Available online at www.rajournals.in

International Journal of Management and Economics Invention

ISSN: 2395-7220

DOI: 10.47191/ijmei/v10i10.05

Volume: 10 Issue: 10 October 2024

International Open Access

Impact Factor: 8.473 (SJIF)

Page no. 3595-3604

Fintech Adoption: Peer-to-Peer Lending for Indonesian Msmes

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ARTICLE INFO

Published Online: 21October 2024

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ABSTRACT

The objective of this research is to examine the conduct of Micro, Small, and Medium Enterprises (MSMEs) concerning their embrace of financial technology linked to peer-to-peer lending. Employing a survey approach, this research collected data from MSME owners in Indonesia using purposive sampling techniques. Structural Equation Modeling (SEM) was employed to evaluate the impact of dimensions within the Unified Theory of Acceptance and Use of Technology on the preparedness of MSMEs to adopt the FinTech model. The results revealed that each dimension of the Unified Theory of Acceptance and Use of Technology, encompassing performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, price value, habit, perceived trust, and perceived risk, plays a crucial role in shaping the behavioral intention of MSMEs toward the adoption of financial technology, specifically peer-to-peer lending. Effort expectancy emerged as the primary factor influencing performance expectancy. Moreover, perceived trust exhibits a close correlation with perceived risk, thereby influencing the behavioral intention of MSMEs. However, perceived risk is the only dimension with a negative impact.

KEYWORDS: financial technology, peer-to-peer lending, social influence, hedonic motivation, behavioral intention.

INTRODUCTION

In 2023, economists expressed concern about Indonesia facing a global recession, causing economic slowdown and decline. At the onset of the year, the Indonesian Minister of Finance highlighted that Indonesia's 2022 economic growth surpassed the global average. The state budget is pivotal in maintaining consumption levels, purchasing power, and business activities, particularly for micro, small, and medium enterprises (MSMEs) (Menkeu, 2023). Despite the potential for a global recession, the Ministers of Tourism and Creative Economy, and Cooperatives and Small and Medium Enterprises believe MSMEs may not be heavily impacted. MSMEs significantly contribute to Gross Domestic Product (GDP), employment, export potential, and loan absorption, especially during crises (McEasy, 2022), underlining their importance to economic growth.

During the COVID-19 epidemic, government policies imposed restrictions affecting many businesses, leading to financial strain and closures. To address cash flow issues, financing companies offer liquidity services. Social restrictions prompt digitalization across sectors, accelerating technology adoption in finance.

Financial technology, particularly peer-to-peer lending, drives non-bank financial industry growth due to IT advancements. Peer-to-peer lending streamlines lending processes for lenders seeking high returns and borrowers in need of quick funds, particularly during crises (Najaf et al., 2021). Amid difficulties in accessing bank credit, peer-to-peer lending appeals to the MSME financing market (Najaf et al., 2021).

A survey on digital literacy in Indonesia (2022) reveals that 18% of respondents are entrepreneurs, potentially MSME owners. In financial services, 57% have not conducted digital transactions, spanning the general public, government, and educational sectors (Survei Literasi Digital, 2022). Most MSME actors lack financial literacy (Suryanto et al., 2020). Despite high peer-to-peer lending adoption and digital literacy, numerous illegal financial technology lenders (3,056) have been shut down (Cabinet Secretariat of the Republic of Indonesia, 2021). Asymmetric information in credit risk assessment hampers peer-to-peer lending's growth (Suryono et al., 2019), indicating room for improvement and safety measures. Nonetheless, MSMEs' interest in peer-to-peer lending will bolster the financial industry.

Intention is crucial in adopting financial technology, especially in peer-to-peer lending applications (Suryono et al., 2019). The Technology Acceptance Models (TAM) literature sheds light on the technology adoption behavior (Venkatesh et al., 2012). The UTAUT theory offers insights into financial technology adoption, particularly peer-to-peer lending (Mudjahidin et al., 2022). Thus, this study explores MSME behavior concerning financial technology adoption, specifically peer-to-peer lending.

The Role of Financial Technology in Peer-to-Peer Lending

Peer-to-peer lending is a form of financial service that adopts technology. Peer-to-peer lending is an information technology-based lending service that allows borrowers and lenders to enter into electronic lending agreements (Suryono et al., 2021). Peer-to-peer lending offers lenders the opportunity to lend directly to borrowers with higher returns, while borrowers can apply for credit directly to lenders with easier terms and a faster process. Therefore, compared to traditional banks, peer-to-peer lending is more beneficial for both borrowers and lenders (Suryono et al., 2019). The advantages of peer-to-peer lending platforms for MSMEs include effective funding, an easy transaction process, access to a wide market, and regular business financial reporting (Kholidah et al., 2022).

In the business model, peer-to-peer lending platforms facilitate transactions between borrowers and lenders, matching the two parties based on risk and maturity criteria (Havrylchyk & Verdier, 2018). Peer-to-peer lending platforms, or marketplace platforms, allow lenders to determine the borrowers to whom they will provide loans selectively (Havrylchyk & Verdier, 2018). Subsequently, the borrower will return the principal loan and interest to the lender. Internally, peer-to-peer lending platforms provide risk assessment, which is a major factor in every project to assess the credit score of potential borrowers. From the external system, peer-to-peer lending platforms provide the convenience of payment transactions in collaboration with banks and provide security by including their operating license from the Financial Services Authority (Otoritas Jasa Keuangan (OJK)). In addition, there is the Indonesian Joint Funding Fintech Association (AFPI), which guarantees the protection of lender funds focusing on fraud risk and credit risk, and the Investment Alert Task Force, which cracks down on illegal peer-to-peer lending platforms (Suryono et al., 2021). The existence of AFPI can provide a sense of security to every user in using peer-to-peer lending financial technology.

The Use of UTAUT with Peer-to-Peer Lending

The research framework is built by referring to UTAUT as a reference that can explain individual behavior regarding adopting financial technology related to peer-to-peer lending. UTAUT is an extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) by adding three constructs from the Motivation Theory (MT) perspective, namely hedonic motivation, price value, and Habit, to explain behavioral intention from the consumer side in adopting technology (Venkatesh et al., 2012). The UTAUT model incorporates various theories that elucidate individual behavior when accepting a technology. These theories include the Theory of Reasoned Action (TRA), Theory of Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TBP), Combined TAM and TBP (C-TAM-TBP), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). The UTAUT model encompasses four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. These constructs shed light on users' behavioral intentions when adopting technology (Venkatesh et al., 2003). Additionally, UTAUT includes three other constructs from Motivation Theory (MT): hedonic motivation, price value, and Habit. This model still requires further research on relevant factors in various countries concerning current technology developments (Venkatesh et al., 2012). Therefore, we added several constructs that are relevant to the industry and MSMEs in Indonesia, including perceived trust (Slade et al., 2015; Mudjahidin et al., 2022), and perceived risk (Slade et al., 2015; Suryono et al., 2019; Lara-Rubio et al., 2020) which serve as additional factors influencing behavioral intentions across different nations. Moderating constructs are not used because we focus on behavioral intention to adopt peer-to-peer lending financial technology. Thus, the research framework can be seen in Figure 1:

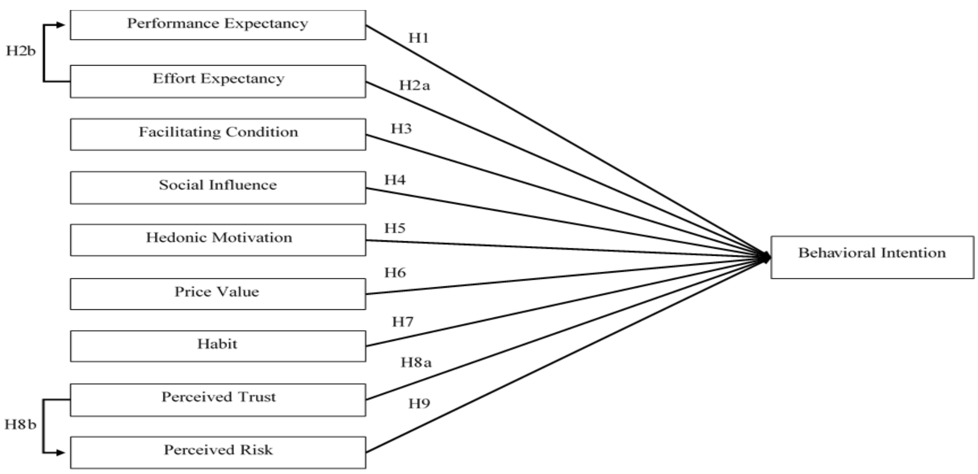

Figure 1. Research Framework

Performance expectancy (PE) refers to a person's belief that using the system will help them achieve their job performance (Venkatesh et al., 2003). People will generally use technologies that offer many benefits (Senyo & Osabutey, 2020). In the context of peer-to-peer lending, perceived usefulness refers to the access to exchange funds for a lending agreement because the greater the perceived benefit, the higher a person's behavioral intention (Lara-Rubio et al., 2020). This indication shows that the usability of this technology is a major concern for driving one's intention in the peer-to-peer lending (Suryono et al., 2019). This concern is understandable, as access to funds is currently a major challenge (Septiani et al., 2020). Therefore, the higher a person's belief about the benefits of a technology, the higher their behavioral intention to adopt it. (Senyo & Osabutey, 2020). Thus, the hypothesis that is built is as follows:

H1: Performance expectancy (PE) affects Behavioral intention (BI)

Effort expectancy (EE) refers to the level of ease of use of technology (Venkatesh et al., 2003). This convenience is a factor that can influence a person's behavioral intention to adopt a technology. This convenience usually intersects between the platform and the user when using their system. In other words, perceived difficulties in using technology will reduce their behavioral intention to adopt technology (Lara-Rubio et al., 2020). This factor must be considered to encourage a person's intention to use peer-to-peer lending (Suryono et al., 2019). In addition, when users feel that the financial technology is easy to use and does not require much effort, they have higher expectations of obtaining the desired performance (Oliveira et al., 2016). Therefore, the easier a technology is to use, the higher their behavioral intention to adopt it (Senyo & Osabutey, 2020). Thus, the hypothesis is as follows:

H2a: Effort expectancy (EE) affects Behavioral intention (BI).

H2b: Effort expectancy (EE) affects Performance expectancy (PE)

Facilitating condition (FC) refers to a person's confidence level that organizational and technical infrastructure is available to support system use (Venkatesh et al., 2003). The presence of necessary infrastructure, including computers, internet access, wifi, and secure websites, is crucial for ensuring that users of financial technology access financial services smoothly, securely, and conveniently (Alalwan et al., 2018). Therefore, if the facilitating condition is available, it provides an impetus for adopting peer-to-peer lending financial technology. Thus, the hypothesis formulated is as follows:

H3: Facilitating condition (FC) affects Behavioral intention (BI)

Social influence (SI) refers to the degree to which a person feels the importance of other people's beliefs that he or she should use the new system (Venkatesh et al., 2003). In financial technology, people considered competent in the financial field and have been recognized by many people can motivate someone to do what they say. This phenomenon shows that opinions and recommendations from other influential and important people can encourage a person's behavioral intention to adopt a technology (Oliveira et al., 2016). Thus, the hypothesis is as follows:

H4: Social influence (SI) affects Behavioral intention (BI)

Hedonic motivation (HM) refers to the pleasure of using the technology (Venkatesh et al., 2012). The more the users feel pleasure in using technology, the higher their behavioral intention. Users need to enjoy using technology and have a pleasant experience so that it can encourage a person's behavioral intention to adopt a technology (Septiani et al., 2020). Therefore, the hypothesis is as follows:

H5: Hedonic motivation (HM) affects Behavioral intention (BI)

Price value (PV) refers to the consumer's cognitive trade-off between the perceived benefits of the app and the monetary cost (Venkatesh et al., 2012). When talking about costs, they cannot be separated from the benefits that can be obtained from these expenses. This price is a sensitive factor, so users must ensure that the benefits they receive exceed their costs (Septiani et al., 2020). In the context of peer-to-peer lending, the costs that must be given in the form of interest that may be considered higher than other financing alternatives must be considered, considering the ease of the lending process offered. Thus, based on these prices and costs, the following hypothesis is developed:

H6: Price value (PV) affects Behavioral intention (BI)

Habit (HBT) refers to the degree to which a person is accustomed to behaving automatically due to learning (Venkatesh et al., 2012). This indication shows the pattern of a person's activities that are done repeatedly to form a habit that is automatically and always done. In financial technology, this Habit is a supporting factor in understanding a certain condition to make its use more familiar. In other words, repeated use builds knowledge that can ultimately motivate users to engage in peer-to-peer lending (Septiani et al., 2020). Thus, the hypothesis is as follows:

H7: Habit (H) affects Behavioral intention (BI)

Trust refers to the recognition of the ability to fulfill expectations. Trust is a subjective belief that a party will fulfill its obligations and plays an important role in electronic financial transactions, where users are at great risk of uncertainty and loss of control (Slade et al., 2015). In the context of peer-to-peer lending, trust is built by both lenders and borrowers to choose a lending platform that can be selected based on reputation and related information (Mudjahidin et al., 2022). Therefore, trust is considered a factor that can influence peer-to-peer lending (Suryono et al., 2019). In addition, trust can also help reduce perceived risk because it can help users overcome uncertainty or fear about behavior and the consequences that may occur (Slade et al., 2015). Thus, the hypothesis is constructed as follows:

H8a: Perceived trust (PT) affects behavioral intention (BI).

H8b: Perceived trust (PT) affects Perceived risk (PR)

Perceived risk refers to the perceived risk of a condition. This perception stems from uncertainty or concern about the behavior and the severity or seriousness of potential negative consequences (Slade et al., 2015). In the context of peer-to-peer lending, the credibility of the data used to determine a borrower's credit score is said to be invalid because it comes from a third party (Suryono et al., 2019). This credibility must be guaranteed to build user confidence in adopting a technology. Therefore, the higher the perceived risk, the lower one's behavioral intention to adopt peer-to-peer lending (Lara-Rubio et al., 2020). Thus, the following hypothesis is built:

H9: Perceived risk (R) affects Behavioral intention (BI)

METHOD

Based on the research objectives that focus on the behavioral intentions of MSMEs in Indonesia regarding financial technology peer-to-peer lending as an alternative to business financing, the population in this study is MSMEs in Indonesia. The sample size determination is calculated by multiplying the estimated parameters by five (5). This research uses a survey method with a quantitative approach for statistical hypothesis testing. A Likert scale of 1–10 (even categories) was used to eliminate dubious answers. A digital questionnaire (Google Forms) provides a questionnaire in the form of questions that represent measurement indicators for each research construct. This questionnaire is used to obtain large data samples, considering that the population studied is MSMEs in Indonesia. Links from digital questionnaires are distributed via social media such as WhatsApp, Telegram, email, and others. The distribution was carried out using purposive sampling. We aim to filter the quality of incoming data according to the research criteria, where MSMEs at least know financial technology peer-to-peer lending as an alternative to their financing.

Structural Equation Modeling (SEM) was used as a research data analysis tool. SEM is a multivariate statistical framework used to model complex relationships between latent variables, both directly and indirectly (Stein et al., 2011). SEM is known as causal modeling, causal analysis, simultaneous equation modeling, analysis of covariance structure, path analysis, or confirmatory factor analysis (Ullman & Bentler, 2012) and has become a powerful analytical technique in statistical modeling widely used in the social and behavioral sciences (Mueller, 1997). Therefore, SEM was chosen as the analytical tool used to test the relationship between variables in this study, including performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, price value, Habit, perceived trust, and perceived risk. The research data analysis was assisted by AMOS 22 software.

RESULTS

The characteristics of respondents in this study can be grouped into three main groups based on the main stakeholders, namely MSME actors who adopt peer-to-peer lending financial technology as an alternative to business financing. For MSME actors, the characteristics are divided into several parameters, namely based on gender, age, type of business, monthly income, length of business, and number of uses of peer-to-peer lending financial technology among 440 selected respondents.

Table 1. Characteristics of MSMEs Actors

Characteristics of Respondents		Amount	Percentage
Gender	Male	202	46%
	Female	238	54%
Age	18-22 years old	44	10%
	23-28 years old	141	32%
	29-34 years old	167	38%
	35-40 years old	57	13%
	> 40 years old	31	7%
Type of Business	Culinary	194	44%
	Fashion	172	39%
	Craft (Creative)	74	17%
Length of Business	<1 year	53	12%
	1 – 10 years	312	71%
	>10 years	75	17%

The data collection results on the characteristics of respondents in this study quantitatively show that 54% of females dominate MSME actors. Meanwhile, based on age, the number of respondents is dominated by the age range of 29–34 years old, or as much as 38%. The number of respondents is also dominated by the type of culinary business, namely as much as 49%. Most respondents have been running their businesses for 1–10 years, for a percentage of 47%.

The loading factor generated above can be used to measure construct validity, where a questionnaire is said to be valid if the statements on the questionnaire can reveal something that is measured by the questionnaire. The minimum number of loading factors is ≥ 0.40, or ideally ≥ 0.7 (Suliyanto., 2011: 293). From this data, it can be concluded that all statements on the indicators used to measure performance expectancy variables, effort expectancy, facilitating conditions, social influence, hedonic motivation, price value, Habit, perceived trust, perceived risk, and behavioral intention can be declared valid. According to the results of the data processing above, it can be seen that each measurement or dimension forming the variable shows good results, namely the CR value, which is greater than 2 x standard error with p smaller than 0.05. In other words, the measurements forming the variables have shown unidimensionality. Then, based on this confirmatory factor analysis, the research model can be used for further analysis without modification or adjustment.

The critical ratio value for normality testing for both skewness and kurtosis obtained the largest limit score of 2.47, which did not exceed the cut-off value of 2.58, and it can be said that the research data has a normal distribution. The results of testing outliers show that the highest number for the minimum univariate is -2,994, and the highest maximum number is 2,727. Computerized results show no values higher than ±3, so it can be concluded that there are no univariate outliers in the research data. As for multivariate, it shows that the maximum Mahalanobis distance in this study is 58.085 or does not exceed the $\chi 2$ value of 69.346. This result shows no multivariate outliers, so data exclusion does not need to be done.

Based on the calculation results, the chi-square value is 136.583, so the tested model is good. According to Noor (2014:136), based on the principle of parsimony, where at least one criterion is fit, the model has been declared fit. The AGFI value that fits is equal to or greater than 0.90. Based on the calculation, the AGFI value is 0.856, so it can be said that the AGFI value is in the marginal fit category. The RMSEA value indicates the goodness-of-fit that can be expected when the model is estimated in the population. The RMSEA value, smaller or equal to 0.08, is an index for the model's acceptability, indicating a close fit based on degrees of freedom. Based on the calculation results, the RMSEA value of 0.049 is obtained to make the model acceptable. A fit GFI value is greater than 0 and smaller than 1, so the value of the GFI can indicate a fit criterion with a value of 0.865. A CMIN/DF value less than or equal to 2.00 indicates an acceptable fit. Based on the calculation, the result is 2.210, included in the marginal fit category. The TLI and CFI values indicate the level of fit when the value obtained is less or equal to 0.95. From the various suitability indicators, it can be concluded that the measurement model on the endogenous structure is fit or has good suitability. So, in this study, the entire research model involving the interaction of the variables performance expectancy, effort expectancies, facilitating conditions, social influence, hedonic motivation, price value, Habit, perceived trust, Perceived risk, and behavioral intentions can be accepted and analyzed further.

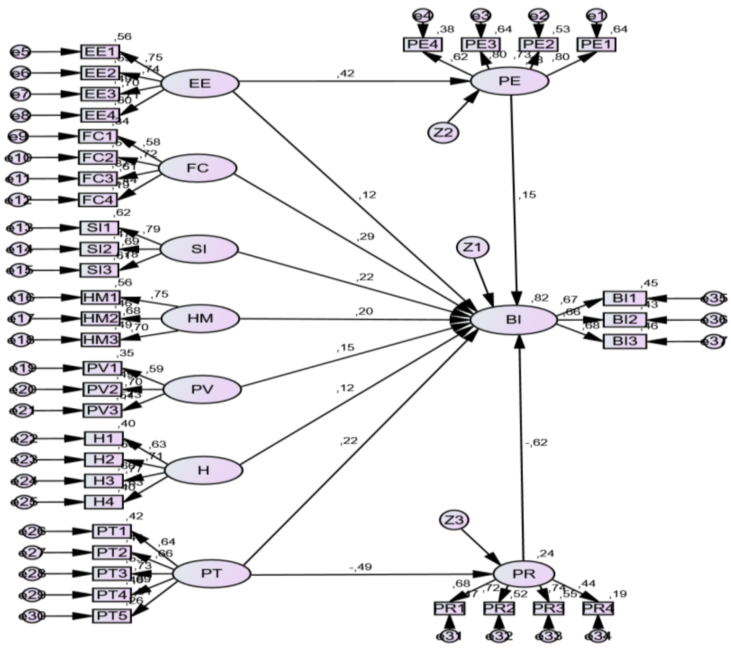

Figure 2. Full Structural Model

The entire structural model produces an adequate estimate value (Gambar 2). Subsequently, hypothesis testing is carried out to determine whether or not independent variables influence dependent variables. A given hypothesis is accepted if the probability value (p) < 0.05. From the result, it is known that all three hypotheses are accepted. The influence of exogenous variables on endogenous variables can be found in the following table:

Table 2. Variable Estimate Value

hypothesis			Estimate
(1)			**(2)**
Performance expectancy	→	Behavioral intention	0,988
Effort expectancy	→	Behavioral intention	0,977
Effort expectancy	→	Performance expectancy	1,014
Facilitating condition	→	Behavioral intention	0,988
Social influence	→	Behavioral intention	0,977
	(1)		**(2)**
Hedonic motivation	→	Behavioral intention	1,014
Price value	→	Behavioral intention	0,988
Habit	→	Behavioral intention	0,977
Perceived trust	→	Behavioral intention	1,014
Perceived trust	→	Perceived risk	0,988
Perceived risk	→	Behavioral intention	0,977

Based on Table 2, it can be concluded that each parameter adapted from UTAUT that includes performance expectancy, Effort expected, facilitating condition, social influence, hedonic motivation, price value, Habit, perceived trust, and perceived risk influences the behavioral intention of MSME actors to adopt peer-to-peer financial technology lending.

H1: Performance expectancy influences behavioral intention

Based on the estimated parameter, the relationship between Performance expectancy and Behavioral intention is 0.145. Testing the relationship between the two variables showed a probability = 0,006 (p < 0,05). So it can be concluded that Performance expectancy positively influences Behavioral intention, with the results showing that the better performance expectance the peer-to-peer lending company has, the better the behavioral intent process in MSME actors to try to adopt fintech products.

H2a: Effort expectancy influences Behavioral intention

Based on the estimated parameter, the relationship between Effort expectancy and Behavioral intention is 0.124. Testing the relationship between the two variables showed a probability = 0.020 (p < 0.05). In this case, the better the effort expectancy given by the peer-to-peer lending company, the better the behavioral intention of the MSME actor will be.

H2b: Effort expectancy influences Performance expectancy

Based on the estimated parameters, the relationship between Effort Expectancy and Performance Expectancy is 0.425. Testing the relationship between these two variables shows probability = 0.000 (p < 0.05). So, it can be concluded that Effort expectancy positively affects Performance Expectancy. In this case, the more the company maximizes Effort Expectancy, the better it is for the company to obtain and maintain Performance Expectancy.

H3: Facilitating condition influences Behavioral intention

Based on the estimated parameters, the relationship between Facilitating conditions and Behavioral intention is 0.285. Testing the relationship between these two variables shows probability = 0.000 (p < 0.05). So, it can be concluded that Facilitating conditions have a positive effect on Behavioral intention, with these results showing that the stronger the Facilitating conditions possessed by MSME actors, the better the Behavioral intention will be in adopting peer-to-peer landing.

H4: Social influence influences Behavioral intention

Based on the estimated parameters of the relationship between Social influence and Behavioral intention, it is obtained at 0.218. Testing the relationship between these two variables shows probability = 0.000 (p < 0.05). So, it can be concluded that Social influence positively affects Behavioral intention. In this case, the higher the Social influence received by MSME actors, the better the Behavioral intention of MSME actors will be.

H5: Hedonic motivation influences Behavioral intention

Based on the estimated parameters of the relationship between Hedonic motivation and Behavioral intention, it is obtained at 0.198. Testing the relationship between these two variables shows probability = 0.000 (p < 0.05). So, it can be concluded that Hedonic motivation positively affects Behavioral intention. In this case, the more the company maximizes the Hedonic motivation of MSME actors, the better it will be for peer-to-peer lending companies to get Behavioral intention.

H6: Price value influences Behavioral intention

Based on the estimated parameters of the relationship between Price value and Behavioral intention, it is obtained at 0.152. Testing the relationship between these two variables shows probability = 0.002 ($p < 0.05$). So it can be concluded that Price value has a positive effect on Behavioral intention, with these results showing that the stronger the Price value a company has, the better the Behavioral intention it will get.

H7: Habit influences Behavioral intention

Based on the estimated parameters, the relationship between Habit and Behavioral Intention is 0.123. Testing the relationship between these two variables shows probability = 0.009 ($p < 0.05$). So, it can be concluded that Habit positively affects Behavioral intention. In this case, the better the Habits that MSMEs have, the better the behavioral intention obtained by the company.

H8a: Perceived trust influences Behavioral intention

Based on the estimated parameters of the relationship between Perceived trust and Behavioral intention, it is obtained at 0.220. Testing the relationship between these two variables shows probability = 0.000 ($p < 0.05$). So, it can be concluded that Perceived trust positively affects Behavioral intention. In this case, the more the company maximizes perceived trust, the better it will be for the company to get and maintain behavioral intention from MSME actors.

H8b: Perceived trust influences on Perceived risk

Based on the estimated parameters, the relationship between Perceived trust and Perceived risk is -0.486. Testing the relationship between these two variables shows probability = 0.000 ($p < 0.05$). So, it can be concluded that Perceived trust hurts Perceived risk, with these results showing that the stronger the Perceived trust held by peer-to-peer lending companies, the lower the Perceived risk felt by MSME actors.

H9: Perceived risk influences on Behavioral intention

Based on the estimated parameters, the relationship between Perceived risk and Behavioral intention is 0.618. Testing the relationship between these two variables shows probability = 0.000 ($p < 0.05$). So, it can be concluded that Perceived risk hurts Behavioral intention. In this case, the lower the Perceived risk felt by MSME actors, the better the Behavioral intention of MSME actors.

DISCUSSION

Performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, price value, Habit, perceived trust, and perceived risk, which are parameters resulting from the adaptation of UTAUT in this research, are proven to have an important role in forming the behavioral intention of MSME actors to adopt peer financial technology -to-peer lending. Each parameter has its consideration function for MSME actors to be able to adopt peer-to-peer lending products to improve their business operations.

Performance expectancy influences behavioral intention. This result shows that performance expectation changes influence a person's intention to use a system. The positive influence explains that the better the performance expectations of peer-to-peer lending companies are, the greater the intention of MSME actors to try to adopt fintech products. This phenomenon is a reflection and benchmark for MSME actors who are optimistic that funding their business using technology can provide better business performance. These results support the findings of Lara-Rubio et al. (2020) and Septiani et al. (2020), who stated that performance expectations regarding perceived benefits influence behavioral intention in adopting peer-to-peer lending.

Effort expectancy influences behavioral intention. This result shows that the ease of use of technology can influence the behavioral intention of MSMEs to use fintech products. Positive results show that the easier the technology is, the faster MSMEs choose fintech products. This result can be a consideration for fintech business players, especially in peer-to-peer lending products, to simplify their systems so they can easily acquire new customers and retain them to build sustainable relationships due to the convenience of using their systems. This result supports the findings of Lara-Rubio et al. (2020) and Senyo & Osabutey (2020) that difficulty using technology will reduce behavioral intention to adopt it. Apart from that, effort expectation also influences performance expectancy. This result explains that the ease of use of a system gives hope to MSME actors in funding their business to obtain the desired performance. Positive results indicate that the easier a system is to use, the greater the expected performance expectancy. These results support the findings (Oliveira et al., 2016) that effort expectancy influences performance expectancy. In other words, the level of ease in using technology can influence expected performance expectations.

Facilitating conditions influence behavioral intention. This result refers to the infrastructure and technical availability level supporting increasing behavioral intention to adopt fintech services. Infrastructure related to adopting technology is an important aspect of financial services. The positive results show that the more complete the availability of facilities or infrastructure owned by MSME actors can increase their behavioral intensity in adopting fintech. These findings support Venkatesh et al. (2012) and Alalwan et al. (2018), state that facilitating conditions are the key to influencing behavioral intention to adopt a technology.

Social influence influences behavioral intention. This result refers to the importance of other people's beliefs that they should use the new system. Positive results indicate that a person's confidence in the results of recommendations from other people who are influential and trusted can increase a person's behavioral intention to adopt fintech. These results support Venkatesh et al. (2003) and Oliveira et al. (2016), state that social influence is crucial in behavioral intention to adopt a technology. This result explains that influencer recommendations can encourage MSME actors to use peer-to-peer lending platforms to adopt fintech.

Hedonic motivation influences a person's behavioral intention in using technology. This result explains that the higher the users feel happy using technology, the higher their behavioral intention to adopt technology. This phenomenon shows that MSME actors enjoy the use of peer-to-peer lending, thereby encouraging their intention to adopt technology. These results support the findings of Septiani et al. (2020), those who stated that the perception that the application of peer-to-peer lending services provides easy access and interesting experiences could encourage fintech adoption. In other words, the greater the hedonic motivation of MSME actors, the greater their behavioral intention to adopt fintech.

Based on research results, price value influences behavioral intention. This result explains that price value changes will influence MSME actors' intention to adopt fintech products. Positive findings suggest that higher price values of a product are associated with an increase in behavioral intention. Price value refers to the trade-off between the benefits and costs of purchasing a product. Price is indeed a sensitive factor when considering selecting a product. However, even though the costs (interest) that must be paid are considered high, this is not a consideration for MSME actors to choose other alternatives for funding their business. This phenomenon happens because peer-to-peer lending is easier than other loans. These results support the findings Septiani et al. (2020), which state that price value influences behavioral intention to adopt peer-to-peer lending. The research results show that Habit influences behavioral intention. This phenomenon explains that the habits of MSME actors in using peer-to-peer lending products shape their behavioral intention in adopting fintech. Positive results show that the more often MSMEs use fintech products, the more familiar they will feel with their use. Therefore, habits encourage the motivation of MSME actors to use peer-to-peer lending products so that their behavioral intention to adopt fintech increases. These results support the findings Septiani et al. (2020), which state that Habit influences behavioral intention to adopt peer-to-peer lending. Repeated use of peer-to-peer lending platforms by MSME actors will shape their habits and encourage easier technology adoption.

Based on research results, trust influences behavioral intention. This result shows that the level of trust of fintech users will cause changes in their behavioral intentions. This belief is subjective in its use based on reputation and related information on peer-to-peer lending platforms. The result demonstrates a direct correlation between the level of trust MSME actors have in peer-to-peer lending platforms and their inclination to use financial technology products. Specifically, a higher level of trust increases the likelihood of encouraging behavioral intention toward adopting fintech products. These results support the findings (Slade et al., 2015), which state that perceived trust influences behavioral intention. This research contributes to following up on the conceptual model by Mudjahidin et al. (2022) as an effort to develop peer-to-peer lending in Indonesia. The results of this research also show that trust affects perceived risk. This result explains that the level of trust of MSME actors can cause changes in their behavioral intention in adopting fintech. The negative results indicate that their trust can mitigate the perceived risk due to their uncertainty and fear of the consequences of peer-to-peer lending, which they choose as an alternative for funding their business. These results support Slade et al. (2015), which states that perceived trust influences and has a negative attachment to perceived risk. In other words, the higher an individual's level of trust will reduce the perceived risk. Apart from that, perceived risk also influences behavioral intention. These results indicate that the perceived risk in a condition originating from uncertainty and the potential consequences of this possibility can influence the intention of MSME actors to use peer-to-peer lending as an alternative to their funding. The negative results illustrated that the greater the risk perceived by MSME actors, the lower their behavioral intention in adopting fintech. These results support the finding that perceived risk contributes negatively and hinders fintech adoption (Slade et al., 2015; Lara-Rubio et al., 2020).

CONCLUSION

Performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, price value, Habit, perceived trust, and perceived risk influence the behavioral intention of MSME actors to adopt peer-to-peer lending financial technology. The better the performance expectancy of a peer-to-peer lending company, the better the behavioral intention process will be for MSME actors to try to adopt fintech products. The better the Effort Expectancy provided by a peer-to-peer lending company, the better the Behavioral Intention of MSME actors will be. Companies that maximize Effort Expectancy can obtain and maintain better Performance Expectancy. The better the facilitating conditions that MSMEs have, the better their behavioral intention will be in adopting peer-to-peer landing. Social influence also has a positive effect on Behavioral intention. In this case, the higher the Social influence received by MSME actors, the better the Behavioral intention of MSME actors will be. Apart from that, Hedonic motivation from MSME actors can provide opportunities for peer-to-peer lending companies to obtain Behavioral Intention. Price value has a positive effect on Behavioral intention, with these results showing that the stronger the price value the company has, the better the Behavioral intention will be. The better the Habits that MSME actors have, the better the company's Behavioral Intention will get. Companies must maximize perceived trust because it will impact the company in gaining and maintaining behavioral intention from MSME actors. Perceived trust also hurts perceived risk, with these results showing that the stronger the perceived trust held by peer-to-peer lending companies, the lower the perceived risk felt by MSME actors. Furthermore, Perceived risk hurts Behavioral intention. In this case, the lower the Perceived risk felt by MSME actors, the better the Behavioral intention of MSME actors.

LIMITATIONS AND FUTURE RESEARCH AGENDA

This research has been carried out according to scientific principles but still has several technical and fundamental limitations. One of the limitations of this research is that the survey area is limited to Indonesia, and further research can be carried out in other countries, especially those with almost the same characteristics, namely developing countries in Southeast Asia, to confirm consistent results. Apart from that, the business actors who are respondents to this research are the MSME category, which operates in limited business fields. Further research can be carried out on business people in different industries to obtain information that may be different from the results of this research. The adaptation of UTAUT parameters used in this research also has general characteristics, where further research can collaborate the UTAUT concept with other models, such as the Information System Success (ISS) model or the S-O-R (Stimulus-Organism-Response) model to obtain more comprehensive research results.

ACKNOWLEDGMENTS

We express our deepest gratitude to all individuals and organizations whose contributions and support were instrumental in the completion of this research. First and foremost, we extend our heartfelt appreciation to the Rector of Siliwangi University and the Head of Research and Public Service Institution of Siliwangi University.

Special thanks go to McEasy for their comprehensive analysis of the role of MSMEs in economic growth during times of crisis, which served as a cornerstone for our research. We are indebted to the respondents who participated in the surveys and interviews, as their contributions provided essential data and insights crucial for our analysis. We also acknowledge the invaluable support and guidance from our colleagues and peers throughout the research process. Their feedback and suggestions have significantly enriched the quality of our work. Lastly, we extend our sincere appreciation to the authors of the relevant literature and research studies cited in this paper, whose pioneering work laid the foundation for our investigation into financial technology adoption among MSMEs. Without the collective efforts and support of all those mentioned above, this research would not have been possible.

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