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Data Article

Dataset on online impulsive buying behavior of buy now pay later users and non-buy now pay later users in Indonesia using the stimulus-organism-response model

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A B S T R A C T

This paper provides a dataset that thoroughly explores online impulsive buying behavior, offering a comparative analysis between Buy Now Pay Later (BNPL) users and non- Buy Now Pay Later users in Indonesia. Utilizing the Stimulus-Organism-Response (S-O-R) model, the research investigates the nuanced interplay of external stimuli, cognitive and emotional responses, and resulting in impulsive purchasing behaviour. The dataset, derived from a detailed survey of 810 online consumers, unveils distinctive patterns in the impulsive buying behaviors of these two user groups, shedding light on the impact of Buy Now Pay Later stimuli on consumer decision-making. The Partial Least Square Structural Equation Model (PLS-SEM) are employ using SmartPLS 4.0 to assess the reliability and validity of the survey data. This research contributes valuable insights for understanding the dynamics of online impulsive buying in the context of emerging digital payment systems. This dataset can contribute to formulating strategic marketing and other crucial decisions by Buy Now Pay Later (E-Paylater) providers. Furthermore, this dataset can be utilized for data analysis by various stakeholders seeking information on the purchasing decisions of digital consumer groups based on age, gender, education, and income levels. Regulators of Buy Now Pay

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Later can also leverage this data to support the creation of regulations and educational programs promoting the responsible usage of Buy Now Pay Later services. This dataset can also be utilized by academics in the field of consumer behavior to analyze the influence of stimuli originating from payment facilities such as Buy Now Pay Later on individuals as organisms, ultimately leading to the emergence of impulsive buying behavior.

Specifications Table

Subject	Business, Management and Decision Sciences
Specific subject area	Finance and Banking, and Marketing especially related to
Data format	Raw, Filtered, Processed
Type of data	a. Raw Data_Paylater and Non Paylater User.csv file (dataset with numbers) b. CodebookData_SEMPLS_IBB.xls file (dataset with labels) c. Questionnaire file
Data collection	The survey was conducted using an online questionnaire modified from previous studies. The online questionnaire link was distributed to all digital consumers in Indonesia who voluntarily participated through various social media platforms, namely Facebook, Instagram, and WhatsApp. The criteria for participating respondents were individuals aged 17 years and older who had previously engaged in online shopping. A total of 810 participants contributed to this survey.
Data source location	The participants in this study were domiciled from various regions across Indonesia, specifically from 23 provinces including: West Sumatera, DKI Jakarta, West Java, Riau, East Java, South Sumatera, Lampung, North Sumatera, Central Java, East Kalimantan, Kepulauan Riau, West Kalimantan, Jambi, Banten, Bengkulu, South Sulawesi, West Nusa Tenggara, DI Yogyakarta, Nangroe Aceh Darussalam, Papua, Maluku, East Nusa Tenggara and Central Sulawesi.
Data accessibility	The dataset discussed in this paper is readily accessible on Mendeley Data repository. Interested parties can find the dataset by searching for the title of the paper or by using the following details: - Repository name: Dataset on Online Impulsive buying behaviour of E-paylater user and non-E-paylater user - Data identification number: 10.17632/wkjdmrmrg4.4 - All data can be accessed at this Direct URL to data: https://data.mendeley.com/datasets/wkjdmrmrg4/4 - **This archive is supported by Mendeley Data**

1. Value of the Data

- The database represents potential data to comprehend impulsive buying behavior among digital consumers, likely resulting from stimulus factors in Buy Now Pay Later (e-paylater) payment options. This database also provides variables that play a role in consumer decision-making from both emotional and cognitive perspectives.
- The available data can be processed as a whole or in groups based on categories such as group, gender, age, as well as income and expenditure levels for online consumption. Furthermore, the dataset can also be analyzed by examining direct relationships between vari-

ables as well as possible combinations based on the available inter-variable theory within the dataset.
- This dataset provides insights for e-paylater providers aiming to grasp potential stimulus factors that influence financial decisions, especially impulsive purchases, among both BNPL users and non- BNPL users.
- Researchers in the fields of marketing, consumer behavior, and financial decision-making can utilize this data for various research endeavors related to the stimulus-organism-response theory in online impulsive buying, e-paylater stimulus factors, the role of cognitive and emotional responses in driving impulsive buying behavior, among other topics. The dataset's respondent characteristics and the number of available variables enable researchers to create several research models and engage in data processing to align with their research object.
- Policy makers, especially the regulators of Buy Now Pay Later (e-paylater), and educational institutions can also utilize this dataset to understand the phenomenon of digital consumer's impulsive buying behavior that is stimulated by the use of buy now pay later services. The findings generated from this dataset may serve as considerations and inputs in formulating the policies to promote responsible use of e-paylater services.

2. Background

The use of e-commerce applications to fulfill consumer needs is rapidly gaining popularity in Indonesia, attibute to the numerous innovations and facilities provided by service providers and e-commerce platforms. One such feature, the “Buy Now Pay Later” or e-paylater, has gained immense popularity among Indonesian users due to its versatile benefits and user-centric attributes [1]. e-Paylater services commonly known as “Buy-now-pay-later” (BNPL) refers to an innovative FinTech solution offering convenient credit for retail purchases, characterized by an initial upfront payment followed by several biweekly payments [2,3]. This digital invoice service, often facilitated by financial providers working with e-commerce platforms, allows customers to defer payment until a later date, typically after the delivery of goods. BNPL represents a new form of credit, allowing users to make purchases using a mobile app, either online or at physical stores [4]. While this feature has numerous advantages, it also carries potential risks if not used wisely, especially for its users. According to several studies, e-paylater has the capacity to stimulate impulsive purchasing tendencies, which can subsequently encourage excessive consumption among consumers [5]. Hence, the purpose of this dataset is to offer valuable input data for conducting a wide range of analyses pertaining to the usage of e-paylater and consumer decision-making, particularly in Indonesia. With its diverse data and demographic attributes, this dataset enables comprehensive as well as segment-wise analyses and tests, based on consumer groups categorized by age, gender, education level, and more.

3. Data Description

3.1. Dataset location and description

In this paper, we provide a comprehensive overview of the dataset sourced from the Mendeley Data repository. The dataset comprises responses collected from a survey of digital consumers in Indonesia conducted between 2022 and 2023 [6]. The dataset folder in the Mendeley Data repository contains one questionnaire file and two distinct data files. The initial file, presented in Microsoft Excel format, comprises of two worksheets. The first worksheet contains a comprehensive collection of survey data that includes demographic information and variable data. The second worksheet serves as the code and detailed information guide for each data presented in the first worksheet. The second data file is available in Microsoft Excel CSV (comma-delimited) format and is particularly suitable for testing and direct data processing in applications such as SEM PLS or SPSS. Researchers can use this file to streamline data processing and analysis, saving time and increasing accuracy.

3.2. Data collection

One of major challenges in designing the sampling strategy of this study and its data collection is that the population of paylater users in Indonesia is unknown. To ensure that the survey can reach a wide range of population groups and demographic characteristics, this study use both multiple offline and online channels and social media platforms, including Facebook, Instagram, Twitter, and WhatsApp. The study adopted a convenience sampling technique for data collection, utilizing an online questionnaire disseminated via Google Forms. Subsequently, the link to the questionnaire from Google Forms was distributed across diverse online social media platforms.

The strategy firstly involved announcing and disseminating the online questionnaire link through various groups and online communities on social media, such as student communities and hobbyist groups. The survey link was distributed through various social media platforms, including Facebook, Instagram, and WhatsApp. In addition, requests for assistance to distribute the questionnaire link were made to official university accounts and local agencies, particularly through Instagram. Although not all of these accounts responded and were willing to assist, the support from those who did greatly aid in the data collection process. These supporting accounts have a wide following ranging from 11 thousand users to over 1 million users. To enhance the response rate, reminders and link distributions were carried out again at the end of each subsequent week for three months. These efforts proved to be successful as they resulted in an increased number of responses, thereby allowing for a more comprehensive dataset to be gathered and analyzed. Another strategy employed to reach a wider audience and gather more responses was the implementation of a snowball sampling method. We encouraged participants who had completed the survey to identify other potential respondents and help us in distributing the survey links.

3.3. Descriptive data analysis

After collecting the survey data, we made sure all responses were complete. Initially, we found that out of 845 responses, 35 (about 4.12 %) had incomplete demographic information and had to be removed. We were left with 810 responses to work with. We then checked these for any missing details or unusual answers. According to our findings in Table 1, there were no missing responses. This was because when we set up the survey on Google Forms, we required every question to be answered (mandatory) before participants could submit their responses. This step ensured that our data was complete and ready for analysis.

To provide a clearer understanding of our survey demographic, Table 2 below shows the distribution of respondents based on the provinces of their residential locations. From the table provided, it can be inferred that the provinces with the highest number of respondents include West Sumatra, DKI Jakarta, and West Java.

Furthermore, The Table 3 provides detailed information about the respondents' profiles.

According to Table 3, the majority of the respondents are female (67.9 %). Additionally, 60 % of respondents belong to Generation Z. This aligns with their educational backgrounds, as 40 % graduated from high school and 34 % obtained a bachelor's degree or diploma IV. The data is further supported by the fact that most respondents are university students, comprising 404 individuals (49.7 %). In second place, most respondents are employed, totaling 337 individuals (41.6 %). Regarding income levels, over 50 % of respondents have relatively low incomes below IDR 2500,000, with only 15.4 % possessing a fairly stable income above IDR 10,000,000. Despite this, the majority of respondents appear cautious when it comes to spending their income on

Table 1
Result for missing value check.

Indicators	Cases					
	valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
IBB1	810	100.0 %	0	0.0 %	810	100.0 %
IBB2	810	100.0 %	0	0.0 %	810	100.0 %
IBB3	810	100.0 %	0	0.0 %	810	100.0 %
IBB4	810	100.0 %	0	0.0 %	810	100.0 %
P1	810	100.0 %	0	0.0 %	810	100.0 %
P2	810	100.0 %	0	0.0 %	810	100.0 %
P3	810	100.0 %	0	0.0 %	810	100.0 %
P4	810	100.0 %	0	0.0 %	810	100.0 %
SI1	810	100.0 %	0	0.0 %	810	100.0 %
SI2	810	100.0 %	0	0.0 %	810	100.0 %
SI3	810	100.0 %	0	0.0 %	810	100.0 %
SI4	810	100.0 %	0	0.0 %	810	100.0 %
SI5	810	100.0 %	0	0.0 %	810	100.0 %
SI6	810	100.0 %	0	0.0 %	810	100.0 %
H1	810	100.0 %	0	0.0 %	810	100.0 %
H2	810	100.0 %	0	0.0 %	810	100.0 %
H3	810	100.0 %	0	0.0 %	810	100.0 %
H4	810	100.0 %	0	0.0 %	810	100.0 %
SC1	810	100.0 %	0	0.0 %	810	100.0 %
SC2	810	100.0 %	0	0.0 %	810	100.0 %
SC3	810	100.0 %	0	0.0 %	810	100.0 %
SC4	810	100.0 %	0	0.0 %	810	100.0 %
SC5	810	100.0 %	0	0.0 %	810	100.0 %
NE1	810	100.0 %	0	0.0 %	810	100.0 %
NE2	810	100.0 %	0	0.0 %	810	100.0 %
NE3	810	100.0 %	0	0.0 %	810	100.0 %
NE4	810	100.0 %	0	0.0 %	810	100.0 %
NE5	810	100.0 %	0	0.0 %	810	100.0 %

Table 2
Geographic distribution of respondents by province.

Province	No. of Respondents
West Sumatera	439
DKI Jakarta	85
West Java	38
Riau	37
East Java	26
South Sumatera	22
Lampung	22
North Sumatera	19
Central Java	17
East Kalimantan	17
Kepulauan Riau	17
West Kalimantan	16
Jambi	14
Banten	13
Bengkulu	10
South Sulawesi	5
West Nusa Tenggara	4
DI Yogyakarta	2
Nangroe Aceh Darussalam	2
Papua	2
Maluku	1
East Nusa Tenggara	1
Central Sulawesi	1

Table 3
Profile of respondents.

	Total	Percentage (%)
Gender:		
Male	260	32.1 %
Female	550	67.9 %
Generation:		
Generation Z (17–26 y.o)	493	60.9 %
Generation Y (27–42 y.o)	190	23.5 %
Generation X (43.−58 y.o)	127	15.7 %
Last Educational Background:		
Until Senior High School	324	40.0 %
Diploma I, II, III	71	8.8 %
Bachelor/Diploma IV	275	34.0 %
Post Graduate	140	17.2 %
Job Status:		
University Students	404	49.9 %
Working	337	41.6 %
Not Working	32	4.0 %
Entrepreneurs	37	4.5 %
Level of Income:		
Below IDR*. 1000,000	299	36.8 %
IDR. 1000,001 to 2500,000	143	17.7 %
IDR. 2500,001 to 5000,000	106	13.0 %
IDR. 5000,001 to 7500,000	70	8.5 %
IDR. 7500,001 to 10,000,000	70	8.6 %
More than IDR. 10.000.000	125	15.4 %
Average monthly expenditure for online shopping in relation to monthly income:		
< 20 %	513	63.1 %
21 % - 40 %	217	26.7 %
41 % - 60 %	60	7.4 %
61 % - 80 %	14	1.7 %
>80 %	6	0.7 %
E-Paylater User status		
E-Paylater User	205	25.3 %
Non E-Paylater User	605	74.7 %

online shopping. Specifically, 63.1 % of respondents can manage the average monthly expenditure for online shopping in relation to their monthly income below 20 %. Less than 10 % of respondents spend more than 40 % of their monthly income on online shopping.

3.4. Outlier detection analysis

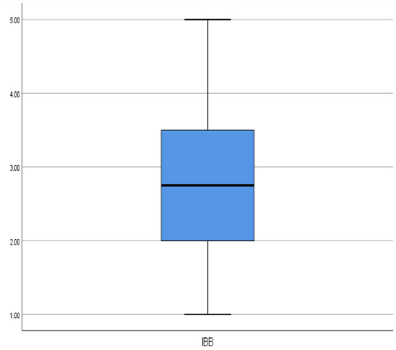
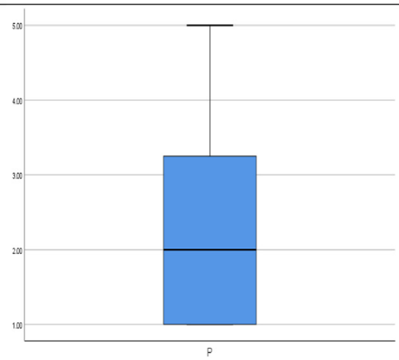
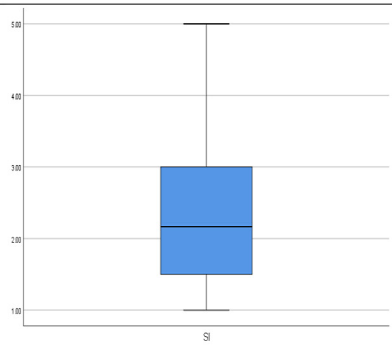
Before analyzing the data, our initial step involves scrutinizing the patterns of responses. In this process, we specifically search for a phenomenon commonly referred to as straight-lining. This occurs when a respondent consistently selects the same answer across a significant number of questions [7]. Based on the straight-lining results, we excluded 4 observations (IDs: 564, 393, 666, 466) from our analysis. This adjustment yields a refined sample size of $n = 806$.

Moreover, the data underwent outlier detection through a series of tests conducted using SPSS 26.0. This involved examining Boxplot diagrams, as illustrated in Table 4 below:

The analysis of outliers through the use of boxplots reveals that, among all the variables examined, only the happiness and self-control variables appear to potentially contain outliers. It is important to note, however, that these potential outliers are not classified as extreme outliers, as they are not marked with asterisks in the boxplots [8]. In order to confirm whether these potential outliers should be removed, a subsequent Z-score analysis was performed. The outcomes of this analysis are detailed in Table 5.

Outliers can be identified through the application of a Z-score, or standardized score value. Hair suggests that in a small sample size (no more than 80), outliers are recognized when the dataset exhibits a Z-score of 2.5 or higher. Conversely, in larger samples (exceeding 80), data points are typically considered outliers if their Z-score reaches or surpasses 4 [9]. Table 5 reveals that the Z-scores for all variables, including Happiness and Self-control, are not greater than 4. Thus, it can be concluded that this data is free from outliers and does not need to be removed..

Table 4
Result for outlier detection.

Variables	Boxplot
Impulsive Buying Behaviour (IBB)	
BNPL Promotion (P)	
Social Influence (SI)	

(continued on next page)

Table 4 (*continued*)

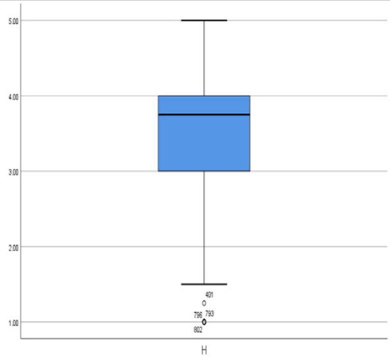
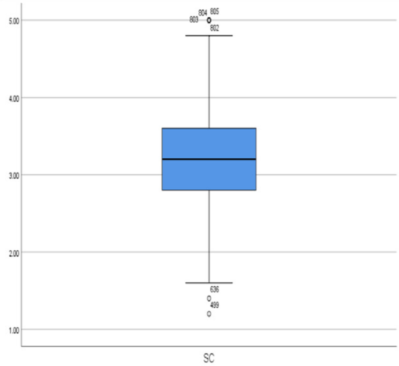
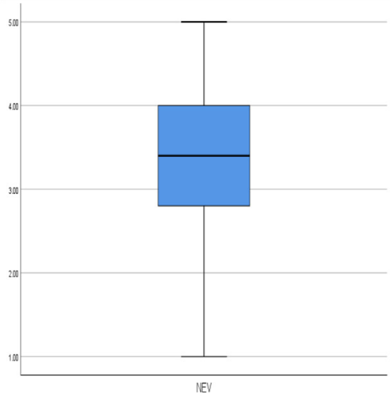
Happiness (H)	
Self Control (SC)	
Normative Evaluation (NEV)	

Table 5
Z scores value.

	N	Minimum	Maximum
Zscore(IBB)	806	−1.99035	2.54615
Zscore(P)	806	−1.18881	2.38234
Zscore(SI)	806	−1.36123	2.65947
Zscore(H)	806	−2.99291	1.79812
Zscore(SC)	806	−3.49723	2.85210
Zscore(NEV)	806	−2.71820	1.76532
Valid N (listwise)	806		

3.5. Data analysis

This dataset offers an in-depth examination of impulsive purchasing behavior online, particularly contrasting those who use BNPL/e-paylater and those who do not in Indonesia. The research methodology was crafted around the Stimulus-Organism-Response (SOR) framework, a widely utilized theory in investigating consumer behavior in online shopping environments. [10]. Research related to the Stimulus-Organism-Response (SOR) theory has extensively employed partial least squares structural equation modeling (PLS-SEM). This is due to the various advantages of PLS-SEM, such as its ability to analyze complex relationships between multiple variables and provide insights into the underlying factors contributing to observed patterns in the data. The use of this model can showcase advanced PLS-SEM applications, including higher-order models, latent class and multigroup analyses, measurement invariance assessment, necessary condition analysis, and nonlinear relationships [11].

Normality assessment was performed to check if the collected data followed a normal distribution. This was done by evaluating Skewness and Kurtosis values as described in Table 6 [12]. The results, presented in the table below, showed that almost all the data points fell within an acceptable range for both Skewness and Kurtosis values. Specifically, the Skewness values ranged between −1 and 1, while the Kurtosis values ranged between −2 and 2, indicating that the data were normally distributed. Minor deviations in kurtosis and skewness were noted in the SC1 and SC2 indicators, which will be more closely analyzed in the upcoming reliability and validity testing phase.

After confirming the normality of the data, the next step is to conduct the reflective measurement using partial least squares structural equation modeling (SEM-PLS). This approach is commonly used to analyze complex relationships between multiple variables, and can provide insights into the underlying factors that contribute to observed patterns in the data. In this study, the proposed model (Fig. 1) was evaluated in line with the reflective measurement criteria [12]. The use of such criteria allowed for a thorough assessment of the model's validity and reliability. This ensured that the model was accurately measuring the constructs under investigation and producing consistent and dependable results. By utilizing reflective measurement, the study was able to provide a robust and reliable analysis of the data.

Additionally, utilizing SEM-PLS will enable us to gain a more comprehensive understanding of the interplay between the variables and identify any potential causal relationships that may exist. In order to conduct a thorough PLS analysis, it is crucial to evaluate the measurement model (outer model) for both reliability and validity [13]. Reliability pertains to the stability and consistency of the instrument's meaning, while validity measures how accurately the instrument captures the intended concepts [14]. The results of the reliability and validity tests can be found in Tables 7 and 8.

Data validity was evaluated using two methods, namely, convergent validity and discriminant validity. Convergent validity was assessed based on the rule of thumb, where the outer loading values were expected to be greater than 0.4, and the average variance extracted (AVE) value was expected to be higher than 0.4. On the other hand, reliability was measured through the composite reliability figure, which is expected to be higher than 0.6 [12]. After conducting the

Table 6
Mean, Standard Deviation, Skewness and Kurtosis.

	Mean	Median	Min	Max	Standard Deviation	Excess Kurtosis	Skewness
IBB1	3.053	3.000	1.000	5.000	1.116	−0.917	−0.302
IBB2	2.749	3.000	1.000	5.000	1.165	−0.844	0.216
IBB3	2.804	3.000	1.000	5.000	1.098	0.911	0.063
IBB4	2.419	2.000	1.000	5.000	1.191	−0.838	0.449
P1	2.307	2.000	1.000	5.000	1.219	−0.809	0.550
P2	2.395	2.000	1.000	5.000	1.215	−1.164	0.347
P3	2.243	2.000	1.000	5.000	1.161	−0.587	0.637
P4	2.394	2.000	1.000	5.000	1.225	−0.916	0.459
SI1	2.493	2.000	1.000	5.000	1.141	−0.824	0.328
SI2	2.416	2.000	1.000	5.000	1.125	−0.674	0.429
SI3	2.342	2.000	1.000	5.000	1.082	−0.523	0.461
SI4	2.328	2.000	1.000	5.000	1.146	−0.418	0.595
SI5	2.198	2.000	1.000	5.000	1.059	−0.220	0.649
SI6	2.368	2.000	1.000	5.000	1.115	−0.579	0.487
H1	3.558	4.000	1.000	5.000	0.885	0.588	−0.761
H2	3.465	4.000	1.000	5.000	0.959	0.031	−0.515
H3	3.481	4.000	1.000	5.000	0.942	0.297	−0.746
H4	3.481	4.000	1.000	5.000	0.922	0.430	−0.689
SC1	3.774	4.000	1.000	5.000	0.804	2.269	−1.153
SC2	3.852	4.000	1.000	5.000	0.846	1.429	−0.974
SC3	2.815	3.000	1.000	5.000	0.976	−0.461	0.370
SC4	2.884	3.000	1.000	5.000	0.997	−0.581	0.339
SC5	3.136	3.000	1.000	5.000	1.125	−0.705	−0.107
NE1	3.526	4.000	1.000	5.000	1.163	−0.629	−0.405
NE2	3.516	4.000	1.000	5.000	1.075	−0.756	−0.212
NE3	3.574	4.000	1.000	5.000	1.121	−0.593	−0.428
NE4	3.379	3.000	1.000	5.000	1.105	−0.654	−0.174
NE5	3.122	3.000	1.000	5.000	1.161	−0.717	−0.007

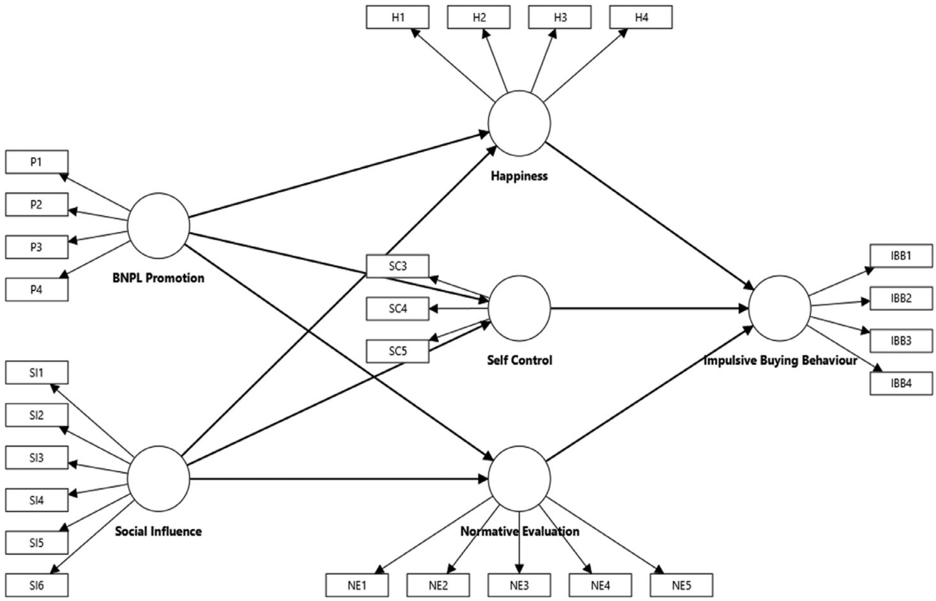


Fig. 1. The proposed model.

Table 7
Reliability and validity.

Variable	Indicators	Factor loading>0.4	Cronbach's Alpha >0.6	Composite Reliability	Average Variance Extracted (AVE) >0.4
E-Paylater Promotion	P1	0.916	0.946	0.961	0.859
	P2	0.922			
	P3	0.929			
	P4	0.941			
Social Influence	SI1	0877	0.949	0.960	0.799
	SI2	0.855			
	SI3	0.943			
	SI4	0.917			
	SI5	0.896			
	SI6	0.871			
Happiness	H1	0.883	0.921	0.942	0.802
	H2	0.930			
	H3	0.841			
	H4	0.924			
Self Control	SC3	0.654	0.778	0.866	0.687
	SC4	0.899			
	SC5	0.908			
Impulsive Buying Behaviour	IBB1	0.829	0.770	0.851	0.592
	IBB2	0.849			
	IBB3	0.595			
	IBB4	0.778			
Normative Evaluation	NE1	0.817	0.851	0.892	0.624
	NE2	0.834			
	NE3	0.807			
	NE4	0.737			
	NE5	0.748			

Table 8
HTMT and Fornell Lacker criterion-discriminant validity.

Construct	HTMT						Fornell-Lacker criterion					
	P	H	IBB	NE	SC	SI	P	H	IBB	NE	SC	SI
P							0,927					
H	0,252						0,258	0,895				
IBB	0,423	0,369					0,380	0,341	0,769			
NE	0,124	0,065	0,185				−0,119	−0,043	−0,158	0,790		
SC	0,285	0,313	0,553	0,113			−0,285	−0,271	−0,459	0,082	0,829	
SI	0,785	0,246	0,520	0,114	0,408		0,746	0,255	0,468	−0,108	−0,389	0,894

validity and reliability tests, two indicators from the self-control variable, namely SC1 and SC2, did not meet the criteria. Therefore, both indicators were removed and not included in the testing. Following the exclusion of SC1 and SC2, a retest was administered, and the data obtained was analyzed. Moreover, the discriminant validity of all constructs was further substantiated by the Heterotrait-Monotrait Ratio (HTMT) and Fornell-Larcker criterion presented in Table 6. The HTMT ratios remained under 0.85, and the square root of the Average Variance Extracted (AVE) for each construct exceeded its largest correlation with any other construct.Therefore, the researchers can proceed with additional analysis.

Based on the model in Fig. 1, Subsequently, we performed an analysis to evaluate the fit of our proposed model by investigating the Standardized Root Mean Square Residual (SRMR) score. The analysis revealed that our model achieved an SRMR score of 0.064. This finding underscores the adequacy of the model's fit, as the score is well beneath the established threshold of 0.08. Consequently, this significantly validates our model's reliability and accuracy in the context it was designed for.

4. Experimental Design, Materials and Methods

This dataset presents a comprehensive analysis of online impulsive buying behavior, specifically comparing E-Paylater users and non-users in Indonesia. The survey was designed based on the Stimulus-Organism-Response (SOR) theory of consumer behavior, which has been extensively used in research on online shopping contexts [10]. According to the SOR theory, the shopping environment provides various stimuli that affect the consumer both emotionally and cognitively, ultimately resulting in a response in the form of behavior, such as impulsive buying. By utilizing this theory, the dataset sheds light on the complex interaction of external stimuli, cognitive and emotional responses, and impulsive purchasing tendencies. The insights gained from this research can be valuable in formulating strategic marketing decisions by Buy Now Pay Later (E-Paylater) providers and other stakeholders.

In order to achieve the goals of creating the dataset, a comprehensive questionnaire was thoughtfully crafted, incorporating questions from various relevant studies. Table 9 below contains the list of questions and their references. A five-point Likert scale was used in this research to gather data effectively.

Six variables were represented by the items on the questionnaire, which were subsequently translated into Bahasa Indonesia to ensure participants' understanding. Google Forms was utilized to construct the questionnaire, while Facebook, Instagram, and WhatsApp were selected to disseminate the questionnaire link due to their significant impact on the everyday lives of Indonesians. The final analysis included a total of 806 valid responses, which were subsequently used in the data analysis.

In accordance with the explanation provided in the preceding section, data analysis was carried out using Partial Least Squares Structural Equation Modeling (PLS-SEM). To ensure the validity of the test results, researchers utilized PLS-SEM to conduct robustness checks, which consisted of:

(1) Endogeneity: The test results presented in Table 10 indicate that most of the Gaussian copulas are not significant (p-value > 0.05). Therefore, we conclude that endogeneity is mostly not present in this study, which supports the robustness of the structural model results in this regard. However, there are 2 Gaussian copulas that are significant and potentially have endogeneity problems. In spite of that, since the proposed model is predictive modeling, controlling for endogeneity is not useful in this case, as it may reduce the model's predictive power [22,23]. For further understanding of handling endogeneity problems, refer to Park and Gupta [24]. Fig. 2.

(2) Unobserved heterogeneity: The subsequent step in enhancing the robustness of our analysis, adhering to the methodology outlined by Startedt et al., focused on addressing potential unobserved heterogeneity in Partial Least Squares (PLS) path models [25]. This step entailed employing the FIMIX-PLS method on our dataset. In line with the approach recommended by Matthews et al., we began this process by presuming a solution that consisted of a single segment. This initial assumption was implemented alongside the default criteria for the stop criterion ((10^{-10}=.10E-10), the maximum number of iterations (5000), and a total of 10 repetitions [26]. To ascertain the maximum number of segments that could be extracted began with calculating the minimum sample size needed for estimating each segment, utilizing the G power calculator. The outcomes indicated a minimum sample size requirement of 105 (within a total sample of 806), thus permitting the extraction of up to eight segments. Consequently, we re-executed the FIMIX-PLS analysis for segment counts ranging from one to eight, maintaining the settings from our initial analysis. The results for the fit indices across segments one through eight are detailed in Table 11.

The findings presented in Table 11 demonstrate that both AIC4 and BIC metrics favor an eight-segment solution. These indicators are employed together due to AIC4's superior efficacy across a broad spectrum of data configurations. AIC4 showcases an impressive success rate of 58 %, making it particularly beneficial for complex model structures. Similarly, BIC also yields

Table 9
Questionnaire item and references.

Item code	Questionnaire item
	Impulsive Buying Behaviour adopted from Hashmi et al. [15]
IBB1	I do most of my online shopping spontaneously.
IBB2	I make purchases without planning, and I do not intend to shop when I open the application.
IBB3	Before opening the website or application, I have no desire to shop.
IBB4	I cannot resist shopping on the application.
	e-Paylater Promotion modified from Kassim and Hussin [16]:
P1	I am interested in shopping online using pay later because of the low/no interest.
P2	I am interested in shopping online using pay later because of shopping discounts when using pay later.
P3	I am interested in shopping online using pay later because of the significant paylater loan limit increase.
P4	I am interested in shopping online using pay later because of direct rewards such as vouchers or items.
	Social Influence adopted from Martin et al. [17,18]**:**
SI1	I am interested in using the e-Paylater credit service because I have seen through social media and mass media that many people already use this service.
SI2	People influence me to use the Paylater credit service app.
SI3	I use the Paylater credit service app because of stories/information from my friends about Paylater credit.
SI4	Important people to me whose opinions I value, including family, think I should use the Paylater credit service app.
SI5	My environment perceives me more positively because I use the Paylater credit service app
SI6	In general, my surrounding environment positively influences the Paylater credit service app I use.
	Happiness adopted from Kalla and Goyal [19]:
H1	Online shopping makes me happy.
H2	Online shopping makes me excited on boring days.
H3	I feel happy when I shop online.
H4	Online shopping makes me feel better.
	Self-Control adopted from Tangney et al. [20]:
SC1	I am good at resisting temptation.
SC2	I never let myself lose control.
SC3	I do things that feel good at the moment but regret later.
SC4	Sometimes I can't resist doing something, even though I know it's wrong.
SC5	I often act without considering all the alternatives.
	Normative Evaluation adopted from Chen and Yao [21]:
NE1	In my opinion, buying products or services impulsively through various online applications is WRONG.
NE2	I view the behavior of buying products or services impulsively through various online applications as IRRATIONAL.
NE3	In my opinion, buying products or services impulsively through various online applications is not a smart choice.
NE4	I can not understand why some people buy products or services impulsively through various online applications.
NE5	In my opinion, buying products or services impulsively through various online applications is very childish.

robust performance with a success rate of 57 %, proving especially effective in models with a larger volume of observations and more varied segment-specific path coefficients [27].

Limitations

One of the most notable limitations of this study is the observed gender bias in the sample population, as the study's participants were predominantly female. Despite the bias, however, the data are still useful to provide valuable insights into impulsive buying behaviour among the predominant demographic of digital consumers. It gives us better understanding about im-

Table 10
Assessment of endogeneity test using the Gaussian copula approach.

	Coeffient	*p* value
GC (BNPL Promotion) -> Happiness	0.131	0.434
GC (BNPL Promotion) -> Normative Evaluation	−0.346	0.094
GC (BNPL Promotion) -> Self Control	0.052	0.786
GC (Social Influence) -> Happiness	−0.668	0.011
GC (Social Influence) -> Normative Evaluation	0.159	0.610
GC (Social Influence) -> Self Control	−0.522	0.038
GC (Normative Evaluation) -> Impulsive Buying Behaviour	−0.125	0.239
GC (Self Control) -> Impulsive Buying Behaviour	−0.348	0.156
GC (Happiness) -> Impulsive Buying Behaviour	0.155	0.123

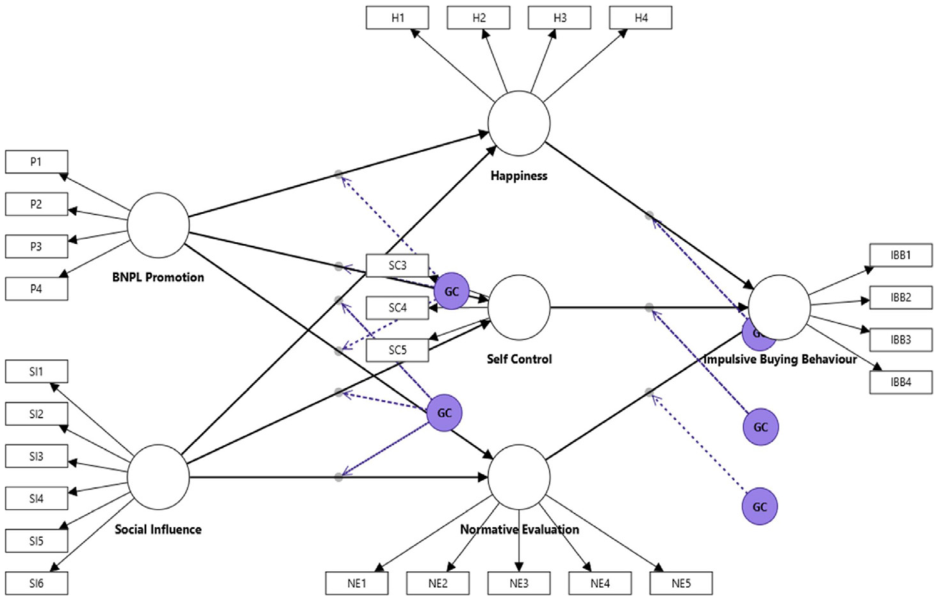


Fig. 2. Endogeneity test- Gaussian copula approach.

pulsive buying behaviour and its financial consequences. The dominant of female participants in this study did not only reflect that they are more willing to participate in the survey, but also reflect a gender disproportion in the broader demographic of digital consumers in Indonesia. Some recent studies have shown that a larger proportion of digital consumers, particularly in the context of e-commerce, are dominated by women [28,29]. While this gender bias is acknowledged and considered a limitation, it provides insights into the dynamics of the digital consumer landscape, particularly in Indonesia.

The implications of our findings should be interpreted in the context of this sample composition. It is essential to recognize that the study's generalizability may be influenced by this gender bias, and caution should be exercised when extending the results to populations with different gender compositions. Insights gained from this study can help E-Paylater providers formulate strategic marketing decisions and aid in crucial decisions. Future research with a more balanced gender representation is recommended to enhance the generalizability of findings and explore potential gender-specific variations in impulsive buying behaviour. In conclusion, the observed gender bias in this study should be taken into account when interpreting the results. it nonetheless contributes to our understanding of the impulsive buying behaviour of digital consumers in Indonesia.

Table 11
Fit indices for the one- to eight-segment solutions.

	segment 1	segment 2	segment 3	segment 4	segment 5	Segment 6	Segment 7	segment 8
AIC (Akaike's information criterion)	8.708.756	8.554.130	8.428.709	8.368.553	8.338.123	8.310.881	8.241.331	**8.077.156**
AIC3 (modified AIC with Factor 3)	8.721.756	8.581.130	8.469.709	8.423.553	8.407.123	8.393.881	8.338.331	**8.188.156**
AIC4 (modified AIC with Factor 4)	8.734.756	8.608.130	8.510.709	8.478.553	8.476.123	8.476.881	8.435.331	**8.299.156**
BIC (Bayesian information criterion)	8.769.754	8.680.816	8.621.085	8.626.618	8.661.877	8.700.324	8.696.463	**8.597.978**
CAIC (consistent AIC)	8.782.754	8.707.816	**8.662.085**	8.681.618	8.730.877	8.783.324	8.793.463	8.708.978
HQ (Hannan-Quinn criterion)	8.732.181	8.602.780	8.502.585	8.467.655	8.462.451	8.460.435	8.416.111	**8.277.162**
MDL5 (minimum description length with factor 5)	**9.117.742**	9.403.561	9.718.586	10.098.876	10.508.892	10.922.096	11.292.992	11.569.263
LnL (LogLikelihood)	−4.341.378	−4.250.065	−4.173.355	−4.129.277	−4.100.062	−4.072.441	−4.023.666	**−3.927.578**
EN (normed entropy statistic)	na	0.810	0.613	0.636	0.662	**0.564**	0.611	0.630
NFI (non-fuzzy index)	na	0.833	0.586	0.589	0.609	**0.485**	0.498	0.505
NEC (normalized entropy criterion)	na	**153.260**	311.603	293.366	272.323	351.025	313.478	298.438

Another potential limitation is the uneven distribution of respondents across different provinces in Indonesia. This uneven distribution could limit the generalizability of the study's findings to the entire population of E-Paylater users in the country. The survey may not have accurately captured the perspectives of E-Paylater users in regions with lower response rates, which could result in an unrepresentative sample. In light of this limitation, it is important to interpret the study's results with caution and to conduct further research to obtain a more representative sample of E-Paylater users across Indonesia. Doing so will help to ensure that the study's findings are more widely applicable to the broader population of E-Paylater users in the country.

Ethics Statement

The survey was carried out utilizing an online questionnaire. Before the questionnaire was disseminated, it was reviewed, discussed, and obtained approval from the supervisory board of the Doctoral Management Study Program at Universitas Andalas. This approval marked the commencement of the research survey. Initially, prior to filling out the questionnaire, participants were given explanations and information about the data collection process. Participants could proceed to independently fill out the questionnaire only if they voluntarily agreed to do so. We assured participants that their data had been fully anonymized and their personal identities (name, email address, phone number) would be kept strictly confidential. The information we collected will be used solely for academic purposes in accordance with the research ethics code at Universitas Andalas. Ethical approval was not deemed necessary, and thus, was not sought.

In addition, the study has set specific criteria for its respondents, limiting it to digital consumers who are 17 years old and hold a national identification card. It is worth noting that the youngest respondent involved in this study is 19 years old, which means that there is no need for informed consent from parents or legal guardians. This approach ensures that the study is conducted with due regard for privacy and ethical standards.

Data Availability

Dataset on Online Impulsive buying behaviour of E-paylater user and non-E-paylater user (Reference data) (Mendeley Data)

CRediT Author Statement

Verni Juita: Conceptualization, Data curation, Methodology, Formal analysis, Validation, Visualization, Writing – original draft; **Vera Pujani:** Project administration, Conceptualization, Supervision, Funding acquisition; **Rida Rahim:** Conceptualization, Supervision, Writing – review & editing; **Rita Rahayu:** Supervision, Methodology, Formal analysis, Writing – review & editing.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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