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Social Media Sentiment and Gender on Peer-To-Peer Lending Performance: Machine Learning Approaches

Muhammad Farhansyah Mondari[1], Putri Fariska[2]

[1,2] School of Economics and Business, Telkom University, Bandung, Indonesia

ABSTRACT: One innovation brought about by fintech is peer-to-peer lending. However, in recent years with rapid growth, unfortunately, there are still many negative sentiments about the peer-to-peer lending industry. Especially with the advancement of technology and the internet, all information about peer-to-peer lending is easily accessible through social media. The amount of negative information about peer-to-peer lending can influence opinions or sentiments towards the performance of peer-to-peer lending platforms and invite the public to comment on social media. Additionally, the gender factor of the information provider also affects the performance of the peer-to-peer market. Based on the explanation above, there has never been any previous research conducted in Indonesia, so this study will examine how the influence of social media information sentiment and the gender factor of the information provider affects peer-to-peer lending performance. The analysis method used is logistic regression, and the data used is obtained through machine learning using the Python programming language on Google Collab from social media opinions and the gender that provides opinions on social media. Meanwhile, the financial performance of peer-to-peer lending is taken from the annual performance report of the Financial Services Authority (OJK) by default. From the results of this study, it was found that the gender of the information provider affects the financial performance of peer-to-peer lending. However, simultaneously, social media sentiment and the gender of the information provider affect the financial performance of peer-to-peer lending.

KEYWORDS: Fintech, Peer-to-peer lending, Sentiment Analysis, Gender, Social Media, Machine learning, Naïve Bayes

I. INTRODUCTION

Indonesia continues to rank among the nations with the highest internet penetration rates despite its notable increase. As more and more people interact online, it is changing many parts of our daily lives, such as how we shop, communicate, and even look up information about specific financial and investing instruments.

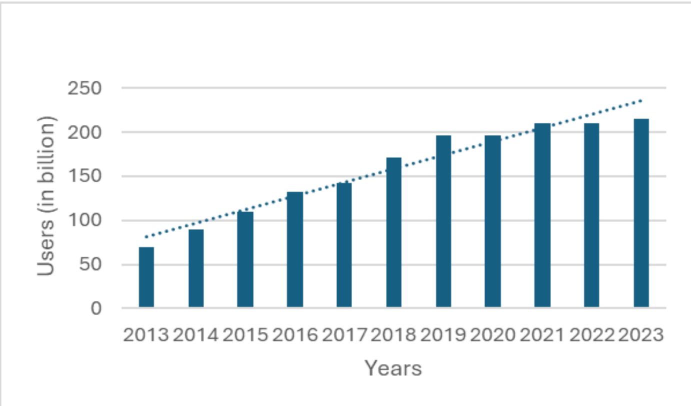

Figure 1 Growth in the number of internet users in Indonesia

Over the past ten years, Indonesia has seen a steady increase in the number of people using the internet, leading to the creation of numerous inventive improvements. One such technical development is the financial industry, which is commonly referred to as fintech, or financial technology.

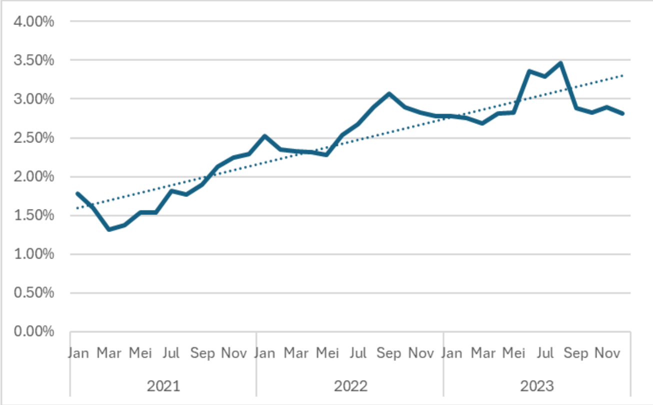

Figure 2. Growth Trends in Peer-to-peer lending Performance in Indonesia

It is evident from the graph above that throughout the last three years, peer-to-peer lending performance in Indonesia has grown. This can be a good growth signal in the peer-to-peer lending industry in Indonesia. With the use of technology and the internet, the role of mass media has a major impact on financial markets, namely as an information intermediary (Kuang et al., 2023). Research (Kuang et al., 2023) conducted by Kuang found that the role of mass media can be a form of resistance to information asymmetry because information asymmetry is one of the causes of existing risks, in this case in peer-to-peer lending. However, the reality is that risks still exist in spite of the advancements made in the internet and the usage of online news sources. Many online news outlets report unfavorable stories regarding the peer-to-peer lending sector and occasionally make reference to an online lending platform.

Furthermore, there has been a 5.44% rise in social media usage in Indonesia over the previous year. According to figure 3, X is one of the most popular social media platforms in Indonesia; it is among the top 10 platforms that Indonesian internet users utilize.

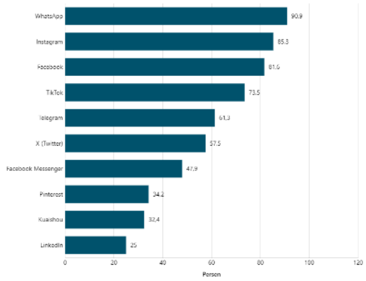

Figure 3. Data on social media platforms in Indonesia

If we look at the development of X usage in the world, Indonesia occupies the top 4 countries with the largest number of X users in the world until 2023, totaling 25.25 million compared to other countries such as the United States and Japan. The data can be seen in Figure 4 below:

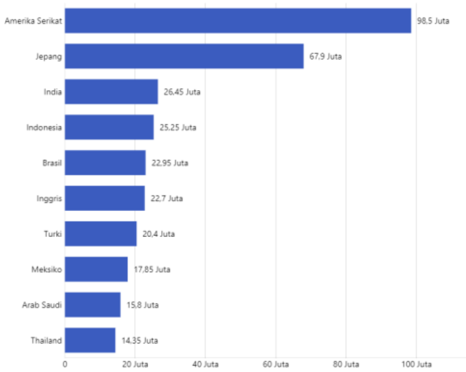

Figure 4. Country data of X users in the world

X is a social media network designed to serve as a discussion board for different tweets, articles, and viewpoints from lenders, borrowers, and investors. Because there are so many tweets about this business, both favorable and negative, it can serve as one of the foundations for decision-making. For example, it can be used to gauge public opinion about the performance of an online lender and act as a preventative measure against information asymmetry.

But the reality is that in these innovative markets or financial markets with low levels of regulation, information asymmetry or imbalance is still a serious problem(Khan, 2022; Kuang et al., 2023). If lenders or borrowers fail to process information or fail to anticipate, it can expose them to risks such as default due to fraud from an online lending platform.

In order to address this knowledge imbalance, human ties in community networks—which are typically conducted online with posts and reviews from lenders and borrower must be included(Chen. D et al., 2014). If more users create negative opinions about the platform, it is possible that both lenders and borrowers will rethink using the platform and more broadly if this is done massively to many platforms, it is also likely to affect the entire industry. Sentiment from news on social media not only reflects market performance, but also has a broad influence on overall market movements (Alamsyah et al., 2019) also researched & found that mass media news & sentiment have an effect on company performance(Fariska et al., 2021).

Apart from the problem of information imbalance that causes losses to lenders and borrowers such as defaults, gender factors also affect this. (Fariska et al., 2021) found that one of the factors affecting platform performance is gender. Contrary to popular belief, peer-to-peer lending organizations view women as more reliable than men when it comes to default. However, in actuality, males are less reliable than females when it comes to their ability to make payments. Based on the aforementioned reasoning, it can be inferred that numerous studies have discovered a gender gap in the peer-to-peer lending markets' financial success; however, no prior research has been done in Indonesia.

II. LITERATURE REVIEW

A. *Behaviour Finance*

Research in the field of behavioral finance has emerged to analyze how investors' attitudes towards the stock market from a psychological perspective and how these attitudes affect the market (Choi et al., 2002; Fariska et al., 2021). This theory explains how individuals make decisions between choices that involve risks that are not entirely consistent with the anticipated profit hypothesis (kahneman, 1979). There have three decision-making processes under conditions of uncertainty, as follows (Fuller, 2000):

1. Normative analysis pertains to the methodical approach to resolving issues encountered.
2. Descriptive analysis relates to how real people actually make decisions correctly.
3. Prescriptive analysis relates to providing advice and practical tools that can help individuals achieve results that are closer to the predictions of normative analysis.

B. *Social Dynamic*

In the context of peer-to-peer lending, interpersonal relationships and information disseminated through social networks play a pivotal role in investment decision-making (Q. Chen et al., 2021; Cheong et al., 2017; M. Wang et al., 2022). The social dynamic theory posits that investment activities are influenced by social interactions and investor sentiment (Shiller et al., 1984). This sentiment is shaped through various channels, including social media, and can significantly impact market behavior (Fariska et al., 2021). Biases and psychological explanations also play a crucial role in investment decisions, especially under conditions of information asymmetry prevalent in markets (Kuang et al., 2023; Zhu et al., 2010). Media news can influence investor sentiment and, consequently, asset prices(Nofsinger, 2005). By understanding market sentiment, investors can predict price movements and make better investment decisions(Zhu et al., 2010).

C. *Sentiment Analysis*

Sentiment analysis is a method for classifying opinions, ethics, or emotions contained within text(Fang & Zhan, 2015). Further elaborated that sentiment analysis can be used to identify correlations between various things, especially when data is sourced from online news and social media (Kuang et al., 2023; POHAN et al., 2020). Applications of sentiment analysis in research often focus on measuring public image and reputation (Suryono & Budi, 2020)(Glaser et al., 2007). There have three levels of sentiment analysis: document, sentence, and aspect. Sentiment classification commonly employs positive, negative, or neutral labels, and methods like Naive Bayes are frequently used for this classification (Kuang et al., 2023; Pohan et al., 2020).

D. *Social Media Big Data*

Define big data as a collection of data that is characterized by its large volume, which cannot be handled by traditional data management tools due to its complexity and size(Halevi et al., 2011). Generally, big data refers to high-volume, high-velocity, and high-variety information that requires cost-effective and innovative approaches for processing, enabling opportunities for enhanced insights, decision-making, and process automation (Gatner, 2015). Specifically, according to Fariska (2021), big data refers to a large collection of data related to individual and societal behavior, which needs to be computationally processed due to its intricacies. In the field of capital markets, social media data is applied to uncover deeper insights, trends, and associations between society and the capital market (Bukovina, 2016; Fariska et al., 2021). This processing of large-scale data is often referred to as sentiment analysi(Fariska et al., 2021).

A numerical method was presented to categorize the sentiment of a brief message (Antweiler & Frank, 2004; Fariska et al., 2021). With this method, a numerical number is assigned to each sentiment (positive, neutral, and negative): 3 for positive sentiment, 2 for neutral sentiment, and 1 for negative feeling. The sentiment of a communication can be determined from the numerical values of the words or phrases in it by applying the formula (2) described above. We are able to quantify the sentiment's intensity thanks to this method.

$$At = 1 - \sqrt{1 - B\frac{2}{t} \in [0,1]} \tag{2}$$

E. Financial Performance

Financial performance reflects a company's operational effectiveness in achieving its objectives and can be evaluated through financial statement analysis (Putri & Wibisono, 2022).Financial ratio analysis, which involves comparing various financial data, is an effective tool for assessing a company's financial condition and potential(Marginingsih, 2017). In the context of peer-to-peer lending, trust is paramount. Therefore, investors need to assess the creditworthiness of each borrower (C. Wang et al., 2021). One crucial indicator used to evaluate the performance of peer-to-peer lending platforms is the 90-day Payment Fail Rate (TWB90), which measures the percentage of loans that were not repaid on time (Otoritas Jasa Keuangan, 2023). A high TWP90 value indicates a platform's poor performance in facilitating loan repayments.

F. Peer-to-peer Lending

Peer-to-peer (P2P) lending, often referred to as online lending in Indonesia, is a process and method through which lenders can lend money to individuals or businesses (Suryono & Budi, 2020). Peer-to-peer lending is a type of microloan, and its method has developed rapidly and effectively, compensating for the weaknesses of the formal financial system and taking on a certain substitutive role for banks (Michels, 2012). This method has replaced mortgage guarantees, reducing information asymmetry problems (M. Wang et al., 2022). It also ensures the smooth operation of the network platform formed from peer-to-peer lending. Potential users who want to borrow or lend must create an account and provide personal information such as name, address, phone number, and social security number. Some peer-to-peer lending platforms also require users to provide bank account information. In this process, the information provided is then verified. Lenders make decisions based on the information in the borrower list and the personal information provided by the prospective borrower (Gupta,2022). Thus, it can be said that P2P is a savings and loan system through a technological intermediary.

G. Gender Demographics

Peer-to-peer (P2P) lending, often referred to as online lending in Indonesia, is a process and method through which lenders can lend money to individuals or businesses (Suryono & Budi, 2020). Peer-to-peer lending is a type of microloan, and its method has developed rapidly and effectively, compensating for the weaknesses of the formal financial system and taking on a certain substitutive role for banks (Michels, 2012). This method has replaced mortgage guarantees, reducing information asymmetry problems (M. Wang et al., 2022). It also ensures the smooth operation of the network platform formed from peer-to-peer lending. Potential users who want to borrow or lend must create an account and provide personal information such as name, address, phone number, and social security number. Some peer-to-peer lending platforms also require users to provide bank account information. In this process, the information provided is then verified. Lenders make decisions based on the information in the borrower list and the personal information provided by the prospective borrower (Gupta,2022). Thus, it can be said that P2P is a savings and loan system through a technological intermediary.

H. Framework and Hypothesis Development

Previous research has demonstrated that textual sentiment from investor comments and online news has a significant impact on the performance of peer-to-peer lending platforms in China(Kuang et al., 2023; C. Wang et al., 2021). Pengnate & Riggins (2020) also found that the descriptions of loans created on social media can influence public sentiment and the performance of peer-to-peer lending. Thus, previous studies consistently show a relationship between online media sentiment and the performance of peer-to-peer lending platforms. Numerous previous studies have investigated investor sentiment towards peer-to-peer lending platforms. M. Wang et al. (2022) compared sentiment on peer-to-peer lending platforms between China and the United States using the social media platform X and found that positive sentiment was more dominant in China. Saleh Ali et al.(2023)also found a majority positive sentiment towards peer-to-peer lending platforms on social media, both in India and Malaysia. Gupta et al. (2022) reported that 75% of Indian citizens had a positive perception of peer-to-peer lending on social media.

H_1 = Social media has a partial effect on peer-to-peer lending market performance.

X. Chen et al. (2020) found that gender is one of the factors influencing platform performance. Further, demonstrated that women generally have higher financial risk levels compared to men(Haryanto, 2022). In the context of riskier peer-to-peer lending, women tend to be more cautious. However, other research found that married women are better at helping online lending company performance (Aliano et al., 2023). This is due to the tendency of married women to delegate financial matters to their partners or other family members. Thus, various studies show significant gender differences in peer-to-peer lending market performance.

H_2 = The gender of information provider has a partial effect on peer-to-peer lending market performance.

Kuang et al. (2023) found that positive sentiment from social media can drive the growth of the peer-to-peer lending market in China, while negative sentiment does not have a significant impact. Saleh Ali et al. (2023) research in Malaysia also showed similar results, with many users on social media platform X expressing positive sentiment towards peer-to-peer lending platforms. H_3 = Social media information and gender of information provider simultaneously affect peer-to-peer lending Performance.

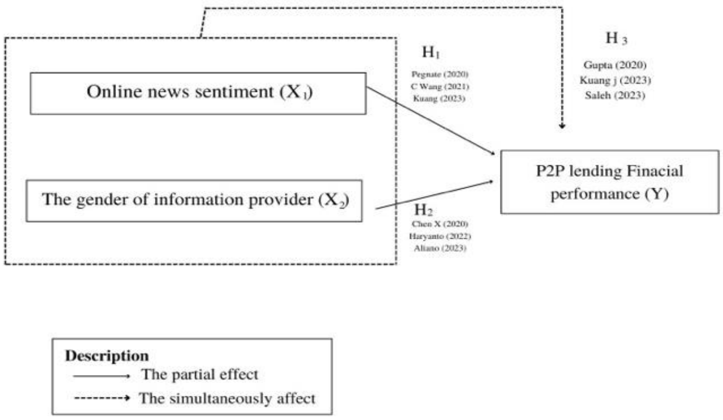

Figure 5 Research Framework

III. RESEARCH METHOD

With a causal research objective-examining the cause-and-effect relationship between independent variables and the dependent variable. This study employs a quantitative research methodology. Peer-to-peer lending performance is the dependent variable in this study, whereas online news media sentiment, social media information, and the gender of the information source are the independent variables.

The statistical performance data of peer-to-peer lending platform businesses registered with the OJK between 2019 and 2023 serves as the study's population. The 90-day delinquency rate, or TWP90 value, is the sample that is utilized as a financial performance indicator. X social media data sentiment analysis is used to generate the independent variable. Python data mining techniques are employed on Google Collaboratory to analyze the sentiment. The analysis techniques used are sentiment classification with the Naive Bayes approach and logistic regression to investigate the association between variables, with 50% of the data used for testing and training.

IV. RESULT AND DISCUSSION

A. Descriptive Analysis

Table 1. Descriptive Analysis

Description	Variable		
	P2P	**Social Media Sentiment**	**Gender**
Mean	0.55	1.68	1.39
Std. Deviation	0.5	0.94	0.49
Minimum	1	1	1
Maximum	2	2	3

From the table above, it can be observed that the dependent variable, peer-to-peer (P2P) lending, exhibits a mean value of 0.55 and a standard deviation of 0.5. This suggests a relatively homogeneous distribution of data for the P2P variable. Given that P2P is a binary variable with values of 0 and 1, the observed minimum and maximum values align with this expectation.

Regarding the independent variables, social media sentiment has a mean of 1.68 and a standard deviation of 0.94, indicating a slightly higher degree of dispersion compared to the P2P variable. Similarly, gender with a mean of 1.39 and a standard deviation of 0.49, shows a less dispersed distribution. Social media variables has minimum and maximum values of 1 and 2, then gender variable has minimum and maximum values of 1 & 3. respectively, suggesting a categorical or ordinal scale of measurement.

B. Naïve Bayes Clasification Analysis

Sentiment analysis was used to categorize textual data into positive, negative, and neutral sentiment categories after the data had been collected and cleaned. The "textblob" package on Google Colab was used to implement the Naive Bayes approach in this study. Textual data was first gathered and cleaned as part of the process. The data was then split into training and testing sets after being classified with sentiments like "Positive," "Neutral," and "Negative." Using the training data, the Naive Bayes model was trained to identify patterns in words or phrases linked to particular emotions. Examples of randomly chosen twitter data for training purposes are shown in table 2 and testing purposes are shown in table 3.

Table 2. Manual Classification Tweet Set Training

Example	Classification
ohh oke deh mba, don't need me yet when searched at home, what kind of brand is it, it turns out pinjol paylater	Neutral
Some time ago, I searched google playsotore fintech because I wanted to know how many online load fintechs were in playstore. Now my Youtube ad is pinjol	Neutral
@FWBESS you want to be cheated for lending means	Negative
Eventhought I'm not like the other who have a lot of debt to pinjol or people hadeeh	Negative
Online loans may indeen have a mission to facilitate people who want to fulfill their needs	Positive

Table 3. Classification Tweet Set Testing

Example	Classification
Don't kill your mentality by thinking about pinjol installments and threats from ilegal pinjol, just sharing and stories first here hehe #Pinjaman Online	Positive
OJK is still not fully able to stop the practice of fraudulent investment in illegal online lending (pinjol) ilegal trading robots and rampant and detrimental to society.	Negative
I'm an idiot, jail this loan shark.	Negative
so make pinjol aja it ktpnyaa kesel bgt if there is a scam like this whata not afraid to eat haram money gt ya	Negative
@hazelnutaddcit _mba mba pinjol	Neutral
/@diyasprdn the installments to use the pinjol platform only mas	Neutral

Using Google Colab, the model achieved an accuracy of 0.814, indicating that it could accurately predict and classify sentiments in 81.4% of cases. Additionally, the researcher employed a manual training set approach for all messages aligned with the research (Sprenger et al., 2014). A Cohen's Kappa test was conducted to measure the consistency between the two methods, resulting in an approximate significance of 0.031. Since this value is less than 0.05, it indicates a significant relationship between the two approaches and a high level of consistency in the assessments made using the training dataset and the manual method. Therefore, it can be concluded that the research utilized valid data.

C. Classic Assumption Test

Obtaining unbiased estimators is the main goal of satisfying classical assumptions in regression models (Suryono, 2019). Stated differently, it is anticipated that the estimations produced will closely resemble the actual population parameters. Wang C. (2021), however, contends that logistic regression does not require normality testing. This is because, in contrast to ordinary least squares (OLS) regression, logistic regression uses a different estimate technique and uses a different kind of dependant variable. As a result, logistic regression does not adhere to the normality requirement that usually governs OLS regression.

Multicollinearity test

Table 4. Multicollinearity Result

Variable	Tolerance	VIF
Social Media Sentiment	0.974	1.027
Gender	0.974	1.027

Based on the test results, the variance inflation factor (VIF) values for independent variables X1and X2 were found to be 1.027, respectively. Given that these VIF values are all less than 10, In this model, it can be concluded that there is no significant multicollinearity. This shows that the independent variables do not significantly correlate with one another, preserving the integrity of the relationship between the dependent and independent variables.

Heteroscedasticity test

Table 5. Heteroscedasticity Result

Variable	df	Sig
Social Media Sentiment	1	0.543
Gender	1	0.004

The significant value of variable X1 is 0.543 and X2 is 0.004. Based on the criteria, the dependent variables of Gender of user information (X_2) pass the heteroscedasticity test, but the variable Social media (X_1) has a significance value above 0.05, which means it does not pass the heteroscedasticity test. To overcome this following Wisudawati (2017) approach has been done using the boostrap method where if the data after being boostrapped and confirmed the problem in logistic regression is assumed to be resolved.

D. Logistic Regression Analysis

Model Fit Analysis

Table 6. Model Fit Analysis

Chi-Square	df	Sig
1.49	2	0.447

The sig. value obtained was 0.447. Based on the criteria established for this study and consistent (Mubarak, 2021), the probability value (sig) of 0.447, which is greater than 0.05, indicates that the model employed in this research is suitable for prediction purposes.

Logistic Regression Equals

Table 7. Logistic Regression Equation

Variable	B	Sig
Social Media Sentiment	-0.471	0.498
Gender	3.115	0.016
Constant	-3.201	0.043

Based on the equation developed by Wisudawati (2019), the peer-to-peer lending performance (Y) can be modeled as follows:

$$Y = -3.201 – 0.471(X1) + 3.115(X2) + e.$$

The following coefficient values for the dependent variable were obtained. Each 1-point increase in social media (X_1) is associated with a decrease in peer-to-peer lending performance by 0.471 points. Conversely, each 1 point increase in the gender of the information provider (X_2) is correlated with an increase in peer-to-peer lending performance by 3.115 point. The negative constant value indicates that when all predictor variables are zero, the baseline level of peer-to-peer lending performance tends to be lower.

E. Hypothesis Testing

Partial Hypothesis Testing (T- test)

Table 8. T-test Result

Variable	df	Sig
Social Media Sentiment	1	0.498
Gender	1	0.016

a. The sig. value of X_1 is 0.498 > 0.05. Therefore, Hypothesis 1 is rejected, indicating that social media sentiment does not have a partial effect on peer-to-peer lending performance.
b. The sig. value of X_2 is 0.016 < 0.05. Therefore, Hypothesis 2 is accepted, indicating that the gender of the information provider has a partial effect on peer-to-peer lending performance.

Simultaneously Testing (F test)

Table 9. F-test Result

Omnibus Test		
Chi-square	**df**	**Sig.**
9.190	2	0.010

The sig. value is 0.010 < 0.05. Therefore, Hypothesis 3 is accepted, indicating that social media sentiment and the gender of the information provider have a simultaneous effect on peer-to-peer lending performance.

F. Determination Test

Table 10. Determination Result

Model Summary	
-2 Loglikelihood	Nagelkerke R Square
25.106[a]	0.412

The Nagelkerke R-square value is 0.412. This coefficient of determination indicates that the independent variables explain 41.2% of the variation in the dependent variable. The remaining variance is attributed to factors outside of the included independent variables (Suyono, 2018).

V. DISCUSSION

First, social media sentiment variables do not significantly affect the performance of the peer-to-peer lending industry. The results of this study seem to contradict some previous studies. Saleh Ali et al.(2023) and M. Wang et al. (2022) found the dominance of positive sentiment towards peer-to-peer lending on social media, especially on platform X, both in China, America, India, and Malaysia. Gupta et al. (2022) also reported a high percentage of positive sentiments among Indians regarding peer-to-peer lending. However, in line with (Maharani & Hidayah, 2021) research, although users find information from social media useful, they do not necessarily use it directly to make investment decisions. This might be a result of the particular circumstances surrounding the COVID-19 outbreak, in which individuals primarily rely on social media for information. Other elements, like personal preferences and other information sources on social media, may become more prominent when things return to normal and there is greater diversity in the information available.

Furthermore, the gender variable of the informant significantly affects the performance of the peer-to-peer lending industry. Previous research like Chen X et al. (2020), Haryanyo (2020) and Aliano et al (2023) shows that women tend to have a higher level of risk than men, so they are more cautious in making investment decisions. Therefore, women are also more active in seeking information and tend to provide more positive information regarding these platforms. However, although in this study women were the dominant active users of social media, the general sentiment on social media regarding peer-to-peer lending tended to be negative. This discrepancy shows that despite women's significant influence, challenges such as inaccurate information and negative sentiment on social media are still an obstacle. If negative reviews from women continue to dominate, the positive potential of women in changing public perception will be wasted and could threaten the sustainability of the peer-to-peer lending industry.

V. CONCLUSION

This study shows that simultaneously social media and gender of the informant affect the performance of the peer-to-peer lending industry. Furthermore, only gender of the informant affect the performance of peer-to-peer lending partially while social media has no effect on the performance of peer-to-peer lending.

For further research, it is necessary to conduct a more in-depth study of various social media platforms and risk factors. Peer-to-peer lending companies need to be proactive in managing their reputation and educating the public. Meanwhile, the government is expected to create better regulations and provide transparent information to the public to increase trust in this industry.

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