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Identifying Key Factors Shaping New Users' Intentions in Mobile Investment Applications

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Abstract

This paper seeks to examine the key factors predicting the behavioral intentions of mobile investment app users. By understanding these influencing factors, the ultimate goal is to encourage more people to adopt and accept these apps. Adopting an integrated approach, the research combines different UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) constructs for hypothesis development and to evaluate the effects on users' adoption and behavior use of such platforms. Through an online survey among 161 users of popular mobile investing applications in Indonesia and applying structural equation modeling for analysis with the SmartPLS statistical tool, this research contributes empirical evidence on factors that drive user behavior in the mobile investment domain. The final model provided a good basis for proving the hypotheses presented and the factors can account for 65.6% of the variability in mobile investment app behavior intention. The results revealed that Habit, Performance Expectancy, and Effort Expectancy are the key factors impacting individual behavioral intention to get mobile investment. These findings will assist researchers and professionals in understanding why individuals utilize mobile investment apps. More importantly, this study's recommendations will help utilize these aspects to enhance these apps' benefits.

A. Introduction

In today's age of industrialization and innovation, the Internet and mobile technology are advancing rapidly, bringing about significant changes. This progress is driving the digitalization of various industries and fostering the growth of digital solutions such as mobile applications. This transformation is particularly noticeable in sectors like health and financial services [1], [2]. Numerous financial organizations, including banks, insurance providers, and fintech startups, are currently shifting their services to digital platforms. They achieve this by introducing mobile smartphone applications that leverage the latest technologies, aiming to offer quicker and improved services to their customers.

In 2020, the COVID-19 pandemic has led to a reduction in activities outside the home and an increased reliance on online platforms. This includes the shift to online classes in education and the use of gadgets for daily necessities, as well as online business activities and stock market investments. As a result of the latter, more people are investing in the stock market who hope to earn another income and profits.

The stock market has seen a significant increase in investors, largely due to a group called retail investors who are essentially new and non-professional individuals to grow their wealth using their individual names. As of November 2022, the number of investors in Indonesia's capital market had increased significantly to 10 million. The increase in question has been a significant subject of discussion since the beginning of the COVID-19 pandemic, as shown by information from the Indonesia Central Securities Depository (KSEI) [3]. During a downturn in capital market indices, many millennials took advantage of the opportunity to enter the stock market as retail investors [4], [5]. However, the growing number of these newcomer investors comes with its challenges. Many retail investors lack technical and fundamental expertise in stock investments and often rely on trends to make quick profits [5].

In studies that explore how individuals begin using mobile services, such as mobile stock trading, the technology adoption models like the UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) model and similar constructs have been widely applied. For instance, Alotaibi published a study based on the M-Tadawul system of the Saudi Arabian stock exchange using the UTAUT model [6]. Rahadi et al. further extended this approach by incorporating factors such as the design of the content and user-friendliness of the interface in their UTAUT2 model, which focuses on how Millennial investors invest in mutual funds online [7].

In another study, Chong et al. wanted to find out what exactly motivates young traders to engage in mobile stock trading [8]. For this purpose, they integrated TPB (Theory of Planned Behavior) and TAM with other factors like perceived benefits, risks, and trust. Rosnidah et al. had a slightly different emphasis. They used the UTAUT model to gain a better understanding of the adoption of mobile payments by the millennials [9].

Adding to this, Afif et al. identified factors influencing young or novice investors' adoption of online trading systems using TAM theory [10]. In another study in Indonesia, Indrawati & Riyadi applied the UTAUT2 model to analyze predictors influencing train passengers' adoption of a self-service electronic payment service, the Kios Tiket Mandiri (KTM) [11].

The practice of online investing is on the rise and several research has been done about it, however, we still lack insights into why new investors especially in developing countries like Indonesia are choosing to make their stocks and mutual fund investments through mobile platforms.

This paper's objective is to explore the driving factors of adoption that lead new users to begin using mobile investment apps, which in turn aims to encourage further acceptance and adoption among potential users. For this purpose, we have selected UTAUT2 as our base theory. The model, in particular, is reliable at exploring what drives individuals to use mobile applications in a consumer situation [12]. Notably, the original UTAUT model primarily focuses on the organizational setting, while UTAUT2 targets the consumer side of things [7], [13]. This study makes a research contribution as it offers a theoretical understanding of the complex dynamics involved in the adoption of mobile investing applications within the financial technology industry and offers recommendations based on the findings.

The paper is organized into different sections for clarity. Section 1 introduces the study's background problems and related theories. Section 2 discusses the research methodology. The findings are then explored in Section 3, while Section 4 wraps up the work with a summary.

B. Research Method

1) Research hypothesis & model

In this paper, the factors that might explain the user's adoption and usage of mobile investment applications were assessed using the UTAUT2 model as this study's research model. The UTAUT2 model highlights eight major factors of technology adoption and use namely: performance expectancies, social influences, hedonic motivation, effort expectancies, habit, facilitating condition, behavioral intention, and price value [12]. This study's research model offers a thorough evaluation of the influential factors that lead to enhancing user adoption in mobile investment applications. This makes it possible for us to provide a thorough response to the research topic. Nine fundamental constructs are included in the research model. The study objectives were achieved by developing hypotheses to quantify user behavior intention with mobile investment applications. These hypotheses were based on prior literature and analyzed using various model factors. The research model for the paper is illustrated in Figure 1 and the 10 hypotheses were then tested:

H1: A significant and positive influence exists between Performance expectancy (PE) and the Behavioral intention (BI) to use mobile investment applications.

H2: A significant and positive influence exists between Effort expectancy (EE) and the Behavioral intention (BI) to use mobile investment applications.

H3: A significant and positive influence exists between Social influence (SI) and the Behavioral intention (BI) to use mobile investment applications.

H4: A significant and positive influence exists between Facilitation conditions (FC) and the Behavioral intention (BI) to use mobile investment applications.

H5: A significant and positive influence exists between Facilitation conditions (FC) and the Usage behavior (UB) to use mobile investment applications.

H6: A significant and positive influence exists between Hedonic Motivation (HM) and the Behavioral Intention (BI) to use mobile investment applications.

H7: A significant and positive influence exists between Price Value (PV) and the Behavioral intention (BI) to use mobile investment applications.

H8: A significant and positive influence exists between Habit (HB) and the Behavioral intention (BI) to use mobile investment applications.

H9: A significant and positive influence exists between Habit (HB) and the Usage Behavior (UB) of mobile investment applications.

H10: A significant and positive influence exists between Behavioral Intention (BI) and the Usage Behavior (UB) of mobile investment applications.

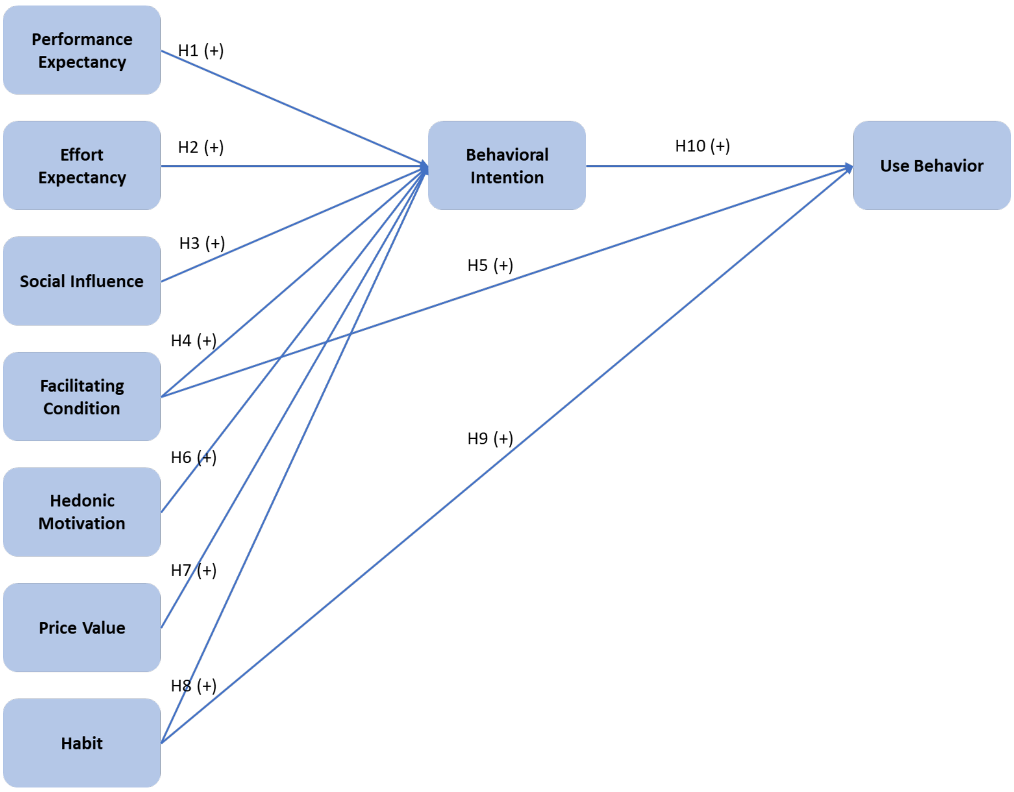

Figure 1. Research model of the study

2) Research design

This study tested the hypothesis of whether constructs have a beneficial influence on user intention in mobile investing applications using a quantitative technique and confirmatory analysis type. This study makes use of both dependent and independent variables. Any alterations in the independent variable lead to modifications in a variable, which is called the dependent variable where the condition or value is measured. Accordingly, a variable that affects the dependent variable is considered an independent variable [14]. The study examines behavioral intention and usage behavior as dependent variables, while this study's independent or exogenous variables included Social Influence, Facilitating Condition, Performance Expectancy, Price value, Effort Expectancy, Hedonic Motivation, and Habit.

3) Research instrument development

A self-administered questionnaire and survey methodology were employed in this investigation. Three segments make up the questionnaire. The demographic information from the respondents was collected in the first segment. In the next segment, a sequence of 26 questions were asked, reflecting the indicators from nine components of the research model. Using a 5-point Likert scale, the respondents answered with 5 representing the strongly agree answer and 1 being the strongly disagree. Finally, they rated the features of mobile investing applications they considered more important first [8].

4) Data collection

To fulfill primary data collection, a web-based survey making use of Google Forms was conducted from June 16 to September 15, 2022. Social media and messaging platforms such as Facebook, WhatsApp, Instagram, and Telegram were used to distribute the questionnaires. A random sample of Indonesian residents who have used a mobile investing application at least once in the last 12 months was used for the screening procedure. The researcher presented potential participants with information about their familiarity and experience requirements with mobile investing applications (including the degree of use and investment knowledge for stocks and mutual funds) in order to ensure that the participants were eligible for the study. In this study, 161 valid responses were gathered in total.

5) Data analysis

Using partial least squares-structural equation modeling (PLS-SEM), the same data that were collected were analyzed. This analytical method integrates the assessment of measurement models (reflective or formative) with the estimation of structural paths, providing a comprehensive framework for researchers to analyze and understand the links between latent constructs in their models [15]. It has a wide application when conventional structural equation modeling may face challenges due to limited data in research, especially in the domains of marketing, management, social sciences, and information systems in a technology adoption context. This study employed SmartPLS 4.0 as a tool for conducting PLS-SEM to evaluate the factors to have a certain amount of consistency, validity, and reliability [16].

Table 1. Demographic characteristics of the survey participants

Item	*Category*	*Frequency*	*Percentage*
Gender	Male	107	66.46%
	Female	54	33.54%
Residence	DKI Jakarta	45	27.95%
	West Java	37	22.98%
	Banten	32	19.88%
	DI Yogyakarta	14	8.70%
	Central Java	12	7.45%
	Others	12	7.45%
Age	< 19 years old	0	0.00%
	20 – 24	22	13.66%
	25 – 29	42	26.09%
	30 – 34	64	39.75%
	35 – 40	21	13.04%
	> 40 years old	12	7.45%
Education	High school	8	4.97%
	Diploma	9	5.59%
	Bachelor	102	63.35%
	Postgraduate	42	26.09%
Job	Private Employee	48	29.81%
	Civil service	13	8.07%
	Entrepreneur	6	3.73%
	SOE Staff	5	3.11%
	Student	5	3.11%
	Others	7	4.35%
Income	No Income	9	5.59%
	< Rp 2.5 mil.	13	8.07%
	Rp 2.5 mil. – Rp 4.9 mil.	18	11.18%
	Rp 5.0 mil. – Rp 7.4 mil.	26	16.15%
	Rp 7.5 mil. – Rp 10 mil.	25	15.53%
	> Rp 10 mil.	70	43.48%
App Usage Period	< 6 mos.	36	22.36%
	6 - 12 mos.	31	19.25%
	1 - 2 yrs.	41	25.47%
	2 - 3 yrs.	26	16.15%
	> 3 yrs.	27	16.77%

C. Result and Discussion

1) Descriptive analysis

Of the 161 participants involved in this study, 66.46% are male while the rest are female. The largest proportion of the respondents is between the age range of 30–34 (39.75%), followed by those who are 25–29 years old (26.09%), while the remaining 7.45% are above 40. No respondent under the age of 19 was found in this survey, and no statistically significant difference was observed in the percentage of respondents aged 20–24 (13.66%) and 35–40 (13.04%). There are 29.81% of employees in the private sector of all respondents, followed by civil services (8.07%), entrepreneurs (3.73%), and 3.11% for both state-owned enterprises staff and students. More than 43% of investors earn more than IDR 10 million each month, and many of them (63.35%) have bachelor's degrees. It is noteworthy that more than 25% of investors have been using the mobile investing app for one to two years, with 22.36% of users having only used it for six months or less. The demographic characteristics of the given sample are summarized in Table 1.

Also, the respondents' ranked features of mobile investing applications are shown in Table 2, along with their mean values. Since the top-ranked mobile investment platform has a robust security mechanism, all of the survey participants consider it significant. User-friendly interfaces and faster execution, which rank second and third respectively, are significant considerations for all investors. Surveyed investors consider online fund transfers and firm fundamentals information to be crucial components of mobile investment apps. The majority of youthful investors prioritize ease of use and quickness of transactions. However, more financial instruments and robo-advisor features are not to their liking.

Table 2. The ranking of features in mobile investment applications [8]

Features	*% responses*					*Mean*	*Rank*
	1	*2*	*3*	*4*	*5*		
System security	-	-	2.48	9.32	88.2	4.86	1
Faster execution	-	-	3.73	22.98	73.29	4.70	3
Low brokerage cost	-	-	12.42	23.6	63.98	4.52	8
Loyalty rewards	1.24	6.21	19.88	24.84	47.83	4.12	13
Technical support	0.62	-	6.21	24.22	68.94	4.61	6
Research reports	-	2.48	9.32	27.95	60.25	4.46	9
Technical analysis tools	-	1.86	9.94	22.36	65.84	4.52	7
Company fundamentals information	-	1.24	5.59	18.63	74.53	4.66	4
Robo-advisor features	2.48	5.59	24.84	34.78	32.3	3.89	15
User-friendly interface	-	0.62	3.11	18.01	78.26	4.74	2
Online fund transfer facilities	-	0.62	5.59	20.5	73.29	4.66	4
More financial products available (e.g. foreign stocks, crypto)	1.24	8.7	15.53	32.3	42.24	4.06	14
In-house software supports	-	3.11	18.63	34.78	43.48	4.19	11
Online support (e.g. live chat)	-	3.73	7.45	32.3	56.52	4.42	10
Built-in online community	-	2.48	20.5	32.92	44.1	4.19	11

2) Measurement model analysis

This study conducts several tests to validate and ensure the measurement model's reliability for the investigated constructs so that the model's compatibility with the collected data can be determined. Parameters related to the constructs were measured using a reflective model. The PLS method was computed to assess various measures including convergent validation, indicator reliability, internal consistency, AVE, and discriminant validation, adhering to the Rule of Thumb for evaluating measurement models [15].

The study examined every loading of the items in order to assess the indicator reliability. Due to low factor loadings (<0.70), three items (FC1, FC3, and FC4) from the initial test were excluded from the analysis. The test was then repeated until the results were satisfactory, as shown in Table 3. It is essential to consider Composite Reliability (CR) and Cronbach's Alpha (CA) to ascertain the actual reliability of the model. Table 3 clearly indicates that all the CRs and CAs surpassed the permissible limit of 0.70 [17]. Another finding in Table 3 shows that convergent validity was deemed acceptable as all factor loadings exceed the criterion of 0.70 and the AVE satisfies the 0.50 threshold.

Table 3. Measurement model analysis results

Constructs	***Items***	***Factor Loadings***	***Cronbach's Alpha (CA) (>0.7)***	***Composite Reliability (CR) (>0.7)***	***Average Variance Extracted (AVE) (>0.5)***
Behavioral Intention	BI1	0.918	0.891	0.932	0.821
	BI2	0.888			
	BI3	0.913			
Effort Expectancy	EE1	0.904	0.906	0.934	0.780
	EE2	0.896			
	EE3	0.876			
	EE4	0.857			
Facilitating Conditions	FC2	1.000			
Habit	HB1	0.869	0.748	0.855	0.664
	HB2	0.781			
	HB3	0.791			
Hedonic Motivation	HM1	0.906	0.812	0.887	0.725
	HM2	0.790			
	HM3	0.854			
Performance Expectancy	PE1	0.844	0.855	0.903	0.699
	PE2	0.878			
	PE3	0.872			
	PE4	0.744			
Price Value	PV1	0.855	0.869	0.911	0.718
	PV2	0.869			
	PV3	0.858			
	PV4	0.808			
Social Influence	SI1	0.787	0.798	0.867	0.620
	SI2	0.823			
	SI3	0.748			
	SI4	0.790			
Usage Behavior	UB1	0.915	0.838	0.903	0.757
	UB2	0.914			
	UB3	0.774			

Turning now to the approach of discriminant validation by involving the cross-loadings along with the Fornell-Larcker criterion [18], [19]. The outer loading technique is a useful tool for managing cross-loading in PLS-SEM. The cross-loading estimation results for this test revealed that the item correlation value of the construct is greater than that of the other constructs (Table 4). The calculation of the Fornell-Larcker criterion involves analyzing the correlation between each factor and all other factors in the model, as well as the square root of the AVE ($\sqrt{\text{AVE}}$) for each factor. Provided that the $\sqrt{\text{AVE}}$ exceeds the correlation, then the discriminant validity is validated. Since the coefficients of the $\sqrt{\text{AVE}}$ correlation surpass all coefficients in the corresponding column and row of each construct, the Fornell-Larcker evaluation confirms the achievement of discriminant validity (Table 5). The test findings demonstrate that all constructs have passed the discriminant validity.

Table 4. Outcomes of cross-loading test

	BI	EE	FC	HB	HM	PE	PV	SI	UB
BI1	**0.918**	0.590	0.459	0.630	0.572	0.623	0.455	0.306	0.611
BI2	**0.888**	0.443	0.289	0.599	0.461	0.587	0.396	0.370	0.546
BI3	**0.913**	0.555	0.397	0.690	0.510	0.560	0.461	0.362	0.679
EE1	0.499	**0.904**	0.521	0.431	0.531	0.453	0.463	0.165	0.402
EE2	0.480	**0.896**	0.439	0.338	0.472	0.427	0.470	0.123	0.332
EE3	0.563	**0.876**	0.501	0.377	0.490	0.626	0.473	0.158	0.429
EE4	0.523	**0.857**	0.603	0.475	0.487	0.493	0.492	0.182	0.463
FC2	0.424	0.586	**1.000**	0.454	0.499	0.471	0.409	0.127	0.398
HB1	0.681	0.531	0.497	**0.869**	0.591	0.526	0.406	0.401	0.740
HB2	0.405	0.335	0.279	**0.781**	0.364	0.296	0.276	0.275	0.590
HB3	0.607	0.222	0.298	**0.791**	0.370	0.440	0.246	0.377	0.544
HM1	0.533	0.501	0.449	0.554	**0.906**	0.496	0.433	0.411	0.530
HM2	0.359	0.422	0.364	0.400	**0.790**	0.361	0.408	0.302	0.475
HM3	0.529	0.500	0.451	0.453	**0.854**	0.395	0.460	0.381	0.428
PE1	0.571	0.449	0.399	0.428	0.403	**0.844**	0.288	0.143	0.356
PE2	0.533	0.525	0.438	0.378	0.401	**0.878**	0.409	0.058	0.394
PE3	0.555	0.489	0.420	0.435	0.416	**0.872**	0.375	0.081	0.466
PE4	0.512	0.449	0.313	0.535	0.437	**0.744**	0.288	0.215	0.440
PV1	0.421	0.449	0.372	0.372	0.395	0.360	**0.855**	0.328	0.358
PV2	0.368	0.499	0.425	0.310	0.479	0.370	**0.869**	0.211	0.293
PV3	0.413	0.447	0.303	0.293	0.380	0.353	**0.858**	0.192	0.283
PV4	0.431	0.430	0.294	0.335	0.473	0.299	**0.808**	0.355	0.416
SI1	0.258	0.093	0.012	0.278	0.233	0.080	0.147	**0.787**	0.317
SI2	0.290	0.065	0.031	0.339	0.291	0.088	0.238	**0.823**	0.371
SI3	0.259	0.107	-0.036	0.254	0.331	0.059	0.222	**0.748**	0.308
SI4	0.368	0.259	0.312	0.459	0.467	0.204	0.368	**0.790**	0.476
UB1	0.710	0.487	0.424	0.747	0.534	0.538	0.412	0.461	**0.915**
UB2	0.579	0.436	0.397	0.677	0.530	0.415	0.374	0.356	**0.914**
UB3	0.453	0.257	0.186	0.585	0.375	0.311	0.242	0.440	**0.774**

Table 5. Outcomes of Fornell-Larcker score

	BI	EE	FC	HB	HM	PE	PV	SI	UB
BI	0.906								
EE	0.587	0.883							
FC	0.424	0.586	1.000						
HB	0.708	0.460	0.454	0.815					
HM	0.569	0.561	0.499	0.557	0.851				
PE	0.650	0.572	0.471	0.530	0.495	0.836			
PV	0.484	0.538	0.409	0.388	0.509	0.407	0.848		
SI	0.381	0.179	0.127	0.437	0.434	0.148	0.324	0.788	
UB	0.678	0.463	0.398	0.775	0.557	0.495	0.401	0.479	0.870

3) Structural model analysis

There are several ways to test the overall model fit in PLS-SEM analysis, including goodness-of-fit measures such as the R-squared values, Q-squared values, and the average path coefficient values [15]. Using these measures, researchers can determine the model's capacity to clarify the data and predict outcomes. The Goodness-of-Fit measure (R2 or R-squared) demonstrates the predictive ability of the model and the collective impact of exogenous latent variables on the endogenous [15]. The R2 values of this model are 0.656 and 0.635 (Table 6), indicating that the factors can account for 65.6% of the variability in mobile investment app behavior intention and 63.5% of the variability in usage behavior respectively. Q square is a metric of the ability of any change in factors outside or inside of a system to predict the variables within the system. When Q2 equals one, a model is said to be perfect—that is, to mirror reality. Given that Q2 values satisfied the criterion (>0.50), the results demonstrate the structural model's high predictive significance [17].

Table 6. Model fit results

Variable	*R2*	*Q2*
BI	0.656	0.616
UB	0.635	0.613

Further analysis of the data reveals the path coefficient and tests the relationships by performing the bootstrapping process on SmartPLS software. Better statistical power is offered when examining the path coefficients and associated t-statistics using this bootstrapping method. Table 7 reports the assessment analysis results while Figure 2 depicts the structural model which illustrates the influence of certain factors on behavior intention.

Table 7. Structural model analysis output

	Primary Sample (O)	Mean Score (M)	Standard Deviation (STDEV)	T-statistics (|O/STDEV|)
BI→UB	0.255	0.251	0.068	3.757
EE→BI	0.192	0.189	0.073	2.637
FC→ BI	-0.079	-0.079	0.069	1.140
FC→UB	0.025	0.022	0.058	0.427
HB→BI	0.400	0.399	0.066	6.067
HB→UB	0.584	0.589	0.065	8.973
HM→BI	0.051	0.053	0.066	0.773
PE→BI	0.293	0.295	0.065	4.478
PV→BI	0.083	0.083	0.059	1.427
SI→BI	0.090	0.091	0.051	1.764

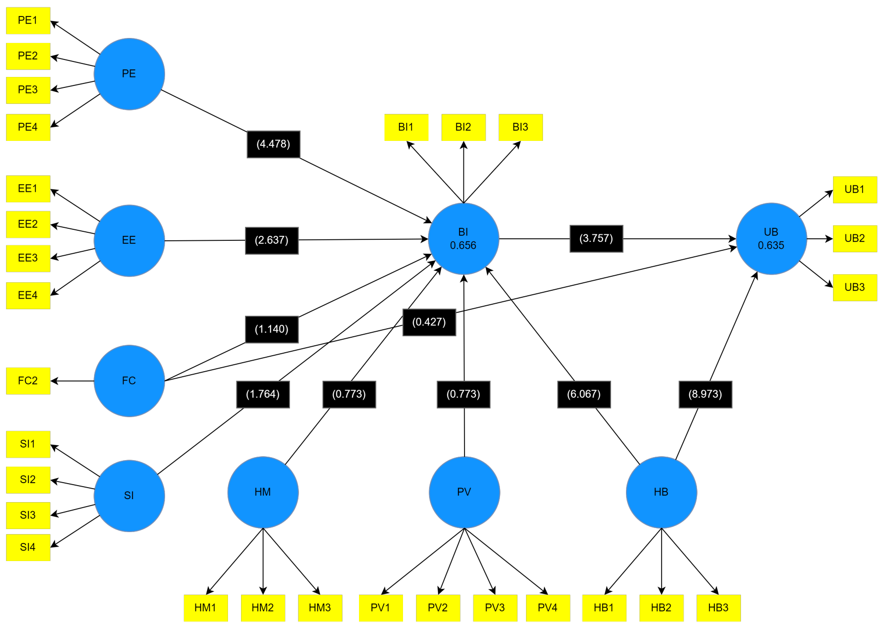

Figure 2. The structural model results

4) Hypothesis test

The hypothesis testing results using structural equation modeling with the smartPLS software are presented in Table 8. A t-statistic value over 1.96 points out the existence of a significant path coefficient when a two-tailed t-test at a 5% significance level is used, and the p-values below 0.05 show that the hypothesis is supported [20].

Table 8. Hypotheses testing results

Hypothesis	*Factors*	*T-statistics*	*P-value*	*Result*
H1	PE → BI	4.478	0.000	Supported
H2	EE → BI	2.637	0.008	Supported
H3	SI → BI	1.764	0.078	Unsupported
H4	FC → BI	1.140	0.255	Unsupported
H5	FC → UB	0.427	0.670	Unsupported
H6	HM → BI	0.773	0.439	Unsupported
H7	PV → BI	1.427	0.154	Unsupported
H8	HB → BI	6.067	0.000	Supported
H9	HB → UB	8.973	0.000	Supported
H10	BI → UB	3.757	0.000	Supported

The testing results suggest that of the ten proposed hypotheses, only five (H1, H2, H8, H9, and H10) are supported, while the remaining five hypotheses (H3, H4, H5, H6, and H7) are rejected. According to the data, effort expectancy, performance expectancy, and habit are highly correlated with mobile investment intention in Indonesia. Habit was found to be the most influential factor (T-statistic = 8.973), followed by performance expectation (T-statistic = 4.478) and effort expectancy (T-statistic = 2.637). On the other hand, facilitating condition was negatively related to mobile investment intention in Indonesia and was considered the least significant factor.

D. Conclusion

To summarize, this study set out to determine the key factors driving and influencing interest in mobile investment applications for users in Indonesia. Analysis of the study's results shows that habit was shown to have a major effect on the behavioral intention of using mobile investing, trailed by the expectancy factors of performance and effort. The structural model explained 65.6% of the variance in mobile investment intention. The fact these factors emerge as influential factors toward behavioral intention suggests a potential synergy. Users who have developed a habit of using the mobile investment application likely do so because they perceive it as beneficial and valuable. This positive perception, combined with the habitual use, contributes significantly to their intention to continue using the application. Other findings in this study show that habit and behavioral intention influence how mobile investment applications are used while facilitating conditions negatively impacting the desire to invest through mobile devices.

The results of this study offer several practical recommendations for stakeholders involved with mobile investment applications. Firstly, enterprise managers need to recognize the significant role that habit plays in influencing user behavior intentions. By encouraging the regular and repeated use of their mobile investment app, they can foster the development of positive usage habits among users. It's crucial to integrate features that seamlessly incorporate the app into the users' routine financial activities, thereby making it an indispensable tool.

Implementing incentive mechanisms for users who consistently engage with the mobile investment app can also be highly beneficial. Whether through loyalty programs, cashback, or providing exclusive access to certain app features, these incentives can motivate users to develop a routine of using the app, reinforcing their positive behavioral intentions and fostering sustained engagement.

However, this research has various limitations that future studies should acknowledge and tackle in addressing associated concerns. A critical limitation is the sample size used in the study; to achieve a more accurate representation of the investor community, it is essential to conduct surveys with a significantly larger number of respondents. This expansion in sample size would enhance the reliability and generalizability of the findings.

Lastly, it's important to acknowledge that the variables considered in this study accounted for only 65.6% of the variance in intentions to use mobile investment applications. This indicates that there are remaining 34.4% other possible significant factors, such as user satisfaction, perceived benefits, and financial literacy, that could influence behavioral intentions. Future research should therefore extend its scope to include these variables to provide a more comprehensive understanding of what drives users towards mobile investment applications.

E. References

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