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Trust in Online Peer-to-Peer Lending in Indonesia from a Cognitive-Based Perspective

Reni Mutiarani Saraswati, Verrel Keung, Fariz Hutama Putra
Institut Bio Scientia Internasional Indonesia (i3L), Jl. Pulomas Barat No.Kav. 88, RT.4/RW.9, Kayu Putih, Kec. Pulo Gadung, Kota Jakarta Timur, Daerah Khusus Ibukota Jakarta 13210, Indonesia

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ABSTRACT

This study investigates the perceptions of peer-to-peer (P2P) lending intermediaries and borrowers on lender trust. The trust model was used to develop the lender's trust in the peer-to-peer (P2P) lending sector by incorporating a similar model from a previous study in China. There are three dimensions of cognitive-based trust used in this model, they are social capital, perceived risk and information quality. A partial least square regression structural equation modeling (PLS-SEM) was used to evaluate the model. A quantitative online survey was distributed to 100 P2P lenders in Jakarta, Indonesia. The data collected was analyzed using PLS-SEM for its convergent validity, reliability, discriminant validity, and model fit. This study's approach integrates the antecedents of trust points to identify the criteria of lenders for achieving a successful loan transaction. The findings of the study revealed that it is essential for borrowers to build a good reputation and provide sufficient information needed to boost a lender's trustworthiness.

Kata Kunci:
Persepsi risiko,
Modal sosial,
Kualitas informasi,
Partial least square structural equation modeling (PLS-SEM).

SARI PATI

Penelitian ini menyelidiki persepsi perantara dan peminjam dalam platform peer-to-peer (P2P) lending terhadap kepercayaan pemberi pinjaman. Model kepercayaan digunakan untuk mengembangkan kepercayaan pemberi pinjaman dalam sektor P2P lending dengan mengadaptasi model serupa dari penelitian sebelumnya di Tiongkok. Terdapat tiga dimensi kepercayaan berbasis kognitif yang digunakan dalam model ini, yaitu modal sosial, persepsi risiko, dan kualitas informasi. Analisis dilakukan menggunakan model persamaan struktural partial least square regression (PLS-SEM). Survei kuantitatif daring didistribusikan kepada 100 pemberi pinjaman P2P di Jakarta, Indonesia. Data yang dikumpulkan dianalisis menggunakan PLS-SEM untuk menguji validitas konvergen, reliabilitas, validitas diskriminan, dan kecocokan model. Pendekatan penelitian ini mengintegrasikan faktor-faktor awal pembentukan kepercayaan untuk mengidentifikasi kriteria pemberi pinjaman dalam mencapai transaksi pinjaman yang sukses. Hasil penelitian menunjukkan pentingnya bagi peminjam untuk membangun reputasi yang baik dan menyediakan informasi yang memadai guna meningkatkan kepercayaan pemberi pinjaman.

Corresponding author:
reni.saraswati@i3l.ac.id

INTRODUCTION

In recent years, the development of information technology has resulted in a significant trend of financial innovations including mobile payment, crowdfunding, digital currency, social lending, blockchain, peer-to-peer lending, and other types of investment, to name a few. Peer-to-peer (P2P) lending—which is regarded as one of the initial manifestations of the financial technology revolution—has undergone transformation and improvement. With the proliferation of online lending platforms, the P2P lending business has expanded rapidly. Its growth was attributed to a confluence of factors, including the broad use of the internet, the availability of a large sum of funds, and the presence of underserved financial needs (Huang, 2018).

The term "peer-to-peer finance" or "P2P" platform is used to describe an online platform that acts as a middleman between borrowers and lenders. It enables individuals to get loans from other individuals without the involvement of conventional financial institutions such as banks (Chen et al., 2014; Huang, 2018; Xu & Chau, 2018). Using the latest technology, online P2P has the potential to obtain funds from a large number of small investors (Chen et al., 2014) and provides lenders with higher rates of returns (A. Basha et al., 2021). In addition, borrowers with restricted access to conventional financial institutions may have better access to loans at lower transaction costs (A. Basha et al., 2021), and thus P2P lending is a favorable form of funding for small and micro businesses (Chen et al., 2014).

In Asia, P2P lending is a fast-growing fintech industry, as seen by its rapid expansion in regions such as China and Indonesia. China has become one of the biggest markets for P2P lending platforms, as there were over 2,300 platforms with a total volume of CNY 9,208 in loans in 2017 (Stern et al., 2017; Suryono et al., 2019). In Indonesia, small and microbusinesses turned to P2P lending as an alternate means of providing loans since loans offered by conventional financial services were not accessible to them (OJK, 2019). Complex business planning and risk evaluations have become impediments, and few businesses can fulfil the loan requirements set by these financial services. As a result, small and microbusiness seek alternative finance that recognizes their limited capabilities. P2P lending, on the other hand, provides less stringent criteria and a faster application procedure than conventional financial services. The criteria set by P2P lending include loan creditworthiness, loan nominal, loan period, interest rates, level of security, loan cost, and loan process, all of which influence small and microbusinesses' ability to obtain funding (Rosavina et al., 2019).

P2P lending has been significantly important for the national economy in Indonesia. This can be seen through the evidence of MSME financing. In this regard, P2P lending recorded a total of 92.4 million beneficiaries, or borrowers, who received IDR 476.89 trillion in P2P lending in 2022. Furthermore, this sector had the second-highest compound annual growth rate (CAGR) among the countries in the G20, with a transaction value of 39%. (Bank Indonesia, n.d.). Likewise, the number of lenders and interest in this lending model have grown in response to the enthusiasm of the market. As of January 2023, the Indonesian Financial Services Authority (OJK) has issued licenses to 102 fintech P2P loan firms, including Danamas, Kredit Pintar, and GandengTangan, among others. In addition to fintech P2P lending platforms for MSME enterprises, some of these lending platforms also enable access to loans for education (e.g., Edufund) and social impact agriculture (e.g. TaniFund) (OJK, 2023). The number mentioned above, does not include illegal lenders, which are those that do not have authorization from or are unable to gain approval from Financial Services Authority. While P2P lending has grown rapidly, there have been several challenges that have caused stakeholders to lose faith in the sector. Information asymmetry, issue in credit risk evaluation, failing to pay, lack of trust in borrowers and intermediaries, moral hazard, inefficient government regulation, fraudulent activities and issues in consumer protection are among the challenges experienced by the P2P stakeholders. Table 1 shows the summary of these problems.

Table 1. Challenges in P2P Lending Activities

Authors	Challenges in P2P Lending								
	Information Asymmetry	Credit Risk Evaluation	Fail to Pay	Trust in Borrowers	Trust in Intermediary	Moral Hazard	Government Regulation	Fraudulent Activities	Consumer protection
(Chen et al., 2014)				√	√				
(Emekter et al., 2015)		√	√						
(He & Li, 2021)							√		
(Hidayat et al., 2020)									√
(Huang, 2018)							√		
(Khan, 2022)					√				
(Lu et al., 2021)			√						
(Ma et al., 2018)	√								
(Niu et al., 2020)				√	√				
(Wang et al., 2020)		√							
(J. Yan et al., 2015)	√	√				√			
(Y. Yan et al., 2018)				√					
(Yu et al., 2021)								√	
(W. Zhang et al., 2020)		√							

The above challenges have impeded the growth of P2P lending, and it is critical to provide an understanding of the issue and a solution to the problems. Among the above issues, trust is an important dimension that should be addressed since it is the first factor established by stakeholders in P2P lending activity (Gefen et al., 2008). Therefore, this study emphasizes the trust model and aims to better comprehend the factors that influence the lender's trust in borrowers and intermediaries in P2P lending.

The Overview of Trust in P2P Lending

Trust is an important aspect in managing risk, addressing uncertainty (ter Huurne et al., 2017), the key factor for individuals using technological services (Beldad et al., 2010), and for the success and growth of e-commerce (Gefen et al., 2008). Multiple academic fields, including social psychology, anthropology, and sociology, have devoted considerable attention to the topic of trust and all have various methods of conceptualizing and defining trust (ter Huurne et al., 2017). The vast majority of scholars have defined trust in accordance with the viewpoint of their particular discipline (McKnight et al., 2002). In this aspect, a consensus among researchers agrees that trust is defined as a psychological state that is characterized by a person's willingness to be vulnerable as a result of the trustor having favorable expectations towards the trustee (PytlikZillig & Kimbrough, 2016).

In interorganizational business relations, there are several types of trust being proposed to include calculative-based trust, affective-based trust, and cognitive-based trust (Akrout & Diallo, 2017). While Lewis & Weigert (1985) suggested cognitive trust, conative trust, and affective trust. Calculative-based trust can be associated with being cautious in the basis for deterrent punishments (Akrout & Diallo, 2017). Cognitive trust is trust that originates in a person's reasoning, confidence in their achievements, competencies, and dependability (Lewis & Weigert, 1985). It involves the anticipation of the action of the other party or person (Akrout & Diallo, 2017). As for affective trust, it derives from empathy, emotional relationships, friendship (Lewis & Weigert, 1985), and security (Akrout & Diallo, 2017). Conative trust is grounded on a person's behavior, where trust in another person may be predicated on that person's ability or willingness to help others, but it can also exist independently of these two qualities (Lewis & Weigert, 1985). In P2P lending, trust is the conviction that the borrower will behave collaboratively to meet the requirements of the lender. Beliefs in a trustee's trustworthiness, which consists of competence, integrity, and goodwill, underlie trust in online contexts (Gefen et al., 2008). People's reluctance to participate in online transactions is sometimes attributed to a lack of trust (Beldad et al., 2010). Initial trust creation is crucial since lenders are often unfamiliar with borrowers. Initial trust is based mostly on cognition rather than past encounters since there are no such things as "repeated interactions" between lenders and borrowers. This form of cognition-based trust is based on immediate, cognitive indications of initial conception (McKnight et al., 2002).

Research Model

Decisions in peer-to-peer (P2P) lending were often made by borrowers as well as lenders based on information that was either inadequate or only partly accurate (Kim et al., 2008). As a result, they are often subject to risks and uncertainty in their lending choices. Building up people's initial trust in one another is necessary before any transactions can take place. Furthermore, since the borrower and the lending platform may both be sources of potential risk, lenders should work to gain trust with the borrower as well as the platform. In this study, cognition-based trust was used to examine the P2P lending, and the variables used include perceived risk, social capital, and information quality.

Cognition-Based Trust: Social Capital

According to Tang et al. (2012), social capital refers to the resources that can be acquired through the social network and utilized to establish connections with the community. Social capital contributes to the well-being of individuals and society through the exchange of information. The majority of websites that specialize in peer-to-peer lending offer social interaction opportunities, including discussion boards and direct messaging. Users are afforded a diverse array of alternatives for cultivating their own Social Capital. In the model of peer-to-peer lending, lenders will submit bids for a borrower's listings if the borrower can demonstrate or convince the lenders that they are trustworthy for loans by exhibiting a positive image, trustworthiness, or a sense of security. In this regard, the probability of a borrower being trusted by lenders is directly proportional to the borrower's social capital. Therefore, the hypothesis that this investigation suggests is as follows:

H1: Perception of lender in borrower's social capital level positively influences the lender's trust in the borrower

Cognition-Based Trust: Perceived Risk

The term "perceived risk" refers to a lender's estimation of the likelihood that they would suffer a financial loss as a result of the failure of their borrowers in online lending. Previous research has shown that a customer's perception of the level of risk involved in a transaction has a substantial influence on trust and purchase intention (Pavlou & Gefen, 2004). A lender's primary objective is to generate profits with minimal risk. Lenders will evaluate any loan-related activity before making a decision. If lenders perceive that borrowers are likely to engage in malevolent behavior, they will be hesitant to develop trust. Thus, the hypothesis proposes:

H2: Perception of lender in borrower's perceived risk level negatively influences the lenders' trust in the borrower.

Cognition-Based Trust: Information Quality

Building confidence in online financial transactions, such online lending, requires the provision of information. This underscores the significance of "information quality," which pertains to the extent to which the information provided by a borrower is accurate and complete. This information consist of borrowing-related details or listing information such payback mechanism, interest rates, borrower trustworthiness (T. Zhang et al., 2014), and financing probability (Berkovich, 2011).

One of the most critical indicators of the success of information systems is information quality (Xu & Chau, 2018). The information quality driven by user acceptance and adoption of the system influences user behavior and is significant for users' decision making. By using the appropriate information technologies and implementing suitable features, P2P lending platforms may operate as an intermediary to allow the exchange of resources such as information and funds and build trust between participants in financial transactions (Xu & Chau, 2018). In addition to the platform, the quality and content of the information provided by the borrower has a substantial effect on P2P lending results (Berkovich, 2011). In other words, the information quality is crucial for obtaining the trust of lenders and, hence, funding outcomes. Accordingly, the hypothesis proposes,

H3: Perception of lender in borrower's information quality level positively influences the lender's trust in the borrower.

METHODOLOGY

Scope of the Research

The primary objective of this study was to develop a trust model for the stakeholders engaged in P2P lending, and the participants in this study were the borrowers and lenders who are involved in online lending that reside in Jakarta. The correlations between independent and dependent variables following the occurrence of an activity were identified through causal-comparative research in this study. The researchers aim to determine whether the independent variable influences the dependent variable or the result by comparing two groups of participants. To acquire results that are reliable, the minimum number of participants contributing to the data collection for analysis should be greater than 100 (Streiner, 1994). Consequently, owing to the number of questioners in this research, the minimum sample size was established at the minimum 100 respondents.

Methods, Measurements and Data Processing

This study used primary data that came from the research participants' responses to the questionnaires. The structural equation modelling (SEM) methodology was used which allows researchers to model and evaluate concurrently complex relationships among several independent and dependent variables (Dzin & Lay, 2021; J. F. Hair et al., 2021). In accordance with the participants' communication preferences, the questionnaire was disseminated via platforms such as WhatsApp. The questionnaire contains questions on the antecedents of trust outcomes, such as perceived risk, social capital, and information quality (Chen et al., 2014).

For the purpose of determining variable scores, a 7-point Likert scale was used since it gives a better level of description of the theme and it practically appeals to the participants' reasoning (Joshi et al., 2015). The scale ranges from strongly disagree to strongly agree. Each variable involves two to three questions. The data is processed using SmartPLS application tool and the results will be portrayed in the form of tables and graphical charts. Several test will be conducted as part of the PLS-SEM computation to include convergent validity and reliability test, discriminant validity test, R-squared and path coefficient test. A reliability test is carried out to assess an instrument's consistency. Cronbach's alpha and composite reliability are used to assess the dependability of the instruments. As for the measurement for data validation, convergent validity coefficients were used in this study. Finally, Path Coefficient analysis and T-Statistics were used to assess hypothesis testing, commonly known as bootstrapping.

RESULTS AND DISCUSSION

A total of 100 responses were obtained from peer-to-peer lenders in Jakarta. The characteristics of the respondents were quite diversified, as shown in Table 2 and Table 3.

Table 1. Respondent characteristics on age, gender, and education level

Respondent Characteristics	Results	Percentage (in %)
Age:		
1. <20	0	0
2. 20-29	34	33.7
3. 30-39	40	39.6
4. 40-49	18	17.8
5. 50 years	9	8.9
Gender:		
1. Male	66	65.3
2. Female	35	34.7
Education level:		
1. Highschool	17	16.8
2. Diploma	11	10.9
3. Bachelor's degree	53	52.5
4. > bachelor's degree	20	19.8

Table 3. Respondent characteristics on income, period, and frequency of intermediary use

Respondent Characteristics	Results	Percentage (%)
Monthly income:		
1. Below minimum wage	7	6.9
2. IDR 4 million ≤ X < IDR 8 million	10	9.9
3. IDR 8 million ≤ X < IDR 12 million	21	20.8
4. IDR 12 million ≤ X < IDR 17 million	27	26.7
5. IDR 17 million ≤ X < IDR 21 million	16	15.8
6. ≥ IDR 21.5 million	20	19.8
Time period of intermediary usage		
1. < 1 month	21	20.8
2. 1 month ≤ X < 3 months	28	27.7
3. 3 months ≤ X < 5 months	21	20.8
4. 5 months ≤ X < 7 months	8	7.9
5. 7 months ≤ X < 9 months	9	8.9
6. 9 months ≤ X < 11 months	4	4
7. X ≥ 11 months	10	9.9
Frequency with which an intermediary is used monthly:		
1. 0 - 1 time		
2. 1 – 3 times	28	27.7
3. 4 – 6 times	52	51.5
4. 7 – 9 times	14	13.9
5. ≥ 9 times	5	5
	2	2

PLS-SEM Analysis

The data processing begins with an assessment of the factor loading which indicates the variation described by the variable on a certain component. Based on SEM method, a factor loading of 0.7 or greater means that the structure is well-defined, which is objective of any factor analysis. With a sample size of 100, factor loadings of 0.55 or higher are considered statistically significant (Hair et al., 2019). This is congruent with this study, since there were 100 participants in this study.

Following data computation, the results reveal that question 1 of the Perceived Risk (PR1) has an item loading of 0.42, indicating that it did not meet the requirement required for data analysis. As a result, the item was excluded from the analysis. After PR1 was deleted, the data was processed again, and the results show factor loading values between 0.71 and 0.92, or above the threshold of 0.7, suggesting that they are acceptable.

Table 4. Result: Factor Loading

Variable	Item	Loading
Perceived Risk (PR)	PR2	0.76
	PR3	0.87
Information Quality (IQ)	IQ1	0.83
	IQ2	0.83
	IQ3	0.74
Social Capital (SC)	SC1	0.84
	SC2	0.92
	SC3	0.87
Trust in Borrower (TB)	TB1	0.83
	TB2	0.84
	TB3	0.71

The next step of the research is to estimate the value of average variance extracted (AVE), which is a method that can be used to assess validity based on the convergent validity of each measure. A minimum AVE value of 0.50 shows significant convergent validity, implying the average proportion of variance retrieved from a construct's items, or more than half of the variance in its indicator is explained by the latent variable (J. F. Hair et al., 2017, 2021). The findings of the analysis of variance were between 0.63 and 0.78. Therefore, the fact that the items are greater than the threshold of 0.5 indicates that the variation of the items is acceptable.

Table 5. Result: Average Variance Extracted (AVE)

Construct	Average Variance Extracted (AVE)
Information Quality (IQ)	0.65
Perceived Risk (PR)	0.66
Social Capital (SC)	0.78
Trust in Borrower (TB)	0.63

Cronbach Alpha and Composite Reliability were used to evaluate internal consistency and reliability. The findings are shown in Table 4, where Cronbach's alpha is between 0.71 and 0.86 for all items, which is above the reliability threshold of 0.7. The only item with a Cronbach's alpha score below 0.7 is the perceived risk item, which has a score of 0.49. Composite reliability values were between 0.80 and 0.91, significantly higher than the minimum reliability value of 0.70 (J. F. Hair et al., 2017).

Table 6. Result: Reliability of Analysis

Measurement	Cronbach Alpha	Composite Reliability
Social capital • The borrower is active in interacting with others on the peer-to-peer lending service. • The borrower and I (the lender) have good interaction and communication. • The borrower has a good image and is respectable.	0.86	0.91
Perceived Risk (PR) • I will not use the lending service if I lose my money. • The risk to lend my money to the borrower is very high.	0.49	0.8
Information quality (IQ) • I think the borrower provides reliable information. • The borrower provides sufficient information when I try to make a transaction.	0.73	0.84
Trust in Borrower (TB) • The borrower is trustworthy. • The borrower gives me the impression that she/he would keep promises. • I expect that the intention of the borrower is benevolent.	0.71	0.83

Discriminant validity is a construct validity component that indicates the extent to which two similar concepts are different in scales (J. F. Hair et al., 2014). To test discriminant validity, the AVE of any latent construct must be greater than its highest squared correlation with any other latent construct (J. F. Hair et al., 2011). The findings presented in Table 6 indicate that the discriminant validity of each construct is acceptable since the inter-construct correlation between variables is greater than the correlation between any other constructs.

Table 7. Result: Fornell-Larcker Criterion

Construct	IQ	PR	SC	TB
Information Quality (IQ)	**0.8**			
Perceived Risk (PR)	-0.21	**0.81**		
Social Capital (SC)	0.46	0.01	**0.88**	
Trust in Borrower (TB)	0.56	-0.22	0.53	**0.79**

An alternative approach for determining Discriminant Validity is Cross Loading Analysis. This approach analyzes if each item loaded on a build has a higher value than on other constructs or the loadings of an indicator should be greater than all of its cross loadings (J. F. Hair et al., 2011). The data shown in Table 7 indicates that the cross-loading value of an item in its particular construct is greater than the item value of other constructs, indicating adequate Discriminant Validity.

Table 8. Result: Cross Loading Criterion

Item	IQ	PR	SC	TB
IQ1	0.83	-0.12	0.4	0.5
IQ2	0.83	-0.17	0.4	0.43
IQ3	0.74	-0.21	0.3	0.43
PR2	-0.23	0.82	0.02	-0.19
PR3	-0.107	0.0807	0.003	-0.18
SC1	0.36	-0.02	0.8	0.4
SC2	0.35	0.01	0.92	0.46
SC3	0.49	0.05	0.9	0.53
TB1	0.53	-0.15	0.4	0.83
TB2	0.45	-0.17	0.3	0.83
TB3	0.36	-0.21	0.5	0.71

SEM was also used to assess the structural research model. Various analyses were performed on the data obtained to achieve the structural model's fit, measuring correlation effectiveness, assess and validate the hypotheses, study the endogenous variables, and the relevance of the variables in the hypotheses. Methods such as R-square analysis, t-statistics, path coefficient analysis, predictive relevance by constructing cross-verified redundancy, and model fit can be used to evaluate the structural model.

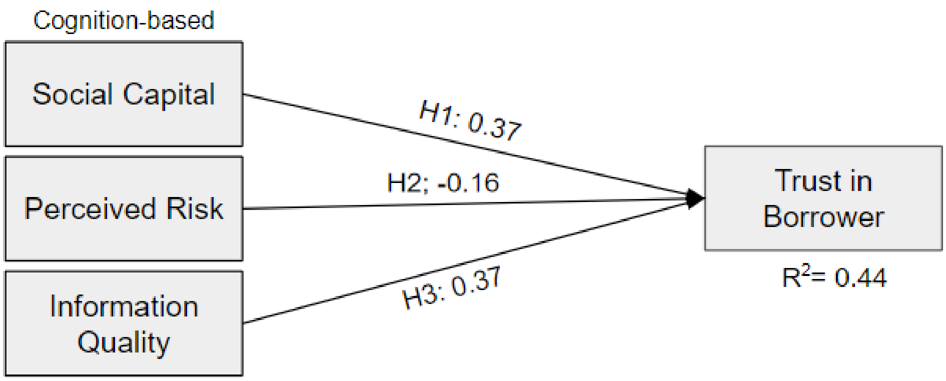

Figure 1. The Research Model

PLS-SEM was used to assess the model, yielding a chi-square value of 174.037. The findings also indicated an acceptable SRMR value of 0.098 since it was lower than 0.1 value of threshold (Hu & Bentler, 1999). Furthermore, an NFI of 0.61 indicates that the structural model is 61% fit. Next, the R-squared value of the model was calculated. The results revealed that the endogenous variable, Trust in Borrower, has an R-squared value of 0.44. A good rule of thumb for an R-squared value is that it should have a low value if it is 0.12 or lower, a medium value if it is between 0.13 and 0.25, and a high value if it is 0.26 or higher (Cohen, 1992), hence the R-squared value of this model is acceptable. Finally, path Coefficient Analysis was performed so that the impact of an exogenous variable on an endogenous variable could be determined from a single independent variable rather than from an exogenous variable as a whole.

Table 9. Path Coefficient and T-Statistics Analysis

Hypothesis	Construct Correlation	Path Coefficient	T-Statistics	P Values	Result
H1	SC → TB	0.37	4.76	0.00	Supported
H2	PR → TB	-0.16	2.09	0.04	Supported
H3	IQ → TB	0.37	3.45	0.001	Supported

The table above presented the findings of this study. Hypothesis 1 (H1) proposed that the perception of lender in borrower's social capital level positively influences the lender's trust in the borrower. The findings revealed that the path coefficient value of 0.37 exceeds zero and the t-statistics value of 4.76 exceeds 1.96 of threshold value, indicating a high degree of significance. Since the hypothesis had a p-value of 0.00, this value was less than 0.05. Hence, H1 is accepted.

Hypothesis 2 (H2) proposed that the perception of lender in borrower's perceived risk level negatively influences the lenders' trust in borrower. The results showed that the path coefficient value of -0.16 is less than 0, and the t-statistics value of 2.09 is less than 1.96 of threshold value, both of which point to a high degree of significance. Since the hypothesis had a p-value of 0.04, which is less than 0.05. Therefore, H3 is accepted.

Hypothesis 3 (H3) proposed that the perception of lender in borrower's information quality level positively influences the lender's trust in the borrower. The findings demonstrated that the path coefficient value of 0.37 exceeds zero and the t-statistics value of 3.45 exceeds 1.96 of threshold value, indicating a high degree of significance. Since the hypothesis had a p-value of 0.001, which is less than 0.05. Thus, the hypothesis is accepted.

Discussion

This study employs a trust model to investigate the lender's trustworthiness in the online P2P lending environment in Jakarta area of Indonesia as well as examining the perspective of borrower towards the lender's trust. The trust model incorporated trust's antecedents and outcomes and was tested on 100 participants in Jakarta using PLS-SEM.

It is crucial for borrowers to earn the trust of lenders by establishing a good reputation, instilling confidence and security, and providing detailed, high-quality information on the loan they're seeking. The study focusses on exogenous factors, which are the antecedents of cognition-based trust, and endogenous variables, which indicate borrower's trust. The data presented in this study was derived from the path coefficient and t-statistics analyses.

The first hypothesis of the study implies that the social capital of the borrower positively influences the trust of the lender in the borrower. This means that the borrower has the capability to gain the lender's trust and, therefore, finances. If a borrower can build social capital by making the lender feel secure and trustworthy, the borrower will be able to persuade the lender to trust the borrower. Literature suggests that the social capital of borrowers contributes to the lenders' trust (Chen et al., 2015), and a lender's willingness to invest is influenced by the trust in the borrower (Chen et al., 2014).

The second hypothesis that was tested in this study is that the lender's perception of risk may have a negative influence on the level of trust they have in the borrower. In this aspect, perceived risk is associated with the perception of the lenders in the possibility of financial loss in a transaction owing to a borrower's failure. Due to the high level of risk associated with the investment, the lender would no longer use the intermediary as a consequence of this. Thus, perceived risk promotes negative expectancies, resulting in a negative attitude toward transaction intents (Zhu et al., 2009).

Particularly in the context of online P2P lending, perceived risk is a significant challenge for lenders.

The third hypothesis that was tested in this study suggests that the lender's trust in the borrower will increase if the lender has a favorable perception that the borrower's information is of high quality. Lenders have few possibilities for gathering sufficient information about potential borrowers. As a result, lenders rely heavily on the information in the borrowing listing (T. Zhang et al., 2014) facilitated by the intermediary. Issues related to a lack of information accuracy should be addressed by intermediaries by enhancing the platform and its capability to gather detail information from the borrowers. For example, platforms may verify key user data, user identification and other crucial information to help establish the lender's trust (Akhmedova et al., 2020). The more information a borrower provides, the more credible they are in the eyes of lenders. Numerous thorough research on P2P lending indicate that having a complete information has a crucial effect on loan decision making (Berkovich, 2011; T. Zhang et al., 2014). Thus, the information quality of the borrowing listing is becoming more vital to obtain the trust of lenders.

CONCLUSION

This study aims to provide P2P lenders, borrowers, intermediaries, and the government with recommendations to stimulate the use of P2P financing and support SMEs' growth and development. This study examined the level of trust between borrowers and lenders in the P2P lending system, and it has established a trust model to analyze this relationship quantitatively using PLS-SEM method. The model incorporates cognitively based trust to explore the phenomenon of trust among P2P lenders. The model is broken down into three distinct types of cognitive-based trust beliefs that influence the lender’s trust in borrowers such as social capital, perceived risk, and information quality. The model is empirically tested using data from a survey of 100 online P2P lenders located in Jakarta.

The findings of the research revealed that social capital and information quality are important dimension in building the lender’s trust. In this regard, the capacity of a borrower to develop a positive image and reputation based on lender’s perspective is the most crucial aspect of winning the lender's trust. In addition, providing sufficient information is also important to increase borrower’s credibility and acceptance by the lenders. Apart from that, government engagement might be beneficial and foster community trust, which ultimately makes it easier to do business online. In this regard, the government should impose laws governing information disclosure for lending intermediaries to reduce information asymmetry between lenders and borrowers. This will ultimately result in better decision making on the part of lenders and lower the risk that the lenders take on.

The research has limitations owing to its preliminary nature. The population coverage and technique of sampling were constrained by time and resource limitations. Furthermore, since this study only covers the online P2P lending environment in Jakarta, sampling bias may have occurred. Therefore, future study in this area should involve a cross-cultural analysis and comparison across various locations in Indonesia to better understand behavioral disparities among lenders. A research investigation that was carried out in China and acquired a total of 785 data points from online P2P lenders led to findings that were much more significant than those found in a study with a smaller sample. Likewise, a larger sample size may result in more reliable trust indicators and a more representative sampling for the study of the Indonesian P2P market.

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