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Determining Factors of Peer-to-Peer (P2P) Lending Avoidance: Empirical Evidence from Indonesia

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Abstract: P2P lending offers loans to the public with easy processes and terms. However, the level of P2P lending disbursements is still lower than that of the banks. In addition, a comparison of the number of users of P2P lenders and the productive age population of Indonesia shows that there are still many people who do not use P2P lending. This paper examines the factors that make Indonesians avoid P2P lending. This study used an online survey approach for its data collection and structural equation modeling (SEM) to analyze the data from 499 responses. The study found that the perceived threat from P2P lending is influenced by its perceived severity, perceived susceptibility, and risk tolerance. This perceived threat and social influences cause people's avoidance motivation. This study contributes to the fintech literature by providing empirical evidence on the avoidance of P2P lending from the borrowers' perspectives using the TTAT model. Other implications are an input for regulators/governments to enforce the rules for user protection and input for the P2P lending service providers to provide educational programs regarding the use of P2P lending.

Keywords: fintech, P2P lending, TTAT, SEM, multi-group analysis, Indonesia
JEL Classification: G23, G41, Q55

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Introduction

The fintech industry is rapidly growing globally, and there are enormous amounts of money invested in fintech companies, as opportunities are wide open in this sector. Globally, the funds invested in fintech in various countries reached $98 billion in the first half of 2021 (KPMG, 2021). Whereas in the Asia-Pacific region, investment in fintech reached $7.5 billion (KPMG, 2021). In Indonesia, until the end of the second quarter of 2020, among four categories of fintech business models, online or P2P lending was the most dominant (44%), followed by fintech in the digital financial innovation category (24%), digital payments (17%), and crowdfunding services (1%) (Indonesia Fintech Association, 2020). P2P lending is a financial service that connects lenders and loan receivers to form a loan and borrowing arrangement in rupiah directly over the internet (Financial Services Authority, 2016). This system makes financial institutions (banks), who act as intermediaries between borrowers and lenders, unnecessary (Berger and Gleisner, 2009).

P2P lending is a financing alternative that Indonesian people can access widely. More than 70% of the adult population of countries in the ASEAN region, including Indonesia, is still unbanked (Bain & Company, Google, and Temasek, 2019). The number of P2P lenders registered with the OJK[1] as of t July 2021, reached 121 companies, of which 68 companies have had business licenses (Financial Services Authority in Indonesia, 2021a). However, various problems relating to P2P lending services that can occur in the field seem to have had an impact on the intention of Indonesians to use this digital-based financial service.

The Investment Alert Task Force in Indonesia (SWI[2]) had closed 3,365 illegal P2P lending services between 2018 and July 2021 (Financial Services Authority in Indonesia, 2021c). Further, the Minister for Communication and Information stated that from 2018 to August 17, 2021, the Ministry of Communication and Information in Indonesia cut off access to 3,856 sources of fintech-related content that violated the laws and regulations, including unauthorized/illegal online lending platforms (Bank Indonesia, 2021). The Indonesian National Police Chief stated that the violations committed by illegal P2P lending services include, for example, accessing the borrower's data (contacts on the cellphone), collecting loans that were not following the rules of the OJK, not having a contact and office location, not deleting the borrower's data even though the loan had already been paid, and also using the borrower's I.D. card data to make a loan in another application (Burhan, 2021).

The level of P2P lending disbursements only reached Rp. 20,612 billion as of April 2021 (Financial Services Authority in Indonesia, 2021b) compared to bank disbursements, which reached Rp 5,477.5 trillion on April 2021 (Victoria, 2021). The OJK also revealed

[1]OJK (*Otoritas Jasa Keuangan*), defined as Financial Services Authority in Indonesia
[2]SWI (*Satgas Waspada Investasi*), defined as Investment Alert Task Force in Indonesia

that the number of borrowers using P2P lending as of June 2021 amounted to 22,908,720, both individually (22,906,503) and business entities (2,217) (Financial Services Authority in Indonesia, 2021b). Compared with the projection of Indonesia's productive age (15-64 years) population in 2021, which should reach 187,213,800 people (Indonesian Central Bureau of Statistics, 2018), the number of individual P2P lending borrowers has only reached 11.8% of Indonesia's productive age population. This data shows that many Indonesian people are not using P2P lending.

This research is conducted to investigate the factors that influence Indonesians to avoid P2P lending. In contrast to previous studies that focused on the use of P2P lending in terms of lenders (Chen, Lai, and Lin, 2014); (Wang et al., 2014); (Chen, Lou and Van Slyke, 2015); (Xu et al., 2019); (Sangmin Lee, 2017), as well as the use of P2P lending from the borrowers' side (Rosavina et al., 2019); (Liu et al., 2018); (Wang et al., 2020); (Huang, Qian, and Xu, 2020), this study focuses on avoidance measures against the use of P2P lending from the borrowers' side using the technology threat avoidance theory (TTAT) as the basis for this research. Liang and Xue (2009) stated that the TTAT explains that a threat assessment determines individual avoidance behavior (perceived susceptibility, perceived severity, and perceived threat) and a coping appraisal (individual self-efficacy, perceived cost, and perceived effectiveness). The TTAT can use the positive feedback loop principle to describe the processes and determinants of individual avoidance behavior against information technology's dangers. In the context of P2P lending, positive feedback loops are defined as conditions for individuals to avoid the dangers of P2P lending, where the dangers of P2P lending are undesirable conditions. In addition to using the positive feedback loop principle, the TTAT also explains that a threat assessment determines individual avoidance behavior from the dangers of information technology (perceived susceptibility, perceived severity, and perceived threat) and a coping appraisal (individual self-efficacy, perceived cost, and perceived effectiveness).

This study uses respondents that are familiar with P2P lending but who chose not to use the P2P lending services. The data were collected using the snowball sampling method, which gathered 499 respondents. The data were analyzed using SEM by utilizing SmartPLS 3.0. The study's results indicated that the motivation for individual avoidance of P2P lending services was caused by individual perceptions that P2P lending was a threat. This study provides empirical evidence that individual threat perceptions of P2P lending were positively associated with the perception of severity and susceptibility related to P2P lending services.

Further, this study finds that the perceived threat and the social influence factors are positively associated with the individual's motivation for avoiding P2P lending. This research contributes to stakeholders, especially P2P lending service providers, by evaluating and improving their services and the government with regard to the P2P lending regulations in Indonesia. This study also contributes to the information systems literature by providing empirical evidence on the factors that influence the avoidance of P2P lending through the TTAT.

This paper proceeds as follows. In the literature review section, this study explains what P2P lending is, its practices in Indonesia, and what the technology threat avoidance theory (TTAT) says. This is followed by the research model and hypotheses development section. The following sections detail the method and results, in which this study discusses the analysis results. This study ends with conclusions, limitations and suggestions for future studies.

Literature Review

P2P Lending

Chen et al. (2014) define P2P lending as a financing platform connecting lenders and borrowers directly through online intermediaries without financial institutions. The lenders and borrowers can be individuals or businesses (Galloway, 2009). Based on the Regulation of Financial Services Authority Number 77/POJK.01/2016, P2P lending is the provision of financial services to bring together lenders and loan recipients to enter into lending and borrowing agreements, in rupiah, directly through an electronic system using the internet. P2P lending financial services are an alternative to traditional financing for the population, offering easy terms and processes. P2P lending can provide benefits such as easy use of the platform (Lin, Prabhala, and Viswanathan, 2013) and low transaction costs (Chen and Han, 2012). However, P2P lending also has several risks, including default risk. Namvar (2013) states that the risk of default on the loans will be increased because P2P loans do not require collateral. Moreover, operational risk is when the platform loses money once the nonperforming loans rise above guaranteed income (Chen 2013).

P2P Lending in Indonesia

In Indonesia, as of July 2021, the number of P2P lenders registered with the OJK had reached 121 companies, of which 68 companies have business licenses (Financial Services Authority in Indonesia, 2021a). Furthermore, the OJK revealed that the number of borrowers using P2P lending as of June 2021 was 22,908,720, comprising both individuals and business entities, with an accumulated loan disbursement of 23,377.9 billion rupiahs (Financial Services Authority in Indonesia, 2021b). The Indonesian government regulates P2P lending services through an OJK regulation (Financial Services Authority in Indonesia, 2017). This regulation specifies, for example, the limit of transactions, P2P licensing, customer data protection, and the security of the P2P platform. In addition, the OJK also appointed the Indonesian Joint Funding Fintech Association (AFPI[3]) to be the official association for information technology-based lending and borrowing service providers in Indonesia, based on letter S-5/D.05/2019 (Financial Services Authority in Indonesia, 2019). The AFPI has been appointed to oversee the market conduct of P2P lending services (Nabila, 2018).

Even though the government has established regulations for P2P lending, based on data from the LBH (The Jakarta Legal Aid Institute, 2020), there are still problems in practice. Davis, Maddock, and Foo (2017) reveal that the challenges of P2P lending in Indonesia are related to the lack of infrastructure, geographic conditions, and low levels of financial inclusion. Hidajat (2019) also explains that Indonesia's financial literacy and regulation enforcement levels are still low. Concerning the risks, Hidajat (2019) reveals there are many illegal P2P lending service providers in Indonesia. The SWI has closed 3,365 illegal P2P lending services between 2018 and July 2021 (Financial Services Authority in Indonesia, 2021c). Pranata and Farandy (2019) found that the OJK has not authorized most of the apps for P2P lending in Google Play, and these illegal apps had worse review ratings than the authorized apps. In addition, Pranata and Farandy (2019) also found many negative reviews related to unethical debt collecting and excessive interest rates. This finding is in line with the Indonesian National Police Chief's statement that mentions several illegal P2P lending service violations, including accessing the borrower's data (contacts on the cellphone), collecting loans that did not follow the rules of the OJK, not having a contact and office location, not deleting the borrower's data even though the loan had already been paid, and also using the borrower's I.D. card data to make a loan in another application (Burhan, 2021).

Technology Threat Avoidance Theory (TTAT)

Liang and Xue (2009) first developed the TTAT to describe the processes and determinants of individual behavior when avoiding information technology threats. The TTAT is based on the cybernetics theory (Wiener, 2019) as it is considered to follow the expectancy theory (Vroom, 1995) and is generally accepted as a theoretical framework for explaining human behavior (Edwards, 1992). According to Carver and Scheier (1982), cybernetics' main idea is that humans regulate their behavior based on feedback loops. Carver (2006) divided feedback loops into two parts: negative and positive feedback loops. A negative feedback loop reduces the difference between the present state and the desired state. In contrast, a positive feedback loop enlarges the difference between the present and the undesirable state.

Several theories in the information systems literature focus more on negative feedback loops to explain the acceptance of information technology (I.T.), for example, the

[3]AFPI (*Asosiasi Fintech Pendanaan Bersama Indonesia*), defined as Indonesian Joint Funding Fintech Association

diffusion theory (Rogers, 1975), the TRA[4] (Ajzen and Fishbein, 1980), TAM[5] (Venkatesh et al., 2003) and the TPB[6] (Ajzen, 1991). Unfortunately, these theories are not really appropriate to explain the process of individuals avoiding information technology. Therefore, Liang and Xue (2009) introduced the TTAT based on a positive feedback loop, which explains that when individuals feel that I.T. dangers are very close to their current state, they will try to avoid these situations.

Some of the literature on information systems has used the TTAT in various research contexts, for example, crowdsourcing (Alomar, Alsaleh and Alarifi, 2019), health-related fitness data (Boysen et al., 2019), online social networks (Ikhalia et al., 2019); smartphone security (Chen and Li, 2017), phishing attacks (Arachchilage and Love, 2014), email security services (Herath et al., 2014), and personal computers (Liang and Xue, 2010). The TTAT explains that individual avoidance behavior is determined by a threat assessment (perceived susceptibility, perceived severity, and perceived threat) and a coping appraisal (individual self-efficacy, perceived cost, and perceived effectiveness) (Liang and Xue, 2009). This research will use the TTAT to explain individuals' avoidance motivation toward P2P lending services.

Research Model and Hypotheses Development

In investigating the factors that influence individuals to avoid P2P lending services, this study adapted the TTAT. Consistent with the TTAT, we proposed that individuals' avoidance motivation is determined by a perceived threat, self-efficacy, and social influence. The perceived threat is influenced by perceived susceptibility, perceived severity, and risk tolerance. The original model of the TTAT (Liang and Xue, 2009) included perceived effectiveness, perceived cost, perceived avoidability, and avoidance behavior. Perceived effectiveness and perceived cost are excluded in this study because the factors are not entirely relevant in the context of P2P lending avoidance; Liang and Xue (2009) define perceived effectiveness and perceived costs as safeguards for anticipating malicious I.T.

The TTAT is used to describe an individual's avoidance behavior. As previously described, several other theories in the information systems literature are not appropriate because they explain the phenomenon of technology acceptance instead of avoidance. Studies that explain individual avoidance of P2P lending using the TTAT theory are scarce, based on our literature review. This study also includes control variables, such as gender, education level, and monthly income. Figure 1 below is the research model used in this paper.

[4]TRA is defined as the theory of reasoned action
[5]TAM is defined as a technology acceptance model
[6]TPB is defined as the theory of planned behavior

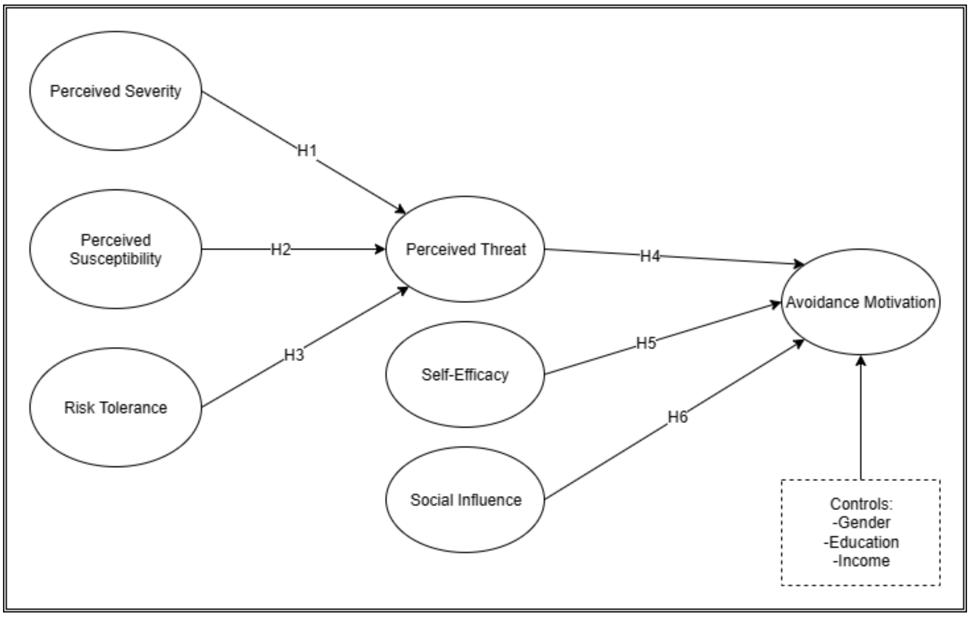

Figure 1. Research Model

Hypotheses Development

Perceived Susceptibility, Perceived Severity, and Perceived Threat

Liang and Xue (2009) define threat perception as the level of individual perception that decides malicious I.T. is dangerous. Previous research into health protection behavior defines health threats into two characteristics: perceived susceptibility and perceived severity (Weinstein, 2000). This study defines perceived susceptibility as an individual's subjective assessment that malicious I.T. will have a negative impact on the individual; in contrast, perceived severity is defined as an individual's perception that malicious I.T. will have a severe negative impact on him/her (Liang and Xue, 2009).

Research in the health sector states that individuals' perceived susceptibility and severity to health threats will motivate them to take protective action (Janz and Becker, 1984); (Rosenstock, 1974). The protection motivation theory states that when individuals are faced with a threatening event, each individual will assess the threat as a step to taking further action (Rogers, 1975). When assessing threats, individuals will consider the negative consequences of these threats and the types of threats that will affect them (van Bavel et al., 2019). Based on the TTAT, Liang and Xue (2009) stated that individuals' perceived susceptibility and perceived severity to I.T. threats affect individual threats. Liang and Xue (2010) found that computer users' threat perceptions increase when they believe that malicious I.T. will attack them and severely negatively impact them.

In this study, perceived susceptibility and severity are individual subjective assessments that negatively impact P2P lending users. Individuals will receive a very severe negative impact when using P2P lending services. Yadika (2019) stated that there were complaints from consumers to the YLKI[7] regarding P2P lending companies because of the provision of irrational loan fines and the tapping of consumers' data. Therefore, this study predicts that when individuals judge P2P lending services as being dangerous, they will feel that the P2P lending services are threats. Furthermore, when individuals consider that P2P lending services will severely impact them, they will feel that the P2P lending services are threats. Thus, hypotheses H1 and H2 are described as follows:

H1: Individuals' perceived severity toward P2P lending is positively associated with the perceived threats.

H2: Individuals' perceived susceptibility to P2P lending is positively associated with the perceived threats.

Risk Tolerance and Perceived Threat

Risk tolerance is widely discussed in the realm of financial decisions. Grable (2000) defined risk tolerance as individuals' uncertainty when making financial decisions. Although risk tolerance is widely discussed in a financial context, Barsky et al. (1997) stated that individuals tend to show the same tolerance response in every risky situation. Furthermore, Liang and Xue (2009) consider the risk tolerance in their framework related to avoiding malicious I.T. This proposition is based on the cybernetics theory, which argues that the greater the individual's risk tolerance is, the less likely it is that he/she will feel threatened (Liang and Xue, 2009). Carpenter et al. (2019) use the term risk propensity to describe an individual's risk tolerance for I.T. threats. They found that individuals with a higher risk propensity were less likely to feel threatened by I.T.'s dangers. This study defines risk tolerance as the amount of security uncertainty individuals tolerate when using P2P lending services. Chen and Liang (2019) state that the more tolerant the individual is to risk, the more tolerant the individual tends to be in dangerous situations. The risks of using fintech can include financial, legal, and data security risks (Ryu, 2018). Therefore, the greater the individual's tolerance for these risks, the lower the perception that P2P lending is a threat will be.

H3: Individual risk tolerance for P2P lending is negatively associated with the perceived threats.

Perceived Threat and Avoidance Motivation

Liang and Xue (2009) suggest that perceived threats determine the intention to avoid I.T.'s dangers. The perceived threat is an individual's perception that malicious I.T. is dangerous (Liang and Xue, 2009). According to the TTAT, when individuals feel threatened by I.T.'s dangers, they tend to take protective action (Liang and Xue, 2009). Ikhalia

[7] YLKI (*Yayasan Lembaga Konsumen Indonesia*) defined as The Indonesian Consumers Foundation

et al. (2019) find that when individuals feel threatened by malware attacks through online social networks, they are motivated to avoid these threats. In the context of fitness and health applications, Boysen et al. (2019) find that individuals are more motivated to use safeguards when they feel that their data will be stolen.

This study defines the perceived threat as an individual's perception that P2P lending is dangerous. In the context of information technology services, such as P2P lending, Schierz, Schilke, and Wirtz (2010) state there is a high potential for privacy, data, and personal transactions violations. Furthermore, complaints submitted to the LBH in June 2019 reached 4,500, an increase from 1,330 in December 2018 (Respati, 2019). These complaints were related to personal consumer data, billing with threats, and very high-interest rates from P2P lending companies. Based on the TTAT, this study predicts that when individuals feel threatened by the dangers of P2P lending, they intend to avoid using these services.

> **H4:** Individual perceived threats to P2P lending are positively associated with avoidance motivation.

Self-Efficacy and Avoidance Motivation

Self-efficacy is the level of individual confidence regarding executing a job, to achieve certain goals (Bandura, 1982). Several studies into information systems have examined the effect of self-efficacy on the intention to adopt information technology (Arachchilage and Love, 2014);(Liang and Xue, 2010); (Lai, Li, and Hsieh, 2012); (Yoon and Kim, 2013). Arachchilage and Love (2014) find that the higher an individual's self-efficacy is, the higher their desire to anticipate online data theft will be. In line with these findings, Yoon and Kim (2013) find that individuals take computer protection measures when they believe they can take such protective measures. Chen and Li (2017) also found that smartphone users tend to be motivated to take protective action to maintain their privacy when they have high self-efficacy.

In the context of P2P lending services, this study defines self-efficacy as an individual's belief in avoiding the dangers of P2P lending. Arachchilage and Love (2014) state that self-efficacy is related to procedural and conceptual knowledge. In other words, individual knowledge regarding the dangers of P2P lending could make individuals more confident about making relevant decisions regarding the use of such lending services. Thus, this study predicts that the higher the self-efficacy is, the higher the individual's motivation to avoid P2P lending services will be.

> **H5:** Individual self-efficacy toward P2P lending is positively associated with avoidance motivation.

Social Influence and Avoidance Motivation

Ajzen (1985) explains that social influence occurs when individuals' emotions, opinions, and behavior are influenced by people who are considered to be the most important to them. Liang and Xue, (2009) explain that social influence affects individuals' I.T. threat avoidance behavior. This proposition is supported by Lai, Li, and Hsieh (2012). They find that when individuals are influenced by social pressure to avoid the dangers of information technology, individuals tend to be motivated to avoid it.

In this study, social influence comes from the closest person, which suggests individuals avoid P2P lending services' dangers. Individuals tend to follow the opinions of people whom they consider to be important to them (Ajzen and Fishbein, 1980). In other words, when the closest person, or a person considered important by an individual, thinks of avoiding P2P lending services, the individual tends to follow that person's opinion. Thus, this study predicts that the higher the social influence is to avoid using P2P lending services, the more likely individuals will be motivated to avoid P2P lending services.

H6: Social influence regarding P2P lending is positively associated with avoidance motivation.

Methods

Measurement

Based on this research theory, the survey instrument was built by modifying previous research questions to identify and capture the factors that influence Indonesian people to avoid P2P lending services. There were 25 questions in total which were measured by a 5-point Likert scale (starting with 1 indicating "strongly disagree" up to 5 indicating "strongly agree"). The questions used in the constructs in this study are shown in the appendix. The operational definition of the variables in this study is as follows:

Table 1. Operational Definition of Variables

Variable	Definition	Source
Perceived Susceptibility	An individual's subjective judgment that P2P lending services are dangerous	(Liang and Xue, 2009); (Liang and Xue, 2010)
Perceived Severity	Individual perceptions that P2P lending services have a very severe negative impact	(Liang and Xue, 2009); (Liang and Xue, 2010)
Perceived Threat	Individual perceptions that P2P lending services are a threat	(Liang and Xue, 2009); (Liang and Xue, 2010)
Risk Tolerance	Individual's level of tolerance for risk	(Chen and Liang, 2019)

Social Influence	The influence of the social environment on individuals, related to the use of P2P lending services.	(Lai, Li, and Hsieh, 2012)
Self Efficacy	The individual's belief that he/she is able to choose the right P2P lending services	(Lai, Li, and Hsieh, 2012)
Avoidance Motivation	The individual's intention not to use P2P lending services	(Chen and Liang, 2019); (Liang and Xue, 2009)

Data Collection

The population of this study was respondents who understood P2P lending but chose not to use the services provided by P2P lending. The snowball sampling technique was used, in which the researcher submitted an online questionnaire link to parties who were thought to avoid P2P lending and then asked each party to share this with their friends or acquaintances. This study used screening questions at the beginning of the survey to ensure that the respondents knew about P2P lending services, but had not used them. The snowball sampling technique was used because it made it easier to identify difficult-to-access "hidden"populations, either because of the small number of potential respondents or because of the topic's sensitivity (Goodman, 1961) (Browne, 2005); (Heckathorn, 2011). Furthermore, Chen, Chen, and Xiao (2013) demonstrate that snowball sampling is a better sampling method for recovering social intercorrelation problems as it is better at capturing relationships among sample members, because the sampling is carried out by following links from fellow sample members.

The level of P2P lending only reached Rp. 19,038.60 billion as of April 2021 (Financial Services Authority in Indonesia, 2021b) compared to bank disbursements, which had reached Rp 5,477.5 trillion by April 2021 (Victoria, 2021). These figures indicate that there are not as many P2P lending users in Indonesia as there are banking service users. This study assumed that the number of respondents who understood P2P lending and avoided the service was estimated to be small and hidden. Previous research in the fintech area has used this approach, for example, research in Bangladesh (Aziz and Naima, 2021); (Lee et al., 2021), Turkey (Eren, 2021), Malaysia (Khan and Xuan, 2021), and an international study (Abu Daqar et al., 2021). The total number of respondents collected by this study amounted to 499.

Data Analysis

This study used the variance-based SEM or SEM-PLS.[8] type (i.e., SmartPLS 3.0) to measure the structural model and the hypotheses proposed in the study. There were sever-

[8]SEM-PLS is defined as Structural Equation Modelling - Partial Least Square

al reasons for using SEM-PLS in this study: SEM-PLS is suitable for use in the early stages of theory development (Joreskog and Wold, 1982), SEM-PLS is not limited by sample size requirements and residual distributions (Chin, Marcolin and Newsted, 2003) and SEM-PLS is able to test complex models with latent variables (Kotz, 1982). The PLS algorithm and the bootstrap re-sampling method with 499 cases and 5,000 re-samples were used to estimate the model's significance of the path coefficients.

Results

Descriptive statistics

Four hundred and ninety-nine respondents participated in this survey. Of the respondents, 67.1% were aged between 21-30 years old, and 20.2% were between 30-40 years old. Fifty-five-point, nine percent of the respondents, were female, and almost 50% had graduated from college. In terms of their occupations, college students comprised 30.5% of the respondents, followed by private employees at 29.7%. Half of the respondents (50.7%) had an income between 1 to 5 million rupiah per month. The respondents were from various provinces in Indonesia; the three biggest provinces in Indonesia contributed the three highest percentages (Central Java 12.2%, East Java 10%, and West Java 9.8%). Finally, most respondents knew about fintech from social media (53%) and friends (19%). Detailed demographic data about the participants are presented in Table 2.

Table 2. Participants' Demographic Data

Age	Under 20 years	4.8
	21-30 years	67.1
	31-40 years	20.2
	41-50 years	5.2
	Over 50 years	2.6
Gender	Male	44.1
	Female	55.9
Level of education	High school	10.8
	Diploma	5.6
	Undergraduate	49.7
	Master's degree	30.7
	Doctoral Degree	2.8
	Others	0.4
Profession/Occupation	Government employees	14.4
	Private employees	29.7
	College student	30.5
	Entrepreneur	5.8
	Others	19.6

Income per month	Less than Rp. 1,000,000	21
	Rp. 1,000,000 - Rp. 5,000,000	50.7
	Rp. 5,000,001 - Rp. 10,000,000	21.6
	Rp. 10,000,001 - Rp. 15,000,000	3.8
	More than Rp. 15,000,000	2.8
Province	Aceh	0.8
	Banten	2.2
	Bali	1.4
	Bengkulu	0.2
	Yogyakarta	23
	DKI Jakarta	9.2
	Jambi	0.8
	West Java	9.8
	Central Java	12.2
	East Java	10
	East Kalimantan	0.6
	Central Kalimantan	0.8
	South Borneo	0.8
	Bangka Belitung Islands	0.8
	Riau islands	0.8
	Lampung	4.2
	West Nusa Tenggara	1
	East Nusa Tenggara	0.8
	Papua	2
	West Papua	1
	Riau	1.6
	South Sulawesi	3
	Central Sulawesi	0.4
	Southeast Sulawesi	0.6
	North Sulawesi	7.8
	West Sumatra	1.2
	South Sumatra	1.4
	North Sumatra	1.4
Source of Information of Fintech	Television Advertisement	13
	Social Media	53
	Newspaper	11
	Friends	19
	Family	5

Outer Model Testing

To assess the measurement properties of all of the constructs in the research model, this study conducted several tests (Churchill, 1979; Straub, 1989). The tests conducted were reliability (i.e., composite reliability), convergent validity (i.e., AVE[9]) and discriminant validity tests. Based on the composite reliability test results in Table 3, it was found that the result of testing the composite reliability of all the theoretical constructs was more than 0.7 (see Table 3). This result meant that all the constructs were reliable. For testing the convergent validity, this study calculated the AVE value for each construct and found that the entire AVE value calculation was above 0.5 (see Table 3). The discriminant validity test results also showed that the square root of the AVE value for each construct showed a value greater than its correlation with the other constructs. Each TTAT construct in this study fulfilled the discriminant validity requirements.

Table 3. Composite Reliability scores, AVEs, and Cross-Correlations

Construct	CR	AVE	1	2	3	4	5	6	7
1. Perceived susceptibility	0.952	0.833	**0.913**						
2. Perceived severity	0.876	0.638	0.779	**0.799**					
3. Risk tolerance	0.886	0.662	-0.240	-0.182	**0.814**				
4. Perceived threat	0.948	0.819	0.821	0.763	-0.238	**0.905**			
5. Self-efficacy	0.939	0.793	-0.431	-0.338	0.319	-0.434	**0.891**		
6. Social influence	0.881	0.655	0.510	0.534	-0.291	0.577	-0.235	**0.809**	
7. Avoidance motivation	0.971	0894	0.628	0.560	-0.223	0.610	-0.360	0.591	**0.945**

Structural Model Results

The R^2 value showed that the theoretical model in this study could explain the variance of avoidance motivation by 47.1% (see Figure 2). Based on the structural model testing, this study showed that individual motivation to avoid using P2P lending services was significantly influenced by individual perceived threats (b = 0.348, p = 0.000). This result meant that Hypothesis H4 in this study was supported. Furthermore, this study found that individual threat perception was significantly determined by perceived susceptibility (b = 0.565, p = 0.000), perceived severity (b = 0.315, p = 0.000), and risk tolerance (b = -0.045, p = 0.100.). This result indicated that hypotheses H1, H2, and H3 were also supported. The test results were in line with various research results in the field of information systems that used the TTAT model to explain individual avoidance behavior (Alomar, Alsaleh and Alarifi, 2019); (Arachchilage and Love, 2014); (Boysen et al., 2019); (Carpenter et al., 2019); (Liang and Xue, 2009); (Liang and Xue, 2010); (Ikhalia et al., 2019). This study's findings provided confidence in the idea that the motivation for individuals' avoidance of P2P lending services was caused by individuals' perceptions that P2P lending was a threat. Specifically, the perceived threat results from perceptions of individuals' susceptibility and severity, related to P2P lending services. Individuals felt that P2P lending services were a threat when they considered that P2P lending services could have a negative impact and there was the possibility of the individual being affected.

Figure 2 also shows that individuals' motivation to avoid P2P lending services was

[9]AVE is defined as Average Variance Extracted

determined by their threat perceptions and social influence. Social influence was found to positively affect individuals' avoidance motivation (b = 0.334, p = 0.000). This result meant that Hypothesis H6 was supported. This result indicated that individual avoidance motivation was caused by being socially influenced into avoiding P2P lending services. This finding aligns with (Liang and Xue, 2009), who state that social influences can influence individual avoidance motivation. Individual behavior can be influenced by individual judgments regarding the extent to which the behavior can be accepted by the social environment (Lai, Li, and Hsieh, 2012). Therefore, when their environment influences individuals to avoid P2P lending services, individuals tend to avoid them.

Additionally, this study found that self-efficacy negatively affected individuals' avoidance motivation (b = -0.125, p = 0.000) which meant the higher an individual's self-efficacy was, the lower his/her motivation to avoid P2P lending services would be. This result was inconsistent with this study's prediction that individuals' self-efficacy positively affects individuals' avoidance motivation. The same thing was found by Carpenter et al. (2019), and Tsai et al. (2016), where individual self-efficacy negatively affected individual avoidance motivation. Lai, Li, and Hsieh, (2012) explain that individual self-efficacy depends on individual knowledge. A low level of knowledge regarding financial issues results in unsecured decisions about P2P loans and personal loans (Wang et al., 2020). Therefore, the possible explanation for this finding is that individuals with high self-efficacy may have more knowledge about P2P lending services, and choose P2P lending services that are not detrimental to themselves.

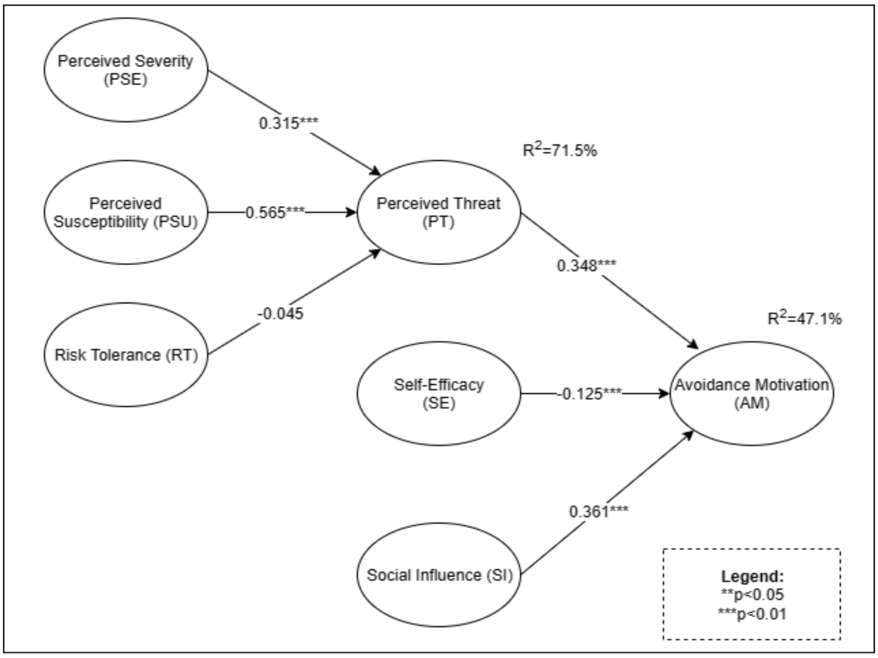

Figure 2. Structural Model Results - SEM SmartPLS 3.0

Multigroup analysis

This study examined the effect of control variables such as gender, education level (Li, Jiang and Yang, 2021), and income level (Tao, Dong, and Lin, 2017), which may affect people's behavior in using P2P lending. Li, Jiang, and Yang (2021) explain that education positively relates to intelligence, cognitive abilities, and personal income. The higher the level of education and income an individual has, the higher his/her financial knowledge is. Gender also has significant differences when seeking information and risk aversion (Li, Jiang, and Yang, 2021). Testing was carried out, using a multi-group analysis technique with PLS, by dividing the sample data by gender (male vs. female), educational level (low vs. high), and income level (low vs. high) (Qureshi and Compeau, 2009). The level of education was divided into respondents with a low level of education (from elementary to senior high school) and respondents with a high level of education (from college to Ph.D. level). The respondents' data were divided into low-income levels (ranging from 1 million rupiah to 5 million rupiah per month) and high income (ranging from 5 million to more than 15 million rupiah per month).

Table 4 below shows the results of the multi-group analysis from PLS, displaying the patch coefficients and t-statistics for the three control variables tested.

Table 4. Multi-Group Comparison for Three Variables (Gender, Education, and Income)

Panel A							
Relationship	**Male (n =194)**		**Female (n =255)**		**Path Coeff. Diff**	**t-value**	**p-value**
	Path Coeff.	**t-stat.**	**Path Coeff.**	**t-stat.**			
PSE → PT	0.364	5.039***	0.224	3.106***	0.140	1.349	0.089*
PSE → PT	0.523	6.725***	0.599	8.633***	-0.077	0.735	0.231
RT → PT	0.005	0.096ns	-0.088	1.824**	0.083	0.751	0.227
PT → AM	0.395	5.010***	0.312	4.161***	0.092	1.345	0.090*
S.E. → AM	-0.184	3.382***	-0.066	1.389ns	-0.118	1.643	0.051*
S.I. → AM	0.262	4.002***	0.409	5.145***	-0.147	1.368	0.086*
Panel B							
Relationship	**Low Education (n = 48)**		**High Education (n = 399)**		**Path Coeff. Diff**	**t-value**	**p-value**
	Path Coeff.	**t-stat.**	**Path Coeff.**	**t-stat.**			
PSE → PT	0.418	4.066***	0.260	4.691***	0.159	0.972	0.166

PSU → PT	0.527	4.838***	0.574	10.397***	-0.047	0.288	0.387
RT → PT	0.087	0.756^{ns}	-0.052	1.474^{ns}	0.423	2.482	0.007***
PT → AM	0.719	6.138***	0.296	5.145***	0.139	1.268	0.103
S.E. → AM	0.034	0.285^{ns}	-0.136	3.524***	0.169	1.436	0.076*
S.I. → AM	0.045	0.369^{ns}	0.381	7.149***	-.0.336	2.110	0.018**

Panel C

Relationship	**Low Income (n = 320)**		**High Income (n = 129)**		**Path Coeff. Diff**	**t-value**	**p-value**
	Path Coeff.	**t-stat.**	**Path Coeff.**	**t-stat.**			
PSE → PT	0.267	4.289***	0.324	3.902***	-0.057	0.512	0.304
PSU → PT	0.561	9.139***	0.587	7.267***	-0.025	0.233	0.408
R.T. à P.T.	-0.042	1.028^{ns}	-0.054	1.294^{ns}	-0.137	1.145	0.126
PT → AM	0.307	4.727***	0.445	4.477***	0.012	0.178	0.429
SE → AM	-0.130	2.774***	-0.127	2.388***	-0.003	0.035	0.486
SI → AM	0.365	6.063***	0.280	2.925***	0.085	0.759	0.224

*Notes: ns, not significant. *p<0.10; **p<0.05; ***p<0.01*

Panel A of Table 4 shows the group analysis by gender (male vs. female). From this table, it can be seen that there was a relatively significant difference between the two groups for the impact of perceived severity on the perceived threat (path coefficient difference = 0.140, p <0.1), perceived threat to avoidance motivation (path coefficient difference = 0.092, p <0.1), self-efficacy on avoidance motivation (path coefficient difference = -0.118, p <0.1), and social influence on avoidance motivation (path coefficient difference = -0.147, p <0.1). Overall, the female respondents indicated that the perceived severity factor had more of an impact on their perceived threat from P2P lending services when compared to the male respondents. This perceived threat factor also impacted female respondents, providing them with the motivation to avoid P2P lending fintech services. On the other hand, male respondents indicated that self-efficacy and social influence impacted their avoidance motivation for P2P lending services. This result is consistent with Li, Jiang, and Yang (2021), who found that gender differences influenced people's behavior in borrowing from P2P lenders. In contrast, female borrowers are less likely to participate in online loans. This finding may be because the female participants have a strong information-seeking ability, risk aversion and spend more time monitoring information about the P2P lending market (Li, Jiang, and Yang, 2021).

Panel B Table 4 shows the group analysis by the level of education (low vs. high). From the table, it can be seen that there was a significant difference between the two groups for the impact of perceived risk tolerance on perceived threats (path coefficient difference = 0.423, p <0.01), self-efficacy on avoidance motivation (path coefficient difference = 0.169, p <0.1), and social influence on avoidance motivation (path coefficient difference = -0.336, p <0.05). These results indicated that respondents with a high level of education had a low-risk tolerance compared to respondents with a low level of education. This result indicated that respondents with a low level of education perceived P2P lending services to be relatively less threatening than respondents with a high level of education did. Furthermore, for respondents with a low level of education, the self-efficacy factor had more impact on their avoidance motivation toward P2P lending services when compared to respondents with a high level of education. On the other hand, respondents with a high level of education indicated that social influence factors had more impact on their motivation to avoid fintech P2P lending services. This result follows Li, Jiang, and Yang (2021), who show that differences in the education levels affect borrowers' behavior in P2P lending, whereas people with lower levels of education participated more in P2P lending.

Panel C Table 4 presents the group analysis results based on income levels (low vs. high). From the table, it can be seen that there was no significant difference between the two groups for factors that impacted the perceived threats and avoidance motivation. This result is in line with Alomar, Alsaleh, and Alarifi, (2019) and Tsai et al., (2016), who all state that the income level does not affect individuals' avoidance motivation. Prior studies showed mixed findings in which individuals with a high income tended to use P2P lending (Lyons and Kass-Hanna, 2021; Tao, Dong, and Lin, 2017). On the other hand, Chen et al., (2020) find that individuals with middle to low incomes were more likely to engage in P2P lending.

Conclusions

This study investigates the factors that influence individuals to avoid using P2P lending services, using Indonesians as the research's respondents. The results show that the perception of threats is positively associated with the perception of susceptibility and severity, related to P2P lending services. Individuals will feel that P2P lending is a threat when they consider that P2P lending services are more likely to negatively impact them in the future, such as violating their privacy, increasing the interest on their debt, and billing them using threats.

This study finds that the effect of self-efficacy on individuals' avoidance motivation does not match the researchers' initial predictions. The possible explanation for this result is that individuals with high self-efficacy are more likely to have more knowledge about P2P lending, so they are more careful when choosing P2P lending services. On the contrary, external factors, namely social influences, can motivate individuals to avoid P2P lending services. When individuals get calls from their social environment to avoid P2P lending, they tend to be motivated to avoid it. We also highlight the significant impact of demographic factors (i.e., gender, education, and income) on individuals' motivation to avoidance. We found that gender (males vs. females) and education (high vs. low) have different impacts on the factors that affect the perceived threat from, and avoidance motivation of, P2P lending services. However, the income level (high vs. low) does not significantly impact the factors that affect P2P lending's perceived threat and avoidance motivation. Overall, this study's research framework can explain the phenomenon of individual avoidance behavior toward P2P lending services.

This research is expected to provide several implications. First, empirically, this research contributes to the fintech literature. As far as can be concluded from the literature review conducted by the researchers, this research is the first to investigate the factors that influence individuals' motivation and avoidance behavior towards P2P lending services using the TTAT research model Liang and Xue (2009). Second, this research is an input for regulators/governments to improve law enforcement for P2P lending crimes in Indonesia. When law enforcement against P2P lending crimes is poor, the potential for P2P lending helping public funding in Indonesia will be covered by the public. Third, this research provides P2P lending service providers with an input to design a program that can encourage people's confidence that P2P lending will positively impact and protect individuals' personal information. These programs can be in the form of educational programs or more vigorous promotions. The educational programs are important because this study's results indicate that individuals' perceptions of P2P lending are a threat that will increase their motivation to avoid P2P lending services.

Limitations and Future Studies

This study has some limitations that need to be considered, and suggestions for future research. First, this study only captures the avoidance motivation and avoidance behavior toward P2P lending services from the borrower's perspective. In practice, individuals can act as borrowers or lenders in P2P lending services. Future research can examine the avoidance motivation and avoidance behavior of P2P lending services from the lender's perspective. Second, this study uses a limited number of respondents and uses snowballing sampling, which may not represent the targeted population. Future studies may involve more respondents and use other research methods with greater internal validity (random sampling and experiment approach).

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Appendix

Table A.1. Constructs

Construct	Questionnaire	Reference
Perceived Susceptibility (PSU)	PSU1. Online loan services have the opportunity to harm me. PSU2. Online loan services have a high chance of hurting me in the future. PSU3. I feel that online loan services will hurt me in the future. PSU4. I have a high chance of being harmed by online loan services.	(Liang and Xue, 2009); (Liang and Xue, 2010)
Perceived Severity (PSE)	PSE1. Online loan services will steal my personal information. PSE2. The online loan service will provide my personal information to other parties. PSE3. Online loan services will increase the amount of my debt by a large amount. PSE4. Online loan services will collect the debt using threats.	(Liang and Xue, 2009); (Liang and Xue, 2010)
Perceived Threat (P.T.)	PT1. Online loan services are dangerous for me. PT2. If I use an online loan service, then it is risky for me. PT3. Online loan services are a threat to me. PT4. The difficulties caused by online loan services threatened me.	(Liang and Xue, 2009); (Liang and Xue, 2010)
Risk Tolerance (R)	R1. I feel challenged by high risk things. R2. I am used to high risks. R3. I enjoy high risk. R4. I will take risks to get a high return.	(Chen and Liang, 2019)
Self-Efficacy (S.E.)	SE1. I believe that I can afford to avoid online loan services. SE2. I believe that I can avoid online loan services even though no one recommends them. SE3. I believe that I can avoid online loan services even though I have never used them before. SE4. I believe that I can afford to avoid online loan services after observing other people using them.	(Lai et al., 2012)

Social Influence (S.I.)	SI1. The people around me thought that I should not use online loan services. SI2. The people around me do not help me with using online loan services. SI3. In general, the people around me do not support me in using online loan services. SI4. The people closest to me seem to think that I should not use online loan services.	(Lai et al., 2012)
Avoidance Motivation (AM)	AM1. I have no intention of using online loan services. AM2. I predict that I will not use online loan services. AM3. I do not plan to use online loan services. AM4. I do not want to use an online loan service.	(Chen & Liang, 2019); (Liang and Xue, 2009)