the most prominent innovations in this transformation is cryptocurrency, a digital asset that uses *blockchain* and cryptography mechanisms to enable secure *peer-to-peer transactions* without relying entirely on traditional financial intermediaries. Cryptocurrencies are no longer understood solely as digital payment instruments, but also as investment assets, speculative commodities, and technological innovations in the global financial ecosystem. This development reflects a broader shift in financial behaviour, where digital platforms are increasingly influencing how users' access, evaluate, and adopt financial products (Alt & Puschmann, 2012; Dapp et al., 2014; Gomber et al., 2017; Lee & Yoon, 2026; Muslim, 2024).

Global cryptocurrency adoption has steadily increased in recent years. The 2024 *Geography of Cryptocurrency report* by Chainalysis (2024) shows that crypto adoption has become a global phenomenon, particularly in developing countries where users often seek alternative financial instruments and digital transaction systems. Indonesia is also one of the countries with significant crypto activity. Reuters (2024) reported that Indonesia recorded crypto inflows of approximately US$157.1 billion from June 2023 to July 2024, despite the fact that cryptocurrencies are not permitted as legal tender and are largely treated as investment assets. This indicates that cryptocurrency adoption in Indonesia is driven not only by transactional needs but also by investment motives and public interest in digital assets.

Although cryptocurrency adoption continues to grow, its acceptance among users remains complex, involving technological, financial, psychological, and regulatory considerations. Users must understand digital wallets, *blockchain networks*, private keys, exchange platforms, transaction fees, and market volatility before deciding to adopt or invest in crypto assets. Furthermore, risks such as fraud, hacking, *phishing*, price fluctuations, and regulatory uncertainty can influence users' intention to adopt cryptocurrencies. Therefore, cryptocurrency adoption cannot be explained solely by technological availability but must also be analyzed through user perceptions, trust, perceived risks, and awareness of the digital financial system.

To explain user acceptance of technology, *the Technology Acceptance Model* (TAM) is one of the most widely used theoretical frameworks. Davis introduced TAM by emphasizing two key constructs, namely perceived usefulness *and* perceived ease *of use*, as the main determinants of technology acceptance. Perceived usefulness refers to the extent to which users believe a technology can improve their performance or provide many benefits, while perceived ease of use refers to the extent to which users can believe a technology is easy to understand and operate. In the context of cryptocurrencies, perceived usefulness can include investment opportunities, transaction efficiency, financial autonomy, and portfolio diversification. Meanwhile, perceived ease of use can include the simplicity of creating an account, using a crypto wallet, buying and selling assets, and accessing reliable information.

Previous research has shown that TAM remains relevant in explaining cryptocurrency and fintech adoption. Research on crypto application acceptance found that perceived ease of use, perceived usefulness, subjective norms, and perceived risk are important variables in understanding user acceptance of crypto applications. Another study on Bitcoin purchase intentions also showed that perceived usefulness and perceived ease of use can significantly influence an individual's intention to purchase or use Bitcoin. These findings suggest that user adoption of cryptocurrency is closely related to how users perceive the benefits and usefulness of crypto-based platforms.

However, cryptocurrency adoption differs from general technology adoption because it involves high financial uncertainty. Unlike traditional digital applications, cryptocurrencies expose users to potential financial losses due to market volatility, cybercrime, weak literacy, and platform credibility issues. Therefore, several studies recommend expanding the TAM by including external variables such as trust, perceived risk, perceived security, and technology awareness. In fintech adoption research, trust and perceived risk are often considered important variables because users must feel confident that the platform is secure, reliable, and capable of protecting their assets and personal information.

Trust is a crucial factor in cryptocurrency adoption because these systems operate in a decentralized digital environment. Users need confidence not only in *blockchain technology* but also in crypto exchanges, wallet providers, regulatory bodies, and information sources. Without sufficient trust, users may hesitate to adopt cryptocurrencies even when they perceive them as useful. At the same time, perceived risk can reduce adoption intentions because users are aware of potential losses caused by hacks, fraud, price volatility, and sudden regulatory changes. This suggests that cryptocurrency adoption is heavily influenced by the balance between perceived benefits and perceived risks.

Furthermore, technological awareness and financial literacy can also influence cryptocurrency adoption. Users who understand *blockchain technology,* digital wallets, crypto exchanges, and investment risk management tend to evaluate cryptocurrencies rationally. Conversely, users with low literacy may adopt cryptocurrencies due to speculation, social influence, or fear *of missing out,* rather than informed decision-making. A study on cryptocurrency adaptability in Indonesia found that technological awareness and government support can shape perceptions of benefits, convenience, and risks, while behavioral intentions among young users can also be influenced by non-technical factors such as speculative motives and FOMO.

Based on these problems, this study aims to analyze the factors that influence cryptocurrency adoption using the Technology Acceptance Model. This study focuses on perceived usefulness, perceived ease of use, trust, perceived risk, technological awareness, and behavioral intention. The novelty of this study lies in the expansion of TAM by integrating psychological and contextual variables that are highly relevant to cryptocurrency adoption, particularly in the Indonesian context. Unlike previous studies that primarily examined general fintech adoption or Bitcoin acceptance in other countries, this research specifically targets Millennials and Generation Z in Indonesia, the largest demographic of crypto users in the country. This research is expected to provide theoretical contributions to the development of technology adoption studies, especially in the context of digital financial assets, as well as practical contributions for crypto platforms, regulators, and financial educators in encouraging safer, more responsible, and information-based cryptocurrency adoption. The purpose of this study is to analyze the effect of Perceived Usefulness on Behavioral Intention. The contribution of this research lies in the development of the Technology Acceptance Model (TAM) framework through the integration of psychological and contextual variables (namely Trust, Perceived Risk, and Technology Awareness) to provide a more in-depth explanation of the adoption of digital financial technology that has high uncertainty, particularly in the rapidly growing Indonesian crypto market.

METHOD

This study used a quantitative explanatory approach with a causal-explanatory design to analyze the influence of Technology Awareness, Trust, and Perceived Risk on Behavioral Intention, with Perceived Usefulness and Perceived Ease of Use as mediating variables. The study population is Millennials and Generation Z in Indonesia who understand cryptocurrency. The sample was determined using a non-probability sampling technique with the snowball sampling method, with a target of at least 150 respondents. Primary data were collected through an online questionnaire based on Google Forms using a 5-point Likert scale, while secondary data were obtained from books, journal articles, official reports, and publications related to cryptocurrency adoption. Data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with the help of SmartPLS. Testing was carried out through an outer model evaluation to assess the validity and reliability of the instrument, and an inner model evaluation to examine the relationship between variables. Hypothesis testing was carried out through a bootstrapping procedure with the criteria of a T-statistic value ≥ 1.96 and P-values ≤ 0.05. The research was conducted in Kuningan, West Java in December 2025 with attention to research ethics principles, including respondent confidentiality and informed consent.

RESULTS AND DISCUSSION

This study tested a structural model that links *Technology Awareness, Trust,* and *Perceived Risk* to *Behavioral Intention* through the mediation of *Perceived Usefulness* and *Perceived Ease of Use.* Figure 1 presents a path diagram of the research model along with the path coefficients (numbers on the arrows between constructs) and *outer loadings* (numbers on the arrows from constructs to indicators) of each variable.

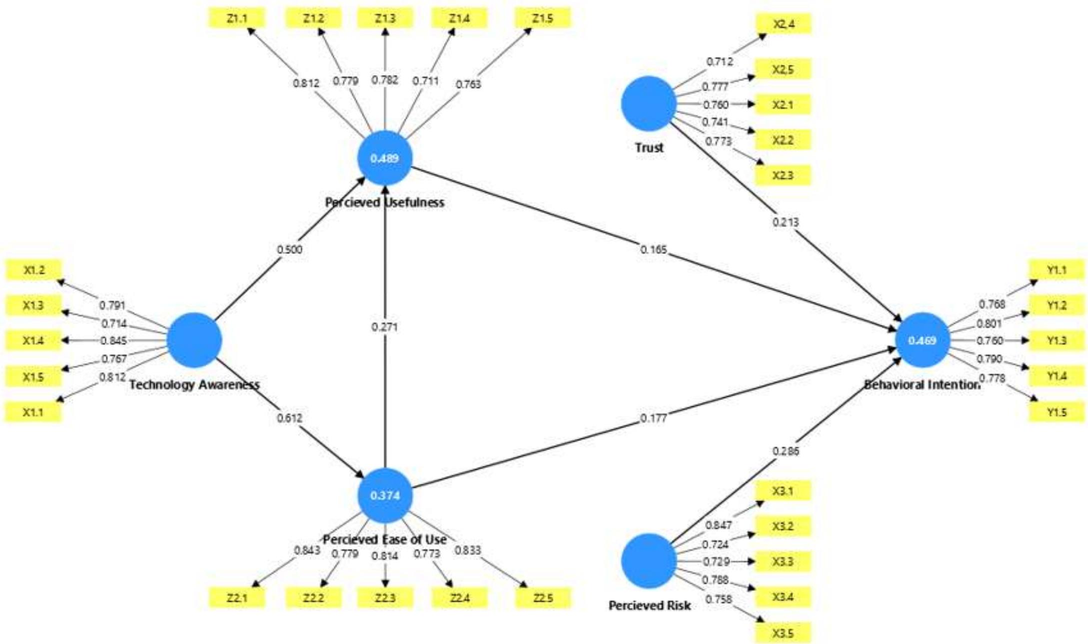

Figure 1

Based on Figure 1, all indicators have *outer loading values* above 0.70, indicating good convergent validity. Furthermore, the results of the validity and reliability tests are presented in the following tables.

Convergent Validity Test (Loading Factor & AVE)

Loading Factor

An indicator is considered valid if it has an *outer loading value* of ≥ 0.70, indicating that the indicator is able to explain at least 50% of the variance of its construct (Hair et al., 2014). However, in exploratory research or the initial stages of scale development, loading values between 0.50–0.69 are still tolerable as long as the AVE and *composite reliability* (CR) values meet the criteria.

Based on the results of data processing using SmartPLS, all indicators in this study have adequate *outer loading values.*

Table 1

	Outer loadings
X1.2 <- Technology Awareness	0.791
X1.3 <- Technology Awareness	0.714
X1.4 <- Technology Awareness	0.845
X1.5 <- Technology Awareness	0.767
X2.4 <- Trust	0.712
X2.5 <- Trust	0.777
X2.1 <- Trust	0.760
X2.2 <- Trust	0.741
X2.3 <- Trust	0.773
X3.1 <- Perceived Risk	0.847
X3.2 <- Perceived Risk	0.724
X3.3 <- Perceived Risk	0.729
X3.4 <- Perceived Risk	0.788
X3.5 <- Perceived Risk	0.758
Y1.1 <- Behavioral Intention	0.768
Y1.2 <- Behavioral Intention	0.801
Y1.3 <- Behavioral Intention	0.760
Y1.4 <- Behavioral Intention	0.790
Y1.5 <- Behavioral Intention	0.778
Z1.1 <- Perceived Usefulness	0.812
Z1.2 <- Perceived Usefulness	0.779
Z1.3 <- Perceived Usefulness	0.782
Z1.4 <- Perceived Usefulness	0.711
Z1.5 <- Perceived Usefulness	0.763
Z2.1 <- Perceived Ease of Use	0.843
Z2.2 <- Perceived Ease of Use	0.779
Z2.3 <- Perceived Ease of Use	0.814
Z2.4 <- Perceived Ease of Use	0.773
Z2.5 <- Perceived Ease of Use	0.833
X1.1 <- Technology Awareness	0.812

Based on Table 1, all indicators have *outer loading values* above 0.70, with the lowest value ranging from 0.711 (Z1.4) to 0.847 (X3.1). This indicates that each indicator statistically adequately explains its construct, so no indicators need to be removed from the measurement model. Therefore, all indicators are deemed convergently valid.

Average variance extracted (AVE)

In addition to *factor loading,* convergent validity is also assessed through the AVE value, which measures the average proportion of variance explained by indicators within a construct. The recommended AVE value is ≥ 0.50, which means the construct is able to explain more than half of the variance of its indicators (Fornell & Larcker, 1981). The results of the AVE test for each construct are presented in Table 4.3.

Table 2

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Perceived Risk	**0.828**	**0.831**	**0.879**	**0.594**
Behavioral Intention	**0.838**	**0.839**	**0.886**	**0.608**
Perceived Ease of Use	**0.868**	**0.869**	**0.904**	**0.654**
Perceived Usefulness	**0.828**	**0.832**	**0.879**	**0.593**
Technology Awareness	**0.845**	**0.850**	**0.890**	**0.619**
Trust	**0.809**	**0.811**	**0.867**	**0.567**

Based on the results in Table 2, it appears that all constructs have AVE scores above the minimum criterion of 0.50; the recorded figures range between 0.567 (for Trust) and 0.654 (for Perceived Ease of Use). This means that the average level of variance explained by each construct for its indicator exceeds 50%. This condition leads to the conclusion that the convergent validity of all research variables is satisfactory.

When viewed from the overall process, the results of this convergent validity test prove that the measurement instrument used has met the standard rules in the PLS-SEM methodology. Both the *outer loading values* are all not less than 0.70 and the AVE values are all above 0.50, both provide empirical evidence that the indicators in question work consistently to measure the contract that is its target. Implications, the measurement model (*outer model*) is considered valid and has met the requirements to move on to the next phase, namely the evaluation of the structural model (*inner model)* and testing the research hypothesis.

Discriminant Validity Test (Fornell-Larcker & Cross Loadings)

Discriminant Validity Test (Fornell-Larcker)

Discriminant validity testing is essentially intended to demonstrate that each construct has a significant difference from other constructs, as seen theoretically and empirically. In this research, discriminant validity verification was carried out using two benchmarks: the Fornell-Larcker criteria and *cross-loadings*.

Table 3

	Behavioral Intention	Perceived Ease of Use	Perceived Risk	Perceived Usefulness	Technology Awareness	Trust
Behavioral Intention	0.779					
Perceived Ease of Use	0.546	0.809				
Perceived Risk	0.586	0.525	0.770			
Perceived Usefulness	0.514	0.577	0.503	0.770		
Technology Awareness	0.558	0.612	0.585	0.665	0.787	
Trust	0.562	0.578	0.582	0.485	0.511	0.753

The results in Table 3 show that all AVE root coefficients located on the diagonal of the matrix have higher values than the correlation coefficients between constructs outside the diagonal. For example, the *Behavioral Intention* (BI) construct recorded an AVE root of 0.779, while its strongest correlation with other constructs occurred with *Perceived Risk* (PR), which was only 0.586. The Fornell-Larcker requirement was declared fulfilled because 0.779 > 0.586. The same thing was also observed for *Perceived Ease of Use* (PEOU) with an AVE root of 0.809, which is still greater than its highest correlation with other constructs, namely with *Technology Awareness* (TA) which was 0.612. This pattern applies consistently to all latent variables. Overall, these findings confirm that the measurement model has met the criteria for good discriminant validity according to the Fornell-Larcker approach.

Cross Loadings

In addition to the Fornell-Larcker criteria, discriminant validity is also evaluated through *cross-loading values.* An indicator is declared to have good discriminant validity if the indicator's *loading value* for its own construct (in bold) is higher than the *cross-loading value* for other constructs. The results of the *cross-loading analysis* are presented in Table 4.5 below.

Table 4

	Behavioral Intention	**Perceived Ease of Use**	**Perceived Risk**	**Perceived Usefulness**	**Technology Awareness**	**Trust**
X1.2	0.458	0.481	0.473	0.543	0.791	0.407
X1.3	0.367	0.484	0.370	0.457	0.714	0.383
X1.4	0.460	0.519	0.529	0.561	0.845	0.450
X1.5	0.457	0.388	0.419	0.496	0.767	0.307
X2.4	0.394	0.453	0.436	0.311	0.371	0.712
X2.5	0.431	0.409	0.439	0.407	0.432	0.777
X2.1	0.413	0.408	0.448	0.312	0.364	0.760
X2.2	0.410	0.418	0.403	0.353	0.317	0.741
X2.3	0.464	0.487	0.464	0.431	0.433	0.773
X3.1	0.469	0.484	0.847	0.408	0.509	0.522
X3.2	0.418	0.368	0.724	0.355	0.431	0.324
X3.3	0.424	0.331	0.729	0.328	0.370	0.400
X3.4	0.488	0.449	0.788	0.457	0.500	0.516
X3.5	0.454	0.381	0.758	0.378	0.433	0.462
Y1.1	0.768	0.446	0.449	0.385	0.421	0.434
Y1.2	0.801	0.409	0.460	0.428	0.441	0.457
Y1.3	0.760	0.447	0.465	0.400	0.497	0.454
Y1.4	0.790	0.412	0.473	0.401	0.429	0.418
Y1.5	0.778	0.415	0.437	0.388	0.383	0.429
Z1.1	0.437	0.489	0.445	0.812	0.549	0.395
Z1.2	0.371	0.449	0.398	0.779	0.578	0.386
Z1.3	0.386	0.432	0.363	0.782	0.501	0.404
Z1.4	0.357	0.384	0.338	0.711	0.421	0.305
Z1.5	0.426	0.457	0.382	0.763	0.499	0.369
Z2.1	0.453	0.843	0.406	0.500	0.542	0.523
Z2.2	0.414	0.779	0.435	0.444	0.473	0.415
Z2.3	0.426	0.814	0.440	0.488	0.506	0.457
Z2.4	0.430	0.773	0.389	0.418	0.493	0.484

	Behavioral Intention	Perceived Ease of Use	Perceived Risk	Perceived Usefulness	Technology Awareness	Trust
Z2.5	0.485	0.833	0.456	0.479	0.458	0.457
X1.1	0.453	0.522	0.495	0.553	0.812	0.449

Based on Table 4, all indicators have the highest *outer loading values* for the constructs they measure. For example:

- Indicator Y1.2 has the highest *loading on the Behavioral Intention construct* (0.801) compared to *the Perceived Ease of Use* (0.409), *Perceived Risk* (0.460), *Perceived Usefulness* (0.428), *Technology Awareness* (0.441), and *Trust* (0.457) constructs.
- Indicator Z2.1 has the highest *loading* on the *Perceived Ease of Use construct* (0.843) compared to the *Behavioral Intention* (0.453), *Perceived Risk* (0.406), *Perceived Usefulness* (0.500), *Technology Awareness* (0.542), and *Trust* (0.523) constructs.
- Indicator X3.1 has the highest *loading* on the *Perceived Risk construct* (0.847) compared to the *Behavioral Intention construct* (0.469), *Perceived Ease of Use* (0.484), *Perceived Usefulness* (0.408), *Technology Awareness* (0.509), and *Trust* (0.522).
- Indicator Z1.1 has the highest *loading on the Perceived Usefulness construct* (0.812) compared to other constructs.
- Indicator X1.4 has the highest *loading* on *the Technology Awareness construct* (0.845) compared to other constructs.
- Indicator X2.3 has the highest *loading* on the *Trust construct* (0.773) compared to other constructs.

The same pattern is also seen across all other indicators, where the *loading value* for each construct is consistently higher than the *cross-loading value* for the other constructs. This indicates that each indicator is better at measuring its own construct than the others.

Overall, based on the criteria *Based on the Fornell-Larcker test and cross-loading* values, it can be concluded that this research instrument has adequate discriminant validity. This indicates that each construct in this study is truly empirically distinct from the other constructs, making this measurement model worthy of proceeding to the structural model evaluation stage (*inner model)*.

Reliability Test (Cronbach's Alpha & Composite Reliability)

Reliability testing aims to measure the level of internal consistency (reliability) of indicators in measuring their constructs. In PLS-SEM, reliability is evaluated using two main criteria: **Cronbach's Alpha** and **Composite Reliability (CR).** The recommended value for both measures is ≥ 0.70, which indicates that the instrument has good reliability (Hair et al., 2014). However, in PLS-SEM, Composite Reliability is more recommended because it tends to provide more accurate estimates than Cronbach's Alpha, especially in exploratory research or the early stages of scale development.

Table 5

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavioral Intention	0.838	0.839	0.886	0.608
Perceived Ease	0.868	0.869	0.904	0.654

of Use				
Perceived Risk	0.828	0.831	0.879	0.594
Perceived Usefulness	0.828	0.832	0.879	0.593
Technology Awareness	0.845	0.850	0.890	0.619
Trust	0.809	0.811	0.867	0.567

Based on Table 5, all research constructs have **Cronbach's Alpha values** above the minimum limit of 0.70, with a range between 0.809 (Trust) and 0.868 (Perceived Ease of Use). This indicates that all constructs have good internal consistency.

Furthermore, **the Composite Reliability (rho_c) values** for all constructs were also above the threshold of 0.70, with a range between 0.867 (Trust) and 0.904 (Perceived Ease of Use). Composite Reliability values higher than Cronbach's Alpha indicate that the instrument has excellent reliability, as Composite Reliability is less sensitive to the number of indicators than Cronbach's Alpha.

Overall, based on these two criteria **Cronbach's Alpha** and **Composite Reliability** it can be concluded that all constructs in this study have good and consistent reliability. Thus, the research instrument is deemed reliable and suitable for use in measuring each construct studied.

Structural Model Evaluation (*Inner Model*) – R-Square

After *the outer model* has passed the validity and reliability tests, the analysis proceeds to assess *the inner model*. This evaluation stage aims to measure the accuracy of the model's predictions regarding the dependent variable. In PLS-SEM, the mainstay indicator for this assessment is the R- *square* (coefficient of determination). In practice, R^2 measures the proportion of variation in endogenous variables that can be attributed to the independent variables. The R^2 score ranges from 0 to 1; the higher the number, the greater the model's explanatory power. Following Chin's (1998) guidelines, a threshold of 0.67 represents a strong category, 0.33 a medium category, and 0.19 a low category. It should be emphasized that in the social sciences, this classification is not rigid and allows for adjustments based on the characteristics of the study in question. The detailed findings from this structural model evaluation are presented in Table 6.

Table 6

	R-square	R-square adjusted
Behavioral Intention	**0.469**	**0.459**
Perceived Ease of Use	**0.374**	**0.371**
Perceived Usefulness	**0.489**	**0.484**

Referring to the data presented in Table 6, it is revealed that *the Behavioral Intention* (BI) construct has an R^2 value of 0.469. This figure reflects that the four antecedent variables *Perceived Ease of Use* (PEOU), *Perceived Usefulness* (PU), *Trust,* and *Perceived Risk* (PR) collectively contribute 46.9% to the total BI variance. The remaining 53.1% is influenced by other elements not included in the model, such as social dynamics, experience track record, and personal attributes of respondents. Using Chin's (1998) benchmark, the 0.469 value is considered moderate, meaning the model is considered quite reliable in predicting the behavioral tendencies of research subjects.

For the *Perceived Usefulness* (PU) variable, the coefficient of determination was 0.489. This result indicates that *Technology Awareness* (TA) and PEOU simultaneously contributed 48.9% to the PU variance, while the remaining 51.1% came from unexamined external factors. This value classification is also in the moderate position, so the model has sufficient accuracy to predict respondents' perceived usefulness.

As for *the Perceived Ease of Use* (PEOU) construct, the R^2 value obtained was 0.374. In this case, the TA variable alone was able to explain 37.4% of the variance in PEOU, and the remaining proportion (62.6%) was determined by other variables outside the model. Although this figure is still grouped into the medium category, the findings confirm that TA plays a significant role. However, there are still other factors that may have a greater influence, such as practical user experience, the quality of interface design, and the availability of technical support facilities.

As a complement to the raw coefficient of determination, this analysis also includes the adjusted R-square value, which *takes* into account the number of predictor variables used. For *the Behavioral Intention construct,* the adjusted R^2 shows a figure of 0.459—almost insignificantly different from the initial R^2 (0.469). This minimal difference suggests that the presence of independent variables does not trigger significant overfitting symptoms. A similar condition also applies to *Perceived Usefulness* (adjusted $R^2 = 0.484$) and *Perceived Ease of Use* (adjusted $R^2 = 0.371$), where changes in value are relatively small. Thus, the overall model structure is considered to have guaranteed stability.

A holistic view reveals that the structural model's predictive capacity for the three endogenous variables is at an intermediate level. This finding suggests that the set of independent variables included is still limited in fully describing the diversity that occurs in both the mediating and the primary dependent variables. Therefore, future research is strongly recommended to expand the model's scope by including other factors strongly suspected of influencing it, in order to improve the model's *predictive power.*

Hypothesis Testing (Bootstrapping)

After a series of confirmations confirming that *the outer model* is valid in terms of validity and reliability, and *the inner model* has adequate predictive power, the next analytical step is to test the research hypothesis. In the context of PLS-SEM, this test was conducted using *bootstrapping techniques* on 5,000 subsamples, following the recommendations of Hair et al. (2014) to obtain a precise estimate of *the standard error. The significance level set was 5% ($\alpha = 0.05$) with a two-tailed test direction.* Statistical decisions were based on the following provisions: the hypothesis is declared proven if the T-statistic value ≥ 1.96, the P-value ≤ 0.05, and the 95% confidence interval does not flank the zero. Conversely, the hypothesis is considered not proven if the T-statistic < 1.96, the P-value > 0.05, or the 95% CI still contains the zero value. The results of this test are summarized in Table 4.8. The results of the hypothesis testing are presented in Table 7 below.

Table 7

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Perceived Ease of Use -> Behavioral Intention	0.177	0.174	0.086	2,053	0.040
Perceived Ease of Use -> Perceived Usefulness	0.271	0.274	0.073	3,701	0.000
Perceived Risk -> Behavioral Intention	0.286	0.289	0.081	3,535	0.000
Perceived Usefulness -> Behavioral Intention	0.165	0.165	0.072	2,287	0.022
Technology Awareness -> Perceived Ease of Use	0.612	0.612	0.054	11,224	0.000
Technology Awareness -> Perceived Usefulness	0.500	0.500	0.070	7,110	0.000
Trust -> Behavioral Intention	0.213	0.218	0.082	2,594	0.010
	Original sample (O)	Sample mean (M)	Bias	2.5%	97.5%
Perceived Ease of Use -> Behavioral Intention	0.177	0.174	-0.003	0.016	0.353
Perceived Ease of Use -> Perceived Usefulness	0.271	0.274	0.003	0.121	0.407
Perceived Risk -> Behavioral Intention	0.286	0.289	0.003	0.123	0.437
Perceived Usefulness -> Behavioral Intention	0.165	0.165	0.000	0.024	0.310
Technology Awareness -> Perceived Ease of Use	0.612	0.612	0.001	0.490	0.706
Technology Awareness -> Perceived Usefulness	0.500	0.500	0.000	0.355	0.630
Trust -> Behavioral Intention	0.213	0.218	0.005	0.043	0.366

Based on Table 7, of the seven proposed path hypotheses, **all hypotheses (H1 to H7) were statistically accepted**. The following is a detailed explanation of each hypothesis:

- **H1: Technology Awareness has a significant effect on Perceived Usefulness** Statistical analysis shows that *Technology Awareness* has a significant positive impact on *Perceived Usefulness*, as indicated by a path coefficient of 0.500. In terms of significance, the T-statistic value of 7.110 (> 1.96) and *P-value of* 0.000 (< 0.05) confirm that this relationship does not occur by chance. Therefore, **H1 is accepted.** This indicates that individuals with higher technological awareness tend to perceive *cryptocurrency* as more functionally useful.
- **H2: Technology Awareness has a significant effect on Perceived Ease of Use** The analysis results show that *Technology Awareness* has a positive and significant effect on *Perceived Ease of Use* with a path coefficient of 0.612, a T-statistic value of 11.224 (> 1.96), and *a P-value of* 0.000 (< 0.05). Thus, **H2 is accepted.** This finding is logical because a strong basic knowledge of how digital technology works can reduce uncertainty and confusion when users first operate a crypto asset platform.

- **H3: Perceived Ease of Use has a significant effect on Perceived Usefulness** The test results show that *Perceived Ease of Use* has a positive and significant effect on Perceived Usefulness *with* a path coefficient of 0.271, T-statistic of 3.701 (> 1.96), and *P-value of* 0.000 (< 0.05). Thus, **H3 is accepted.** This is in line with the basic concept *of the Technology Acceptance Model* (TAM), where an easy-to-operate system will make users freer to feel the benefits or usefulness of the technology.
- **H4: Trust has a significant effect on Behavioral Intention** The results of the analysis show that *Trust* has a positive and significant effect on *Behavioral Intention* with a path coefficient of 0.213, a T-statistic value of 2.594 (> 1.96), and *a P-value of* 0.010 (< 0.05). Therefore, **H4 is accepted.** Considering the decentralized nature *of the cryptocurrency system,* the level of user trust in the security of the exchange and the transparency of the system are important factors that directly drive their intention to invest.
- **H5: Perceived Usefulness has a significant effect on Behavioral Intention.** The analysis results show that *Perceived Usefulness* has a positive path coefficient of 0.165 with a T-statistic value of 2.287 (> 1.96) and *a P-value of* 0.022 (< 0.05). Because it meets the significance threshold requirements, **H5 is declared accepted.** Although significant, the relatively small path coefficient (0.165) provides an interesting finding. This indicates that rational perceptions of the benefits of technology are not the only main driver. Motives for crypto adoption among young users are often driven more strongly by non-technical factors, such as *Fear of Missing Out* (FOMO) or short-term speculation.
- **H6: Perceived Ease of Use has a significant effect on Behavioral Intention** The results of the analysis show that *Perceived Ease of Use* has a positive and significant effect on *Behavioral Intention* with a path coefficient of 0.177, a T-statistic value of 2.053 (> 1.96), and *a P-value of* 0.040 (< 0.05). Thus, **H6 is declared accepted.** Similar to H5, although statistically significant, its influence is not too dominant. For users who are *digital natives,* ease of use is no longer the main barrier, but has become a standard expectation, so the focus of their decisions is more based on risk profiles and potential benefits.
- **H7: Perceived Risk has a significant effect on Behavioral Intention** The results of the analysis show that *Perceived Risk* has a positive and significant effect on *Behavioral Intention* with a path coefficient of 0.286, a T-statistic value of 3.535 (> 1.96), and a *P-value of* 0.000 (< 0.05). Thus, **H7 is declared accepted.** What is interesting and novel *in* this finding is **the direction of the positive relationship,** which means that the higher the perceived risk, the higher the individual's intention to use or invest in *cryptocurrency.* This finding indicates the presence of risk *-seeking behavior* among respondents. The risk of high volatility is not seen as an obstacle, but rather is perceived as a major opportunity to obtain large returns (profits) in a short time.

This study aims to analyze the factors influencing *cryptocurrency adoption* using an extended *Technology Acceptance Model* (TAM) approach. Based on the results of the hypothesis testing conducted in the previous chapter, all seven hypotheses proposed were statistically accepted. However, several findings regarding the direction of the relationships and the strength of the influence differ, requiring critical interpretation.

The Influence of Technology Awareness on Perceived Usefulness (H1)

Research result shows that *Technology Awareness* (TA) has a positive and significant influence on *Perceived Usefulness* (PU) with a path coefficient of 0.500, a T-statistic value of 7.110 (>1.96), and a P-value of 0.000 (<0.05). This finding indicates that the higher an individual's awareness and understanding of *cryptocurrency* and *blockchain technology*, the higher their perception of the usefulness or benefits that can be obtained from these digital assets. This result is in line with research by Irfan et al. (2022) which states that technological awareness is a fundamental prerequisite for individuals to evaluate the benefits of a technology. In the context of *cryptocurrency*, users who have a basic understanding of how *blockchain works, peer-to-peer* transaction mechanisms, and the potential for digital investment tend to be better able to appreciate the functional value of crypto assets, such as transaction efficiency, financial autonomy, and portfolio diversification.

The Influence of Technology Awareness on Perceived Ease of Use (H2)

Analysis results **The results** show that *Technology Awareness* has a positive and significant influence on *Perceived Ease of Use* (PEOU) with a path coefficient of 0.612, a T-statistic of 11.224 (>1.96), and a P-value of 0.000 (<0.05). This finding indicates that understanding *cryptocurrency technology* contributes to the perception that the crypto platform and application are easy to use. This relationship can be explained through the logic that prior knowledge of how the technology works can reduce uncertainty and confusion when first using a crypto application. Users do not need to learn everything from scratch, so the adoption process becomes smoother and more efficient. This finding supports previous research that confirms that ease of use is strongly influenced by the user's level of familiarity with similar technologies (Davis, 1989; Venkatesh & Bala, 2008).

Influence of Perceived Ease of Use on Perceived Usefulness (H3)

The results showed that *Perceived Ease of Use* (PEOU) has a positive and significant influence on *Perceived Usefulness* (PU) with a path coefficient of 0.271, a T-statistic of 3.701 (>1.96), and a P-value of 0.000 (<0.05). This finding confirms the fundamental proposition in TAM (Davis, 1989) that perceived ease of use is an important antecedent of perceived usefulness. This means that when users perceive a *cryptocurrency platform* as easy to operate, they tend to perceive the technology as more useful. Ease of use reduces barriers to adoption and allows users to focus more on the functional value offered. This finding is consistent with research by Lopez (2023) and Kurniawan (2025).

The Influence of Trust on Behavioral Intention (H4)

The analysis results show that *Trust* has a positive and significant influence on *Behavioral Intention* (BI) with a path coefficient of 0.213, a T-statistic value of 2.594 (>1.96), and a P-value of 0.010 (<0.05). This finding indicates that the higher the level of user trust in the security, transparency, and reliability of the *cryptocurrency system,* the higher their intention to adopt. Trust is a crucial factor because this system operates in a decentralized environment. Users need confidence in the security of crypto exchanges and privacy protection. This finding is in line with research by Meyliana, Fernando, and Surjandy (2019) and Wijaya et al. (2024) which proves that trust is an important determinant in *FinTech adoption decisions.*

The Influence of Perceived Usefulness on Behavioral Intention (H5)

The analysis results show that *Perceived Usefulness* (PU) has a positive and significant influence on *Behavioral Intention* (BI) with a path coefficient of 0.165, a T-statistic of 2.287

(>1.96), and a P-value of 0.022 (<0.05). Statistically, this hypothesis is accepted. However, the relatively small path coefficient (0.165) indicates that the influence is relatively weak. Although someone perceives *cryptocurrency* as technically useful, it does not dominantly drive their intention to invest. Several potential explanations for this finding are:

1. Non-Technical Factors: Adoption motives among the younger generation are often driven more by non-technical factors such as FOMO and short-term speculation than purely functional evaluation (Ramadhan & Andajani, 2019).
2. The Specificity of the Cryptocurrency Context: The decision to adopt crypto involves complex financial considerations. Someone may recognize the benefits of *blockchain technology* but remain hesitant to invest due to limited initial capital or regulatory uncertainty.

The Effect of Perceived Ease of Use on Behavioral Intention (H6)

The analysis results show that *Perceived Ease of Use* (PEOU) has a positive influence on *Behavioral Intention* (BI) with a path coefficient of 0.177, a T-statistic of 2.053 (>1.96), and a P-value of 0.040 (<0.05). Statistically, this hypothesis is accepted, but its effect is also relatively weak. Several explanations for this finding are:

1. Digital Literacy and Experience: Younger generations who grew up as *digital natives* have a high level of adaptability to application interfaces. Ease of use is no longer a key differentiator or significant barrier for them.
2. Prioritizing Profit Potential: The primary appeal *of cryptocurrency* to young users lies in the potential for financial gain. They are willing to deal with complex interfaces as long as the returns offered are commensurate.

The Influence of Perceived Risk on Behavioral Intention (H7)

The analysis results show that *Perceived Risk* (PR) has a positive and significant influence on *Behavioral Intention* (BI) with a path coefficient of 0.286, a T-statistic value of 3.535 (>1.96), and a P-value of 0.000 (<0.05). The direction of this relationship is positive, meaning the higher the perceived risk, the higher the intention to use *cryptocurrency.* This empirical finding is very interesting because it contradicts the common theoretical assumption that risk is always a barrier to adoption. Some potential explanations for this finding are:

1. Speculative Motives and Risk-Seeking Behavior: Respondents, predominantly Generation Z and Millennials, tend to have a high-risk tolerance. The risk of extreme price volatility is perceived as a major attraction, promising large *returns* in a short time, rather than a deterrent.
2. The Fear of Missing Out (FOMO) Phenomenon: The pressure of investment trends on social media makes the younger generation put aside rational risk considerations for fear of missing out on profit momentum.
3. Information Paradox: Individuals with high technological awareness recognize the risks involved, but they are confident they can manage them through diversification strategies and portfolio management.

CONCLUSION

Based on the research results and discussions that have been conducted, several main conclusions were drawn. First, Technology Awareness was shown to have a positive and significant influence on Perceived Usefulness and Perceived Ease of Use. This indicates that initial understanding of cryptocurrency technology is an important foundation for forming perceptions of usefulness and ease of use. Second, Perceived Ease of Use was shown to have a positive influence on Perceived Usefulness, which confirms the fundamental proposition in the TAM model. Third, Trust was shown to have a significant positive influence on Behavioral Intention, confirming the importance of trust in the security of crypto systems in driving adoption. Fourth, this study found a risk-seeking behavior phenomenon where Perceived Risk has a positive influence on Behavioral Intention. The high risk inherent in crypto assets is actually perceived by the younger generation as an opportunity to reap large profits, rather than as an obstacle. Fifth, although Perceived Usefulness and Perceived Ease of Use have a positive and significant effect on Behavioral Intention, the strength of the influence is relatively weak. This indicates that in the context of cryptocurrency adoption among the younger generation in Indonesia, psychological and contextual factors (such as speculation, risk, and trust) play a much more dominant role than purely technical utilitarian considerations. Overall, this extended TAM model is proven to have adequate predictive ability, being able to explain 46.9% of the variance in user behavioral intentions.

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