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# Optimizing Marketing Strategy by Predicting Fear of Missing Out: Machine Learning Approach

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**ABSTRACT**
Fear of Missing Out (FoMO) is one of the most popular concepts recently due to the ease of access to social media. This concept surprisingly contributed significantly to purchase intentions and customer decision-making. Thus, this study aimed to classify FoMO classes based on the factors that influence them. The data in this study was analyzed using a machine learning predictive classification model, Naïve Bayes, utilizing RapidMiner. Based on these research findings, gender and educational level had almost no influence, age group had a weak influence, daily social media use duration and peer comparison had a moderate influence, and the most used social media platform had a strong influence on FoMO. Accordingly, it was found that individuals ranging from 36 to 45 years old, with longer durations of daily social media use and moderate peer comparison frequency, using TikTok and Facebook as platforms, are more likely to be classified within a group experiencing FoMO. These findings differed from other studies, as no other study discussed the factors of FoMO feelings from a holistic view, and there was a lack of studies utilizing machine learning. By understanding this concept, marketers could gain a better view of how to categorize the FoMO feelings of their customers and use this knowledge to develop effective digital marketing strategy that could enhance customer purchase intention.

**Keywords :** Demographic Characteristic; Social Media Use; Peer Comparison Frequency Level; Fomo Level; Digital Marketing Strategy.

## INTRODUCTION

In the digital era, the rapid growth of technology and the ease of access to the internet have made social media inseparable from everyday life, which allows individuals to interact anywhere and anytime (Tandon et al, 2021). It is proven by 139 million people, representing 49.9% of the Indonesian population, who are users of various social media platforms, with the most popular platforms being WhatsApp (90.9% of social media users), Instagram (85.3%), Facebook (81.6%), TikTok (73.5%), Telegram (61.3%), and X/Twitter (57.5%) (Annur, 2024). These platforms provide unlimited access to information, entertainment, connections, and engagements (Zhang et al., 2022). The large amount of information available on social media can influence how users think, feel, and react to several kinds of situations, including the development of the Fear of Missing Out (FoMO) feelings. In the marketing field, FoMO plays a significant role in influencing customer behavior, which will precede purchase intention and customer decision making, especially for the one that exposed by the social media content regularly (Dinh & Lee, 2022; Hodkinson, 2019).

Many studies investigating the relationship between demographic characteristics, social media use, and social comparison toward FoMO have been conducted in a variety of industries within the last few years. Saritepeci & Kurnaz (2024) conducted research that found there is a significant impact of social comparison towards FoMO in the digital media industry, which is supported by the research done by Eitan & Gazit (2024) in a similar industry in Israel. In terms of demographic characteristics, Eitan & Gazit (2024) stated that age has no significant influence on FoMO. In contrast, Hylkilä et al. (2023), Jo et al (2022), and Eitan & Gazit (2023)found that there is a significant influence of age on FoMO in the Finnish digital media industry, the United States and China digital media industry, and the technology industry, respectively. Other than age, gender is also considered to influence the level of FoMO according to Avcı & Kula (2023) research in the Turkish education industry, Hylkilä et al (2023) research in Finland’s digital media industry, Brailovskaia et al (2023) research in Brazil’s digital media industry, and research in Germany’s digital media industry. In contrast, Li et al (2022) research in the

Chinese education industry shows that there is no effect of gender on FoMO but educational level do have a significant influences. Apart from demographic characteristics, according to Avcı & Kula (2023), Jabeen, Tandon, Sithipolvanichgul, Srivastava, & Dhir (2023), and Li et al (2022) research, the use of social media has a significant influence on FoMO. Conversely, Kostić et al (2022), Zoonen et al (2022) and Sultan (2023) show that FoMO is the one that influences social media use, specifically in the context of problematic social media use (Hylkilä et al., 2023; Servidio et al., 2021).

Based on various previous research, this study finds several gaps in the results, such as the differences in the significance of age and gender towards FoMO and in how they affected it, as well as the relationship direction between social media use and FoMO. Other than that, there is a lack of research that investigates the combination of demographic characteristics, social media use, and peer comparison variables simultaneously to classify FoMO. Since most of them are only focusing on some of the variables by using the methods of regression and PLS SEM (Structural Equation Model), this study aims to classify FoMO classes based on the factors that influence them from a holistic perspective by combining those three variables that often emerge in separate studies about FoMO by utilizing one of the machine learning prediction methods, Naïve Bayes, with the tools of RapidMiner in the Indonesian digital media industry. This classification method will give an efficient model to interpret the data provided more clearly in order to make decision making process easier (Fy et al, 2017). This method is efficient for a large dataset and well-performed binary classification, in which the labeled data consist of two classes that are going to be predicted by the model, and it is also suitable to analyze nominal data (Sharda et al, 2021), which is the best fit for the purpose and the type of data in the dataset used by this study. It is supported that Naïve Bayes is the best classifier by the research with a similar data type in various industries, including Saputro & Alamsyah (2024) entertainment industry), Patil et al. (2023, digital media industry), Tanza & Utari (2022, bank industry), and Delvika et al. (2022, health industry). By understanding this concept, marketers will get a better view of how to categorize the FOMO feelings of their customers and utilize them to arrange an effective marketing strategy and provide relevant content that could enhance their customer purchase intention.

This study is based on the theory of social comparison which proposed by Festinger (1954). The theory explains how individuals assess their abilities and opinions by comparing themselves to others. It includes upward social comparison, where individuals compare themselves to those they perceive as superior, and downward social comparison, where they compare themselves to those, they consider less capable (Festinger, 1954). This theory explains how individuals, influenced by social media, often compare their lives to others' online representations, leading to feelings of FoMO, which are affected by various factors. Therefore, social comparison theory is frequently used to understand customer behavior, particularly in relation to their motivation to purchase products driven by a fear of missing out on trends. Other than that, this study implements the concepts of FoMO, demographic characteristics, social media use, and social/peer comparison from the previous theory developed by several researchers. The concept of FoMO is highly related to narcissism (Brailovskaia et al., 2023), which is indicated by the feelings of anxiety, insecurities, anger, and stress (Brailovskaia et al., 2023; Fabris, Marengo, Longobardi, & Settanni, 2020). The feeling of anxiety itself is preceded by an aggressive smartphone user (Elhai, Yang, Rozgonjuk, & Montag, 2020). It is caused by too much information gained and high social interaction (Sultan, 2023).

In the context of digital media, the usage of social media is positively correlated by the usage of the internet, which will increase the user's interest in knowing about other activities, leading to an increased FoMO level. This feeling could be aggravated when the social media usage behavior turns into an addiction (Avcı & Kula, 2023). This statement is supported by Jabeen et al. (2023), who find that the excessive time spent on social media and the anxiety that comes with it will contribute to the occurrence of FoMO, which could happen continuously. According to Eitan & Gazit (2023), the duration of social media use is not the only stimulus; the type of social media that they used also gives different experiences, which will lead to a different FoMO level.

FoMO is also influenced by demographic characteristic which is defined as the science of human populations and the variations in size brought about by migration, fertility, and death (Klimczuk, 2021). Demography itself is also referenced as a characteristic description of a population, including gender, population composition and distribution (Klimczuk, 2021),age, martial status, education status (Cornoni-Huntleyl et al., 1993). The demographic characteristic age has a significant influence on the FoMO level of individuals (Eitan & Gazit, 2023; Hylkilä et al., 2023; Jo et al., 2022). According to , Gosain & Yadav (2020), and Jo et al. (2022), the younger the age, the higher the FoMO level. On the other hand, gender also contributes to the FoMO (Brailovskaia et al., 2023). According to , Brailovskaia et al. (2023), Avcı & Kula (2023), Hylkilä et al. (2023), and Santos et al (2021) males have a higher FoMO level, which is contradictory to the research of Avcı & Kula (2023), Hylkilä et al. (2023), and Santos et al. (2021) that states females contributed to a higher FoMO. Furthermore, the educational level of an individual also influences the FoMO level, which indicates that the lower the educational level, the higher the FoMO level (Avcı & Kula, 2023; Li et al., 2022).

Furthermore, social/peer comparison, which is defined as the personal opinions people have when contrasting themselves with others (Gibbons & Buunk, 1999), has a significant influence on the FoMO level. Since social media provides the user with information about others, which is the early part of the social comparison process, this comparison behavior could be the mediator of social media browsing towards the FoMO level, which indicates that the higher the social media activities, the higher the comparison that will lead to a higher FOMO level (Burnell et al, 2019). The theories referenced in this study serve primarily to support the development of the classification model. As a result, this study does not include any hypotheses, as its primary objective is to explore the development of a classification model for different classes of FoMO, considering various influencing factors.

The model in this study is being predicted by machine learning. Machine learning is part of artificial intelligence used widely in the predictive model, where the computer learns from the historic data to result in a prediction of future data effectively and efficiently in terms of the decision-making process (Dinata & Hasdyna, 2020; Sharda et al., 2021). This method is used to do a classification and regression type of prediction with a complex dataset and model that cannot be analyzed by the traditional method (Sharda et al., 2021). The data needed in machine learning consists of training data, the dataset used by the machine to learn the model, and testing data, the dataset used to evaluate the model developed by the machine learning (Kubat, 2017). Machine learning is divided into two categories: supervised and unsupervised learning. Supervised learning needs labelled training data; this includes the algorithms of regression and classification, while unsupervised learning uses unlabelled training data, which includes the algorithms of clustering and PCA (Kubat, 2017).

## METHODS

This study uses a descriptive quantitative methodology to classify FoMO classes of Indonesian social media users. The data is obtained from a secondary source, Kaggle's online real database platform. The population of this research is Indonesian social media users, which is up to 139 million users (Kemp, 2024). The data is focused on the respondent with an age range of 18–55, based on the majority of Indonesian social media users who are above the age of 18 (Kemp, 2024) , which includes the attributes of gender, education level, most-used social media platform, daily SM use, peer comparison level, and FoMO level, with a total of 4527 respondents shown in Table 1. This data is analyzed by utilizing the machine learning predictive classification method with the tools of RapidMiner 10.3.001. However, the data must undergo the pre-processing process which includes data cleaning, data transformation, feature selection, and data discretization.

**Table 1.**
**Data Profile After Pre-Processing (N= 4,527)**

| Variable | Dimension | Type | Value | N | % |
|---|---|---|---|---|---|
| **Demographic characteristic** = The science of human populations and the variations in size brought about by migration, fertility, and death (Klimczuk, 2021) | Gender | Binomial | Male | 2249 | 50.3% |
| | | | Female | 2278 | 49.7% |
| | Age group | Nominal | 18-25 years old | 1118 | 24.7% |
| | | | 26-35 years old | 1158 | 25.6% |
| | | | 36-45 years old | 1111 | 24.5% |
| | | | 46-55 years old | 1140 | 25.2% |
| | Education level | Nominal | High school | 1480 | 32.7% |
| | | | Bachelor's | 1504 | 33.2% |
| | | | Master's | 1543 | 34.1% |
| **Social media use** = The use of digital platform, services and apps (Bengtsson & Johansson, 2022) | Daily SM Used (Min) | Numeric | 60-720 minutes | 4527 | 100% |
| | Most used SM platform | Nominal | Tiktok | 1102 | 24.3% |
| | | | Facebook | 1128 | 24.9% |
| | | | Instagram | 1143 | 25.2% |
| | | | Twitter | 1154 | 25.5% |

| | | | | |
|---|---|---|---|---|
| **Peer comparison frequency** = The personal opinions people have when contrasting themselves with others (Gibbons & Buunk, 1999) | Numeric | 1-10 | 4527 | 100% |
| **FoMO (Fear of Missing Out)** = The feelings of anxiety, insecurities, anger, and stress (Brailovskaia et al., 2023; Fabris et al., 2020). | Nominal | FoMO<br>Non-FoMO | 2254<br>2273 | 49.8%<br>50.2% |

Source: Kaggle, Database Platform (2024)

Furthermore, the features in this study must underwent a selection process. Those features will be tested by the chi-square test. This test is used to examine the correlation or association between categorical features (Rana & Singhal, 2015) which really fits the study since the dataset used mostly consists of a categorical nominal data type. The formula for Chi-square test can be expressed as follows:

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}$$

O: observed frequency; E: expected frequency

The features that have a high correlation with the labelled data, will be classified using the Naïve Bayes algorithm. Naïve Bayes is a popular classification method based on probability theory, used to mostly classify the nominal data from the Bayes Theorem concept, which is part of supervised learning (Sharda et al., 2021). The model development process includes data pre-processing (making sure the data type is nominal; if it is numerical, discretizing must be performed), developing the model (data training and testing), which results in the output of the probability of each feature towards the labelled data, and the and the evaluation towards the performance of the model (Sharda et al., 2021). The probability formula for Naïve Bayes can be expressed as follows:

$$P(YX) = \frac{P(XY)P(Y)}{P(X)}$$

P(Y) = Probability of Y; P (X) = Probability of X; P(X|Y) = Probability of X given by Y; P(Y|X) = Probability of Y given X

The evaluation of the Naïve Bayes model is measured by its accuracy and AUC (area under the ROC/receiver operating characteristic curve). Accuracy is the most often used machine learning statistic, and the rate of correctly classifying examples ranges from 1% to 100% (Qayyum et al., 2024). ROC is a graph that shows the true positive rate (TPR) and false positive rate (FPR) of classification for various thresholds. Since it gauges performance across all potential classification thresholds in a particular model, the Area Under the ROC Curve (AUC) represents the calibre of outcomes regardless of the model (Qayyum et al., 2024). The closer the value of AUC to 1, the more accurate the model, but closer to 0 means no accuracy (Mandrekar, 2010). The formula for classification accuracy can be expressed as follows:

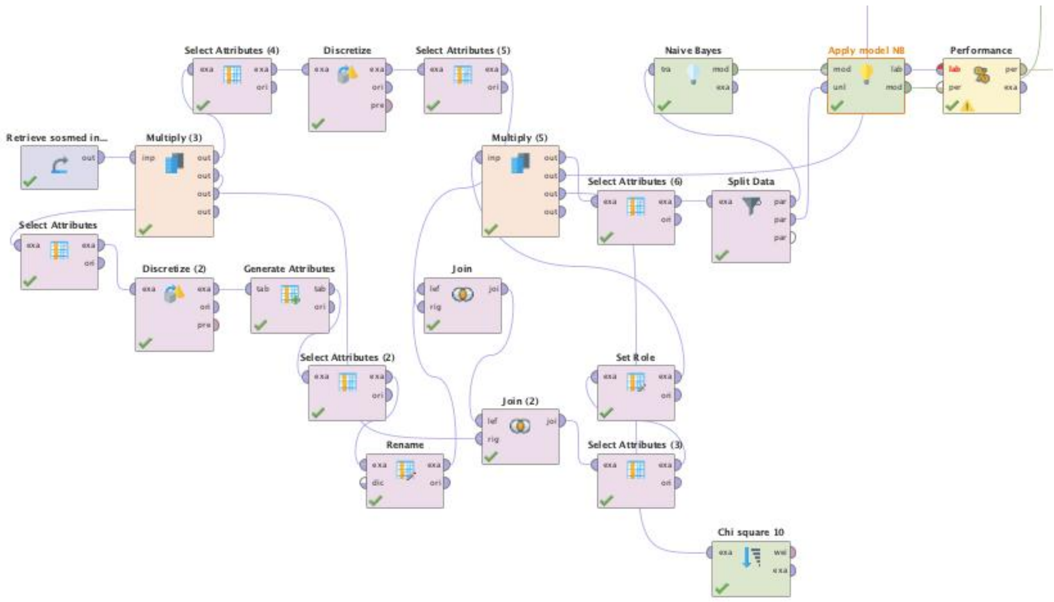
$$\text{ACC} = \frac{\sum_{i=1}^{n} t_{i,i}}{\sum_{i=1}^{n}\sum_{j=1}^{n} t_{i,j}}$$

$$\text{AUC} = \frac{A\hat{U}C - 0.5}{\text{SE}\ (A\hat{U}C)}$$

AUC = Estimated AUC value; SE (AUC) = Standard error of AUC value

## RESULT

The process of this study's modelling is shown in Figure 1, utilizing the tools of RapidMiner. The model shown starts with Indonesian social media user data input, then undergoes a pre-processing step consisting of the discretization of the attribute. The attribute that is being discretised will then be joined with other attributes. After the data pre-processing process, the attribute will be run through a chi square test, the factor with a strong and moderate correlation will be chosen for the classification process. Before being classified, the data must be partitioned into trained and tested data, then classified utilizing Naïve Bayes model. The classification model was then evaluated for accuracy and AUC.




Source: processed data

**Figure 1**
**RapidMiner Model**

*Data Prepocessing*

The data obtained can't be modelled directly; it must be prepared through several pre-processing stages. Given that the data is already clean, the next step involves adjusting several attributes to meet the criteria for the Naive Bayes classification algorithm, which is designed to classify nominal data types. Specifically, several attributes, including daily social media use and FoMO level, should undergo a data-discretisize process in order to divide them into certain categories of data (Sharda et al., 2021). Discretize is often used in machine learning prediction to enhance the accuracy of the result as a process of changing the continuous numerical data to a discrete data type or into several categories (Liu, 2002). In this case, the FoMO level is divided into 2 bins ("fomo and non-fomo") and daily social media use into 10 bins ("low, medium, and high"). The number of bins for FoMO level depends on its classification type, binary, which needs to be divided into two categories, while the number of bins for social media use is based on the ten bins technique. This technique is widely used in numerous studies, which state that the number of bins (k) is assigned to be 10 in every size of the data (Dougherty et al, 1995). After being defined, each range will be named after the category by using the generate attributes operator and joined with the inner join with the rest of the colomn. Inner join is referenced as joining multiple tables by matching the row by the primary key from each table. The FoMO attribute that has been discretized is then labelled as the dependent variable.

*Descriptive Analysis*

According to the data resulting from the pre-processing process, It shows that the gender of the respondent is almost equal between male (50.3%) and female (49.7%), with the age group between 18 and 55 years distributed equally every 10 years. The education level is dominated by a master's degree with 34.1%, followed by a bachelor (33.2%) and high school (32.7%). The social media used duration per person is in the range of 60–720 minutes, with the most used social media platforms being Twitter, Instagram, Facebook, and TikTok consecutively with a similar proportion. The peer comparison ranges from 1 to 10, and the last one is the FoMO category, with non-FoMO (level 1–5) respondents at 50.2% and FoMO (level 6–10) respondents at 49.8%.

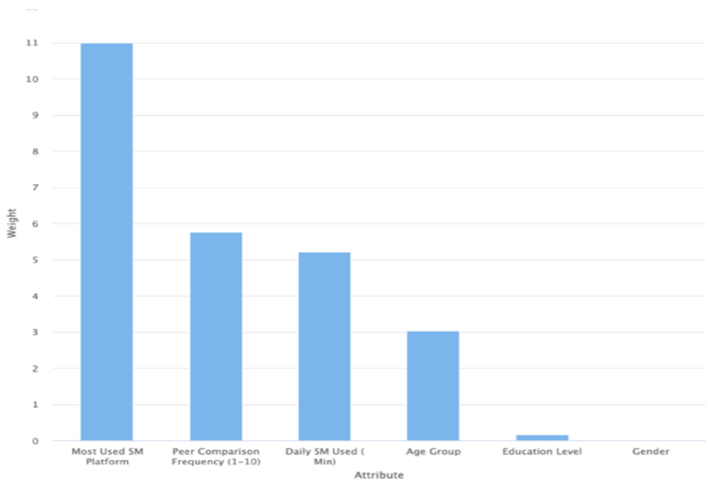
*Feature Selection*

All the features included in this study underwent feature selection and filtering with chi-square testing. This is due to the lack of knowledge of how the correlation between factors is towards the dependent variable in the context of the data set examined by this research. Therefore, not all of the features can be included in the classification model; only the features that have a significant correlation with the labelled data can be included in this model. As a result, the chi-square weight in Table 2 shows that the most used platforms have a very high correlation, daily social media use and peer comparison have a medium correlation, age group has a low correlation, and education level and gender almost have no correlation with FoMO. So, gender and educational level will be eliminated from the classification model development. The result comparison visualization graphic of this test is shown in Figure 2

**Table 2**
**Chi-Square Weight**

| Attribute | R-Square |
|---|---|
| Gender | 0.027 |
| Educational Level | 0.156 |
| Age Group | 3.025 |
| Daily SM Used | 5.214 |
| Peer Comparison Frequency | 5.752 |
| Most Used SM Platform | 10.990 |

Source: processed data




Source: processed data

**Figure 2**
**Chi-Square Weight Graphic**

*Modelling*

In terms of performing the modelling technique, the dataset should be partitioned into data training and data testing. The training data will be used as the learning material for the machine to develop the classification model, while the testing data will be used to test the performance of the developed model (Kubat, 2017). In this study, the dataset is partitioned with a 70% as the training data and 30% as the testing data allocation since it is the best ratio to get a balanced variance of data for the modelling process (Fong et al, 2023; Nguyen et al, 2021). The partition data is then inputted into the modelling operator (training data for model development; testing data to apply the model operator). Then, since we are using Naïve Bayes, the results are in the probability model. Table 3. shows that the labelled data consist of FoMO (0.498) and non-FoMO (0.502), indicating that the data distribution is balanced.

**Table 3**
**Description of Model**

| Class | Distribution Model |
|---|---|
| FoMO | 0.498 |
| Non-FoMO | 0.502 |

Source: processed data

Table 4 and Figure 3 shows the distribution of the model, which is segmented based on the value of each attribute. The daily social media use attribute consists of a 1–10 value since it’s divided by the total number of bins. Range 1 shows the shortest duration of social media used daily, while range 10 shows the longest duration. Those with shorter social media usage durations (ranging from 1-4 hours) are more likely to belong to the group that does not experience FoMO, while those with longer usage durations (5-10 hours) tend to fall into the group that experiences FoMO. The likelihood of experiencing FoMO increases as the time spent on social media increases.This finding is supported by the research conducted by Avcı & Kula (2023), Jabeen et al. (2023), Li et al. (2022). Thus, marketers could target users with a higher duration of social media use by providing an intense amount of content so that they will easily become FoMOs and pay more attention to the company’s product.

The social media platform also has a contribution to the classification, not only the duration. From the Table 4 and Figure 3, it can be seen that users who use TikTok and Facebook are more likely to be classified within a group experiencing *FoMO* than those who use Twitter and Instagram, which is supported by Eitan & Gazit (2023) and Obar & Wildman (2015) research. Therefore, marketers could use TikTok and Facebook as their main platforms to distribute their content if their main goals are to increase users FOMO and awareness.

Furthermore, other attributes, such as the age group, are segmented into 4 groups consisting of 18–25 years old, 26–35 years old, 36–45 years old, and 46–55 years old, as shown in Table 4 and Figure 4. As can be seen from the model, the 36–45 age group are more likely to be classified within a group experiencing *FoMO* compared to other groups. Other than that, there is no certain correlation pattern in this model which is supported by Eitan & Gazit (2024) research. Consequently, marketers could reach users between the ages of 36 and 45 since they are more easily converted into FoMOs with the right platform and content that suit their language and lifestyle.

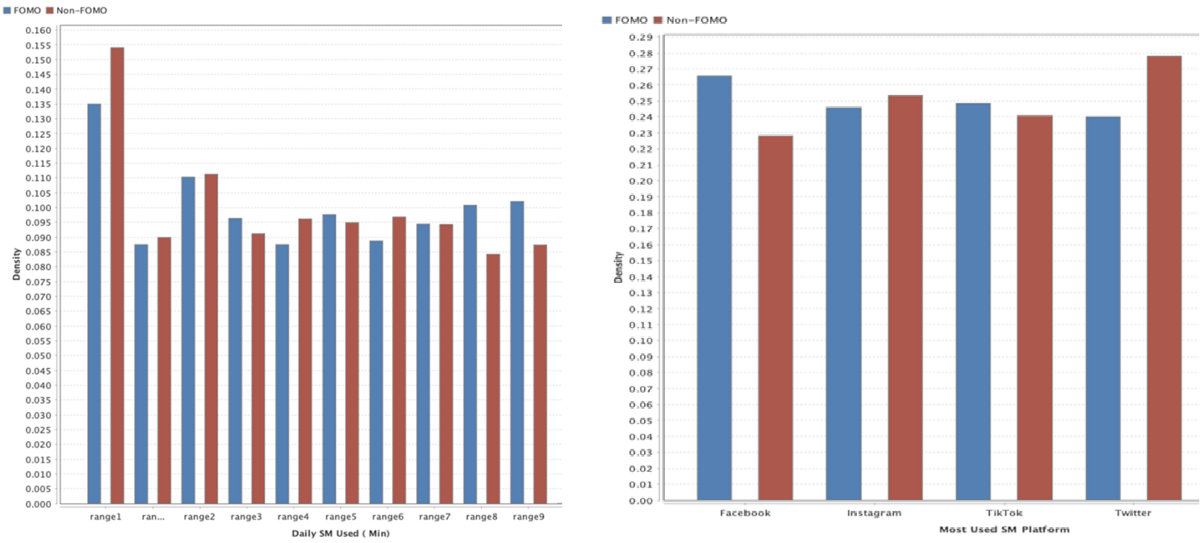
Table 4 and Figure 4 also shows the distribution of peer comparison frequency towards FoMO and non-FoMO class classifications. It shows that individuals with peer comparison frequencies between 3-6 will are more likely to be classified within a group experiencing *FoMO*. Other than that, there is no certain correlation pattern in this model which is in contrast with Saritepeci & Kurnaz (2024) research. Thus, marketers should make content that suits the user's moderate peer comparison level so that it can increase their FoMO level when buying the company's product.

**Table 4**
**Model Distribution**

| Attribute | Parameter | FoMO | Non-FoMO |
|---|---|---|---|
| Daily SM Used (Min) | Value=range1 | 0.135 | 0.154 |
| Daily SM Used (Min) | Value=range2 | 0.110 | 0.111 |
| Daily SM Used (Min) | Value=range3 | 0.096 | 0.091 |
| Daily SM Used (Min) | Value=range4 | 0.087 | 0.096 |
| Daily SM Used (Min) | Value=range5 | 0.098 | 0.095 |
| Daily SM Used (Min) | Value=range6 | 0.089 | 0.097 |
| Daily SM Used (Min) | Value=range7 | 0.094 | 0.094 |
| Daily SM Used (Min) | Value=range8 | 0.101 | 0.084 |
| Daily SM Used (Min) | Value=range9 | 0.102 | 0.087 |
| Daily SM Used (Min) | Value=range10 | 0.087 | 0.090 |
| Most Used SM Platform | Value= Facebook | 0.266 | 0.228 |
| Most Used SM Platform | Value= Twitter | 0.240 | 0.278 |
| Most Used SM Platform | Value= Instagram | 0.246 | 0.253 |
| Most Used SM Platform | Value= TikTok | 0.248 | 0.241 |
| Age Group | Value= 18-25 | 0.239 | 0.253 |

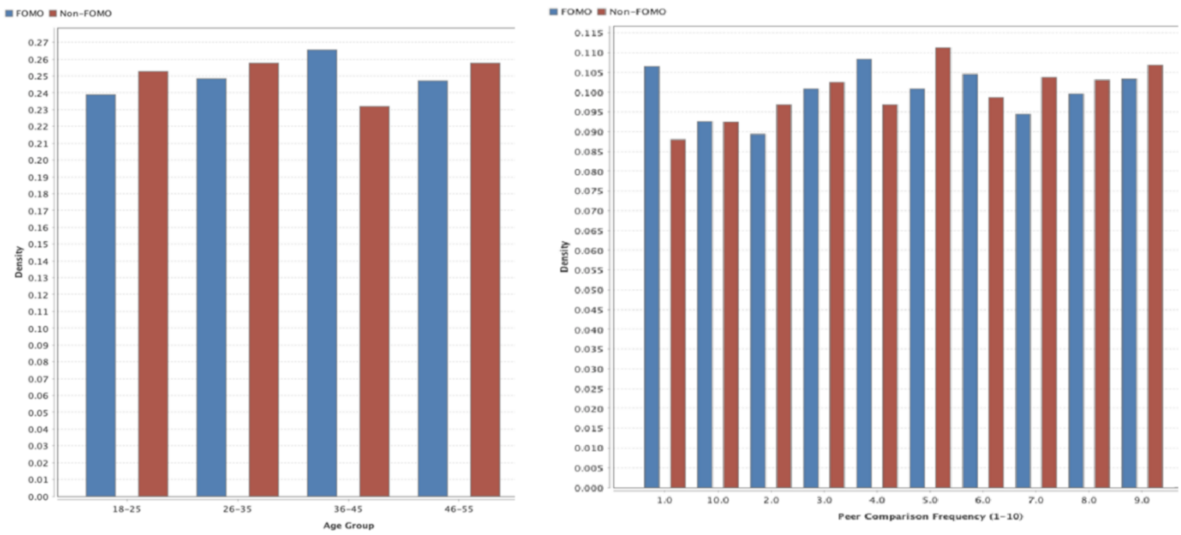
| | | | |
|---|---|---|---|
| Age Group | Value= 26-35 | 0.248 | 0.258 |
| Age Group | Value= 36-45 | 0.266 | 0.232 |
| Age Group | Value= 46-55 | 0.247 | 0.258 |
| Peer Comparison Frequency | Value= 1 | 0.106 | 0.088 |
| Peer Comparison Frequency | Value= 2 | 0.089 | 0.097 |
| Peer Comparison Frequency | Value= 3 | 0.101 | 0.102 |
| Peer Comparison Frequency | Value= 4 | 0.108 | 0.097 |
| Peer Comparison Frequency | Value= 5 | 0.101 | 0.111 |
| Peer Comparison Frequency | Value= 6 | 0.105 | 0.099 |
| Peer Comparison Frequency | Value= 7 | 0.094 | 0.104 |
| Peer Comparison Frequency | Value= 8 | 0.099 | 0.103 |
| Peer Comparison Frequency | Value= 9 | 0.103 | 0.107 |
| Peer Comparison Frequency | Value= 10 | 0.093 | 0.092 |

Source: Processed Data




Source: Processed Data

**Figure 3**
**Daily Social Media Use Distribution and Most Used Social Media**




Source: Processed Data

**Figure 4**
**Age Group Distribution Figure and Peer Comparison Distribution**

*Evaluation*

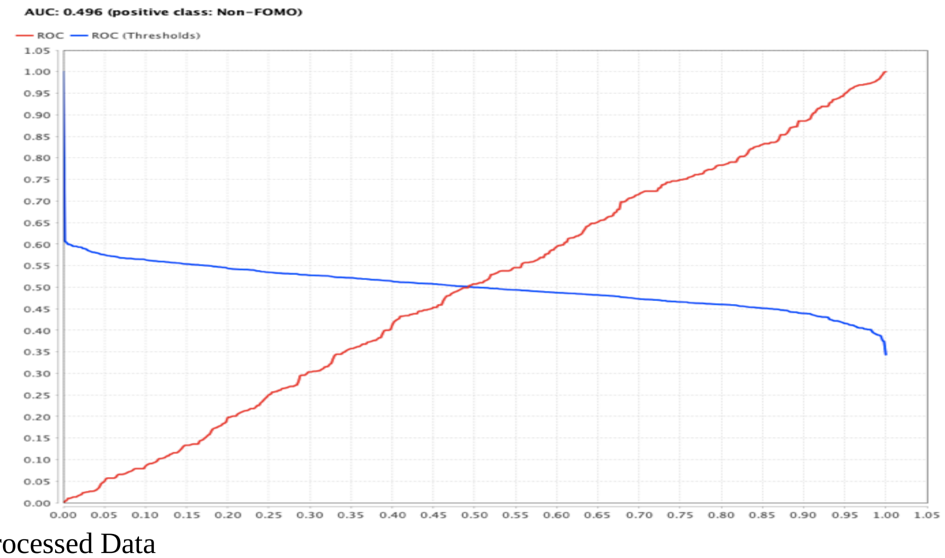
The performance of the classification model developed in this study was evaluated by measuring the accuracy and AUC of the model. Accuracy is considered the most important and standardized performance evaluation indicator in many modeling techniques. Table 5 shows the recall and precision percentages for each labeled data point: FoMo and non-FoMO. Precision for each class indicates the percentage of accurately classified positives (Qayyum et al., 2024). Each class in this study has a precision of 50%, suggesting moderate precision in classifying each class. Furthermore, class recall indicates the percentage of true positives that the model correctly identifies (Qayyum et al., 2024). Each class in this study has a recall of 50%, indicating moderate ability to recognize classes in the dependent variable. The overall accuracy of the model is 50.37%, indicating a moderate level of classification accuracy, which means the model is correctly classifying over half of the instances, and it's better than random guessing.

**Table 5**
**Model Performance (Accuracy)**

| | True FoMO | True Non-FoMO | Class Precision |
|---|---|---|---|
| Pred. FoMO | 340 | 338 | 50.15% |
| Pred. Non-FoMO | 336 | 344 | 50.59% |
| Class Recall | 50.30% | 50.44% | 50.37% |

Source: Processed Data

Figure 5 shows the AUC graphic of the classification model in this study with a value of 0.496. AUC shows the quality of the result, which is more accurate if it is closer to 1. Therefore, the quality of this model's prediction does not meet the desired standards, suggesting that it has some difficulty differentiating between the positive and negative classes in the dataset. It could happen because the feature that is used in this research didn't give enough information to the model. The model's performance could be improved with a more balanced dataset, ensuring that each class is represented evenly.




Source: Processed Data

**Figure 5**
**Model Performance (AUC and ROC)**

This study is contributing to the theoretical field in terms of theory validation about the influences of demographic characteristics (age, gender, education level), social media use (most use of social media platforms, daily duration of social media use), and peer/social comparison towards the occurrence of Indonesian social media user's FoMO feelings and classify it, where there is no study that investigates all these variables simultaneously in a holistic view. This study does not only look at some factors in a certain area that have a potential contribution towards FoMO but also at all the connected possible factors inside the relationship. In terms of the managerial implications, these study findings could provide a better guideline on how to measure the FoMO level of a company target audience, including what factors influence FoMO and how they influence FoMO, so that marketers could arrange an optimal marketing strategy to deliver more suitable content to their audiences and finally enhance the purchase intention of the target market.

## CONCLUSION

This study aims to classify FoMO based on demographic characteristics (age, gender, education level), social media use (most use of social media platforms, daily duration of social media use), and peer/social comparison by utilizing machine learning prediction methods. According to this study, gender and educational level have almost no influence, age group has a weak influence, daily social media use duration and peer comparison have a moderate influence, and the most used SM platform has a strong influence on FoMO. It was found that individuals aged 36 to 45, who spend longer periods on social media daily, engage in moderate peer comparisons, and primarily use platforms like TikTok and Facebook, are more likely to be classified as experiencing FoMO. This finding is different from other studies because it seeks a holistic view of a more complicated factor that could possibly classify FoMO level with the help of a machine learning prediction model, Naïve Bayes classifier.

Marketers could adjust their way of creating and delivering marketing activities based on this study result. They could target users with a higher duration of social media usage by providing an intense amount of content, use TikTok and Facebook as their main platforms to distribute their content if their main goals are to gain users with high FOMO posibility, reach users between the ages of 36 and 45 since they are more easily converted into FoMOs with the right platform and content, and create content that suits the user's moderate peer comparison level. Hence, it will indirectly enhance the purchase intention of their target market.

There are several limitations on this study. First, the data in this study is limited to certain social media platform users, which are TikTok, Instagram, Facebook, and Twitter. Hence, it doesn’t show Indonesian social media users in general. Second, some of the attributes that are used in this are in the form of a subjective perspective, including the peer comparison frequency level and FoMO level. Third, some of the classification results don’t show a certain pattern to be learned, which is age group and peer comparison frequency level. Thus, the prediction will be performed in a more difficult way. Lastly, the accuracy of the model used in this study is still moderate, indicating that the model has some difficulty in analyzing this type of data

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