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AN INVESTIGATION OF THE CENTRALIZED EXCHANGE (CEX) APP USING AN EXTENDED TECHNOLOGY ACCEPTANCE MODEL

Bambang Sugiantoro[1,*] and Ade Kurniawan[2]

[1]Department of Informatics
Universitas Islam Negeri Sunan Kalijaga
Jl. Laksda Adisucipto, Yogyakarta 55281, Indonesia
[*]Corresponding author: bambang.sugiantoro@uin-suka.ac.id

[2]Department of Information Networking
Osaka University
1-5 Yamadaoka, Suita, Osaka 565-0871, Japan
k-ade@ist.osaka-u.ac.jp

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Abstract. *The blockchain technology that serves as the foundation for digital currencies like Bitcoin and Ethereum is its most well-known use. These decentralized digital currencies are now widely utilized for various transactions, including commerce, investing, and online payments. The Technology Acceptance Model (TAM) is a well-known and widely used model in the field of information systems that seeks to explain and predict the acceptance of new technologies by individuals. The model proposes that an individual's acceptance of new technology is influenced by two key factors: perceived usefulness and perceived ease of use. However, there are several potential disadvantages to using the TAM to understand and predict user acceptance of technology. This study extends the Technology Acceptance Model (TAM) with eTAM. We added a few variables: Actual Use, Trust, and Risk. We investigate Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Towards Using (ATU), Behavioral Intention to Use (BITU), Actual Use (AU), Trust (T), and Risk (R) using 184 users Centralized EXchange (CEX) application for buying, selling, and saving Bitcoin. The results show that the variables PEOU, PU, ATU, BITU, and T can explain AU, a person's acceptance of using the CEX application. Interestingly, our research found that R is not a factor that affects a person's intention to use a cryptocurrency trading application. This is because from the start someone already understands that transacting cryptocurrency is risky.*

Keywords: Bitcoin, Blockchain, Centralized exchange, Cryptocurrencies, Technology acceptance model

1. **Introduction.** Cryptography is a set of techniques to secure communication and protect data from unauthorized access. It is an essential part of blockchain technology, as it is used to secure the integrity and confidentiality of data stored on the blockchain [1]. In the context of blockchain, cryptography is used to secure communication between nodes on the network and to ensure that data stored on the blockchain cannot be tampered with or altered without detection. Blockchain is a decentralized, digital ledger that records transactions on multiple computers so that the record cannot be altered retroactively without altering all subsequent blocks and the network consensus [2]. This allows for the creation of a secure and transparent record of transactions. There are a few examples of successful applications of blockchain technology: supply chain management, identity verification, healthcare, real estate, and cryptocurrencies [3].

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Cryptocurrencies: The most well-known use case for blockchain is the underlying technology for cryptocurrencies like Bitcoin and Ethereum. These decentralized digital currencies have gained widespread adoption and have been used for a variety of purposes, including online payments [4], trade [5], and investment [6].

As an investment and trading instrument, Bitcoin is highly speculative and volatile. Its price can fluctuate significantly over short periods, and there is no guarantee that we will be able to sell Bitcoin for a profit. Because of these risks [7, 8], it is essential to potential dangers before investing in Bitcoin or any other cryptocurrency [9]. Some people see Bitcoin as a store of value [10, 11], similar to gold because it is limited in supply and has a decentralized network that makes it difficult to counterfeit. However, it is essential to note that Bitcoin has no inherent value, and its price is determined solely by the market. This means its value can fluctuate significantly based on various factors, including public perception, regulatory changes, and investor demand [7].

Users can use a Centralized EXchange (CEX) or Decentralized EXchange (DEX) to buy, trade, and save Bitcoin. A Centralized EXchange (CEX) is a platform that allows users to buy and sell cryptocurrencies using traditional fiat currency, such as dollars or euros, or with other cryptocurrencies [12]. These exchanges typically have a website or App that users can access to buy and sell cryptocurrencies. The exchange acts as a middleman, facilitating the transaction and taking a fee for its services. A Decentralized EXchange (DEX) is a platform that allows users to buy and sell cryptocurrencies without the need for a central authority [12]. Both CEXs and DEXs have their advantages and disadvantages. CEXs are typically more user-friendly and offer a more comprehensive range of cryptocurrencies to trade. Still, they may be subject to more regulatory oversight and require users to provide personal information [13]. DEXs offer more privacy and control over funds but may be less user-friendly and have fewer cryptocurrencies to trade [13].

The Technology Acceptance Model (TAM) [14] is a theoretical model that explains how individuals form their perceptions and attitudes toward technology and how they decide whether or not to adopt it [15]. The Technology Acceptance Model (TAM) is a well-known and widely used model in the field of information systems that seeks to explain and predict the acceptance of new technologies by individuals. The model proposes that an individual's acceptance of new technology is influenced by two key factors: perceived usefulness and perceived ease of use [14]. There have been many success stories of using the TAM in a variety of settings, including the following: Healthcare [16], Agriculture [15], Education [17], Business [18], and Government [19]. Overall, the TAM has been widely used and found to be an effective tool for understanding and predicting the acceptance of new technologies by individuals in various settings.

However, there are several potential disadvantages to using the TAM as a framework for understanding and predicting user acceptance of technology. These include limited scope [20]: TAM is specifically designed to predict user acceptance of information technology and may not apply to other technology or non-technological innovations. Assume rational decision-making [21]: TAM assumes that individuals make decisions about technology adoption based on rational cost-benefit analysis. However, research has shown that emotions and other non-rational factors can also influence adoption decisions. Insufficient attention to context [22]: TAM does not consider the context in which technology is being used, which can significantly affect adoption decisions.

In this study, we extend the TAM [14] model with the name eTAM. The motivation behind extending the Technology Acceptance Model (TAM) with the name eTAM is to improve its applicability in the context of users' perceptions and attitudes towards buying, selling, and investing in cryptocurrencies on Centralized EXchanges (CEXs) such as Binance. The study aims to investigate the factors that influence users to adopt CEX apps, including perceived usefulness, attitude towards using, behavioral intention to use, actual use, trust, and risk. By extending the TAM model with additional variables, namely actual use, trust, and risk, the eTAM model can provide a better understanding of the users' behavior towards adopting CEX apps. The research was conducted in Indonesia from January 2022 to October 2022 using 184 respondents.

In summary, our main contributions of this study are the investigation of the factors influencing users' adoption of CEX apps, the extension of the TAM model to include actual use, trust, and risk, and the development of the eTAM model for understanding user behavior in the context of cryptocurrency exchanges.

The rest of this paper is organized as follows. We discuss the work related to our research in Section 2. In Section 3, we describe the eTAM method. We presented the results and discussed them in Section 4. Finally, we conclude the paper in Section 5.

2. **Related Work.** The use of the TAMs method for acceptance technologies has been proposed, as shown in Table 1.

TABLE 1. The previous work related to our research

Researchers	Domain	Number of variables used	The variable they used	Number of respondents
Davis [14]	Education	2	Perceived Usefulness and Perceived Ease of Use	152
Li et al. [16]	Healthcare	3	Perceived Usefulness, Perceived Ease of Use, and Perceived Intention to Use	113
Al Kurdi et al. [17]	Education	3	Perceived Usefulness, Perceived Ease of Use, and Self-Efficacy	270
Inayatulloh [18]	SME	3	Perceived Usefulness, Perceived Ease of Use, and Attitudes Towards Using	Not mentioned
AL-Zahrani [19]	Government	3	Perceived Usefulness, Perceived Ease of Use, and D&M Model	211
Doanh et al. [15]	Agriculture	3	Perceived Usefulness, Perceived Ease of Use, and Barrier Factors	398
This study	Finance	7	Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Towards Using (ATU), Behavioral Intention to Use (BITU), Actual Use (AU), Trust (T), and Risk (R)	184

Davis proposed a theoretical model to understand how people evaluate and decide to adopt new information technologies, such as computer software or hardware systems. The Technology Acceptance Model (TAM) is based on the idea that people's decisions to use technology are influenced by their perceptions of its usefulness and ease of use. TAM is based on two key factors: perceived usefulness and perceived ease of use [14]. Perceived usefulness refers to the degree to which an individual believes using a particular technology will enhance their job performance or overall quality of life. On the other hand, perceived ease of use refers to the degree to which an individual believes using a particular technology is effortless and convenient. TAM posits that perceived usefulness and ease of use lead to the formation of attitudes towards technology, which influence adoption behavior. It also suggests that external variables, such as the opinions of others and the overall social context, can affect an individual's perceptions of technology and, ultimately, their adoption decision.

Li et al. [16] asked students in Department of Health Care Management who are native speakers of Chinese and were chosen using a purposive sampling method to complete an online healthcare management terminology test to determine their knowledge of healthcare management terminology and an online healthcare management terminology test based on the EZ-HCM App to confirm the students' abilities to use the App for assistance to complete an online healthcare management terminology test. 49 freshmen, 22 sophomores, 13 juniors, 14 seniors, and 15 postgraduate students were recruited to participate in the study to assess the App using a convenience sample method. Introduction to Health Care Delivery Systems may be to blame for this since first-year students are required to complete the course in a semester. If students are required to put in a large amount of work to utilize m-learning, they are more likely to be dissatisfied with the system and hence less likely to use it in the future.

Al Kurdi et al. [17] sought to assess the association between university students' intention to use E-learning and specific attributes like perceived usefulness, perceived ease of use, and self-efficacy. Based on the perceived ease of use, the online delivery system may be preferred by the students, keeping in mind their ability to use the Internet and other electronic communication systems. These students are also interested in individual learning.

[18] found, the problem is that many of the small communities in culinary businesses face various limitations, such as a lack of knowledge and creative ideas in developing their businesses. SMEs are reluctant to use information technology such as smartphones due to several factors, such as limited knowledge and difficulties in using smartphones to support their business. With a knowledge management system, an organization will easily manage its knowledge, bringing success to the company. Adopting the technology acceptance model will make it easier for novice SMEs to use information technology, especially as a supporter or part of a knowledge management system. The resulting model can be used to increase the knowledge of SMEs where the knowledge acquired must go through a process of verification and validation in advance so that the knowledge that will be used according to needs has good quality.

AL-Zahrani's [19] research used DeLone and McLean's (D&M) [23] success model. Additionally, it applied the Technology Acceptance Model (TAM) with cybersecurity considerations; both models were used to determine the level of Information System (IS) success before looking into cybersecurity facets that affect service effectiveness and efficiency in the Kingdom of Saudi Arabia. AL-Zahrani [19] developed a model to examine the IS success model and cybersecurity elements that affect the efficacy and Use of E-Gov services. Two hundred eleven users of E-Gov services were polled. Using structural equation modeling, a quantitative approach was used to arrive at all research findings (SEM). The results showed that the tenets of the (IS) success model are fundamentally influencing users' satisfaction with the E-Gov services and that the fundamental principles of cybersecurity with TAM also appear to have a significant impact on perceived risk, both of which affect the usability and efficacy of the E-Gov services.

To investigate tea farmers' intention to participate in Livestream sales in four Northern midlands and hilly regions of Vietnam, Doanh et al. [15] combined the TAM and barrier variables. They discovered that more excellent perceived utility and simplicity of Use of Livestream sales encourage tea farmers to improve their desire to sell tea goods via the Livestream by using General Structural Equation Modeling (GSEM) and interview data from 398 tea farm families. However, regard the things that operate as barriers, information, knowledge, and experience.

Based on the literature review presented, several shortages and gaps aim to be addressed. The existing literature on technology adoption and acceptance has focused primarily on factors such as perceived usefulness and ease of use. While studies have explored the relationship between these factors and adoption behavior in various contexts, there is still a lack of research on the factors that influence individuals' intention to adopt specific technologies.

Moreover, most studies have examined technology adoption behavior in the context of traditional hardware or software systems and have not explored the adoption of emerging technologies, such as cryptocurrencies. Additionally, while some studies have used the Technology Acceptance Model (TAM) to understand technology adoption behavior, few have examined the role of other important variables such as trust and risk. In this study, we address these gaps in the literature by examining the intention to use a specific Cryptocurrency EXchange (CEX), Binance, in Indonesia.

We extend the TAM model by including trust and risk as additional variables that may influence individuals' adoption intention. By doing so, we provide a more comprehensive understanding of the factors that affect cryptocurrency adoption behavior. Furthermore, our study contributes to the literature by focusing on the adoption of a specific CEX, Binance, which has not been extensively studied in the literature. By examining the adoption of Binance, we provide insights into the unique factors that may affect adoption behavior in the context of this specific CEX. Overall, our study fills important gaps in the literature on technology adoption and acceptance by examining the adoption of a specific emerging technology and by including additional variables such as trust and risk in the TAM model.

3. Method.

3.1. **Type of research.** This type of research is quantitative research using the survey method. One of the advantages of the survey method is that it allows researchers to gather data from a representative sample of the population, which can be used to make inferences about the broader population. However, the accuracy of the results depends on the quality of the survey instrument and the ability of the respondents to report their characteristics or experiences accurately.

The survey method used in this research is explanatory, where primary data is collected with the help of a questionnaire. Explanatory research is conducted by testing, finding, and explaining the causal relationship between two or more variables using hypothesis testing. The initial stage of explanatory research is identifying the relationship between variables based on relevant theories and previous research.

3.2. **Location, time, application, and a sample of research.** The research was conducted in Indonesia from January 2022 to October 2022, with Binance acting as the CEX trading application for buying, selling, and saving Bitcoin. Binance is a cryptocurrency exchange platform founded in 2017 by Changpeng Zhao [24]. It is one of the largest cryptocurrency exchanges [25] by trading volume and is known for its low fees and fast transaction processing.

According to the Indonesian Commodity Futures Trading Supervisory Agency (Bappebti) [26], the number of crypto investors has reached 16.27 million people as of September 2022, far more significant than stock exchange investors, who got 9.54 million. There are 11 CEXs in Indonesia, including Binance, Bitfinex, Paxful, Indodax, HitBTC, Coinbase, CoinSpot, Kraken, OKcoin, Bitcoin Indonesia, and Abra. The number of active users of Binance worldwide is 120 million [27], but we did not officially find the number of users of the Binance application in Indonesia. Therefore, we assume the number of Binance users in Indonesia is 1-2 million active users.

Qualitative research requires a sample. Sampling technique is a way to determine a representative sample of a population so that a sample can be created that truly represents the characteristics or conditions of the population [28]. The sampling technique in this study is non-probability sampling, which is a sampling technique that does not provide equal opportunities or opportunities for all members of the population to become part of the sample. One of the non-probability sampling techniques is purposive sampling. Purposive sampling is a sampling technique that researchers can use when there are specific problems with sampling. In this study, every user of the cryptocurrency trading application cannot be sampled because the criteria needed are users of the Binance application for Bitcoin trading or investment purposes. The sample size used in this study was 184 people, and the determination of the sample size was based on the fact that the number of samples in the study was at least seven to ten times more than the total population [28].

3.3. **Research hypothesis.** We illustrate the framework of this study in Figure 1 and research hypothesis in Table 2.

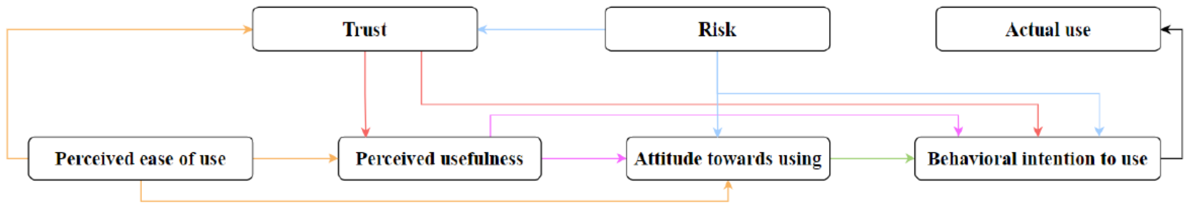

FIGURE 1. Framework of eTAM

TABLE 2. Research hypothesis

Research	Description
H1	PU has a positive influence on ATU.
H2	PU has a positive influence on BITU.
H3	PEOU has a positive effect on ATU.
H4	PEOU has a positive effect on PU.
H5	T has a positive effect on PU.
H6	T has a positive effect on ATU.
H7	T has a positive effect on BITU.
H8	R has a negative effect on ATU.
H9	R has a negative effect on BITU.
H10	R has a negative effect on T.
H11	ATU has a positive effect on BITU.
H12	BITU has a positive effect on AU.

The framework will explain the relationship between variables of factors that influence a person in adopting or using a CEX application. These variables are Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Towards Using (ATU), Behavioral Intention to Use (BITU), Actual Use (AU), Trust (T), and Risk (R).

The framework of the study suggests that the adoption and usage of CEX applications are influenced by several factors, including perceived ease of use, perceived usefulness, attitude towards using, behavioral intention to use, actual use, trust, and risk. The study aims to investigate the relationships between these factors and how they affect the adoption and usage of CEX applications. Perceived ease of use refers to the user's perception of how easy it is to use the CEX application. Perceived usefulness, on the other hand, refers to the user's perception of the usefulness of the application in meeting their needs or solving their problems. These two factors are expected to have a positive effect on attitude towards using and behavioral intention to use the application. Trust refers to the user's perception of the reliability, credibility, and security of the application and the information it provides. Trust is expected to have a positive effect on perceived usefulness, attitude towards using, and behavioral intention to use the application. Conversely, risk refers to the potential negative consequences associated with using the application. Risk is expected to have a negative effect on attitude towards using, behavioral intention to use, and trust. Attitude towards using refers to the user's overall evaluation of the CEX application and their likelihood of using it. Behavioral intention to use refers to the user's intention to use the application in the future. These two factors are expected to have a positive effect on actual use, which refers to the user's actual usage of the application. Overall, the study aims to provide a better understanding of the factors that influence the adoption and usage of CEX applications and how these factors interact with each other. The results of the study could have implications for the design and development of CEX applications and could help organizations increase user adoption and usage, ultimately leading to increased customer satisfaction and loyalty.

3.4. **Property of extended Technology Acceptance Model (eTAM).**

3.4.1. *Perceived ease of use.* Perceived ease of use is the degree to which a person believes technology does not require more effort [29]. [14] explains two user beliefs that can affect other variables: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Then these two variables can influence user attitudes and intention. Simultaneously user attitudes and intention will affect the actual use of the system. According to [17], there are several indicators related to user convenience, namely an easy operating system, easy to use, easy to remember, easy to understand, there are user instructions, and easy to access. Indicators in the perspective of convenience, namely, getting convenience and flexibility in using technology and convenience, are also related to achieving goals [15, 16, 17]. Thus, perceived ease of use is a cryptocurrency trading or investment application that is easy to use, flexible, and can fulfill user goals.

3.4.2. *Attitude towards using.* Attitude towards using is a form of acceptance or rejection of technology [15]. Attitude is a factor that can influence behavior, cognitive/perspective, affective and other components related to one's behavior [17, 18]. [29, 30] describe indicators of user attitude, namely whether or not a technology is good to use. Attitude indicators are also related to enjoying the use of technology as a whole [15]. Thus, the indicators of attitude in using technology in this study are whether or not the trading application is suitable, user satisfaction, and enjoying using the cryptocurrency trading or investment application.

3.4.3. *Behavioral intention to use.* Behavioral intention to use is a measure of attentiveness shown by users after using or trying a technology, for example, adding supporting tools, being motivated to keep using, and wanting to motivate other users to use [31]. Behavioral intention to use is a person's motivation to use a technology [14]. There are several indicators used to measure behavioral intention to use variables, namely the intention to use and continue to use and take advantage of opportunities to use [29, 32, 33, 34]. Behavioral intention to use in this study relates to a person's intention to use a cryptocurrency trading or investment application.

3.4.4. *Actual use.* Actual use is related to the actual use of technology by someone. Actual use is measured by the frequency and time spent using a technology [18]. Technology not only attracts new users but maintaining old users is also essential. Someone will continue using technology if they trust it based on their experience [19]. There is a strong relationship between satisfaction and loyalty, so someone tends to continue using technology if they are satisfied with it [17, 18, 20]. In this study, a person is likely to use and will continue to use a cryptocurrency trading or investment application if they feel the convenience and benefits, as well as other variables that are considered influential such as attitude, intention, perceived risk, and trust.

3.4.5. *Trust.* Trust is a condition that a person feels for behavior in economic transactions. Someone tends to want to know what, when, why, and how someone behaves in economic transactions. Trust can influence a person buying, selling, and storing Bitcoin at CEX [10]. Someone tends to put trust based on the reputation owned by an online vendor [5]. Trust is related to the willingness to take risks based on confidence, integrity, competence, and expectations of cryptocurrency transactions [3]. Trust is also related to the uncertainty perceived in the future and based on the freedom that others can do. When a person acts in an uncertain situation, trust plays a role in overcoming the possible risks that can be obtained. Trust is necessary to deal with uncontrollable future uncertainty [8]. Trust is also related to a sense of security and privacy in cryptocurrency transactions [12]. In this study, trust plays an essential role in a person's decision to use a cryptocurrency trading or investment application.

3.4.6. *Risk.* Risk is a person's belief about the potential negative consequences obtained from the decisions taken [8]. [35] defines risk as the uncertain consequences of using a product or service. The level of risk and how a person tolerates the risk itself can be a factor that can influence a person's behavior toward adopting a technology. In the past, the risk was synonymous with fraud and product quality that did not meet expectations [36]. As time progresses, the risk is more focused on certain things such as product performance, physical, financial, social, psychological, and time when someone transacts online [13]. The risk in cryptocurrency transactions is about volatility; cryptocurrency tends to change in value at any time due to the lack of legal regulations on cryptocurrency [12]. The value of cryptocurrency is very volatile, namely the symptoms of rising and falling prices due to demand and supply [11]. Measurement of the level of risk in this study is related to the possibility of risk that can be obtained by a person when transacting with a cryptocurrency trading or investment application.

3.5. **Data collection techniques and research instruments.** Data collection aims to obtain data used to answer research problems through research hypotheses. Data collection instruments must be adapted to research problems to produce accurate data. The data collection instrument used in this study was a questionnaire. The questionnaire is in the form of questions or statements given to people who the sample of a study are. The questionnaire or survey for this study was compiled into a web form using the Google Forms tool.

The measurement scale used in this study is the Likert scale [37], as shown in Table 3. The Likert scale can measure the attitudes, perceptions, or opinions of a person or group about social phenomena. With the help of the Likert scale, respondents more easily understand the questionnaire questions and answer them quickly and according to their ideas. The measurement scale used is a 1-5 scale.

TABLE 3. Likert scale 1-5

Scale	Description
1	Strongly Disagree (SD)
2	Disagree (D)
3	Undecided (U)
4	Agree (A)
5	Strongly Agree (SA)

The instrument in this study is used to measure the level of user acceptance of the adoption of cryptocurrency trading or investment applications using the Technology Acceptance Model (TAM) theoretical framework, which has seven variables, namely Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Towards Using (ATU), Behavioral Intention to Use (BITU), Actual Use (AU), Trust (T), and Risk (R), as shown in Table 4.

3.6. **Data analysis technique.** Data collection in this study was carried out using an instrument in the form of a questionnaire presented in the form of an online form using Google Forms. Data is shared online via a link to facilitate the data collection process. The data that has been collected is then analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method [38]. SEM analysis with the Partial Least Square (PLS) method can be used on small samples. PLS does not require data requirements to be normally distributed [39].

The Partial Least Squares (PLS) method determines the complexity of the relationship between variables and other variables and the relationship between variables and their indicators. By looking at the purpose of the Partial Least Square (PLS) method, this method consists of two equations: the inner model, also known as the structural model, and the outer model or measurement model. In this study, PLS-SEM analysis was performed using SmartPLS software. The data processing steps are as follows.

3.6.1. *Measurement model (outer model).* The measurement model defines the relationship between indicators and underlying variables [38]. Model measurement is carried out to determine the validity and reliability of the measuring instrument used. The steps of model measurement are convergent validity, discriminant validity, composite reliability, and structural model.

Convergent validity is used to see the correlation value between the score generated by the variable or construct and the score generated by its indicator. The convergent validity value can be seen in the factor loading value and the Average Variance Extracted (AVE) value [38]. The measurement will be considered valid if it gets an outer loading value greater than 0.70 (> 0.70) and an Average Variance Extracted (AVE) value greater than 0.50 (> 0.50) [38].

Discriminant validity measures whether items or indicators correctly measure the underlying latent variable. The principle is that each item or indicator must be highly correlated with the underlying latent variable. We measure discriminant validity by looking at the cross-loadings and Forrnell-Larcker criterion values. The value of cross-loadings on each variable is evaluated to ensure that the variable correlation is more significant with its indicator than the variable correlation with other variables. Meanwhile, the Forrnell-Larcker criterion compares the square root value of each variable's Average Variance Extracted (AVE) with the correlation between other variables. The measurement model has a good discriminant validity value if the square root value of the AVE of each variable is greater than the correlation value between variables and other variables [38].

Table 4. Research instruments

Variable	Symbol	Indicator
Perceived Ease of Use	PEOU 1	I find it easy to use this App to buy, sell, and save Bitcoin on CEX.
	PEOU 2	Using this App can achieve my goal of buying, selling, and storing Bitcoin on CEX.
	PEOU 3	Overall, I found the App easy to understand on CEX.
Perceived Usefulness	PU 1	This App can improve my performance in buying, selling, and storing Bitcoin on CEX.
	PU 2	I find this App makes it easy to buy, sell, and store Bitcoin on CEX.
	PU 3	Overall, this App is helpful for me in transacting, buying, selling, and storing Bitcoins on CEX.
Attitude Towards Using	ATU 1	I find this App good to use for buying, selling, and storing Bitcoin on CEX.
	ATU 2	I feel satisfied using this App to buy, sell, and store Bitcoin on CEX.
	ATU 3	Overall, I enjoyed using this App to transact buying, selling, and storing Bitcoin on CEX.
Behavioral Intention to Use	BITU 1	I intend to use this App to transact buying, selling, and storing Bitcoin on CEX.
	BITU 2	I intend to continue using this App to transact buying, selling, and storing Bitcoin on CEX.
	BITU 3	If there is an opportunity, I intend to use this application to transact buying, selling, and storing Bitcoin on CEX.
Actual Use	AU 1	I often use this App to buy, sell, and store Bitcoin on CEX.
	AU 2	I used this App to transact buying, selling, and storing Bitcoin over the past week on CEX.
	AU 3	I have used this App to buy, sell, and store Bitcoin for the past month on CEX.
Trust	T 1	I feel this App is safe to use for buying, selling, and storing Bitcoin on CEX.
	T 2	I feel like this App has thought of the best way for me to buy, sell, and store Bitcoin on CEX.
	T 3	The App considers my current and future interests in buying, selling, and storing Bitcoin on CEX.
Risk	R 1	I feel unsafe using this App to transact cryptocurrency, buying, selling, and storing Bitcoin on CEX.
	R 2	I was worried about fraud and hacker infiltration when using this App to transact buying, selling, and storing Bitcoin on CEX.
	R 3	Buying, selling, and storing Bitcoin with this App is more financially risky.

Measuring variable reliability is used to determine an instrument's accuracy, consistency, and precision in measuring latent variables. Measuring variable reliability can be done by looking at composite reliability and Cronbach's alpha. A variable is reliable if the composite reliability and Cronbach's alpha values are more significant than 0.70 [38].

The structural model also called the inner model, is used to see the correlation between latent variables in research. The stages of testing the structural model are R-square, predictive relevance, path coefficient, and T-test.

R-square measurement shows the correlation or relationship between exogenous and endogenous latent variables. This is done to determine whether the variables under study affect each other. Predictive power can be seen through the results of the R-square measurement. R-square measurement has three criteria, namely, the value of 0.67 means vital, 0.33 is moderate, and 0.19 is weak [38].

Q-square (Q2) measurement or cross-validated redundancy is used to see the goodness of the observation value. Q2 value > 0 indicates that the model has real observation power on a variable, while Q2 value < 0 indicates that the model has less predictive relevance power.

The path coefficient (β) is measured to determine the significance and strength of the relationship between these variables. The path coefficient (β) is defined from $+1$ to -1. The closer the value is to $+1$, the stronger the relationship between variables. Conversely, if the value is close to -1, it indicates a weak relationship between variables [40].

Hypothesis testing is to see the t-statistic value for each path or relationship that describes hypothesis testing. Testing is done by comparing the t-statistic value with the t-table value. A confidence level of 95% and an accuracy level $(\alpha) = 0.05$ (5%) has a t-table value of 1.96. The hypothesis is rejected if the t-statistic value is smaller than the t-table value (t-statistic < 1.96). Otherwise, the hypothesis is accepted if the t-statistic value is greater than the t-table value (t-statistic > 1.96).

3.7. **Profile of respondents.** The research was conducted on all Binance CEX application users in Indonesia. Testing was conducted on a sample of 184 respondents. We display the respondent profile, such as gender in Table 5, age in Table 6, educational strata in Table 7, occupation in Table 8, and income in Table 9.

Demographics of respondents based on age category, most users of the Binance CEX application are in the age range of 19-25 years, as many as 140 people, then followed by the age range 26-35 years, as many as 37 people.

Table 5. Respondent data based on gender

Gender	Frequency	Percentage
Male	106	57.6%
Female	78	42.4%

Table 6. Respondent data based on age

Age	Frequency	Percentage
< 18	3	1.6%
19-25	140	76.1%
26-35	37	20.1%
36-45	3	1.6%
46-55	1	0.5%
> 56	0	0%

Table 7. Respondent data based on education

Education	Frequency	Percentage
High school	55	29.9%
Diploma 1 (D1) associate degree	3	1.6%
Diploma 2 (D2) associate degree	0	0%
Diploma 3 (D3) associate degree	26	14.1%
Bachelor's degree	91	49.5%
Master's degree	8	4.3%
Doctoral degree	1	0.5%

Table 8. Respondent data based on occupation

Occupation	Frequency	Percentage
Students	81	44%
Civil servants	7	3.8%
Private sector employee	50	27.2%
Self-employment	24	13%
Others	22	12%

Table 9. Respondent data based on income

Income	Frequency	Percentage
$<$ Rp. 1,000,000	115	62.5%
Rp. 1,000,001-Rp. 4,000,000	48	26%
Rp. 4,000,001-Rp. 7,000,000	17	9.2%
$>$ Rp. 7,000,000	4	2.2%

The currency used in buying and selling transactions at CEX is the Rupiah (IDR), where the ratio of 1$ USA = Rp. 14,851 at the time of this research.

4. **Result and Discussion.** This section describes the results and discussion of the test results and analyzes user acceptance of adopting the CEX application using eTAM.

4.1. **Evaluation of measurement models.** The Structure Equation Modeling (SEM) data analysis technique uses the Partial Least Square (PLS) method to determine the complexity of the relationship between variables and other variables and the complexity of the relationship between variables and their indicators. The Partial Least Square (PLS) method consists of two equations: the inner model, also known as the structural model, and the outer model, also known as the measurement model [38]. In this study, SEM-PLS analysis was conducted on 184 respondents who used cryptocurrency trading applications using SmartPLS software. An overview of the measurement model evaluation results can be seen in Figure 2.

4.1.1. *Measurement model results (outer model).* The measurement model or outer model is carried out to determine the validity and reliability of the measuring instrument used. The outer model measurement stages are convergent validity, discriminant validity, and composite reliability.

Convergent validity can be seen in the loading factor value and the Average Variance Extracted (AVE) value. The measurement will be considered valid if the outer loading value is more significant than 0.7 ($>$ 0.7) and the Average Variance Extracted (AVE) value is more significant than 0.5 (> 0.5) [38]. The outer loading results can be seen in Table 10.

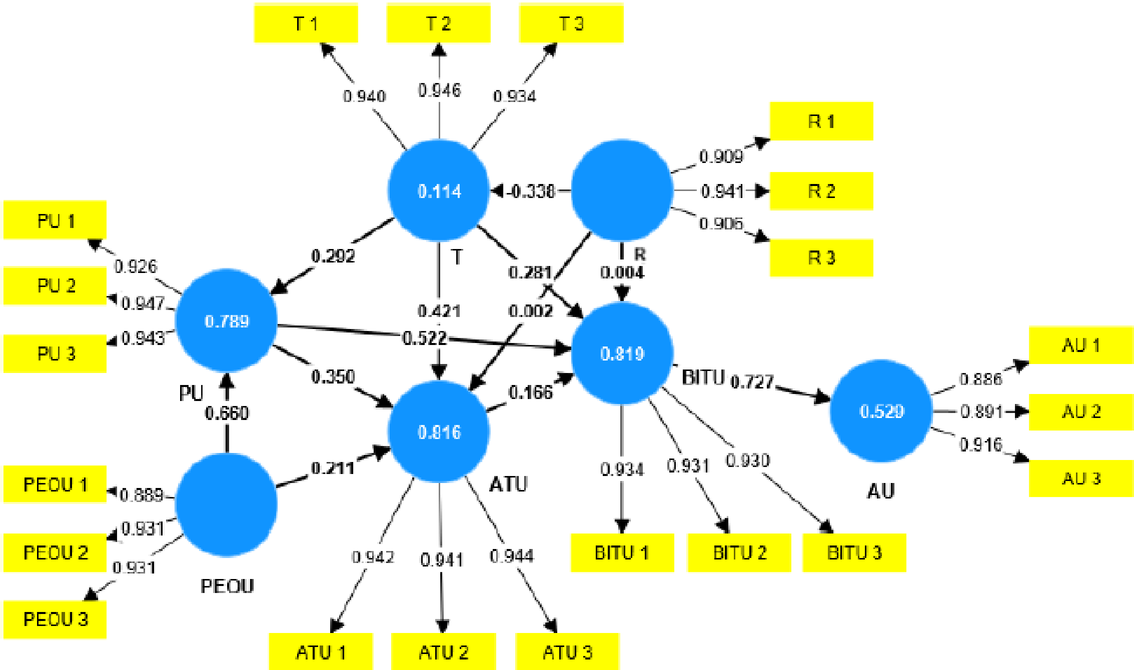

FIGURE 2. Measurement model evaluation results

TABLE 10. Variable loading results

Variables	Outer loadings
ATU 1 ← ATU	0.942
ATU 2 ← ATU	0.941
ATU 3 ← ATU	0.944
AU 1 ← AU	0.886
AU 2 ← AU	0.891
AU 3 ← AU	0.916
BITU 1 ← BITU	0.934
BITU 2 ← BITU	0.931
BITU 3 ← BITU	0.93
PEOU 1 ← PEOU	0.889
PEOU 2 ← PEOU	0.931
PEOU 3 ← PEOU	0.931
PU 1 ← PU	0.926
PU 2 ← PU	0.947
PU 3 ← PU	0.943
R 1 ← R	0.909
R 2 ← R	0.941
R 3 ← R	0.906
T 1 ← T	0.94
T 2 ← T	0.946
T 3 ← T	0.934

From the measurement results in Table 10, it is obtained that the outer loading value on all indicators is above the minimum limit of more than 0.70 (> 0.70). With these results, eating all existing indicators, namely 21 indicators, is declared valid. Furthermore, to see the validity of the indicator through the Average Variance Extracted (AVE) value, the AVE value can be seen in Table 11.

Table 11. Result of Average Variance Extracted (AVE)

Variables	AVE
ATU	0.888
AU	0.806
BITU	0.868
PEOU	0.841
PU	0.881
R	0.844
T	0.883

From the measurement results contained in Table 11, it is obtained that the AVE value of all variables has a value above the minimum limit of more than 0.50 (> 0.50). With these results, all existing variables, namely the variables of Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude Towards Use (ATU), and Behavioral Intention to Use (BITU). Researchers also included other variables, namely Actual Use (AU), Trust (T), and Risk (R), which were declared valid.

Based on the results of the measurement of convergent validity that has been carried out, the results obtained from the extreme loadings value and the AVE value describe the validity of the underlying indicators and latent variables so that the indicators used in the variables in this study are considered valid and suitable for further measurement.

We are measuring discriminant validity by looking at the cross-loadings and Forrnell-Larcker criterion values. The cross-loading value on each variable is used to ensure that the variable correlation is more significant with the indicator than the correlation of the indicator with other variables. The cross-loading value can be seen in Table 12.

From the measurement results contained in Table 12, it is found that all cross-loading values for each indicator have a higher correlation value with their variables than the correlation value of indicators with other variables. With these results, in measuring cross-loadings, all indicators in this study are said to be valid. Furthermore, the Forrnell-Larcker criterion measurement compares the square root value of the AVE of each variable with the correlation between other variables. The results of the Forrnell-Larcker criterion measurement can be seen in Table 13.

From the measurement results contained in Table 13, each variable has a higher correlation value with itself than its correlation value with other variables. From the Forrnell-Larcker criterion measurement results, the indicators used in the variables in this study are considered valid.

Measuring variable reliability is used to determine an instrument's accuracy, consistency, and precision in measuring latent variables. Variable reliability can be measured using composite reliability and Cronbach's alpha. A variable is reliable if the composite reliability and Cronbach's alpha values are more significant than 0.70 [38]. The value of Cronbach's alpha and composite reliability can be seen in Table 14.

From the measurement results in Table 14, Cronbach's alpha and composite reliability values on all variables meet the minimum value limit, which is above 0.70, so the indicators used in this study are reliable.

Table 12. Cross-loadings value

Indicators	ATU	AU	BITU	PEOU	PU	R	T
ATU 1	0.942	0.683	0.819	0.793	0.823	−0.369	0.8
ATU 2	0.941	0.672	0.79	0.747	0.798	−0.33	0.765
ATU 3	0.944	0.716	0.763	0.735	0.776	−0.345	0.782
AU 1	0.725	0.886	0.728	0.613	0.667	−0.239	0.715
AU 2	0.587	0.891	0.585	0.401	0.514	−0.096	0.63
AU 3	0.643	0.916	0.628	0.512	0.603	−0.126	0.711
BITU 1	0.808	0.712	0.934	0.755	0.823	−0.317	0.784
BITU 2	0.748	0.67	0.931	0.705	0.795	−0.357	0.713
BITU 3	0.789	0.649	0.93	0.776	0.817	−0.329	0.762
PEOU 1	0.73	0.475	0.726	0.889	0.785	−0.417	0.612
PEOU 2	0.738	0.522	0.736	0.931	0.783	−0.371	0.651
PEOU 3	0.748	0.584	0.738	0.931	0.806	−0.389	0.651
PU 1	0.803	0.657	0.799	0.807	0.926	−0.403	0.715
PU 2	0.783	0.588	0.826	0.807	0.947	−0.383	0.684
PU 3	0.802	0.636	0.828	0.815	0.943	−0.33	0.716
R 1	−0.354	−0.159	−0.322	−0.422	−0.402	0.909	−0.325
R 2	−0.342	−0.175	−0.347	−0.4	−0.387	0.941	−0.304
R 3	−0.32	−0.156	−0.319	−0.355	−0.299	0.906	−0.302
T 1	0.79	0.718	0.736	0.661	0.72	−0.31	0.940
T 2	0.778	0.745	0.761	0.622	0.691	−0.347	0.946
T 3	0.774	0.698	0.783	0.679	0.708	−0.296	0.934

Table 13. Fornell-Larcker criterion measurement results

Variables	ATU	AU	BITU	PEOU	PU	R	T
ATU	0.942						
AU	0.732	0.898					
BITU	0.84	0.727	0.932				
PEOU	**0.806**	**0.576**	**0.8**	**0.917**			
PU	0.848	0.668	0.872	0.863	0.939		
R	**−0.369**	**−0.178**	**−0.358**	**−0.428**	**−0.396**	**0.919**	
T	0.831	0.767	0.809	0.696	0.751	−0.338	0.940

Table 14. Value of Cronbach's alpha and composite reliability

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
ATU	0.937	0.938	0.960
AU	0.881	0.890	0.926
BITU	0.924	0.925	0.952
PEOU	0.905	0.905	0.941
PU	0.932	0.932	0.957
R	0.907	0.909	0.942
T	0.934	0.934	0.958

4.1.2. *Structural model results (inner model).* The structural model, also called the inner model, is a measurement model used to see the correlation between latent variables or hypothesis testing in research. The stages of testing the structural model are R-square, predictive relevance, path coefficient, and T-test. An overview of the hypothesis test results can be seen in Figure 3.

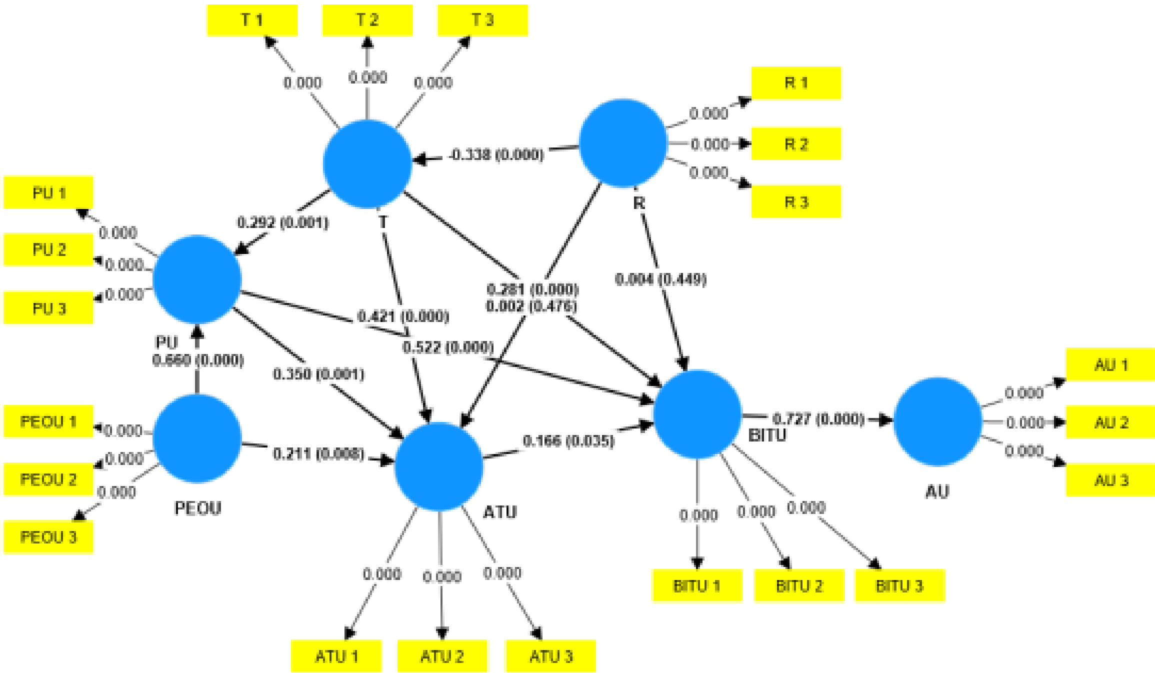

FIGURE 3. Hypothesis test results

The R-square measurement or the coefficient of determination is carried out to see if the exogenous variables can explain the endogenous variables. The expected coefficient of determination (R2) value is between 0 and 1 [38]. [15, 17] divide the R2 value into 3, namely 0.75 (Strong), 0.50 (Moderate), and 0.25 (Weak).

The measurement results of the coefficient of determination (R2) show that the variables ATU (0.816), BITU (0.819), PU (0.789), and T (0.114) have a value (R2) in the strong category, while the AU variable (0.529) is in the moderate category according to [41], as shown in Table 15.

TABLE 15. Measurement results of the determinant coefficient (R2)

Variables	R-square
ATU	0.816
AU	0.529
BITU	0.819
PU	0.789
T	0.114

Q-square (Q2) or cross-validated redundancy measurement is a measurement to see the ability of good observation of a variable. The value of Q2 > 0 indicates that the model has real predictive relevance to a variable, while Q2 < 0 indicates that the model has less predictive relevance. The results of the predictive relevance (Q2) measurement can be seen in Table 16.

Table 16. Predictive relevance measurement results (Q2)

Variables	Q2 predict
ATU	0.535
AU	0.245
BITU	0.518
PU	0.708
T	0.093

From the measurement results contained in Table 16, the predictive relevance (Q2) value on all variables has a value of more than 0 (Q2 > 0), which indicates that the model has real predictive relevance to a variable.

The path coefficient (β) is measured to determine the significance and strength of the relationship between these variables. The path coefficient (β) is defined from $+1$ to -1. The closer the value is to $+1$, the stronger the relationship between variables. Conversely, if the value is close to -1, it shows a weak relationship between variables [41]. The results of measuring path coefficients (β) can be seen in Table 17.

Table 17. Measurement results of path coefficients (β)

Variable correlation	Path coefficients
ATU $\rightarrow$ BITU	0.166
BITU $\rightarrow$ AU	0.727
PEOU $\rightarrow$ ATU	0.211
PEOU $\rightarrow$ PU	0.66
PU $\rightarrow$ ATU	0.35
PU $\rightarrow$ BITU	0.522
R $\rightarrow$ ATU	0.002
R $\rightarrow$ BITU	0.004
R $\rightarrow$ T	-0.338
T $\rightarrow$ ATU	0.421
T $\rightarrow$ BITU	0.281
T $\rightarrow$ PU	0.292

From the measurement results in Table 17, the path coefficients (β) value on all variables positively correlates with other variables. The R variable, which correlates with T, has a negative correlation.

Hypothesis testing is to see the t-statistic value for each path or relationship that describes hypothesis testing. Testing is done by comparing the t-statistic value with the t-table value. A confidence level of 95% and an accuracy level (α) = 0.05 (5%) has a t-table value of 1.96. The hypothesis is rejected if the t-statistic value is smaller than the t-table value (t-statistic < 1.96). Otherwise, the hypothesis is accepted if the t-statistic value is greater than the t-table value (t-statistic > 1.96). The results of the hypothesis measurement can be seen in Table 18.

4.2. **Discussion of measurement model evaluation results.**

4.2.1. *Discussion of the measurement model (outer model) results.* Measurement model testing is done to see the relationship built by indicators with the underlying latent variables. The measurement model can be used as a measurement model in research if it is considered valid and reliable. Validity is known using two stages of testing, convergent

TABLE 18. Hypothesis measurement results

Hypothesis	T-statistics (|O/STDEV|)	P values	Description
ATU → BITU	1.809	0.07	Rejected
BITU → AU	15.591	0	Accepted
PEOU → ATU	2.39	0.017	Accepted
PEOU → PU	7.546	0	Accepted
PU → ATU	3.273	0.001	Accepted
PU → BITU	7.935	0	Accepted
R → ATU	0.06	0.952	Rejected
R → BITU	0.129	0.897	Rejected
R → T	4.222	0	Accepted
T → ATU	3.757	0	Accepted
T → BITU	3.441	0.001	Accepted
T → PU	3.242	0.001	Accepted

validity and discriminant validity while determining reliability using composite reliability testing. Convergent validity determines the relationship between indicators and the underlying latent variable. The convergent validity test results in an external loadings value greater than 0.7 and an AVE value greater than 0.50. Then test discriminant validity by looking at the value of cross-loadings and the Forrnell-Larcker criterion. The result is that all cross-loadings values on each indicator have a higher correlation value to the variable than the correlation value of the indicator to other variables. In contrast, the Forrnell-Larcker Criterion value of each variable has a higher correlation value with the variable itself than the correlation value with other variables. The test results, namely convergent and discriminant validity, show that all variables in this study are valid.

While in composite reliability testing, it can be seen through the composite reliability value and Cronbach's alpha. Variables are reliable if the composite reliability and Cronbach's alpha values are above 0.70. Based on the test results, the composite reliability and Cronbach's alpha values are more significant than 0.70. Based on the validity and reliability tests carried out, the variables and indicators in this study are considered valid and reliable, so they are considered reasonable, and testing can be continued at the next stage, namely structural model testing.

4.2.2. *Discussion of the structural model (inner model) results.* The structural model, also called the inner model, is a measurement model used to see the correlation between latent variables in research. The stages of testing the structural model in this study are R-square, predictive relevance, path coefficient, and T-test testing. This study's relationship between latent variables is explained as a research hypothesis. The hypothesis in this study is designed based on research objectives, namely, to determine the level of acceptance of a person to buy, sell and invest in Bitcoin in the CEX application.

H1: PU has a positive influence on ATU.

From the results of hypothesis testing that has been carried out, the PU → ATU variable has a positive and significant effect because it has a path coefficient (β) value of 0.35 (more than 0.1), a t-statistics value of 3.273 (more than 1.96). This can be interpreted that the higher the benefits a person feels in using a cryptocurrency trading or investment application, the person will have a good attitude toward the application. Then the hypothesis is accepted.

H2: PU has a positive influence on BITU.

From the results of hypothesis testing that has been carried out, the PU $\rightarrow$ BITU variable has a positive and significant effect because it has a path coefficient (β) value of 0.522 (more than 0.1), a t-statistics value of 7.935 (more than 1.96). This can be interpreted that the higher the benefits a person feels in using a cryptocurrency trading or investment application, the more likely they will use it. Then the hypothesis is accepted.

H3: PEOU has a positive effect on ATU.

From the results of hypothesis testing that has been carried out, the PEOU $\rightarrow$ ATU variable has a positive and significant effect because it has a path coefficient (β) value of 0.211 (more than 0.1), a t-statistics value of 2.39 (more than 1.96). This can be interpreted that the easier it is for someone to use a cryptocurrency trading or investment application, the person will have a good attitude toward the application. Then the hypothesis is accepted.

H4: PEOU has a positive effect on PU.

From the results of hypothesis testing that has been carried out, the PEOU $\rightarrow$ PU variable has a positive and significant effect because it has a path coefficient (β) value of 0.66 (more than 0.1) and a t-statistics value of 7.546 (more than 1.96). This can be interpreted that the easier it is for someone to use a cryptocurrency trading or investment application, the person will feel a great benefit from the application. Then the hypothesis is accepted.

H5: T has a positive effect on PU.

From the results of hypothesis testing that has been carried out, the T $\rightarrow$ PU variable has a positive and significant effect because it has a path coefficient (β) value of 0.292 (more than 0.1) and a t-statistics value of 3.242 (more than 1.96). This can be interpreted that the more someone trusts the cryptocurrency trading or investment application, the more that person will feel the benefits of the application. Then the hypothesis is accepted.

H6: T has a positive effect on ATU.

From the results of hypothesis testing that has been carried out, the T $\rightarrow$ ATU variable has a positive and significant effect because it has a path coefficient (β) value of 0.421 (more than 0.1), a t-statistics value of 3.757 (more than 1.96). This can be interpreted that the more someone trusts a cryptocurrency trading or investment application, the person will have a good attitude toward the application. Then the hypothesis is accepted.

H7: T has a positive effect on BITU.

From the results of hypothesis testing that has been carried out, the T $\rightarrow$ BITU variable has a positive and significant effect because it has a path coefficient (β) value of 0.281 (more than 0.1), a t-statistics value of 3.441 (more than 1.96). This can be interpreted that the more a person trusts a cryptocurrency trading or investment application, the more likely they will use it. Therefore, the hypothesis is accepted.

H8: R has a negative effect on ATU.

From the results of hypothesis testing that has been carried out, the R $\rightarrow$ ATU variable has a negative and insignificant effect because it has a path coefficient (β) value of 0.002 (less than 0.1), a t-statistics value of 0.06 (less than 1.96). This can be interpreted that the higher the level of risk that a person feels toward a cryptocurrency trading or investment application, the person will have an unfavorable attitude toward the application. Then the hypothesis is accepted.

H9: R has a negative effect on BITU.

From the results of hypothesis testing that has been carried out, the R $\rightarrow$ BITU variable has a negative and insignificant effect because it has a path coefficient (β) value of 0.004 (less than 0.1), a t-statistics value of 0.129 (less than 1.96). This can be interpreted that the higher the level of risk that a person feels towards a cryptocurrency trading or investment application, the person will tend not to use it. Then the hypothesis is accepted.

H10: R has a negative effect on T.

From the results of hypothesis testing that has been carried out, the R $\rightarrow$ T variable has a negative and significant effect because it has a path coefficient (β) value of -0.338 (close to -1) and a t-statistics value of 4.222 (more than 1.96). This can be interpreted that the higher the level of risk that a person feels towards a cryptocurrency trading or investment application, the less trust that person has in the cryptocurrency trading or investment application. Then the hypothesis is accepted.

H11: ATU has a positive effect on BITU.

From the results of hypothesis testing that has been carried out, the ATU $\rightarrow$ BITU variable has a positive influence. However, it is not significant because even though it has a path coefficient (β) value of 0.166 (more than 0.1), it has a t-statistics value of 1.809 (less than 1.96). This can be interpreted that the attitude of using has little effect on one's intention to use a cryptocurrency trading or investment application. Therefore, the hypothesis is rejected.

H12: BITU has a positive effect on AU.

From the results of hypothesis testing that has been carried out, the BITU $\rightarrow$ AU variable has a positive and significant effect because it has a path coefficient (β) value of 0.727 (more than 0.1) and a t-statistics value of 15.591 (more than 1.96). This can be interpreted that the more someone intends to use a cryptocurrency trading or investment application, the intensity of a person will increase in using the application. Then the hypothesis is accepted.

5. **Conclusion.** Based on the formulation of the problem in this study, namely knowing a person's acceptance factor for the adoption of cryptocurrency trading or investment applications using the extended Technology Acceptance Model (eTAM) theoretical framework by adding actual use, risk, and trust variables. The measurement model used has met adequate validity and reliability. The results of this study are as follows.

Perceived usefulness has a positive effect on attitude towards using. This can be interpreted that the higher the benefits a person feels in using a cryptocurrency trading or investment application, the person will have a good attitude toward the application.

Perceived usefulness has a positive effect on behavioral intention to use. This can be interpreted that the higher the benefits a person feels in using a cryptocurrency trading or investment application, the more likely they will use it.

Perceived ease of use has a positive effect on attitude towards using. This can be interpreted that the easier it is for someone to use a cryptocurrency trading or investment application, the person will have a good attitude toward the application.

Perceived ease of use has a positive effect on perceived usefulness. This can be interpreted that the easier it is for someone to use a cryptocurrency trading or investment application, the person will feel a great benefit from the application.

Trust has a positive effect on perceived usefulness. This can be interpreted that the more someone trusts the cryptocurrency trading or investment application, the greater the person will benefit from the application.

Trust has a positive effect on attitude towards using. This can be interpreted that the more someone trusts the cryptocurrency trading or investment application, the person will have a good attitude toward the application.

Trust has a positive effect on behavioral intention to use. This can be interpreted that the more someone trusts a cryptocurrency trading or investment application, the more likely they will use it.

Risk has a negative effect on attitude towards using. This can be interpreted that the higher the level of risk that a person feels toward a cryptocurrency trading or investment application, the person will have an unfavorable attitude toward the application.

Risk has a negative effect on behavioral intention to use. This can be interpreted that the higher the level of risk that a person feels towards a cryptocurrency trading or investment application, the person will tend not to use it.

Risk has a negative effect on trust. This can be interpreted that the higher the level of risk that a person feels toward a cryptocurrency trading or investment application, the person will not trust the application.

Attitude towards using positively affects behavioral intention to use but is not significant. This can be interpreted as that attitude towards using has little effect on a person's intention to use a cryptocurrency trading or investment application.

Behavioral intention to use has a positive effect on actual use. This can be interpreted that the more someone intends to use a cryptocurrency trading or investment application, the intensity of a person will increase in using the application.

The findings in this study show that the proposed model can explain the acceptance factors of a person towards adopting the CEX application for selling, buying, and investing in Bitcoin. One of the external factors examined in this study is Trust (T). It is found that users of trading applications are more likely to use cryptocurrency trading or investment applications if they have a strong sense of trust in the application. Furthermore, this trust is also a determining factor for their continued use of the application. The risk factor (Risk) is not a factor that affects a person's intention to use a cryptocurrency trading application. This is because, from the start, someone already understands that transacting cryptocurrency is risky. This can happen because someone has thought about the risks they will get if they use the application in cryptocurrency transactions.

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Author Biography

Bambang Sugiantoro received the B.Eng. and Ph.D. degrees in computer science from Universitas Gadjah Mada, Indonesia, in 2000 and 2016. In an M.S. degree in electrical engineering from Institut Teknologi Bandung, Indonesia, in 2004. He is an Associate Professor at the Department of Informatics, Faculty of Science and Technology, Universitas Islam Negeri Sunan Kalijaga, Yogyakarta, Indonesia. His research interests include computer security, digital forensics, and network computer.

Ade Kurniawan received a B.Eng. degree in computer science from Universitas Ahmad Dahlan, Indonesia, in 2008. In the M.S. degree from Universitas Islam Indonesia, Indonesia, in 2017. Currently, he is a Research Assistant Professor and a Ph.D. student at Department of Information Networking, Graduate School of Information Science and Technology, Osaka University, Japan. His research interests include adversarial examples, artificial intelligence, deep learning, machine learning, and network forensics.