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ANALYSIS OF FACTORS INFLUENCING USER INTEREST IN ADOPTING FINTECH ROBO-ADVISOR IN INDONESIA USING UTAUT 2

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ABSTRACT

In Indonesia, robo-advisors were introduced around 2017, driven by the increasing penetration of internet usage and the adoption of digital technology in the financial sector. The use of robo-advisors grew significantly during the pandemic, as retail investors sought convenient ways to invest without the need for in-person meetings. Several fintech companies, including Bareksa, Bibit, and Moduit, offer wealth management services utilizing robo-advisor technology. While the total *Assets Under Management* (*AUM*) in Indonesia have increased, the growth rate of *AUM* has declined, which may indicate reduced new investment inflows. This study examines the factors influencing users' intention to adopt fintech robo-advisor services in Indonesia, using the *Unified Theory of Acceptance and Use of Technology* (*UTAUT 2*) framework. The research is a quantitative descriptive study focusing on individuals in Indonesia who have used robo-advisor services via Bibit, Bareksa, or Moduit. Using purposive sampling, the study surveyed 150 respondents, with data analyzed through *Partial Least Squares-Structural Equation Modeling* (*PLS-SEM*). The study finds that all independent variables—performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit—significantly influence the adoption of fintech robo-advisors. Moreover, age, gender, and experience were identified as moderating factors. The strongest predictors of behavioral intention were performance expectancy, habit, and hedonic motivation, while habit, behavioral intention, and facilitating conditions were key drivers of use behavior. The study concludes that all factors significantly affect the adoption of fintech robo-advisors in Indonesia, and recommends that fintech companies leverage these findings to improve their features, communication strategies, and digital financial literacy initiatives.

Keywords: *Robo-advisor, Fintech, UTAUT 2*

INTRODUCTION

The presence of fintech has transformed consumer expectations and preferences regarding the use of technology, particularly by enabling financial services that are easier and faster to access via electronic devices, thereby elevating user expectations (Vučinić, 2020). The existence of fintech can positively influence financial stability by fostering a financial system with more diverse activities, greater efficiency in terms of cost and time, and enhanced transparency (Financial Stability Board, 2024). Fintech represents an innovation in financial services that leverages technology to create new business models, processes, and products, all of which have significant impacts on financial markets, service provision, and financial institutions (Financial Stability Board, 2024). Technological advancements are a key driver in the development of fintech .

Fintech has been adopted across various financial services, including payments, lending, insurance, and investment activities, all utilizing technology. *Peer-to-peer* (*P2P*) lending, crowdfunding, payment gateways, investment risk management (*robo-advisor*), and market aggregators are types of fintech that are rapidly growing in Indonesia (Indonesian Fintech Funding Association, 2024). Fintech-driven investment and wealth management emerged from technological advancements that facilitate access to more efficient and affordable financial services. Fintech-based wealth management employs *big data analytics* and *artificial intelligence* to deliver personalized services. The *robo-advisor*, a technology that originated in the United States in 2008, was pioneered by fintech companies such as Betterment and Wealthfront, which introduced automated investment advisory services offering more cost-effective solutions than traditional financial advisors (Nuraeni & Nababan, 2021a; Putri & Santosa, 2022; Siregar et al., 2020).

Investment is essential as it enables the strategic allocation of current resources to generate future growth and financial security (Sutopo & Salija, 2020). A straightforward way to protect funds from inflation is through investment; over the past two decades, Indonesia has experienced an average inflation rate of approximately 5.37% per year, meaning the real value of IDR 1 billion would decrease to around IDR 543,478,260—a depreciation of about 45.7% (Digibank, 2024). Furthermore, investing remains a prudent long-term strategy for wealth accumulation due to its potential to generate higher returns over time (SEC, 2024).

Currently, investment activities are considered more accessible to the public, as they can be conducted online through the adoption of fintech *robo-advisors*. One of the main factors supporting fintech development is technological advancement (Rahadian et al., 2025). However, despite the ease of use and widespread awareness of the benefits of fintech *robo-advisors*, some individuals still opt not to use this AI-powered investment tool (Jackson & Allen, 2024). According to a report by the Financial Services Authority (*OJK*), the total value of *assets under management* (*AUM*) of investment managers in Indonesia decreased by 3.71% year-to-date (*ytd*) to IDR 811.97 trillion as of March 27, 2025 (Bloomberg, 2025).

Based on available data, the *AUM* for the *robo-advisor* market in Indonesia is projected to reach US$8.22 billion by 2024, with a compound annual growth rate (*CAGR*) of 1.51% for the period 2024–2028 (Statista, 2024). However, a significant decline in the *AUM* growth rate occurred in 2020, with a decrease of 142.74% from the previous year, and this downward trend is expected to continue until 2028 (Statista, 2024). This suggests that, although the market continues to expand in size, the pace of investment inflows is slowing considerably.

This decline in growth momentum may reflect reduced investor confidence or market saturation. Supporting this interpretation, a survey on *robo-advisor* usage in Indonesia in 2023 showed a 15% increase in usage frequency among existing users, but in 2024, there was a decline in the frequency of new user adoption (Romero, 2024). These findings highlight a decrease in user interest in *robo-advisor* platforms, even as the overall market continues to grow.

A decline in *AUM* growth can result from falling market prices due to poor market performance or from reduced new investment inflows, as indicated by a declining number of investors (Novianus, 2024). One of the primary triggers for reduced new investment is investor skepticism regarding the investment advice provided by *robo-advisors* (Nguyen, Chew, Muthaiyah, Teh, & Ong, 2023). The skepticism users experience towards adopting new technologies requires further analysis, as previous studies have shown that the adoption of financial technology is influenced by variables such as trust, personal innovativeness, perceived ease of use, and perceived benefits (Solarz & Adamek, 2023).

In Indonesia, *robo-advisors* were first introduced around 2017, driven by increasing internet penetration and the adoption of digital technologies in the financial sector. The use of *robo-advisors* in Indonesia surged during the pandemic, as many retail investors sought convenient investment solutions without in-person meetings. Bareksa, Bibit, and Moduit are among the local fintech companies integrating *robo-advisors* into their mutual fund investment services, leveraging *artificial intelligence* to provide trusted and transparent investment recommendations based on user risk profiles (Alam & Achjari, 2024).

According to the Annual Member Survey 2022/2023 conducted by the Katadata Insight Center (*KIC*) and the Indonesian Fintech Association (*AFTECH*), Java Island, particularly Jakarta (88%), is the primary market for fintech companies in Indonesia, as shown in Chart 1.1 Main Markets of Fintech Companies in Indonesia by Region (Q2-2022) (Muhamad, 2023). As of 2024, 45% of primary fintech users are individuals, an increase from 42.7% in 2022/2023, compared to other segments such as large companies and micro businesses. A more comprehensive comparison of primary fintech user segments is presented in Figure 1.2 Main Users of Fintech Services by Segment (2023 vs 2024). The dominant fintech service in Indonesia is *P2P* lending, accounting for 55% of the market, as indicated by the 97 companies licensed by the OJK (Financial Services Authority, 2024). Other fintech services include market aggregators (21%), payment gateways (12%), crowdfunding (10%), and *robo-advisors* (2%), with 36 market aggregator companies (Kompasiana, 2024), 21 payment gateway companies (Indonesian Payment Gateway Association, 2024), 17 crowdfunding companies (Kontan, 2023), and 4 companies adopting *robo-advisors* (Financial Services Authority, 2024), as depicted in Figure 1.3 Types of Fintech Services in Indonesia.

Provisions regarding *robo-advisor* technology are outlined in the Financial Services Authority Regulation (*POJK*) Number 13 of 2018 concerning Digital Financial Innovation in the Financial Services Sector. The regulation specifies that the scope of digital financial innovation includes services such as *robo-advisors*. Additionally, Financial Services Authority Regulation No. 77 of 2016 concerning Information Technology-Based Money Lending Services defines *robo-advisor* as an information technology-based investment management service that provides automated portfolio management using algorithms to assist investors in managing finances and investments without human investment managers.

The decline in the *AUM* growth rate, which dropped by 142.74% in 2020 and is predicted to continue declining until 2028 (Statista, 2024), aligns with survey findings indicating a 15% increase in *robo-advisor* usage frequency in 2023, followed by a 15% decrease in 2024 (Romero, 2024). The decline in *AUM* growth can be attributed to several factors, including reduced new investment inflows due to a shrinking investor base, which may result from losses caused by declining market prices or poor performance (Novianus, 2024). Additionally, skepticism about the investment advice provided by *robo-advisors* can deter new investment flows (Nguyen et al., 2023).

Previous research has shown that the adoption of digital financial services is influenced by factors such as trust, personal innovativeness, perceived ease of use, and perceived benefits (Solarz & Adamek, 2023). The adoption of digital financial services can be analyzed using various theories. One is the *Innovation Diffusion Theory* (*IDT*), which posits that user adoption of innovations is driven by innovation characteristics, adopter types, communication channels, social systems, and time, providing a technical perspective on innovation adoption (Attié & Waarden, 2022). Another is the *Theory of Reasoned Action* (*TRA*), which explains that user behavior in adopting technology is predicted by intention, influenced by user attitudes and subjective norms (Setiawan et al., 2021). TRA was further developed into the *Theory of Planned Behavior* (*TPB*), which adds behavioral control as a variable (Leniwati, Brilyan, & Wahyuni, 2021). The *Technology Acceptance Model* (*TAM*), an extension of TRA, identifies perceived usefulness and perceived ease of use as key factors influencing attitudes, intention, and actual use (Zhang, Pentina, & Fan, 2021).

The updated *Unified Theory of Acceptance and Use of Technology* (*UTAUT*) includes four independent variables—performance expectancy, effort expectancy, social influence, and facilitating conditions—along with two dependent variables. The latest model, *UTAUT 2*, published in 2012, adds habit, price value, and hedonic motivation as additional factors (Tamilmani et al., 2021). Previous studies using *UTAUT 2* have shown that performance expectancy, effort expectancy, social influence, habit, price value, and facilitating conditions significantly affect users' intention to use fintech services (Amnas, Selvam, & Raja, 2023). Further research indicates that effort expectancy, social influence, facilitating conditions, perceived trust, perceived risk, and habit have significant relationships with behavioral intention, while performance expectancy, hedonic motivation, and price value may not (Hidayat, Aini, & Fetrina, 2020). In Malaysia, research found that performance expectancy, social influence, hedonic motivation, price value, and trust significantly affected behavioral intention to use *robo-advisor* services, while effort expectancy and facilitating conditions did not (Kuah, Chow, & Genevieve, 2024).

Therefore, this study aims to analyze the factors influencing users' interest in adopting fintech *robo-advisors* in Indonesia using the *UTAUT 2* theory. The use of the *UTAUT 2* model allows researchers to examine the influence of seven factors—performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit—on users' behavioral intention and use behavior in adopting *robo-advisors*, with age, gender, and experience as moderating variables. The analysis employs the *Partial Least Squares – Structural Equation Modeling* (*PLS-SEM*) technique to test relationships among multiple variables both partially and simultaneously.

METHOD

The type of research conducted is research with a verifiable descriptive approach with a quantitative approach. The approach is in line with the purpose of the study, which is to provide an overview through the results of the analysis of factors that affect users' interest in adopting fintech robo-advisors in Indonesia using

UTAUT 2 in a systematic and measurable manner. The research criteria are as shown in Table 1 Research Criteria.

Table 1. Research Criteria

No.	Research Criteria	Kind
1	Research Objectives	Studi Hypothesis
2	Types of Investigations	Causal
3	Researcher Intervention	At least
4	Study Situation	*Noncontrived*
5	Study Time Horizon	*Cross Sectional*
6	Unit of Analysis	Individuals who adopt *robo-advisor services* on Bibit, Bareksa, and/or Moduit applications in Indonesia.
7	Research Methodology	Quantitative
8	Research Strategy	Questionnaire

Source: processed data

Furthermore, data analysis is carried out using statistical methods to ensure that the research results are measurable, objective, and can provide clear information about the variables being studied. The population in this study is individuals in Indonesia who have used robo-advisor services on the Bibit, Bareksa, and/or Moduit platforms. It is recorded that until 2024, the number of Bibit users will be 5 million users (Ibrahim, 2024). In 2020, Bareksa was used by around 20.9% of investment platform users in Indonesia (Rahardyan, 2020). It is recorded that until 2023, Moduit has several more than 40 thousand users (Hamdhi & Rahmawati, 2023). However, the exact number of this population is unknown because there is no official data that records all robo-advisor users in Indonesia. The sample from the study was users of robo-advisor services in Indonesia who met the predetermined criteria. Purposive sampling used in the study is a type of nonprobability sampling that is commonly used in studies with a very large population. In this study, the sample criteria are users of robo-advisor services on the Bibit, Bareksa and/or Moduit platforms in Indonesia who are domiciled in Jakarta with the consideration that the main market for fintech companies in Indonesia is in Jakarta. Therefore, the research focuses on users who can be reached through specific platforms, social media, or relevant communications. Thus, this study is considered to be able to represent the population that is the object of the research, although the total population cannot be determined.

RESULTS AND DISCUSSION

Reviews Outer Model

Convergent Validity Test

The results of the research test were carried out on a total of 150 respondents. Based on the results of the convergent validity test on the SmartPLS application seen through the loading factor value and the average variance extracted (AVE) value, the loading factor value for each indicator was >0.6 (shown in Table 2 Loading Factor Value). For example, the loading factor values for the Behavioral Intention variable for all of its indicators have the following values, 0.919, 0.929, and 0.953. More details can be seen in the following table:

Table 2. Value Loading Factor

Information	*Loading Factor* Value
Age <- Age (Z1)	1,000
BI1 <- Behavioral Intention (Y1)	0,919
BI2 <- Behavioral Intention (Y1)	0,929
BI3 <- Behavioral Intention (Y1)	0,953
EE1 <- Effort Expectancy (X2)	0,923
EE2 <- Effort Expectancy (X2)	0,929
EE3 <- Effort Expectancy (X2)	0,917
EE4 <- Effort Expectancy (X2)	0,934
Experience <- Experience (Z3)	1,000
FC1 <- Facilitating Conditions (X4)	0,896
FC2 <- Facilitating Conditions (X4)	0,875
FC3 <- Facilitating Conditions (X4)	0,917

Information	*Loading Factor* Value
FC4 <- Facilitating Conditions (X4)	0,886
Gender <- Gender (Z2)	1,000
H1 <- Habit (X7)	0,935
H2 <- Habit (X7)	0,907
H3 <- Habit (X7)	0,933
HM1 <- Hedonic Motivation (X5)	0,941
HM2 <- Hedonic Motivation (X5)	0,952
HM3 <- Hedonic Motivation (X5)	0,953
PE1 <- Performance Expectancy (X1)	0,920
PE2 <- Performance Expectancy (X1)	0,881
PE3 <- Performance Expectancy (X1)	0,874
PE4 <- Performance Expectancy (X1)	0,915
PV1 <- Price Value (X6)	0,920
PV2 <- Price Value (X6)	0,950
PV3 <- Price Value (X6)	0,940
SI1 <- Social Influence (X3)	0,940
SI2 <- Social Influence (X3)	0,934
SI3 <- Social Influence (X3)	0,937
UB1 <- Use Behavior (Y2)	1,000

Source: SmartPLS

The AVE value (shown in Table 3 AVE Value) for each variable is >0.5. The AVE value of the Performance Expectancy (X1) variable was 0.806, the Effort Expectancy (X2) variable was 0.858, the Social Influence (X3) variable was 0.878, the Facilitating Conditions (X4) variable was 0.799, the Hedonic Motivation (X5) variable was 0.900, the Price Value (X6) was 0.877, Habit (X7) was 0.856, and the Behavioral Intention (Y1) variable was 0.871.

This proves that all research indicators have valid values through convergent validity tests. So it can be concluded that all indicators of research variables have valid values.

Table 3. AVE Values

Information	*Average Variance Extracted* (AVE)
Performance Expectancy (X1)	0,806
Effort Expectancy (X2)	0,858
Social Influence (X3)	0,878
Facilitating Conditions (X4)	0,799
Hedonic Motivation (X5)	0,900
Price Value (X6)	0,877
Habit (X7)	0,856
Behavioral Intention (Y1)	0,871

Source: SmartPLS

Discriminating Validity Test

The discriminant validity test was carried out by looking at the cross-loading value and the Fornell Larcker value. The test results are as shown through Table 4 Cross Loading Values.

It is known through Table 4 Cross Loading Values, the loading factor value for each variable indicator is greater than the loading factor value of the variable indicator in other variables. For example, the loading factor values of the behavioral intention indicators, namely B1, B2, and B3 are 0.919, 0.929, and 0.953, where these values have the largest value when they are in the variable, namely the "Behavioral Intention (Y1)" column. This is in line with all indicators for each study variable where Effort Expectancy (X2), with the variable indicators EE1, EE2, EE3, and EE4 have values of 0.923, 0.929, 0.917, and 0.934. The Facilitating Conditions (X4) variable, with the indicators of the variables FC1, FC2, FC3, and FC4 has values of 0.896, 0.875, 0.917, and 0.886. As well as other variables as stated in the following table:

Table 4. Cross Loading Values

	Age (Z1)	**Behavioral Intention (Y1)**	**Effort Expectancy (X2)**	**Experience (Z3)**	**Facilitating Conditions (X4)**	**Gender (Z2)**	**Habit (X7)**	**Hedonic Motivation (X5)**	**Performance Expectancy (X1)**	**Price Value (X6)**	**Social Influence (X3)**	**Use Behavior (Y2)**
Age	**1,000**	-0,302	-0,537	-0,250	-0,426	0,072	-0,314	-0,323	-0,366	-0,244	-0,403	-0,258
BI1	-0,335	**0,919**	0,724	0,642	0,740	0,101	0,800	0,662	0,749	0,683	0,712	0,802
BI2	-0,313	**0,929**	0,674	0,627	0,703	0,200	0,836	0,643	0,737	0,652	0,685	0,777
BI3	-0,201	**0,953**	0,632	0,619	0,695	0,182	0,818	0,681	0,723	0,687	0,682	0,848
EE1	-0,541	0,651	**0,923**	0,569	0,701	0,067	0,691	0,583	0,689	0,564	0,629	0,594
EE2	-0,452	0,671	**0,929**	0,601	0,768	0,108	0,719	0,673	0,777	0,635	0,650	0,646
EE3	-0,486	0,654	**0,917**	0,562	0,810	-0,007	0,669	0,636	0,733	0,645	0,643	0,614
EE4	-0,512	0,705	**0,934**	0,606	0,778	0,087	0,754	0,635	0,753	0,634	0,671	0,632
Experience	-0,250	0,674	0,632	**1,000**	0,597	0,114	0,673	0,564	0,703	0,601	0,600	0,615
FC1	-0,384	0,665	0,696	0,485	**0,896**	0,003	0,613	0,739	0,770	0,744	0,615	0,659
FC2	-0,423	0,678	0,802	0,578	**0,875**	0,022	0,715	0,669	0,696	0,578	0,685	0,600
FC3	-0,291	0,691	0,707	0,542	**0,917**	0,063	0,649	0,737	0,769	0,732	0,630	0,707
FC4	-0,432	0,695	0,751	0,532	**0,886**	0,028	0,736	0,676	0,686	0,628	0,719	0,612
Gender	0,072	0,172	0,069	0,114	0,033	**1,000**	0,151	0,062	0,040	0,081	0,045	0,181
H1	-0,306	0,838	0,723	0,671	0,794	0,127	**0,935**	0,755	0,777	0,750	0,712	0,836
H2	-0,246	0,735	0,717	0,599	0,659	0,158	**0,907**	0,608	0,700	0,588	0,655	0,658
H3	-0,313	0,850	0,688	0,596	0,641	0,138	**0,933**	0,626	0,656	0,585	0,703	0,745
HM1	-0,332	0,651	0,669	0,518	0,762	0,023	0,643	**0,941**	0,737	0,710	0,659	0,662
HM2	-0,299	0,666	0,639	0,540	0,743	0,079	0,692	**0,952**	0,762	0,742	0,644	0,693
HM3	-0,291	0,700	0,635	0,548	0,743	0,073	0,712	**0,953**	0,764	0,717	0,684	0,700
PE2	-0,319	0,695	0,698	0,597	0,706	-0,021	0,670	0,751	**0,881**	0,760	0,550	0,680
PE3	-0,372	0,670	0,731	0,642	0,765	0,094	0,674	0,685	**0,874**	0,637	0,683	0,619
PE4	-0,300	0,768	0,716	0,663	0,756	0,046	0,770	0,736	**0,915**	0,737	0,664	0,718
PV1	-0,211	0,652	0,589	0,506	0,664	0,091	0,609	0,680	0,694	**0,920**	0,484	0,649
PV2	-0,216	0,686	0,640	0,568	0,730	0,086	0,663	0,719	0,737	**0,950**	0,582	0,692
PV3	-0,258	0,691	0,650	0,613	0,717	0,053	0,684	0,741	0,787	**0,940**	0,583	0,694
SI1	-0,424	0,680	0,666	0,561	0,702	0,062	0,693	0,675	0,678	0,527	**0,940**	0,616
SI2	-0,313	0,685	0,618	0,557	0,678	0,029	0,694	0,641	0,634	0,566	**0,934**	0,640
SI3	-0,395	0,720	0,683	0,569	0,698	0,035	0,712	0,648	0,679	0,559	**0,937**	0,609
UB1	-0,258	0,867	0,671	0,615	0,722	0,181	0,812	0,722	0,737	0,724	0,663	**1,000**
PE1	-0,331	0,692	0,721	0,622	0,710	0,028	0,644	0,682	**0,920**	0,698	0,646	0,624

Source: SmartPLS

Furthermore, the fornell-lacker value is considered valid if the top value of each column is greater than all the columns below it. For example, the value of the variable Effort Expectancy (X2) has a value of 0.926 and the value of the variable Performance Expectancy (X1) has a value of 0.898, as well as the value of other variables. Based on the test results, all values of each research variable are valid. So that the results show that all variables are valid and pass the discriminant validity test.

Reliability Test

The reliability test is seen through the composite reliability value and cronbach's alpha value in Table 5 Reliability Test Results, where the rule of thumb composite reliability for each variable is >0.7 to be considered reliable. As for Cronbach's alpha value, it is considered reliable for each dependent variable if the value is >0.7, although a value of 0.6 is still acceptable. Based on the test results, it is known that all composite reliability and Cronbach's alpha values have a value of >0.7. For example, the variable value of Performance Expectancy (X1) is 0.920 and the value of Effort Expectancy (X2) is value 0.945, where both values are valued >0.7 each. This is also achieved by all research variables as presented in the table. The data passed the reliability test.

Table 5. Reliability Test Results

Information	**Cronbach's alpha**	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**
Performance Expectancy (X1)	0,920	0,923	0,943
Effort Expectancy (X2)	0,945	0,946	0,960
Social Influence (X3)	0,931	0,931	0,956
Facilitating Conditions (X4)	0,916	0,917	0,941
Hedonic Motivation (X5)	0,944	0,946	0,964

Information	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
Price Value (X6)	0,930	0,931	0,956
Habit (X7)	0,916	0,923	0,947
Behavioral Intention (Y1)	0,926	0,927	0,953

Source: SmartPLS

Analyzes Inner Model

R-squared (R^2) Test

The results of the R^2 test are shown in Table 6 of the R-Squared Test Results, where the table shows that the R^2 values for the variables "Behavioral Intention (Y1)" and the variable "Use Behavior (Y2)" are 0.848 and 0.786 which indicates that the two variables referred to in the study can be well explained by the dependent variables in the study. The two values show a strong relationship, considering that if R^2 is closer to 1, then it means that the better the model is in explaining the dependent variable. Or in this study, it can be concluded that the ability of the independent variable in this study to explain the variable "Behavioral Intention (Y1)" is 84.4%. Meanwhile, the ability of independent variables in this study to explain "Use Behavior (Y2)" was 78.6%. Furthermore, for moderation variables such as Age (Z1), Gender (X2), and Experience (Z3) relative had lower R^2 values, namely 0.197, 0.040, and 0.474. This is due to the role of these variables in the moderation effect. In particular, the relatively high R^2 value in Experience (Z3) of 0.474 indicates that user experience has a greater contribution as a moderation variable, where it can strengthen or weaken the relationship between the main constructs. The rest are influenced and explained by other variables outside of this study.

Table 6. R-Squared Test Results

Information	*R-square*	*R-square adjusted*
Behavioral Intention (Y1)	0,820	0,807
Use Behavior (Y2)	0,770	0,761
Age (Z1)	0,197	0,175
Gender (Z2)	0,040	0,013
Experience (Z3)	0,474	0,463

Source: SmartPLS

Predictive Relevance (Q^2) Test

The results of the Q^2 test are shown in Table 4.43 of the Q^2 test results. The Q^2 values for the variables "Behavioral Intention (Y1)" and "Use Behavior (Y2)" were 0.690 and 0.725, while the Q^2 values for the variables "Age (Z1)", "Gender (Z2)", "Experience (X3)", were 0.167, 0.003, and 0.456. The results show the entire value of Q^2>0, which shows the model has predictive relance. Thus, it can be concluded that the variables "Behavioral Intention (Y1)", "Use Behavior (Y2)", "Age (Z1)", "Gender (Z2)", and "Experience (Z3)" can predict the model well.

Path Coefficient Test

The test was conducted to find out how much influence independent variables had on dependent variables in the study. Where the path coefficient value ranges from 1 to -1. The closer the number 1 or the number -1, the stronger the relationship is judged. The relationship will be concluded to have a significant effect if the p-value (< 0.05), considering that the alpha level used in this study is 5%. In addition, this test was carried out to determine the estimated value of the direct influence between variables. Based on the results of the path coefficient test as shown in Table 7 Path Coefficient Test Results, for example, Performance Expectancy (X1) to Behavioral Intention (Y1) has a p-value of 0.0008 which has a value of <0.05. This shows that the influence of the Performance Expectancy (X1) variable is significant on the Behavioral Intention (Y1) variable. Furthermore, if you look at the table, all p-values have a < value of 0.05 so that it can be concluded that the influence between independent variables on the dependent variables in this study is significant.

Table 7. Path Coefficient Test Results

Information	*path coefficient*	*t-statistics*	*p-values*
Performance Expectancy (X1) → Behavioral Intention (Y1)	0,493	3,090	0,002
Effort Expectancy (X2) → Behavioral Intention (Y1)	0,318	2,833	0,005
Social Influence (X3) → Behavioral Intention (Y1)	0,275	2,860	0,004
Facilitating Conditions (X4) → Behavioral Intention (Y1)	0,256	2,703	0,007
Hedonic Motivation (X5) → Behavioral Intention (Y1)	0,322	2,552	0,011
Price Value (X6) → Behavioral Intention (Y1)	0,297	4,801	0,000
Habit (X7) → Behavioral Intention (Y1)	0,385	4,615	0,000
Behavioral Intention (Y1) → Use Behavior (Y2)	0,320	3,390	0,001
Facilitating Conditions (X4) → Use Behavior (Y2)	0,304	2,635	0,009
Habit (X7) → Use Behavior (Y2)	0,362	3,596	0,000
Facilitating Conditions (X4) → Age (Z1) → Behavioral Intention (Y1)	0,156	2,022	0,043
Hedonic Motivation (X5) → Age (Z1) → Behavioral Intention (Y1)	0,166	3,070	0,002
Price Value (X6) → Age (Z1) → Behavioral Intention (Y1)	0,108	2,124	0,034
Habit (X7) → Age (Z1) → Behavioral Intention (Y1)	0,214	2,556	0,011
Facilitating Conditions (X4) → Gender (Z2) → Behavioral Intention (Y1)	0,115	2,904	0,013
Hedonic Motivation (X5) → Gender (Z2) → Behavioral Intention (Y1)	0,169	2,209	0,028
Price Value (X6) → Gender (Z2) → Behavioral Intention (Y1)	0,056	2,854	0,017
Habit (X7) → Gender (Z2) → Behavioral Intention (Y1)	0,211	3,651	0,000
Facilitating Conditions (X4) → Experience (Z3) → Behavioral Intention (Y1)	0,130	2,010	0,044
Hedonic Motivation (X5) → Experience (Z3) → Behavioral Intention (Y1)	0,165	3,120	0,002
Habit (X7) → Experience (Z3) → Behavioral Intention (Y1)	0,232	2,701	0,007
Habit (X7) → Age (Z1) → Use Behavior (Y2)	0,184	2,167	0,034
Habit (X7) → Gender (Z2) → Use Behavior (Y2)	0,176	2,158	0,031
Behavioral Intention (Y1) → Experience (Z3) → Use Behavior (Y2)	0,163	2,816	0,005
Habit (X7) → Experience (Z3) → Use Behavior (Y2)	0,194	2,253	0,025

Source: processed data

Moderation Test

The moderation test was conducted to see whether the moderation variables, namely "Age (Z1)", "Gender (Z2)", and "Experience (Z3"), significantly moderated independent variables against their dependent variables. The results of the mediation test were carried out by looking at the p-value as presented in Table 8 of the Moderation Test Results. For example, Age (Z1) moderated Facilitating Conditons (X4) to Behavioral Intention (Y1) with a p-value of 0.0345 with a value of <0.05. This suggests that age statistically moderates the relationship between Facilitating Conditions (X4) and Behavioral Intention (Y1) significantly, or in other words, the effect of Facilitating Conditions on Behavioral Intention will differ depending on the age of the user. Likewise with the other results in the table. If the p-value for a column that has a moderation variable is < 0.05, then the moderation variable is concluded to significantly moderate the influence of independent variables on its dependents.

Table 8. Moderation Test Results

Information	*t-statistics*	*p-values*
Facilitating Conditions (X4) → Behavioral Intention (Y1)	2,703	0,007
Hedonic Motivation (X5) → Behavioral Intention (Y1)	2,552	0,011
Price Value (X6) → Behavioral Intention (Y1)	4,801	0,000
Habit (X7) → Behavioral Intention (Y1)	4,615	0,000
Behavioral Intention (Y1) → Use Behavior (Y2)	3,390	0,001
Facilitating Conditions (X4) → Use Behavior (Y2)	2,635	0,009
Habit (X7) → Use Behavior (Y2)	3,596	0,000
Facilitating Conditions (X4) → Age (Z1) → Behavioral Intention (Y1)	2,022	0,043
Hedonic Motivation (X5) → Age (Z1) → Behavioral Intention (Y1)	3,070	0,002
Price Value (X6) → Age (Z1) → Behavioral Intention (Y1)	2,124	0,034
Habit (X7) → Age (Z1) → Behavioral Intention (Y1)	2,556	0,011
Facilitating Conditions (X4) → Gender (Z2) → Behavioral Intention (Y1)	2,904	0,013
Hedonic Motivation (X5) → Gender (Z2) → Behavioral Intention (Y1)	2,209	0,028
Price Value (X6) → Gender (Z2) → Behavioral Intention (Y1)	2,854	0,017
Habit (X7) → Gender (Z2) → Behavioral Intention (Y1)	3,651	0,000
Facilitating Conditions (X4) → Experience (Z3) → Behavioral Intention (Y1)	2,010	0,044
Hedonic Motivation (X5) → Experience (Z3) → Behavioral Intention (Y1)	3,120	0,002
Habit (X7) → Experience (Z3) → Behavioral Intention (Y1)	2,701	0,007
Habit (X7) → Age (Z1) → Use Behavior (Y2)	2,167	0,034
Habit (X7) → Gender (Z2) → Use Behavior (Y2)	2,158	0,031
Behavioral Intention (Y1) → Experience (Z3) → Use Behavior (Y2)	2,816	0,005
Habit (X7) → Experience (Z3) → Use Behavior (Y2)	2,253	0,025

Source: processed data

As mentioned earlier, there are four types of mediation that are classified based on their significance to the direct and indirect relationships that occur between independent variables, dependent variables, and moderation variables.

Based on the test results, it was proven that the p-value was < 0.05 (significant) for all direct (X->Y) and indirect (X->Z->Y) relationships. So it can be concluded that the mediation that occurs is partial mediation, where the mediation relationship significantly occurs both in the direct relationship of the variable (X -> Y) and the indirect relationship (X-> M-> Y). As well as all the moderation variables in this study, namely "Age (Z1)", "Gender (Z2)", and "Experience (Z3)" were able to moderate the influence between dependent and independent variables in the study.

Hypothesis Test

The hypothesis test is carried out by considering whether the t-statistics and p-values are significant with predetermined limits. Significant can occur if the t-value > 1.96 and the p-value < 0.05. Hypothesis tests were carried out to find out whether independent variables have a significant influence on dependent variables in the research model. One of the indicators used in this test is the p-value which indicates how likely the researcher is to reject the null (H0) hypothesis that is expected to be true. For example, if a p-value of 0.0008 is obtained which indicates a magnitude of 0.05, then H0 is rejected. This shows that Performance Expectancy significantly affects the user's Behavioral Intention to adopt robo-advisor fintech services. Thus, the results of the hypothesis test for all other independent variables have met the significance requirements as stated in Table 9 Path Coefficient Test Results. Furthermore, the results of the hypothesis test are as follows:

Table 9. Hypothesis Test Results

Code	Information	t-statistics	p-value	Hypothesis Status
H1	Performance Expectancy significantly affects the user's Behavioral Intention to adopt a robo-advisor fintech.	3,090	0,002	H0 rejected
H2	Effort Expectancy significantly affects the user's Behavioral Intention to adopt a robo-advisor fintech.	2,833	0,005	H0 rejected
H3	Social Influence significantly affects the user's Behavioral Intention to adopt a robo-advisor fintech.	2,860	0,004	H0 rejected
H4	Facilitating Conditions significantly affect the user's Behavioral Intention to adopt fintech robo-advisor.	2,703	0,007	H0 rejected
H5	Hedonic Motivation significantly influences the user's Behavioral Intention to adopt a robo-advisor fintech.	2,552	0,011	H0 rejected
H6	Price Value significantly affects the user's Behavioral Intention to adopt a robo-advisor fintech.	4,801	0,000	H0 rejected
H7	Habit significantly affects the user's Behavioral Intention to adopt a robo-advisor fintech.	4,615	0,000	H0 rejected
H8	Behavioral Intention significantly influences users' Use Behavior to adopt robo-advsior fintech.	3,39	0,001	H0 rejected
H9	Facilitating Conditions significantly affect users' Use Behavior to adopt fintech robo-advisors.	2,635	0,009	H0 rejected
H10	Habits significantly affect users' Use Behavior to adopt robo-advisor fintech.	3,596	0,000	H0 rejected
H11	Age moderates the influence of Facilitating Conditions, Hedonic Motivation, Price Value, and Habit on users' Behavioral Intention to adopt robo-advisor fintech.	2,022 3,070 2,124 2,556	0,043 0,002 0,034 0,011	H0 rejected
H12	Gender moderated the influence of Facilitating Conditions, Hedonic Motivation, Price Value, and Habit on users' Behavioral Intention to adopt robo-advisor fintech.	2,904 2,209 2,854 3,651	0,013 0,028 0,017 0,000	H0 rejected
H13	Experience moderated the influence of Facilitating Conditions, Hedonic Motivation, and Habit on users' Behavioral Intention to adopt fintech robo-advisors.	2,010 3,120 2,701	0,044 0,002 0,007	H0 rejected
H14	Age moderated the influence of Habit on users' Use Behavior to adopt robo-advisor fintech.	2,167	0,034	H0 rejected
H15	Gender moderates the influence of Habit on user Use Behavior to adopt robo-advisor fintech.	2,158	0,031	H0 rejected
H16	Experience moderates the influence of Behavioral Intention and Habit on user Use Behavior to adopt fintech robo-advisor.	2,816 2,253	0,005 0,025	H0 rejected

Source: processed data

Performance Expectancy significantly affects users' Behavioral Intention to adopt fintech robo-advisor

In Indonesia, robo-advisors, introduced in 2017, gained popularity during the pandemic as retail investors sought convenient ways to invest without in-person meetings. Fintech companies like Bareksa, Bibit, and Moduit use robo-advisor technology for wealth management, but despite an increase in Assets Under Management (AUM), the growth rate has declined, possibly due to skepticism about robo-advisor investment advice. This study examines factors influencing the adoption of fintech robo-advisor services in Indonesia using the UTAUT 2 framework. Surveying 150 respondents who have used robo-advisor services, the study found that performance expectancy, habit, and hedonic motivation are strong predictors of behavioral intention, while habit, behavioral intention, and facilitating conditions drive use behavior. Age, gender, and experience were found to moderate these relationships. The findings suggest that fintech companies can improve adoption by enhancing features, communication strategies, and digital financial literacy based on these factors, and future research should consider additional variables like financial literacy and use a longitudinal approach.

Effort Expectancy significantly affects users' Behavioral Intention to adopt robo-advisor fintech

The hypothesis that Effort Expectancy significantly influences Behavioral Intention in adopting robo-advisor fintech was confirmed, as respondents generally found robo-advisor services easy to understand, quick to learn, and simple to use. The Effort Expectancy variable, with indicators such as ease of learning, speed to learn, ease of use, and clarity in interaction, demonstrated high validity in measuring the variable, with loading factors and AVE values above 0.6, and the Fornell-Larcker test confirming discriminant validity. Reliability tests, including composite reliability and Cronbach's alpha, exceeded the threshold of 0.7, further validating the variable. In the inner model analysis, Effort Expectancy was shown to have a strong relationship with Behavioral Intention, supported by a positive path coefficient and a significant t-statistic value. These findings align with previous research, such as Senyo & Osabutey (2020), which also highlighted the significant effect of Effort Expectancy on Behavioral Intention in fintech adoption. This study reinforces that the ease of use plays a crucial role in users' intention to adopt fintech services, supporting the UTAUT 2 theory and the goals of Modern Portfolio Theory in simplifying investment processes and enhancing technology adoption (Nababan et al., 2019).

Social Influence significantly affects users' Behavioral Intention to adopt fintech robo-advisor

The hypothesis that Social Influence significantly affects users' Behavioral Intention in adopting robo-advisor fintech was confirmed, with respondents indicating that the opinions of important people, those around them, and respected figures influenced their decisions. This highlights the role of social perception in shaping individuals' adoption of fintech services. The convergent validity test showed that all indicators had loading factors and AVE values above the required threshold, confirming the validity of the Social Influence variable. The discriminant validity test indicated that the cross-loading values for each indicator were higher than for other variables, and the Fornell-Larcker test also supported the validity. Additionally, reliability tests confirmed the consistency of the Social Influence variable with composite reliability and Cronbach's alpha values exceeding the minimum threshold. The internal model analysis revealed a strong relationship between Social Influence and Behavioral Intention, indicated by a high R-Square value and a significant Q-Square value, suggesting good predictive relevance. The path coefficient test confirmed a positive and significant relationship, with a t-statistic value greater than 1.96 and a p-value smaller than 0.05. These findings align with previous research, such as Xie et al. (2021), showing that social factors like family, culture, and the social environment significantly influence users' intentions to adopt fintech. This study reinforces the idea that social influence, such as encouragement from family and peers, is a major factor in fintech adoption, consistent with UTAUT 2's framework. It also supports the view that social influence is a stable and relevant factor in technology adoption models, particularly in Indonesia's context for robo-advisors.

Facilitating Conditions significantly affect users' Behavioral Intention to adopt fintech robo-advisors

The hypothesis that Facilitating Conditions significantly influence users' Behavioral Intention to adopt robo-advisor fintech was confirmed, with most respondents indicating positive responses regarding the availability of facilities, knowledge, and support. The convergent validity test showed that all indicators met the required loading factor and AVE values, confirming their validity in representing the Facilitating Conditions construct. The discriminant validity test also indicated that each indicator's cross-loading value was higher than for other variables, and the Fornell-Larcker test supported adequate discriminant validity. Reliability tests showed that composite reliability and Cronbach's alpha exceeded the minimum thresholds, ensuring the construct's reliability. The internal model analysis revealed that Facilitating Conditions had a significant positive relationship with Behavioral Intention, with a high R-Square and Q-Square value indicating good predictive relevance. The path coefficient test confirmed that better facilitating conditions, such as available resources and technical support, increased users' intention to adopt robo-advisor fintech. These findings align with previous studies, such as Kurniasari et al. (2022), which found that facilitating conditions positively impacted fintech adoption in Indonesia, as well as Ningsih & Hamid (2022) and Hidayat et al. (2020), who observed similar effects in mobile banking and e-wallet usage. The study further supports the UTAUT 2 framework, which identifies facilitating conditions as crucial determinants of behavioral intention. The availability of devices, stable internet, and basic knowledge of application use creates a conducive environment for technology adoption, enhancing the effectiveness of robo-advisors in providing automated, optimal investment recommendations based on Modern Portfolio Theory (Attié & Waarden, 2022; Bajunaied et al., 2023; Basalamah, 2022).

Hedonic Motivation significantly influences users' Behavioral Intention to adopt fintech robo-advisors

The hypothesis that Hedonic Motivation significantly affects users' Behavioral Intention to adopt fintech robo-advisors was confirmed. The Hedonic Motivation variable, measured through indicators of fun, satisfaction, and entertainment, showed strong results in the outer model analysis, with all loading factors and AVE values meeting the required thresholds. The discriminant validity was also satisfied, as each indicator's cross-loading value was higher than those for other variables, and the Fornell-Larcker test confirmed the validity. Additionally, reliability tests indicated good consistency, with composite reliability and Cronbach's alpha values above the acceptable limits. In the inner model analysis, the relationship between Hedonic Motivation and Behavioral Intention was found to be strong, with a significant positive effect, as evidenced by the R-Square value and a Q-Square value indicating predictive relevance (Munandar et al., 2020b; Nababan et al., 2019; Nord, 2018; Nuraeni & Nababan, 2021b). The path coefficient test confirmed a positive and strong influence, and the t-statistic and p-value met the criteria for statistical significance. These findings support previous studies that highlight the role of Hedonic Motivation in shaping users' intentions to adopt fintech. For instance, Khatimah et al. (2019) found that positive user experiences with technology significantly increased Behavioral Intention, while Gillath et al. (2021) showed that comfort and trust in robo-advisors enhanced users' intentions to continue using them. Similarly, Fauziah & Sabandi (2024) found that users preferred digital wallets that were fun and engaging. This study reinforces the empirical evidence that pleasurable experiences play a key role in driving the adoption of robo-advisor fintech, aligning with the UTAUT 2 theory, which suggests that Hedonic Motivation influences technology acceptance. The results demonstrate that robo-advisors, with their automated, efficient investment solutions and user-friendly platforms, offer both financial benefits and enjoyable experiences, increasing their adoption rate (House, 2015; Khosravani et al., 2021; Larson, 2020b).

Price Value significantly affects users' Behavioral Intention to adopt fintech robo-advisors

The hypothesis that Price Value significantly influences users' Behavioral Intention to adopt robo-advisor fintech was confirmed. The Price Value variable, measured through indicators such as price suitability, price alignment with service quality, and service quality, met all validity and reliability criteria. Convergent validity was achieved as all indicators had loading factor values and AVE above the minimum threshold, confirming that they effectively measured the variable. Discriminant validity was also met, with each indicator showing higher cross-loading values within its own variable, and the Fornell-Larcker test confirmed that the correlation values were stronger within the same variable compared to others (Abdillah & Hartono, 2015; Toury, 2012; Wijaya & Nababan, 2021; Zare-Behtash & Firoozkoohi, 2020). The reliability of the construct was ensured, as composite reliability and Cronbach's alpha values exceeded the required limits. In the model analysis, the R-Square value showed that Price Value significantly contributes to explaining Behavioral Intention, and the Q-Square value indicated the model's predictive relevance. The path coefficient test confirmed a positive and significant relationship between Price Value and Behavioral Intention, with t-statistic values exceeding the minimum threshold and p-values below the significance limit. These findings align with previous research, such as Bhatia et al. (2021) and Kuah et al. (2024), which highlighted the importance of perceived value in driving the adoption of robo-advisors, where users' intention to adopt depends on the perceived benefits outweighing the costs. The results also support the UTAUT 2 model, which emphasizes Price Value as a determinant in technology acceptance. For robo-advisors, the benefits of automation and cost-efficiency align with the characteristics of fintech and Modern Portfolio Theory, optimizing investments based on risk and return. The majority of respondents agreed that the compatibility between price and service quality is a crucial factor in shaping their intention to adopt robo-advisors.

Habits significantly affect users' Behavioral Intent to adopt robo-advisor fintech

The hypothesis that Habit significantly affects users' Behavioral Intention to adopt robo-advisor fintech was confirmed. The Habit variable, measured through indicators such as habit, addiction, and necessity, met all validity and reliability test criteria. The convergent validity test showed that all loading factor and AVE values were greater than 0.6, ensuring that the indicators effectively measured the variable. Discriminant validity was also achieved, as the loading factor for each indicator in the Habit variable was greater than the loading factor for indicators in other variables, and the Fornell-Larcker test supported this with higher values in the top row (Bhatia, 2021; Bilgah & Frimayasa, 2024; Bolici, 2020; Bu & Liu, 2023; Cedrell & Issa, 2018). The reliability test confirmed the reliability of the variable, with composite reliability and Cronbach's alpha values exceeding 0.7. In the internal model analysis, the R-Square value indicated a strong relationship between Habit and Behavioral Intention, and the Q-Square value confirmed the model's predictive relevance. The path coefficient test revealed a significant positive relationship between Habit and Behavioral Intention, supported by a t-statistic greater than 1.96 and a p-value less than 0.05. These findings align with previous studies, such as Bilgah & Frimayasa (2024), Meiranto et al. (2024), and Iqbal et al. (2023), which demonstrated that habitual use of digital applications increases the likelihood of adopting fintech services. The results are consistent with the UTAUT 2 model, which states that habits influence technology adoption. In the context of robo-advisors, this supports the efficient use of automated investment solutions based on Modern Portfolio Theory. Additionally, the questionnaire responses from most participants indicated that users are accustomed to and feel the need to use robo-advisor technology in their investment activities, further confirming the role of habit in shaping adoption behavior.

Behavioral Intention significantly affects users' Use Behavior to adopt fintech robo-advisors

The hypothesis that Behavioral Intention significantly influences users' Use Behavior in adopting robo-advisor fintech was confirmed (Dewi, 2022; Duryadi, 2021). The Behavioral Intention variable, measured through indicators of intention, interest, and sustainability, met the criteria for both convergent and discriminant validity, as evidenced by adequate loading factors, AVE, cross-loading, and Fornell-Larcker values. The variable was also found to be reliable, with high composite reliability and Cronbach's alpha values. In the inner model analysis, the R-Square value indicated that Behavioral Intention has a strong influence on Use Behavior, and the model showed good predictive relevance, as indicated by the Q-Square value. The path coefficient and hypothesis tests demonstrated that the influence of Behavioral Intention on Use Behavior was significant, with t-statistic values exceeding the threshold and p-values below the specified significance level, supporting the hypothesis. This study’s findings indicate that users' intentions, including interest and sustainability in using robo-advisors, are translated into actual usage behavior, confirming that Behavioral Intention is a key predictor of Use Behavior. These results align with previous research, such as Odei-Appiah et al. (2022) and Al Halbusi et al. (2024), which found that Behavioral Intention significantly affects Use Behavior in various technology sectors, including fintech and e-pharmacy. According to the UTAUT 2 theory, Behavioral Intention is a crucial determinant of Use Behavior. In the context of robo-advisors, users' intentions are driven by the ease, efficiency, and reliability of the investment algorithm based on Modern Portfolio Theory, which directly influences their usage behavior. The questionnaire responses further supported these findings, with most respondents expressing a strong intention, interest, and desire to continue using robo-advisor technology for their investment activities (Darwish & Alyousef, 2021; Hatim & Munday, 2019; Wijana, 2015; Wisudawanto, 2021).

Facilitating Conditions significantly affect users' Use Behavior to adopt fintech robo-advisors

Based on the data analysis and hypothesis testing, it can be concluded that Facilitating Conditions significantly impact Use Behavior in the adoption of robo-advisor fintech. Support in the form of facility availability, user knowledge, technological compatibility, and access to assistance encourages more active and consistent use of the service. The Facilitating Conditions variables, including facility availability, knowledge, technological compatibility, and assistance availability, met the requirements for convergent validity, as indicated by the loading factor and AVE values exceeding the threshold. Discriminant validity was confirmed through cross-loading and Fornell-Larcker tests, while reliability was established with high composite reliability and Cronbach's alpha values. In the inner model analysis, the relationship between Facilitating Conditions and Use Behavior was strong, with a high R-Square value and good predictive ability indicated by the Q-Square value. The path coefficient test showed a significant positive relationship, confirmed by t-statistic and p-values that met the criteria, making the hypothesis acceptable. Most respondents agreed with the indicators, showing that users felt well-supported in terms of facilities, knowledge, and technology when using robo-advisors for investment. These findings are consistent with previous research, such as Gunawan et al. (2019), which highlighted the positive impact of Facilitating Conditions on technology adoption, especially fintech. The results align with UTAUT 2, which identifies Facilitating Conditions as a key factor influencing Use Behavior. Moreover, the Modern Portfolio Theory-based approach of robo-advisors enhances user confidence in investment decisions, reinforcing the importance of supportive facilities in both encouraging usage and enhancing the perceived effectiveness of the technology.

CONCLUSION

The study, which surveyed 150 respondents using 32 statements to explore factors influencing the adoption of fintech robo-advisors in Indonesia, found that Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit all significantly impact users' Behavioral Intention to adopt robo-advisor services. Furthermore, Behavioral Intention, Facilitating Conditions, and Habit were shown to significantly influence actual Use Behavior. The research also identified Age, Gender, and Experience as important moderating variables, affecting the relationships between Facilitating Conditions, Hedonic Motivation, Price Value, and Habit on Behavioral Intention, and moderating the effect of Habit on Use Behavior. For future research, it is recommended to expand the sample size and diversity, incorporate qualitative methods to gain deeper insights into user motivations and barriers, and explore the impact of emerging technologies and regulatory changes on robo-advisor adoption in Indonesia.

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