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Determinants of Accessibility to Fintech Lending: A Case Study of Micro and Small Enterprises (MSEs) in Indonesia*

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Abstract

Several studies have revealed that information on borrower characteristics plays an important factor in approving their credit requests. Though the extent to which such characteritics are also applicable to the case of fintech lending remain uncertain. The aim of this study is, thus, to investigate the determinant factors that influence MSEs in obtaining credit through fintech lending. Here, we emphasize virtual trust in fintech lending encompasing the dimension of social network, economic attributes, and risk perception based on several indicators that are used as proxies. Primary data used in the study was gathered from an online survey to the respondents of MSEs in Java. The result of the study indicates that determinants of MSEs in obtaining credit from lender through fintech lending are statistically influenced by internet usage activities, borrowing history, loan utilization, annuity payment system, completeness of credit requirement documents and compatibility of loan size with the business need. These factors have a significant effect on credit approval because they can generate virtual trust of fintech lender to MSEs as potential borrowers. It concludes that the probability of obtaining fintech loans in accordance with their expectations are influenced by the dimensions of social network, economic attributes and risk perception.

Keywords: Fintech Lending, MSEs, Trust, Credit Access, Credit Risk

JEL Classification Code: G20, G23, G29, G40, E51

1. Introduction

Micro and small enterprises (MSEs) in Indonesia remain critically important in providing job opportunities and a production sphere for the poor and low-income class (Nugroho et al., 2020; Organisation for Economic Co-operation and Development (OECD), 2010). Interestingly, many MSEs were performing relatively well during the onset of the 1997/98 economic crisis (Sato, 2000). In 2018, the data of MSEs was recorded at about 64.2 million,

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and their contribution to GDP approximately reached 57.2% that provided employment for around 116 million people (96.9% of total workforce). It is estimated that about 54.9% of the total investment in 2018 was carried out by MSEs (State Minister for Cooperatives Small and Medium Enterprises, 2018). However, several studies show that MSEs are being hevily impacted due to the economic crisis as a result of the COVID-19 pandemic. Due to large-scale social restrictions (lockdown policy), scarcity of raw materials, capital and inability to adopt online marketing skills have significantly undermined MSEs sales during the COVID-19 pandemic (Nugroho et al., 2020). It means that the business ability to enter digital-based business era is the key factor to post-pandemic economic recovery.

During the COVID-19 pandemic, a lack of accessing bank loans put the MSEs in a state of difficulty to adapt to the sharp decline in market demand for their products. For example, allocation of bank credit to MSEs was only 19.6% of total credit (Indonesia Financial Services Authority [OJK], 2018), and only 5% used external financing (Central Bureau of Statistics (BPS), 2015). Therefore, as MSEs finance depends solely upon own capital, they are very likely to face financial distress or serious liquidity problems due to reduced business profitability. Their inability to utilize digital technology makes it difficult for the MSEs to respond to the changes in people's shopping patterns, who are more likely to make online transactions. However, a lack of access to the banking services provide a great opportunity for financial technology institutions (fintech) to penetrate the microfinance market. It is a beneficial condition for the fintech players to combine financial services with rapidly growing use of digital technology (Dorfleitner et al., 2017). (Chrishti et al., 2021; Schueffel, 2017) also emphasized that fintech operators can utilize advanced digital technology to provide financial services that are more efficient and effective than conventional finance.

Fintech in Indonesia is growing quite rapidly in response to the increasing use of digital technology in the country. Based on data of (Widarwanto, 2018), 133 million (51%) people are familiar with the use of internet and 106 million (40%) of them are active on the social media. In May 2019, there were 249 fintech companies with a market share dominated by fintech lending companies (43%), payment systems (26%), and the rest were crowdfunding, insurtech, aggregators, and others (Batunanggar, 2019). As far as December 2019, 164 fintech lending companies have been officially registered (Indonesia Financial Services Authority [OJK], 2019). In 2019, fintech borrowers reached 18 million, significantly higher than 2018, which had only 330 thousand customers. The fundamental question is whether the ease of fintech lending services is commensurate with the MSEs characteristics? Can fintech lending with the digital platform identify MSEs' creditworthiness easily and precisely (low risk)?

In virtual lending, information about borrower characteristics is not only an important factor affecting lending availability, but is also closely related to the occurrence of defaults (Liu & Wu, 2020). Virtual lending is practically a credit contract that is based on an assessment of prospective borrower's data that already exist on the internet. Tao et al. (2017) revealed that the borrower's credit profile significantly affects the probability of fulfilling their lending request and predicts its failure. According to Bachmann et al. (2011), although fintech platforms can provide loans without intermediary role of the financial institutions, their market remain inefficient and contains many latent risks. Therefore, it is critically important for potential investors to recognize and analyze each borrower's patterns and characteristics as well as possibilities to avoid moral hazard and adverse selection problems. (Herzenstein et al., 2011) indicates that the more detailed a borrower's statements and information are, the more likely they are to obtain a lending. To avoid such problems in lending decision without collateral, the fintech platform must be able to collect and analyze relevant information about characteristics of various borrowers (Chen et al., 2019). According to Chen et al. (2016), and Lin et al. (2013), social network information will help fintech lending in minimizing loan default by collecting various personal information, such as personal images, list texts, history of interactions in social media and the likes. Serrano-Cinca et al. (2015) statistically identified a correlation between fintech credit ratings and the probability of credit failure. Here, credit rating calculation cover specifically borrowers' income, housing condition, debt value, and lending objectives. Yet, there are no statistical correlation between lending quantity and work experience of borrowers with credit failure.

A study by Rosavina et al. (2019) has identified some particular factors that influence MSEs in utilizing fintech lending, including fast lending processes, interest charged, lending amounts, and flexibility in choosing payment periods. However, what factors determine the ability of MSEs to obtain online lending has not been examined in this study. In this study, we therefore seek to examine the factors that enable MSEs to obtain fintech lendings. It is worthwhile to notice, however, that this study will emphasize trust-related factors considered by lenders through fintech lendings in assessing the creditworthiness of MSEs as borrowers. In this regard, the analysis framework of (Herzenstein et al., 2011) that six characteristics of borrowers are noticeable to have prospects for online lending, including trustworthiness, economic status, hardworking behariour, business success, and moral or religious-related aspects. From the perspective of fintech companies, these factors are percieved vital in online lending as they can indicate information about the creditworthines of borrowers. It is also said that such factors can lead to greater amount of lendings received, though they have no impact on better credit performance (Herzenstein et al., 2011).

2. Literature Review

It is evident that fintech platforms utilize various methods and strategies of lending to enhance their business performance. Minimizing cost and risk are percieved vital for fintech lenders in delivering loans without collateral, as well as face-to-face contacts and interaction with their borrowers. A failure of indentifying and calculating risk of loan default will largerly undermine the business performance of fintech lendings. Thus, the ability to gather and analyze data and information on borrower characteristics is of supreme importance prior to lending decision in virtual lending practices (Nguyen et al., 2020). Moreover, a study on twenty five fintech lending companies by Al-Hashfi & Zusryn (2020) reveals that risk mitigation strategies undertaken by fintech companies include particularly credit scoring, collateral requirement and joint-responsibility between investors and fintech operators. In a similar framework, Klafft (2008) explained that conscientious lenders prefer prospective borrowers according to easy-to-observe selection criteria. This is in principle to minimize risk and a favorable rate of return on credit. In such framework, fintech lending has potential to be profitable, if the active use of their platform is able to overcome asymmetric information problems, i.e. selecting or distinguishing good borrowers from the one having poor investment performance. The information provided by the platform is thus to facilitate investment decisions including borrower's current information on their credit rating score, debt-to-income ratio, past and present delinquency, negative credit-related records, current line of credit, current credit balance, bank card utilization and inquiries within the last six months (Klafft, 2008).

Theoretically, there are many factors related to risk perception and mitigation that will affect fintech lending in making credit approval decisions. According to Möllenkamp (2017), in P2P lending methods, the risk perception will be very substantial for investors, because the majority of fintech lendings generally have no guarantee scheme. Therefore, opportunity to achieve a profitable return from each investment will be determined by the extent to which fintech platform are able of overcoming asymmetric information between borrowers and investors. Hence, credible fintech platforms are those that can provide specific information and characteristics of borrowers to potential investors. As (Everett, 2015) puts forward that default risk determinants in fintech lendings are closely related to the existence of information about borrowers's credit ratings, current arrears value, debt-to-income ratio, lending amount, borrower age, and home ownership (Everett, 2015).

Meanwhile, the digital lending viabilities, mentioned by Lee & Lee (2012), are related to the extent that fintech lending platforms can strategically lead potential investors to lend their money. Its behavior certainly does not assist in completing asymmetry information, because it involves emotional factors that affect investors' lending decision. According to Herzenstein et al. (2011), such approach is described as herding behavior in peer-to-peer lending or 'strategic shepherding'. In the sheepherding strategy, the virtual auction method on partially funded lending schemes (in Prosper.com) become increasingly popular to attract more investors. Based on the data analysis, it was found that members of the relational friendship network, generally received lending application funding more quickly (Lin et al., 2013) and experienced fewer defaults (Möllenkamp, 2017).

Virtual trust is very likely to be a key factor in influencing individuals' willingness to lend in fintech lending. The functioning of such anonimous trust in fintech lending practices will closely be associated with credible information given by prospective borrowers about their socio-virtual networks, trustworhiness, and many other personal characters. This is in turn manifested in perceived risk perceptions by potential investors toward the borrowers' creditworthiness of fintech loans. In this study, socio-virtual networks are seen to be similar with the importance of social capital endowment in traditional microfinancing practices. Several microfinance studies have recognized social capital as an important determinant in constructing informal lenders' perception of a borrower's creditworthiness, such moneylenders, group lending practices and the likes. It is in accordance with previous research that social capital is very important in markets with less developed institutional foundations (Chen et al., 2015). The study in China found that the relationship between social capital and risk was not statistically significant, but that social capital was beneficial in gaining the lenders' trust. In the context of online lending with no collateral involved, and virtual contact and interaction between borrowers and lenders, the inherent risk of default are largely associated with the ability of the fintech platforms to generate and examine viable information about the borrowers' creditworthiness and trustfullness within their socio-virtual networks. Such information is vital as it can indicate the brand image or credibilty of the borrowers, consecutively linked to percived risks of thier loan default.

Duarte et al. (2012) confirms that trust is a determining factor for getting a lending. Similalarly, (Hu et al., 2019) also recognize the importance of virtual trust as one of the influencing factors for investors to utiilize fintech services in their investment portfolio (Hu et al., 2019).

Some financial information and personal characteristics of potential borrowers, including physical attractiveness, virtual networks and interactions, as well as ownership of wealth, are thus important factors in gaining the trust of fintech lenders.

In the virtual credit market, social networks will act as a source of "soft information" about borrowers (Lin et al., 2013). Borrower's social networks provide potential lenders with soft information and serve as a signal of trust. Advances in information technology, such as virtual social communities and discussion groups, obtain and transform social network information, making lendings easier than the traditional lendings. Borrowers with virtual friends on the Prosper.com platform turned out to have better ex ante returns. Friendship will act as a signal of credit quality, and individual investors understand the relationship and incorporate it into their lending decisions (Lin et al., 2013). In this study, variables "internet use activity" and "respondent position in business" are interpreted as proxies for the social networking dimensions. The wider use of internet has significantly changed the consumption behaviour and business practices (Becker & Lee, 2019). Consumptive behaviour has been strengthened by the popular use of online payment and lending services across countries. The popularity of social media is also percieved vital in mediating virtual marketing, as well as consumption behaviour. Such behaviours are virtually recorded within consumers social networks of information. To some extent, this information can help fintech companies to recognize the creditworthiness of potential borrowers percieved vital to attract investors.

Based on the theoretical and empirical review described above, this study considers nine variables that hypothetically affect the trust and lenders' decisions to lend to MSEs through the fintech platform. Referring to Figure 1, variables of internet use activity and position in business are proxies of the social network dimension. Meanwhile, the economic dimension is proxied by ownership of working capital, borrowing history, loan utilization and loan repayment

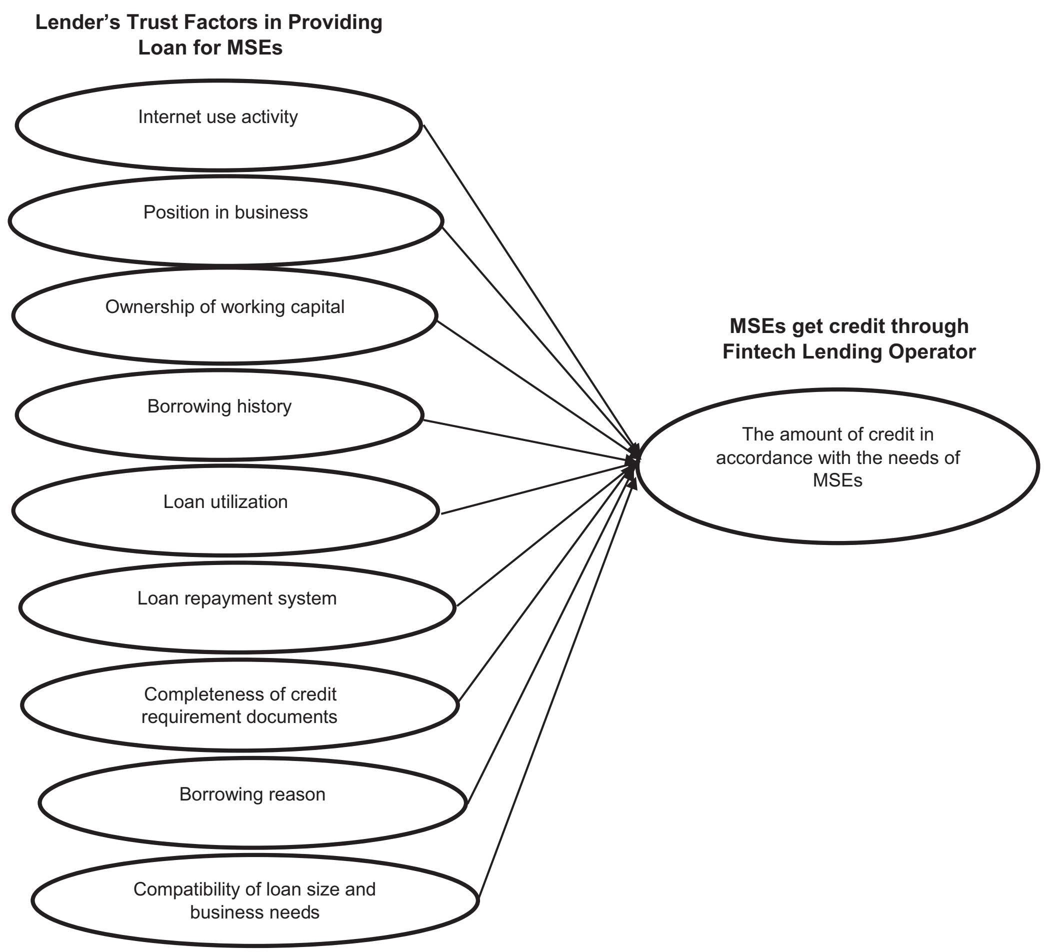

Figure 1: Conceptual Framework of Lender's Decision Factors

systems. The dimension of risk perception is proxied by completeness of credit requirement documents, borrowing reason and compatibility of lending quantity and business need.

In the perception context, if the MSEs risk is considered to be higher then fintech perceives it will be riskier to finance MSEs, so that the total lending will tend to be smaller. On the other hand, if credit risks are perceived to be low, the value of financing will be greater. Therefore, risk management becomes important in fintech, which includes process of identifying, analyzing and accepting or mitigating uncertainty in investment decisions (Ezigbo, 2013). Generally, the main risk in digital peer to peer lending is related to management ability and the ability to mitigate the credit risk (Bernè et al., 2006). Following (Dang et al., 2020), the ability of fintech companies is to identify and calculate risk of udertaking virtual lending. The risk of default in virtual lending is inherently significant for fintech lending schemes as they are mostly delivered without collateral to anonymous borrowers. The challenge is thus the extent to which fintech companies are able to mitigate such risks through utilising and calculating virtual information about creditworthiness of borrowers (Dang et al., 2020) .

Lenders will allocate their funds through fintech lending operators to prospective borrowers by considering "their trustworthiness". In general, behaviour of trusting others involves specific information, public opinions, or faith and often includes emotion-related factors (Ramli et al., 2021). In the context of fintech lending, (Hanafizadeh et al., 2012) recognises the role of trust in indirecttly influencing the use of fintech lendings. In the study, the functiong of trust in fintech lending is through enhancing intention to utilize online lending. This finding is consistent with the previous research undertaken by (Hanafizadeh et al., 2012; Hu et al., 2019). In Vietnam, specifically, the involvement of banks in fintech lending services indicate the importance of virtual trust in online lending practice (Dang et al., 2020).

Following (Das & Teng, 2001), the dimentions of trust and perception on risk in fintech lending are often seen as an interrelated factor influencing the utilization of virtual lending services (Featherman & Pavlou, 2003); (M. K. O. Lee & Turban, 2001). Some studies generally recognize that individuals' perception of risks significantly affect their willingness to adop new method or technology (Yang, 2009). (Wu & Wang, 2005), for instance, underline a significant relationship between perceived risk and the degree of trust as a proxy of intention to utilize mobile device. However, (Koenig-Lewis et al., 2010) argue that no direct relationship between trust and intention exist in using virtual banking. Instead, the indirect corelation is statistically significant through the variables of perceived risk influencing individuals' intention to use virtual banking.

In the context of virtual lending, this factor is influenced by several factors, including social network, economic attributes, and risk perception which consists of nine indicators as proxies. Therefore, if potential investors believe that potential borrowers meet the "trust" indicator, then they will be considered for investors to lend in the same amount as proposed by the MSEs.

H1: *Internet use activities for businesses have a positive effect on lenders' decisions to provide lendings that are equal to the needs of the MSEs.*

H2: *Position in business activities has a positive effect on the lender's decision to provide a lending that is in accordance to the MSEs' requirement.*

H3: *Ownership of working capital has a positive effect on the lender's decision to provide a lending that is in accordance to the needs of the MSEs.*

H4: *Borrowing history have a positive effect on lenders' decisions to provide lending that are in accordance to MSEs' requirements.*

H5: *Loan utilization has a positive effect on the lender's decision to provide a lending that is in accordance to the needs of the MSEs.*

H6: *Loan repayment system has a positive effect on the lender's decision to provide a lending that is in accordance to the MSEs' requirement.*

H7: *Completeness of credit requirement document has a positive effect on the lender's decision to provide a lending that is in accordance to the MSEs' requirement.*

H8: *Borrowing reason has a positive effect on the lender's decision to provide a lending that is in accordance to MSEs' needs.*

H9: *Compatibility of loan size and business need has a positive effect on lenders' decisions to provide lending that is in accordance to the needs of MSEs.*

3. Research Methods

3.1. Method of Collecting Data

The study uses secondary data and primary data. Secondary data necessary to determine sample frame and material for preparing a questionnaire about the factors that influence fintech to finance MSEs. The information is collected from literature studies both journal articles, book chapters, proceedings, previous research and others. Meanwhile, primary data is necessary to obtain empirical data from MSEs about the factors that influence them in obtaining credit through fintech lending according to their requirement.

Primary data has been collected by means of an online survey during May 2019 in five provinces in Indonesia: Jakarta, West Java, Central Java, East Java and Yogyakarta.

Online survey sampling used non-probability sampling with purposive sampling technique on 500 MSEs accessing fintech. By the distribution of questionnaires to all the respondents, there were 345 MSEs who were willing to fill out the questionnaire and who received fintech lendings. However, only 103 respondents gave complete answers and thus only data provided by them was valid for further analysis.

3.2. Data and Variable

Data that has been collected, edited, and then analyzed quantitatively based on the logistic regression model. Dependent variable (Y) is constructed in a binary manner by a question: does the lending received from fintech meet the respondent's expectations or not? In this context, the subjectively appropriate answer was given a score of one (1), and the other was given a score of zero (0). The probability variable is then hypothetically influenced by several variables as presented in Table 2.

3.3. Estimation Model

The logistic model in this study can be written in the following equation:

$$L(i) = \ln = \beta_0 + \beta_{11} + \beta_{22} + \beta_{33} + \beta_{44} + \beta_{55} + \beta_{66} + \beta_{77} + \beta_{88} + \beta_{99} + \varepsilon$$

Description:

$L(i)$ = The amount of credit in accordance with the needs (dummy)
$\beta_{0,}$ = Regression logistic intercept
$\beta_1 \ldots \beta_9$ = Regression coefficients
x_1 = Internet use activity
x_2 = Position in business
x_3 = Ownership of working capital
x_4 = Borrowing history
x_5 = Loan utilization
x_6 = Loan repayment systems
x_7 = Completeness of credit requirement document
x_8 = Borrowing reason
x_9 = Compatibility of loan size and business needs
ε = Error term

4. Empirical Results

This study uses IBM SPSS software to estimate the logistics model that has been described previously. The logistic model estimation is statistically acceptable based on the Omnibus Tests indicators and log-likelihood ratio. The latter ratio decreased from step zero (142.546) to step one (117.723), indicates that the logistic model formulated is relatively more robust. Hosmer test and Lemeshow test showed that significant level of 0.600 which is greater than alpha (0.600 > 0.05). This means that the model is compatible with the observational data, and is suitable for further analysis.

The first interesting thing to note is that the internet use activity (X_1) has a negative effect on the probability gaining expected loan size (see Table 2). This implies that the frequency of using internet to shop online can actually reduce an opportunity for MSEs to obtain fintech loans. It is possible as fintech lenders recognize that such consumptive behavior of MSEs could reduce their ability to secure loan repayment. Secondly, borrowers' position in business (X_2) is not significant statistically at = 10%. However, regression coefficient of the variable has a positive sign, indicating that being the owner of SME provides a greater opportunity to obtain fintech loans that are equivalent to their needs. Conversely, if a business person is not the owner of an

Table 1: Description and Statistics of Variables

Variables	Code	Min	Max	Mean	SD	Data Type
1. The amount of credit in accordance with the needs	Y	0	1	0.4757	0.50185	Binary
2. Internet use activity	X_1	1	3	1.2233	0.54110	Ordinal
3. Position in business	X_2	1	4	3.0388	1.32785	Ordinal
4. Ownership of working capital	X_3	3.00E5	2.50E8	1.6686E7	3.2945E7	Numeric
5. Borrowing history	X_4	0	1	0.6990	0.46092	Binary
6. Loan utilization	X_5	0	1	0.7864	0.41185	Binary
7. Loan repayment systems	X_6	0	1	0.0874	0.288377	Binary
8. Completeness of credit requirement document	X_7	1	3	2.0971	0.88022	Ordinal
9. Borrowing reason	X_8	1	3	2.1359	0.96048	Ordinal
10. Compatibility of loan size with business need	X_9	0	1	0.7379	0.44195	Binary

Table 2: Coefficient Estimation of Logistics Model

Variables	Coeff	S.E	*P*-value	Odds Ratio	95% C.I. for EXP(B)	
					Lower	Upper
Constant	0.215	1.330	0.872	1.240		
X_1	–1.081	0.536	0.044**	0.339	0.119	0.971
X_2	0.212	0.175	0.225	1.237	0.878	1.743
X_3	0.000	0.000	0.114	1.000	1.000	1.000
X_4	1.012	0.551	0.066*	2.752	0.935	8.105
X_5	–0.998	0.605	0.099*	0.369	0.113	1.206
X_6	–2.315	1.076	0.032**	0.99	0.12	0.814
X_7	–0.774	0.321	0.016**	0.461	0.246	0.865
X_8	0.301	0.264	0.255	1.352	0.805	2.269
X_9	1.758	0.610	0.004**	5.799	1.756	19.152

Log-likelihood = 142.546.
Note: **p*-value < 0.05 and ***p*-value < 0.10, significant at the 0.10 level.
Dependent variable: The amount of credit in accordance with the needs.

SME then it becomes difficult to obtain a fintech loan. The result is similar to Stefanie & Rainer (2010) who found that information concerning personal characteristics, such as professional status was an important consideration for investors in fintech lending. Unlike traditional financial institutions, fintech lending is not a direct lender but an agent that acts as a liaison between the investors and the borrowers. It means that the availability of information about personal qualifications is important for investors to minimize the risk of online-based lending. A research by Ding et al. (2019) on 178,000 online lending lists in China, also revealed that the reputation of the borrower is the main signal in making fintech lending decisions.

Ownership of working capital variable (X_3) is not statistically significant. This variable also has no correlation with the suitability of the lending value received by the MSEs as prospective debtors However, the variable of borrowing history (X_4) is statistically significant at 10% level. The positive sign of the coefficient indicates that MSEs with working capital from savings or inheritance has a 2.75 times greater probability of getting loans that is equivalent to its expectations, compared to MSEs with its source of capital from external borrowing. MSEs with a source of working capital from savings or inheritance are considered by lenders to have better loan repayment capabilities.

The regression coefficient for the variable of loan utilization (X_5) of –0.998, indicates that the loans received by MSEs are statistically affected by the purpose of loan usage. MSEs with lending utilisation for consumptive purposes tend to obtain fintech loans that are smaller than expected. In online selection system, fintech operators recognize that such lending purposes are deemed to be riskier than that for productive purposes, such as for improvement in working capital. It means that fintech providers must have the ability to innovate technology (eg. Utilising artificial intelligence (AI) to identifiy such behaviour in order to minime the risk of loan default. According to Boshkov & Drakulevski (2017), risk management makes financial institutions, especially fintech, to necessarily have a framework to manage various financial risks, including procedures to identifying, measuring and controlling risks with AI.

Annuity loan repayment system (X_6) is statistically significant. Regression coefficient of –2.315 indicates that the shorter payment period between annuities will be a consideration for lenders to provide loans for prospective MSEs. Payments on a daily or weekly basis will incur higher costs than on a monthly basis, especially if the debtor MSEs do not pay according to the agreement. This kind of debtor behavior will disrupt cash flow of fintech institutions.

Regarding the variable of completeness of credit requirement document (X_7), it is statistically significant. The regression coefficient of –0.77 indicates that the ownership of basic documents without a business license document, such as an ID card, still has the opportunity to get a fintech lending in accordance with their expectations. It means that the requirements for fintech lending documents tend to be easier and more flexible than the banks. The characteristic makes it easier for MSEs to access fintech loans as stated by Budisantoso et al. (2014) that the major characteristics of suitable credit for MSEs is the utilization of uncomplicated borrowing procedures.

Furthermore, a reason for borrowing variable (X_8) is not statistically significant. However, positive coefficient indicates that the ease of fintech requirements to get a virtual lending has no effect on the amount of loan approved. It means that the convenience factor is not a determining factor for investors (lenders) to provide the lending. Fintech utilizes digital technology to identify potential debtors' abilities, in addition to the collateral ownership factor. The characteristic of fintech is significantly different from banks which generally require collateral as a condition (Widyaningsih, 2018). Therefore, fintech will assess one by one with AI technology before carrying out credit realization to mitigate the risk credit that cannot be returned (Widyaningsih, 2018).

Regression coefficient of compatibility of loan size to business needs (X_9) of 1.758 indicates that the amount of lendings proposed by MSEs as prospective debtors to fintech is approximately equivalent to their business needs. It is possible, because fintech as an operator has offered a lending value ceiling that is adjusted to the target debtor by considering the risk of credit failure. Likewise when the MSEs apply for credit through fintech, they consider their business needs and their ability to repay the loan.

5. Conclusion

The study has investigated the determinants of MSEs in obtaining loans from fintech lending. It concludes that the probability of obtaining fintech loans in accordance with their expectations are influenced by the dimensions of social network, economic attributes and risk perception. The social network factor related to MSEs internet usage activities through social media is one of the considerations for lenders in providing lendings as needed. To minimize the potential risk of investors (lenders), fintech lending operators and lenders obtain information from various online authentications, social media and social networks, where these activities are more numerous and easily accessible via the internet. Some of the information obtained from internet will be used as a reference in the process of assessing creditworthiness of these prospective debtors by fintech lending.

The economic attribute dimension as a determinant will be viewed from the borrowing history, loan utilization and the annuity loan repayment system of the MSEs. These factors are related to the capacity and ability of MSEs to pay. The higher SME's ability, the higher will be the lenders' trust to provide lendings according to the debtor's expectations.

Risk perception dimension relates to the completeness of credit requirement documents and the compatibility of loan size with business needs. Resident identity cards will be used to apply for lendings through fintech lending. It is necessary for MSEs, which generally do not have complete business license documents. Before applying for a lending, MSEs as prospective debtors have obtained information about the credit limit offered by fintech lending, which is adjusted to their business ability to pay.

However, the main limitation of the study is that the trust factor is only observed in several indicators related to the dimensions of social network, economic attributes and risk perception. We suggest that future studies will analyze the determinants of trust for lendings by expanding on other indicators. In terms of methodology, empirical findings from a quantitative approach supported by a qualitative approach and other analytical methods will strengthen the proof of hypothesis.

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