International Review of Management and Marketing

ISSN: 2146-4405

available at http: www.econjournals.com

International Review of Management and Marketing, 2025, 15(5), 266-273.

Public's Adoption Intention on Mobile Investment Platform in An Extended MTAM Framework

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Received: 25 March 2025 **Accepted:** 23 July 2025 **DOI:** https://doi.org/10.32479/irmm.19829

ABSTRACT

Numerous mobile technologies have emerged with the mobile devices' development. Compared with other commonly used mobile technologies, the study of the factors influencing mobile investment adoption intention is still under-researched. Besides, the evidence of mobile self-efficacy, mobile innovativeness and the platform providers' reputation is deficient in the literature. This study attempted to discover these gaps by examining the effect of mobile self-efficacy and innovativeness and the providers' reputation toward the adoption intention on mobile investment platforms. The primary responses of the study consisted of 268 respondents from Malaysia who were gathered through convenient sampling. The partial least squares structural equation modelling (PLS-SEM) result first showed that adoption intention is only significantly influenced by mobile usefulness and perceived reputation. However, mobile self-efficacy and innovativeness significantly affect both mobile ease of use and mobile usefulness, and also indirectly impact adoption intention through mobile usefulness. The study's findings first enrich the current literature by providing evidence in this area as the factors that significantly affect mobile investment among the Malaysian general public are identified. Moreover, the direct and indirect role of mobile self-efficacy and mobile innovativeness, together with the providers' reputation on adoption intention toward mobile platforms also provided. Additionally, some critical implications also derived from the study's findings benefit the stakeholders to cultivate the adoption of mobile investment platforms.

Keywords: Mobile Investment, Mobile Technology Acceptance Model, Perceived Reputation, Mobile Usefulness, Adoption Intention
JEL Classifications: M150, M310

1. INTRODUCTION

With the usefulness of mobile technology, it has been widely adopted in numerous business activities and, thus, shifted traditional business to mobile-based (Ling et al., 2024). Similarly, investment transactions can now be done through mobile technology, which refers to "mobile investment" or "mobile investing." Fan (2022) defines mobile investment as investment-related activities through mobile devices, such as information searching, performing analysis, and/or placing investment transactions. Unlike the traditional investment approach, these mobile investment platforms offer numerous advantages, such as managing investment portfolios anytime and anywhere (Chong et al., 2021). Additionally, with minimal cost, multiple financial services such as information searching, performance analysis, and comparison can be done using mobile devices. Therefore, individuals could gain more flexibility and transparency in managing their investments by adopting these mobile investment platforms (Chong et al., 2021). Currently, GO+, Raiz, StashAway, and MYTHEO are some of the mobile investment platforms that are available in the market. But, the usage of these platforms is unsatisfactory (Ling et al., 2024). This has become an unanswered issue and is worth further investigation.

Empirically, literature has documented the factors that significantly influenced the adoption of information systems and information technology in different research contexts from different perspectives. Likewise, the factors that affect mobile technology usage are well-studied. For example, Loh et al. (2022) studied about the wearable payment adoption. Mobile payment adoption was also further investigated by Ling et al. (2025) and Tew et al. (2022), while Wan et al. (2022) studied the intention of mobile tourism shopping. Besides, the adoption intention (AI) on mobile augmented reality applications was also studied by Khan et al. (2024). However, studies investigating the determinants of mobile investment AI are still lacking. As yet, Ling et al. (2024) explored the factors for adopting mobile investment platforms among investors. Besides, Chong et al. (2021) studied the use of intention in stock trading applications among young investors. The influence of the investors' characteristics on mobile investment technology adoption has also been studied by Fan (2022).

Additionally, the mobile technology acceptance is not solely affected by the technology's features, such as usefulness and ease of use. As revealed in previous studies, the individuals' self-efficacy and innovativeness are vital in affecting their intention to use technology, but with inconclusive findings. For example, Lew et al. (2020) and Zhang et al. (2023) found the crucial effect of mobile self-efficacy (MSe) on the intention to use, while an insignificant effect of MSe on use intention was also found in other studies (Loh et al., 2022; Tew et al., 2022). Also, Ling et al. (2024) and Loh et al. (2022) also remarked on the substantial role of mobile innovativeness (MIn) on technology adoption. Still, Yan et al. (2021) found the insignificant effect of personal innovativeness on the QR code mobile payment. This inconclusive evidence should be further investigated to provide a clear picture regarding the effect of both self-efficacy and innovativeness on mobile investment AI. Besides the direct influence of both MSe and MIn on intention to adopt, this study further utilized both mobile ease of use (MEoU) and mobile usefulness (MUse) as mediators to mediate the relationships between MSe and MIn. With that, the direct and indirect role of both MSe and MIn will be examined in the study, providing solid evidence regarding the role of MSe and MIn. Furthermore, this study also included the perceived reputation (PRep) of the platform providers to investigate its effect on the AI, as the individual is usually likely to use that platform if the providers have a good reputation.

As mobile investment platforms become increasingly popular, there's still a significant gap in understanding what drives the general public in Malaysia to use these platforms. Most research has centered around experienced retail investors, leaving out the broader population, including those who don't invest yet. This focus limits the applicability of the findings to everyone. Moreover, past studies have been unclear about how factors like mobile self-confidence and a person's willingness to embrace new technology influence their decision to use these platforms. This highlights the need for more research in this area to provide clearer insights. Therefore, two objectives wish to be answered in this study: (1) to examine the role of the MSe, MIn, and PRep on the mobile investment AI using an extended mobile technology acceptance model (MTAM), and (2) to investigate the indirect role of MSe and MIn on the mobile investment AI through MEoU and MUse. By answering these objectives, the study's findings are expected to contribute theoretically and practically. Firstly, this study provides new evidence regarding mobile investment adoption from the general public (including non-investors) by using an extended MTAM, and this would further enrich the literature as the evidence from this perspective is limited. Besides, the results further proved that MSe and MIn have direct relationships with MEoU and MUse but only indirectly affect the intention to adopt through MUse. The study further discovered the importance of the platform providers' reputation as it is the most crucial factor in determining AI. Furthermore, the study's results are also useful for several relevant stakeholders such as regulators, investment banks and institutions, fund management companies, and others in promoting the usage of mobile investment platforms.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

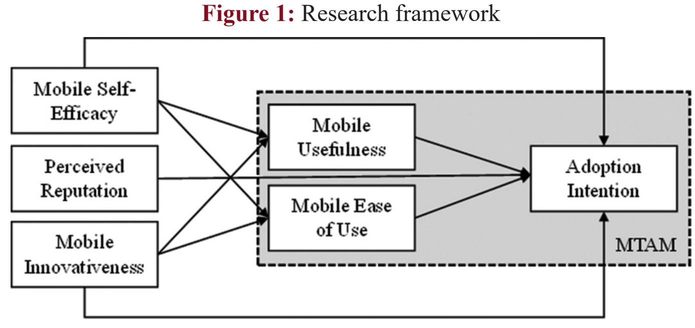
2.1. Mobile Technology Acceptance Model

Ooi and Tan (2016) introduced the MTAM to overcome the limitations of the existing model on mobile technology adoption, as current models are mainly introduced for general technology. Since the inception of the MTAM, this model has been widely adopted in prior studies, especially in the different mobile technologies (Akram et al., 2024; Khan et al., 2024; Ling et al., 2025; Ng et al., 2022; Tan et al., 2025; Yan et al., 2021). Nevertheless, only two predictors are proposed in the MTAM (mobile ease of use and mobile usefulness), and this may limit the predictability of the framework. With that, some additional predictors should be included to extend the existing MTAM model to better explain the subject matter (Tew et al., 2022). This is paralleled with most of the previous studies that also extended the MTAM, with the predictors that may capture better the research topic (Lau et al., 2021; Ling et al., 2024; Loh et al., 2022; Wan et al., 2022). For that reason, this study extends the MTAM with three predictors, MSe, MIn, and PRep, to provide a more thorough understanding of the subject matter. Mobile investment platform adoption is not only affected by technology features like MEoU and MUse. Still, it is also influenced by personal factors like MSe and MIn, as well as the PRep of the platform providers. Therefore, Figure 1 below demonstrates the study's research framework.

2.2. Mobile Ease of Use on Adoption Intention

MEoU is defined as the personal opinions on the easiness of adopting mobile technologies (Ooi and Tan, 2016), and the person tends to adopt the technology if it is user-friendly without any extra effort (Yan et al., 2021). Therefore, it suggests that

Figure 1: Research framework



the intention to adopt will be higher if the mobile technologies are less complex and require minimal effort. The postulation is supported by numerous evidence that also found the vital role of MEoU on AI on different mobile technologies in other contexts. For example, Loh et al. (2022) concluded the substantial effect of MEoU in the use intention on wearable technology. Similarly, Tan et al. (2025) and Tew et al. (2022) also found the same result in mobile payment, while Wan et al. (2022) also revealed the significant effect of MEoU in mobile tourism contexts. Recently, Ashoer et al. (2024) and Tan et al. (2025) further documented the positively significant effect of MEoU on behavioural intention in mobile fintech and mobile payment contexts, respectively. Furthermore, the context of use can alter the importance of MEoU. In high-stakes environments, such as financial investments, users might tolerate a steeper learning curve if the perceived benefits and security of the platform are high. Conversely, in everyday applications, ease of use might be a more critical determinant due to the frequent and casual nature of interactions. With that, the hypothesis below is proposed.

H_1: MEoU is positively significant with adoption intention.

2.3. Mobile Usefulness on Adoption Intention

Ooi and Tan (2016) defined MUse as the personal opinions on performance improvement through using mobile technology. Numerous benefits are associated with mobile technology, and thus, it is expected that it may improve the results of technology usage (Ling et al., 2024). Therefore, a person tends to have a high intention to use mobile technology if they perceive the MU is higher, and this supposition is supported by empirical evidence in the literature in different contexts. For instance, Lau et al. (2021) found that mobile taxi use intention is significantly impacted by MUse. Likewise, Ling et al. (2025) and Tew et al. (2022) also found that mobile payment use intention is also affected by MUse. Similarly, the positive significant influence of MUse toward the use intention on mobile fintech (Ashoer et al., 2024) and mobile payments (Tan et al., 2025). Therefore, the hypothesis below is formulated.

H_2: MUse is positively significant with adoption intention.

2.4. Perceived Reputation on Adoption Intention

The platform provider's PRep is defined as the personal opinions of the platform providers on their ability, trustworthiness, and benevolence (Xin et al., 2015). As the mobile technology is designed for a specific virtual purpose, the platform providers' PRep is vital in determining the person to use it. As remarked by Ling et al. (2024), investors tend to use mobile technology offered by a reputable platform provider. Aligned with Ling et al. (2024), this study also hypothesised that the PRep of platform providers significantly influences user intention. Also, the significant effect of reputation on technology adoption is proved in other contexts, such as Islamic banking (Warsame and Ireri, 2018) and mobile banking (Nguyen et al., 2022). The significant role of reputation toward continuance intention to use multimodal language learning education is also further remarked by Huang et al. (2024). Moreover, a good reputation can also reflect the platform's commitment to customer service and user satisfaction. Platforms that respond promptly to inquiries, resolve issues effectively and continuously improve their services are likely to be viewed more favourably. This positive perception encourages both new and experienced investors to engage with the platform, as they feel more confident about its credibility. With that, the hypothesis below is proposed.

H_3: PRep is positively significant with adoption intention.

2.5. Mobile Self-Efficacy on Mobile Ease of Use, Mobile Usefulness, and Adoption Intention

Lew et al. (2021) defined MSe as the personal opinion regarding their ability to learn and adopt mobile technology. Theoretically, this self-efficacy tends to influence MEoU and MUse, as the higher the self-efficacy toward the technology, the more it tends to increase the ease of use and usefulness. For instance, Lew et al. (2020) revealed the significant relationship between the MSe on the MEoU and MUse. Likewise, the significant influence of MSe on both MEoU and MUse was also shown by Loh et al. (2022) and Tew et al. (2022) in the study on wearable technology and mobile payment, respectively. Recently, Khan et al. (2024) also remarked on the similar significant influence of MSe on both MEoU and MUse toward the use of mobile augmented reality applications. Furthermore, as remarked by Zhang et al. (2023), the self-efficacy of an individual is crucial in affecting technology usage. The significant impact of the MSe on mobile technology has been documented in the literature. For example, Lew et al. (2020) concluded that MSe significantly influenced consumers' AI on mobile wallets. Similarly, Khan et al. (2024) also found that MSe has a significant effect on behavioural intention on mobile augmented reality applications. Therefore, the hypotheses below were proposed.

H_4: MSe is positively significant with MEoU.

H_5: MSe is positively significant with MUse.

H_6: MSe is positively significant with adoption intention.

2.6. Mobile Innovativeness on Mobile Ease of Use, Mobile Usefulness, and Adoption Intention

MIn is defined as the magnitude of an individual's willingness to try to use a new technology (Loh et al., 2022). An individual's innovativeness level is crucial to determining their use of a new technology (Ling et al., 2025). However, the empirical evidence also demonstrated that this innovativeness also significantly influences the ease of use and usefulness. For instance, Loh et al. (2022) revealed MIn significantly affects both MEoU and MUse. Moreover, some other studies also found a significant effect of MIn on mobile technology adoption. For example, Ling et al. (2024) and Loh et al. (2022) showed that mobile investment and wearable technology AI are significantly influenced by the MIn, respectively. Similarly, Ling et al. (2025) also revealed that MIn significantly influenced users to adopt mobile payment. Thus, the hypotheses below were suggested.

H_7: MIn is positively significant with MEoU.

H_8: MIn is positively significant with MUse.

H_9: MIn is positively significant with adoption intention.

2.7. Mediator Role of Mobile Ease of Use and Mobile Usefulness

In addition, this study also further examines the indirect relationship of the MSe and MIn on the intention to use through the MTAM's constructs (MEoU and MUse). This postulation aligns with the findings in the previous studies that documented the significant mediating effect of both MEoU and MUse on the associations between proposed predictors and the use intention on mobile technology. For example, Ooi and Tan (2016) revealed that MEoU and MUse significantly mediate the association between mobile-perceived compatibility and use intention on smartphone credit cards. Similarly, Tan et al. (2018) also found that MSe indirectly affects behaviour and intention to use mobile social media advertising via both MEoU and MUse. Likewise, the significant mediating role of MEoU and MUse on the influence of MSe and MIn on the intention to adopt wearable technology is also acknowledged by Loh et al. (2022). With that, this study also hypothesised the mediating role of MEoU and MUse on the associations between MSe and MIn on the AI on mobile investment platforms and proposed the following hypotheses.

H_{10}: MEou mediates the effect of MSe and adoption intention.
H_{11}: MUse mediates the effect of MSe and adoption intention.
H_{12}: MEou mediates the effect of MIn and adoption intention.
H_{13}: MUse mediates the effect of MIn and adoption intention.

3. RESEARCH METHODOLOGY

A quantitative research method was adopted to gather the responses from the target population, which is the Malaysian general public. A convenient sampling technique is used to collect the responses through the online survey using Google Forms. This study collected responses through an online survey using Google Forms between February 2023 and April 2023, resulting in 286 usable responses. This number is sufficient for the proposed research framework as it met the minimum sample size of 166, which was determined by the power analysis with a medium effect size, a power level of 0.95, and nine predictors.

The questionnaire of the study was developed by adapting 24 validated measurement items from earlier studies, such as Lau et al. (2021), Loh et al. (2022), and Chandra et al. (2010). The respondents are required to measure these measurement items using the seven-point Likert scale, from strongly disagree (1) to strongly agree (7). These useable responses were first assessed through Mardia's multivariate coefficient procedure to determine the normality of the dataset, and the result indicated that the responses collected for the study are not normally distributed as the kurtosis coefficient (78.1325) of the study is >20 (Byrne, 2013; Kline, 2011). The non-normally distributed data further indicates the suitability of the partial least squares-structural equation modelling (PLS-SEM) in analysing the collected responses (Hair et al., 2019).

Then, several validity and reliability tests were used to further assess the appropriateness of these measurement items, such as outer loading, average variance extracted (AVE), composite reliability (CR), and heterotrait-monotrait (HTMT) ratio of correlation. Outer loadings were examined to ensure that all items had sufficient loading values on their respective constructs. Average variance extracted (AVE) values were determined to measure the convergent validity, with all constructs having AVE values greater than the 0.5000 threshold, indicating good convergent validity (Bagozzi and Yi, 1988). Composite reliability (CR) values were also calculated to assess the internal consistency, with all constructs exceeding the 0.7000 threshold (Gefen et al., 2000). Discriminant validity was also measured by using the heterotrait-monotrait (HTMT) ratio of correlations, and the threshold of 0.9000 was referred to (Henseler et al., 2015).

4. ANALYSIS RESULTS

4.1. Profiles of Participated Respondents

Table 1 shows the respondents' demographic profile of the study. The respondents were dominated by male respondents (61115), compared to females (38%). Besides, 45% of the respondents are aged between 26 and 35, followed by 19-25. In terms of occupation, 56% are employees, 28% are students, 13% are self-employed, and 3% are others. Regarding the highest education level, a third-fourth of the respondents have tertiary education, and post-graduate education accounts for 15%, while the rest only received primary and secondary education.

4.2. Outer Model Assessment

The measurement items and constructs were first assessed through the reliability and validity tests, and the results were presented in Table 2. The results indicated that both internal consistency and convergent validity were confirmed as the loading value for all items exceeded 0.5000 (Bagozzi et al., 1991), and also the AVE for all constructs was higher than 0.5000 (Bagozzi and Yi, 1988). The CR values of all constructs that are >0.7000 further showed that internal consistency is ensured (Gefen et al., 2000). The result of the HTMT in Table 3 also demonstrated that the discriminant validity is also satisfactory, as the HTMT values are <0.9000 (Henseler et al., 2015). Lastly, the values of the variance inflation factor (VIF) in Table 2 that are below 5 indicate that the study has no multicollinearity issues (Hair et al., 2017).

4.3. Inner Model Assessment

The study then proceeded to validate the structural model and test the proposed hypotheses. Firstly, the result showed that both MSe and MIn explained around 57.33% and 63.86% of the variances in MEoU and MUse, respectively. Besides, 68.54% of the variation in AI was predicted by the five predictors (MEoU, MUse, PRep, MSe, and MIn). In addition, the predictive relevance (Q^2) values for MEoU (0.4052), MUse (0.5209), and AI (0.5762) were all >0, and this signified the model's predictive validity (Hair et al., 2017).

Table 1: Summary of respondents' profiles

Profiles	Categories	Frequency	Percentage
Gender	Male	165	61.57
	Female	103	38.43
Age range	19-25 YO	96	35.82
	26-35 YO	120	44.78
	36-45 YO	35	13.06
	45 YO and above	17	6.34
Occupation	Employee	149	55.60
	Self-employed	36	13.43
	Students	75	27.99
	Others	8	2.99
Education level	Primary and Secondary Education	26	9.70
	Certificate, Diploma, and Bachelor Degree	202	75.37
	Master and PhD	40	14.93

Moreover, according to Cohen's (1988) guidelines, MSe and MIn possess a moderate effect on MEoU and MUse. Besides, MEoU, MSe, and MIn had no effect on the AI ($f^2 < 0.02$), while MUse had a small effect on the AI ($0.02 < f^2 < 0.15$), and PRep demonstrated a medium effect on the AI ($0.15 < f^2 < 0.35$).

The summary result of the hypotheses testing is provided in Tables 4 and 5, together with Figure 2. In Table 4, six direct hypotheses were supported (H_2, H_3, H_4, H_5, H_7, and H_8), while the remaining three direct hypotheses were failed to supported (H_1, H_6 and H_9). Precisely, only MUse ($\beta = 0.3124$, $P < 0.05$) and PRep ($\beta = 0.3135$, $P < 0.05$) have significantly influenced the AI, while MEoU, MSe, and MIn insignificantly affect AI. Besides, MSe and MIn are significantly affected by both MEoU and MUse.

Table 2: Results of outer model assessment

Constructs	Items	Loading	AVE	CR	VIF
MEoU	MEoU1	0.6968	0.7185	0.9268	3.645
	MEoU2	0.8667			
	MEoU3	0.9061			
	MEoU4	0.8942			
	MEoU5	0.8575			
MUse	MUse1	0.8967	0.8229	0.9489	4.552
	MUse2	0.9124			
	MUse3	0.9058			
	MUse4	0.9135			
PRep	PRep1	0.8975	0.8204	0.9320	2.035
	PRep2	0.9302			
	PRep3	0.8891			
MSe	MSe1	0.8712	0.6468	0.8796	2.607
	MSe2	0.7896			
	MSe3	0.7967			
	MSe4	0.7552			
MIn	MIn1	0.8111	0.6531	0.8825	2.505
	MIn2	0.8629			
	MIn3	0.7456			
	MIn4	0.8087			
AI	AI1	0.9301	0.8521	0.9584	3.179
	AI2	0.9244			
	AI3	0.9363			
	AI4	0.9013			

Table 3: Result of HTMT

	MEoU	MUse	PRep	MSs	MIn	AI
MEoU						
Muse	0.8988					
PRep	0.6823	0.6799				
MSe	0.7931	0.8397	0.6064			
MIn	0.7984	0.8197	0.5976	0.8225		
AI	0.7691	0.8171	0.7549	0.7492	0.7253	

Furthermore, Table 5 further displays the summary results of the indirect hypotheses testing. Even though both MSe and MIn have no direct influence on the AI, the indirect hypotheses testing further verified that both MSe and MIn indirectly significantly impacted the AI through MUse and supported H_{11} and H_{13}. However, MEoU is found to mediate the relationships between MSe and MIn on AI insignificantly, and thus, H_{10} and H_{12} were unsupported.

5. DISCUSSION AND IMPLICATIONS

The study adopted an extended MTAM to examine the role of self-efficacy and innovativeness as well as the PRep of the platform providers in influencing the public to adopt mobile investment platforms. The result signified that MUse significantly influences AI but is insignificantly affected by MEoU, and this result is in harmony with Lau et al. (2021), Ling et al. (2025), Yan et al. (2021), and Zhang et al. (2023) in other research contexts. This outcome suggests that the person is more concerned about the usefulness of the platform as they tend to adopt this platform for investment purposes if they perceive it would enhance their performance in making their investment transactions. However, the respondents were dominated by the younger generation, and they are highly educated, which could be the reason for the insignificant effect of MEoU on intention to use, as these respondents could find that the mobile investment platforms are easy to use and require minimal efforts and costs in using it. Consistent with Ling et al. (2014), Nguyen et al. (2022), and Warsame and Ireri (2018), the study also proved the reputation of the providers played a crucial role in determining a person's intention to adopt mobile investment platforms. With that, this signified that MUse and PRep were the two main determinants that could stimulate the public to use mobile investment.

The significant effect of MSe on both MEoU and MUse was also found in this study. It is paralleled with Lew et al. (2020), Loh et al. (2022), Khan et al. (2024), and Tew et al. (2022), who also revealed the substantial role of MSe on MEoU and MUse in the study on mobile wallet, wearable payment, and mobile payment, respectively. Therefore, the individual will find it easy to use, and the platform's usefulness will further improve if they have high self-efficacy toward this mobile technology. An insignificant role of the MSe in AI is further revealed in this study, and this is opposed to the studies of Lew et al. (2020), Khan et al. (2024), and Zhang et al. (2023). However, prior studies also found the insignificant influence of MSe on the use intention of different mobile technologies (Loh et al., 2024; Tew et al., 2022). This could

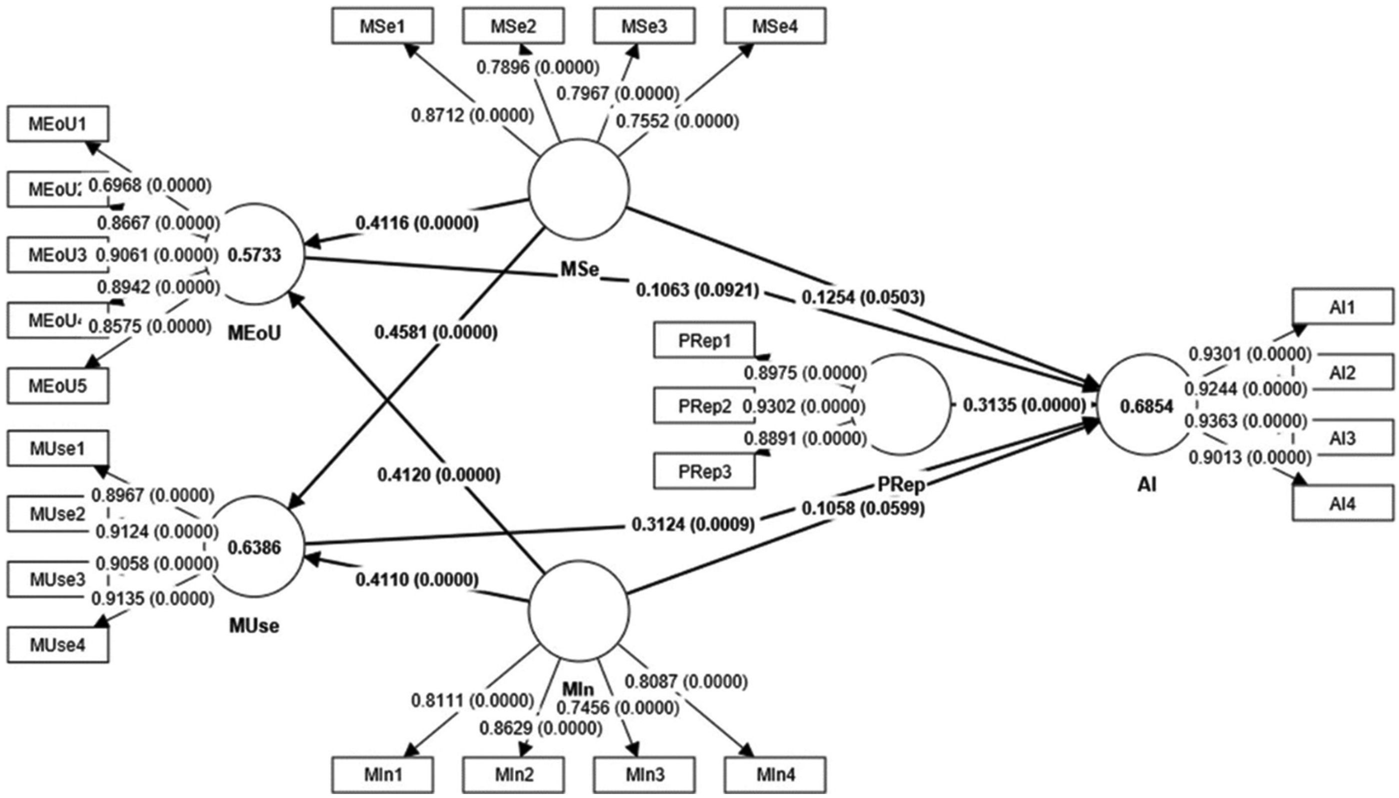
Table 4: Summary of the direct hypotheses testing

Hypotheses	Path	Coefficient	T-statistic	P-values	f^2	Remark
H_1	MEoU -> AI	0.1063	1.3281	0.0921	0.0100	Not supported
H_2	MUse -> AI	0.3124	3.1259	0.0009	0.0732	Supported
H_3	PRep -> AI	0.3135	6.5133	0.0000	0.1814	Supported
H_4	MSe -> MEoU	0.4116	5.9628	0.0000	0.2079	Supported
H_5	MSe -> MUse	0.4581	6.7376	0.0000	0.3041	Supported
H_6	MSe -> AI	0.1254	1.6423	0.0503	0.0195	Not supported
H_7	MIn -> MEoU	0.4120	5.0937	0.0000	0.2083	Supported
H_8	MIn -> MUse	0.4110	5.8044	0.0000	0.2448	Supported
H_9	MIn -> AI	0.1058	1.5561	0.0599	0.0144	Not supported

Table 5: Summary of the indirect hypotheses testing

Hypotheses	Path	Coefficient	T-statistic	P-values	f^2	Remark
H_{10}	MSe -> MEoU -> AI	0.0438	1.2464	0.2127	0.0019	Not supported
H_{11}	MSe -> MUse -> AI	0.1431	2.4241	0.0154	0.0205	Supported
H_{12}	MIn ->MEoU -> AI	0.0438	1.2742	0.2026	0.0019	Not supported
H_{13}	MIn -> MUse -> AI	0.1284	3.0666	0.0022	0.0156	Supported

Figure 2: Research model with path coefficient and P-values



be due to the study's respondents being formed from a group of highly educated people, as more than 90% of respondents received tertiary education, and they may have high confidence in using these investment platforms. Therefore, their self-efficacy in the mobile investment doesn't directly impact their AI.

Consistently, the study's findings also showed that MIn significantly impacts both MEoU and MUse, and this is congruent with Loh et al. (2022) in the context of wearable payment. The result signified that the person would perceive that mobile investment is effortless to use and also further enhance their investment's usefulness if they are more innovative with mobile investment platforms. Similar to MSe, MIn demonstrated no significant association with intention to use, which contradicts empirical evidence in other research settings (Ling et al., 2024; Loh et al., 2022). The younger generation with high education dominated the study's respondents, and this could signify that they may be very familiar and savvy with these novel technologies. Therefore, their innovativeness seems to be less crucial in affecting their AI.

Furthermore, the study further examined the indirect effect of the MSe and MIn on mobile investment AI through mediators of MEoU and MUse. The mediating analysis findings demonstrated that MSe played a significant indirect effect on AI through MUse, and this finding mirrored the results of Loh et al. (2022) and Tan et al. (2018). Likewise, MIn also has an indirect significant influence on AI via MUse, and this is in agreement with Loh et al. (2022). Again, MEoU has no significant mediating effect on the effect of MSe and MIn on intention to use, which contradicts Loh et al. (2022). The significant indirect role of both MSe and MIn further proved that both MSe and MIn still played a vital effect in determining the use intention on mobile investment platforms, even though both MSe and MIn are insignificantly influenced toward AI.

The study provides some important implications, either theoretically or practically. The study's findings contribute to the existing literature on mobile technologies' adoption as evidence of the mobile investment platforms adoption is provided. Numerous studies have investigated determinant factors that affect individuals using mobile technologies such as mobile payment, mobile wallet, mobile shopping, mobile tourism, and others. Nevertheless, the evidence on mobile investment adoption is relatively scarce in the literature. The study enriches the literature by providing new evidence from investors and non-investors, which could benefit future studies. Besides, this study also particularly investigates the effect of self-efficacy and innovativeness, together with the PRep of the platform providers. The adoption of mobile technologies is not solely influenced by the technology's characteristics like MEoU and MUse. This extended framework would offer a more holistic understanding of this area. In addition, this study also further studied the mediating effect of the MEoU and MUse in affecting AI on mobile investment platforms. This would further provide new evidence on the mediating effect of the MTAM's constructs, especially on the indirect role of MSe and MIn on the intention to adopt mobile investment.

Also, the study's findings benefit stakeholders, such as Securities Commissions, investment banks and institutions, fund management companies, and others, in cultivating the usage of these platforms. As the study shows, the platform providers should emphasise the MUse and PRep as the two critical factors in determining AI. For example, the platform providers have to improve the platform's usefulness, such as providing several analytic techniques like fundamental analyses that are useful to determine the stock's intrinsic values and select the potential stocks. Besides, the platform also has to embed technical analyses as they are useful in determining the timing of investment. Incorporating both analyses would offer a more comprehensive platform for the investors to select the "right" stock, invest in the "right" timing, and eventually increase profitability.

Besides, the reputation of the platform providers also played an important role. A mobile investment platform is a virtual platform used for investment activities. Thus, the platform providers' reputation would be the main consideration for the investors in adopting these platforms. With that, the platform providers must improve their reputation, as the investors will only adopt a platform with a high reputation and trustworthiness. The user's privacy and confidentiality should be highly protected, and the platform systems should be stable and capable of resisting hacker attacks to avoid any unfavourable events such as scams and frauds.

Lastly, the stakeholders should focus on both MSe and MIn, as they directly affect both MEoU and MUse and indirectly affect intention to adopt through MUse. Therefore, activities and programs that may enhance the user's self-efficacy must be organised to upskill the users' capability and confidence toward the mobile investment platforms. In addition, the events that may assist in increasing the users' innovativeness must also be organised as they would introduce these novel technologies to the potential users. As found in the study, people will have higher MEoU and MUse when they have high self-efficacy and high innovativeness. Eventually, this influence will indirectly affect their AI.

6. CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

The study investigated the influence of self-efficacy and innovativeness and the platform providers' reputation on mobile investment use intention. An extended MTAM has been proposed by examining the direct and indirect influence of the additional factors. The study used convenient sampling to gather two hundred sixty-eight usable responses from the Malaysian public. The results of PLS-SEM found that only MUse and PRep significantly affected AI. Besides, MSe and MIn significantly influenced both MEoU and MUse and directly influenced intention to use through MUse. These findings provide a holistic understanding of the adoption of mobile investment platforms which enrich the literature in the subject matter as it remained deficient. Besides, the direct and indirect role of the MSe and MIn were further proven in the study together with the significant role of PRep on mobile investment use intention. These findings are expected contributions theoretically and practically.

Some recommendations could be considered in future research. Firstly, this study only uses convenient sampling to focus on the Malaysian general public. This may limit the generalizability and the representativeness of the study's findings. Future study is recommended to expand the study's scope to different countries, and a comparison study could be considered. The forthcoming study should consider examining the impact of respondents' demographic factors such as age, income level, and education on the adoption of mobile investment platforms. Besides, purposive or simple random sampling would be a better technique to increase the generalizability and representativeness of the study's findings. Additionally, other predictors such as trust, government support, and the like could be included in future studies as other predictors prove to be affected by mobile technology adoption. Moreover, the multi-group analysis would be another area that can be considered as the respondents usually consist of different sub-cultures. This may lead to bias in the study's findings if this heterogeneity is not properly considered.

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