

Impulse buying behavior in mobile commerce: a partial least squares structural equation modeling analysis

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Article Info

Article history:

Received Nov 22, 2024

Revised May 13, 2025

Accepted Jun 8, 2025

Keywords:

Enticing advertisement

Impulsivity

M-commerce

Online impulse buying

Smartphone addiction

ABSTRACT

Efficient online transactions now thrive through websites (e-commerce) and mobile apps (m-commerce). With the growth of m-commerce, marketers aim to boost profits by understanding impulsive buying behavior. This study investigates factors influencing online impulse buying (OIB) in m-commerce by analyzing key variables. Data were gathered via questionnaires from 449 Indonesian consumers who had made digital payments and impulsive purchases using smartphones. The framework includes sales promotion (SP), attractive advertising (EA), and mobile digital payment systems (MDPS) as situational factors; hedonic shopping motivation (HSM) as a motivational factor; and impulsiveness (I) and smartphone addiction (SA) as personal traits. Analysis used partial least squares structural equation modeling (PLS-SEM), with gender, income, and smartphone usage time as control variables. Results show that EA, MDPS, HSM, I, and SA significantly influence OIB, while SP does not. For consumer segmentation, t-distributed stochastic neighbor embedding (t-SNE) outperformed ISomap and principal component analysis (PCA), achieving a silhouette score of 0.72. A paired t-test ($p < 0.01$) confirmed t-SNE's superior clustering accuracy. These findings reveal that t-SNE better captures consumer segmentation patterns, helping businesses refine marketing strategies and deepen their understanding of psychological drivers behind impulsive m-commerce purchases.

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1. INTRODUCTION

Mobile commerce (m-commerce) is the latest trend that simplifies online transactions with just a touch of a finger [1]. It refers to applications or service platforms that businesses provide for various commercial activities using mobile devices [2]. Through m-commerce applications, consumers can search for products, compare brands, and make instant purchases via smartphones [3]. These platforms enhance convenience by offering competitive pricing, seamless digital payment systems, and engaging advertising strategies to encourage impulsive buying. Consumers with high impulsivity tend to be more motivated by immediate rewards rather than long-term consequences [4]. In Indonesia, m-commerce adoption has surged. In 2020, 76% of internet users made purchases via smartphones, compared to only 37% using desktops or laptops. This trend accelerated in 2020, when 80% of internet users engaged in smartphone-based transactions due to the COVID-19 pandemic [5]. This not only indicates that e-commerce users are shifting towards m-commerce but also demonstrates that the emergence of the pandemic has changed the way people shop from traditional to digital [6]. On the other hand, the majority of the Indonesian population often

engages in impulsive buying [7]. Consumers make immediate decisions because they either do not plan to purchase in advance or lack a predefined plan for their purchases [8]. Consequently, consumers tend to follow their feelings when they want to buy desired items or are simply attracted to particular products [9].

Numerous studies have examined impulsive buying behavior in digital environments. Mei *et al.* highlighted how psychological and emotional factors drive impulse purchases [4]. Widagdo and Roz identified website design and user experience as key drivers in e-commerce impulsive buying [10]. Meanwhile, Lee and Chen found that personalized advertising significantly increases impulse buying [11]. Digital payment systems also play a critical role. Yang *et al.* discovered that mobile payment services enhance impulsive purchases through convenience and incentives [12]. Additionally, Nyrhinen *et al.* established a link between smartphone addiction (SA) and excessive online shopping, suggesting that prolonged engagement with smartphones fosters impulsive tendencies [13]. While past research has extensively covered impulsive buying in e-commerce, studies on m-commerce remain limited. Specifically, little attention has been given to mobile-specific factors, such as SA and digital payment systems, that shape impulsive online buying behavior. Furthermore, existing research has largely relied on traditional statistical models, overlooking the potential of clustering techniques like t-distributed stochastic neighbor embedding (t-SNE) for segmenting consumer behavior.

This research addresses these gaps by employing partial least squares structural equation modeling (PLS-SEM) to analyze key factors influencing online impulse buying (OIB) in m-commerce, focusing on sales promotion (SP), advertising appeal, mobile digital payment systems (MDPS), hedonic shopping motivation (HSM), impulsive behavior, and SA. Additionally, t-SNE is applied to cluster consumer behavior, providing a more effective segmentation approach. The research is structured as follows: section 2 discusses the empirical findings, demonstrating the influence of the key. Section 3 presents the research methodology, detailing the PLS-SEM model and clustering techniques. Section 4 explores the theoretical and practical implications, offering insights for businesses. Finally, section 5 concludes with key takeaways and recommendations for future research.

2. LITERATURE REVIEW

This section reviews previous studies related to OIB, SA, and related behavioral theories. It highlights research gaps, theoretical foundations, and key variables that guide this research. The literature is organized into several themes to provide a comprehensive understanding of the topic.

2.1. Disparities and innovation

Impulsive behavior is often associated with risk-taking behavior and various addictive behaviors such as substance abuse, a tendency toward alcohol misuse [14], addictive behaviors like gambling [15], food addiction [16], smoking addiction [17], depression [18], mental and behavioral disorders, including antisocial personality disorder [19], and suicide [20]. However, there is very little previous research that discusses impulsive behavior in relation to self-control, particularly in the context of smartphone use, known as SA. From the results of previous research obtained using Google Scholar, the topic of SA has been extensively studied. However, when searching for SA related to OIB, there is very little research available in the last three years. Considering the significance of impulsive buying and the factors influencing online impulsive purchasing for literature knowledge, strategies, and business considerations, particularly in the field of marketing, this research will contribute to addressing the literature gap.

2.2. Mobile commerce

M-commerce is a sub-category of e-commerce and represents the smartphone version of e-commerce. M-commerce refers to all activities, both direct and indirect, involving financial transactions and internet networks using mobile devices [21], [22]. With the increasing use of smartphones in people's daily lives, m-commerce harnesses the potential of wireless technology, such as mobile phones, smartphones, or personal digital assistants (PDAs), and networks to access information, conduct transactions, and expand the reach of e-commerce users anytime and anywhere. M-commerce applications can be used to support transactions between sellers and consumers [23]. Currently, m-commerce has encompassed nearly all aspects of life and has contributed to the growth of existing processes, such as digital purchasing and delivery, digital money transfers, payments through applications, and mobile banking [24]. Thanks to increasingly advanced technology, m-commerce has made consumers more flexible in their shopping activities, creating more opportunities for impulsive purchases [25].

2.3. Online impulsive buying

Several previous studies define impulsive buying as involving sudden decision-making actions, where buyers tend to feel compelled to acquire a product as quickly as possible [26]. The impulse to make a

purchase can occur once or multiple times for the same consumer. Typically, these purchases are based on strong emotional decisions, dominating as the foundation for unplanned buying motives where the buyer did not have a prior intention to purchase [27]. In their day-to-day decision-making, individuals with these characteristics tend to prefer consuming a particular product immediately rather than planning to consume it over time to maximize long-term satisfaction [28].

2.4. Relationship between variables

Relationship between variables refers to the relationship, connection, or dependency between two or more characteristics or quantities used in this research. These variables are assessed to determine how one may influence or predict the behavior of another. Understanding these relationships helps to explain the factors that significantly affect OIB behavior in mobile commerce.

SPs have been shown to significantly influence OIB. Consumers tend to react positively when promotional offers align with their expectations, particularly when they are price-sensitive or encounter innovative discounts [29], [30]. Several studies confirm that such promotions evoke positive emotions and stimulate spontaneous purchases [31], [32]. In the Indonesian context, factors like discount strategies and easy payment options are primary triggers for impulsive behavior [33]. Research also indicates that these strategies boost price sensitivity and short-term sales [34]. Based on this, it is proposed in hypothesis H1 that SP positively affects OIB.

Advertising remains a critical tool for shaping consumer behavior and enhancing brand awareness [35]. It informs consumers about product benefits, availability, and value, thereby influencing both attitude and purchasing decisions. Studies suggest that exposure to appealing advertisements motivates consumers to make impulsive purchases, especially when the ads highlight perceived benefits [36]. This trend is particularly evident in Indonesia, where internet-facilitated advertisements on e-commerce platforms contribute to impulsive buying behavior [37]. Therefore, hypothesis H2 proposes that enticing advertisement (EA) positively influences OIB.

The evolution of digital payment systems has made mobile-based transactions more practical and secure, leading to widespread adoption [12]. Mobile digital payments offer users benefits such as convenience, security, efficiency, and ease of access via smartphones [38]. Additionally, promotional rewards like cashback or discounts linked to digital payments further enhance the likelihood of impulse purchases [39]. As people now prefer seamless transactions, this convenience fosters changes in consumption patterns that can result in impulsive or excessive spending. Hence, hypothesis H3 states that MDPS positively influences OIB.

HSM, driven by emotional and sensory pleasure, also plays a vital role in influencing impulsive purchases. Online shopping via smartphones provides an enjoyable experience, drawing in consumers who seek pleasure and gratification through shopping [40]. Studies have established a significant relationship between hedonic motivation and impulsive buying, especially when the purchases involve non-essential or luxury items [41]. As emotional enjoyment becomes a goal, individuals with high hedonic tendencies are more prone to impulsive shopping behaviors [42]. This leads to hypothesis H4, which suggests that HSM has a positive influence on OIB.

Impulsive behavior itself, characterized by low self-control and spontaneous decision-making, directly affects how consumers shop online. Online shopping provides consumers with a wide array of choices and instant gratification, which caters to impulsive tendencies [43]. Individuals with higher impulsivity are more likely to act on momentary desires without deliberate planning [42], [44]. Such impulsive tendencies, especially when fueled by emotional states, increase the likelihood of online impulsive purchases. Accordingly, hypothesis H5 proposes that impulsive behavior positively influences OIB.

SA has also been recognized as a contributing factor to impulsive buying behavior. With smartphones integrated into daily life for both social and utilitarian purposes, users become increasingly reliant on them [45]. Although smartphones facilitate ease in many tasks, excessive usage may lead to addiction, especially among youth [46]. This dependence, coupled with constant exposure to social media and targeted marketing, diminishes self-control and encourages unplanned purchases [13], [47]. Hence, hypothesis H6 suggests that SA positively influences OIB.

3. METHOD

To ensure that the research findings are replicable and methodologically sound, data collection followed a purposive sampling technique, targeting Indonesian consumers who have previously engaged in impulsive online purchases via smartphones and used digital payment systems such as e-wallets or mobile banking. A structured online questionnaire was distributed, yielding 500 responses, of which 449 valid responses were retained after data cleaning. The sample composition included 67.9% female and 32.1% male

respondents, with 88.2% aged between 17-25 years, reflecting a relevant demographic for understanding consumer behavior in m-commerce impulsive buying.

The theoretical foundation of this research is based on latent state-trait (LST) theory, which postulates that human behavior is influenced by both situational (state) and individual (trait) factors. In this context, external stimuli, such as advertising and ease of digital payment, interact with internal predispositions, such as impulsivity and SA, ultimately leading to impulsive buying decisions [48], including in e-commerce and s-commerce [49]. Previous research has demonstrated that situational factors can amplify impulsive tendencies in digital shopping environments, yet limited research has explored these dynamics specifically within m-commerce. To empirically examine these relationships, PLS-SEM was chosen as the primary analytical tool due to its capability to handle complex relationships, accommodate non-normal data distributions, and simultaneously evaluate measurement and structural models. The PLS-SEM analysis process follows these steps: outer model evaluation, inner model evaluation, and multicollinearity checks. In addition to PLS-SEM, t-SNE was implemented as a novel clustering approach to segment impulsive consumers based on behavioral tendencies rather than conventional demographic variables. Unlike principal component analysis (PCA) and ISomap, t-SNE better preserves local structures, making it a more effective tool for analyzing consumer behavioral patterns. The clustering accuracy was validated by comparing silhouette scores, where t-SNE achieved 0.72, outperforming ISomap (0.58) and PCA (0.49). A paired t-test ($p < 0.01$) further confirmed the statistical significance of t-SNE's superiority in behavioral segmentation.

To ensure methodological rigor, this research conducted multiple validation procedures, including Fornell-Larcker and Heterotrait-Monotrait ratio of correlations (HTMT) criteria for discriminant validity, as well as confirmatory factor analysis (CFA) for construct reliability testing. Ethical considerations were upheld by ensuring participant anonymity and voluntary participation. The dataset and full methodological details are available upon request to allow for replicability and further research development. Figure 1 presents the research framework, illustrating the influence of state, trait, motivation, and SA on OIB, with gender, income, and usage time as control variables.

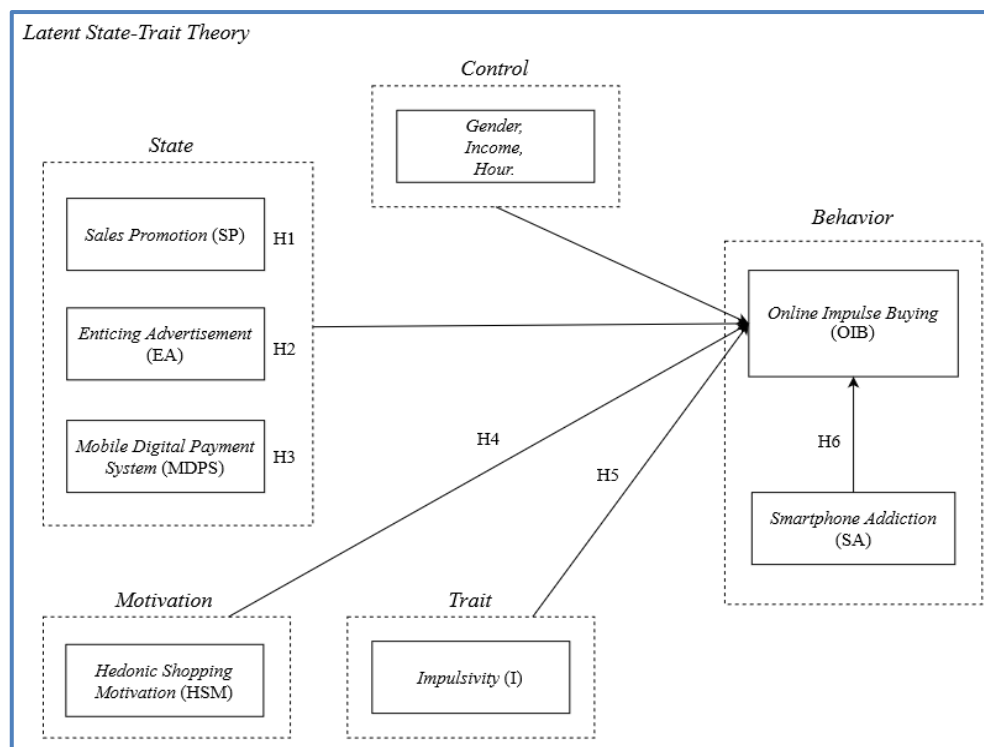


Figure 1. Research framework

Based on the research framework above, several independent variables, namely SP, EA, and MDPS, are considered as environmental or situational characteristics (states). Additionally, HSM is considered a motivation, impulsivity behavior is regarded as an individual trait, and SA is seen as a behavior that positively

influences OIB, considered a behavioral characteristic. These variables are the dependent variables. This study includes gender, income, and smartphone usage time (hours) as control variables.

In this research, most of the measurement items were adapted from previous research and then modified to better suit the research topic. The Likert scale in this research employs two categories, which are a 7-point Likert scale with agreement and frequency levels. The 7-point Likert scale for agreement levels ranges from 1-strongly disagree to 7-strongly agree and is used for the research on the relationship between six independent variables and OIB: SP, EA, SA, MDPS, and HSM. Furthermore, the 7-point Likert scale for frequency levels ranges from 1-never to 7-always and is used for the research questions of the impulsive behavior variable, measured with the 15-item Barratt impulsiveness scale (BIS-15) with brief questions proposed by Spinella [50].

The questionnaire underwent a pilot test with a small subset of respondents to assess clarity, reliability, and validity before full deployment. The final instrument was refined to ensure that all items were clear, relevant, and aligned with the theoretical framework. To mitigate potential response bias, the survey incorporated randomized item ordering and reverse-coded questions for select items. The research instrument was digitally administered, making it accessible to a wide range of respondents across different geographical regions within Indonesia. Data collection and management procedures adhered to ethical guidelines, ensuring confidentiality, informed consent, and voluntary participation.

4. RESULTS AND DISCUSSION

This research highlights the significance of advertising appeal, MDPS, HSM, impulsive behavior, and SA in influencing OIB within m-commerce. While previous research focused primarily on website design and user experience in e-commerce [10], our findings emphasize the growing role of smartphone dependency and seamless mobile payment methods in shaping consumer behavior. Notably, our results contradict the assumption that SP significantly influences impulsive buying. While previous research suggests that discounts and promotions trigger spontaneous purchases [11], our research indicates that in m-commerce, convenience and ease of access play a more dominant role than price-based incentives. This finding aligns with previous research [12], which demonstrated that cashless payment systems significantly enhance impulsive purchases through their frictionless nature. Similarly, a previous study [13] highlighted how SA correlates with excessive online shopping, which supports our findings that SA has a significant positive impact on OIB ($p < 0.05$).

Additionally, the integration of t-SNE for clustering consumer behavior offers a novel approach for understanding buyer segmentation. Compared to ISomap and PCA, t-SNE demonstrated superior clustering accuracy, suggesting that future research can expand on this technique to develop more precise consumer profiling strategies in digital marketing. The silhouette score of t-SNE (0.72) was significantly higher than that of ISomap (0.58) and PCA (0.49), reinforcing its ability to preserve local structures in high-dimensional consumer behavior data. The paired t-test ($p < 0.01$) further confirmed the statistical significance of t-SNE's superiority. The implications of these findings are significant for both academia and industry. Marketers should focus on enhancing ad personalization rather than relying solely on discount-based promotions. M-commerce platforms can leverage behavioral segmentation using machine learning techniques to predict impulsive buying patterns more effectively.

Data collection was conducted from October 19, 2022, to November 27, 2022, using a non-probability purposive sampling method. The criteria for respondents needed in this research were individuals residing in Indonesia who have made online digital payments through m-commerce and have engaged in OIB through smartphones (m-commerce). Out of the 500 respondents who participated in this research, 51 respondents were deemed invalid and removed. The following are the demographic statistics of the 449 respondents who participated in this research, with the highlighted orange representing the majority of respondents choosing that option over other response choices.

Based on the data collected from 449 respondents, Table 1 shows that the highest percentage of respondents by gender, which is 305 (67.9%), are females. Consequently, this research provides valuable insights regarding gender disparities in impulsive buying. Additionally, the majority of participating respondents were aged 17 to 25 years, totaling 396 respondents (88.2%). Furthermore, the highest percentage by profession, as shown in Table 1 (see APPENDIX), is students or pupils, with 360 respondents (80.2%). Subsequently, based on four income categories, 329 respondents (73.3%) had an income level of less than IDR 5,000,000 per month.

Once the data was collected, the next step was to analyze the data using the PLS-SEM method with SPSS and SmartPLS version 4. There were several steps in the data analysis process, including analyzing the measurement model (outer model) by measuring validity and reliability using CFA and assessing discriminant validity using Fornell-Larcker and HTMT methods. After that, the analysis proceeded to the

structural model (inner model) to ensure there was no multicollinearity, observe significant relationships between variables, and evaluate the goodness-of-fit of the PLS-SEM model.

Table 2 shows that there are five hypotheses supported in this study, ranging from hypothesis two to hypothesis six. However, the one highlighted in red, which is the first hypothesis (H1), and the other three control variables, namely gender, income, and hours of smartphone usage, linked to OIB, did not yield significant results because the values obtained did not reach 1.96 in t-value or 0.05 in p-value. The following is an image of the path coefficient output from SmartPLS 4. The path coefficient values range from -1 to 1. A path coefficient value within the range of 0 to 1 indicates a positive relationship, while a value in the range of -1 to 0 indicates a negative relationship.

Table 2. PLS-SEM path analysis table

Hypothesis	Path	Path coefficient	t-value	p-value	Path coefficient 95% confidence interval		f-square	VIF inner model
					Lower limit	Upper limit		
Main								
H1	SP→OIB	0.087	1.466	0.143	-0.036	0.200	0.008	2.670
H2	EA→OIB	0.166*	3.258	0.001	0.067	0.266	0.031	2.644
H3	MDPS→OIB	0.109*	2.385	0.017	0.016	0.196	0.024	1.489
H4	HSM→OIB	0.133*	2.651	0.008	0.036	0.234	0.020	2.566
H5	I→OIB	0.371*	7.043	0.000	0.269	0.474	0.162	2.517
H6	SA→OIB	0.110*	2.085	0.037	0.004	0.211	0.013	2.780
Control								
	Gender→OIB	0.007	0.116	0.908	-0.109	0.129	0.000	1.045
	Income→OIB	-0.013	0.435	0.663	-0.076	0.045	0.001	1.049
	Hour→OIB	0.007	0.257	0.797	-0.047	0.061	0.000	1.039

Based on Figure 2, the path coefficient value of the income variable falls within the range of -1 to 0, indicating a negative relationship with online impulsive purchases OIB. Meanwhile, the other variables fall within the range of 0 to 1, signifying a positive relationship with online impulsive purchases OIB. Additionally, further analysis was conducted using the SPSS application on three control variables for OIB. These three control variables include gender (gender), income (income), and usage time (hours).

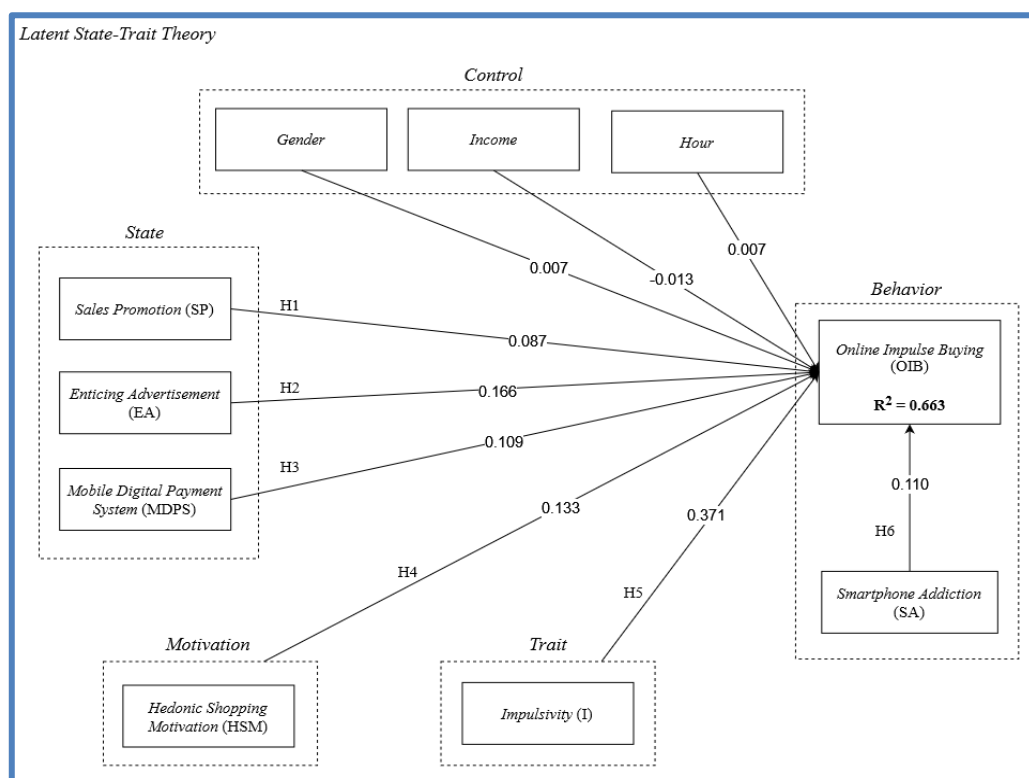


Figure 2. The resulting path coefficient output

The following table presents the statistical results for each of these control variables. Table 3 presents the t-test results for gender, showing a significant difference in OIB between male and female respondents ($p=0.029$). Males have a slightly higher mean score ($M=5.459$) than females ($M=5.299$), indicating gender plays a role in impulsive buying behavior. Table 4 summarizes the results for income groups using one-way ANOVA. The analysis reveals a significant difference among income levels ($p=0.003$), suggesting that income influences the tendency toward online impulsive purchases, with the highest mean found in the IDR 5,000,000 to IDR 10,000,000 income group. Table 5 examines smartphone usage time. The ANOVA results show significant differences across usage groups ($p=0.002$), with the highest OIB mean found in the 1 to 3-hour usage group ($M=5.571$). This suggests that shorter smartphone usage duration is associated with higher impulsive buying tendencies.

Table 3. Control variables gender

Gender	N	Mean	Std. deviation	Levene's test F	Sig.	t-value	Sig.
Man	144	5.459	0.890	6.343	0.012	2.199	0.029
Woman	305	5.299	1.043				

Table 4. Income control variables

Income	N	Mean	Std. deviation	Levene's test Levene stat.	Sig.	F-value	Sig.
<IDR 5,000,000	329	5.217	0.055	0.973	0.405	4.737	0.003
IDR 5,000,000-IDR 10,000,000	88	5.649	0.099				
IDR 10,000,000-IDR 15,000,000	20	5.327	0.239				
>IDR 15,000,000	12	5.592	0.254				

Table 5. Control variables for smartphone usage time

Usage time (hours)	N	Mean	Std. deviation	Levene's test Levene stat.	Sig.	F-value	Sig.
1-3 hours	28	5.571	0.948	0.358	0.783	5.067	0.002
4-5 hours	86	5.180	1.010				
6-8 hours	145	5.119	0.993				
>8 hours	190	5.3160	1.001				

Based on the results of the independent t-test and Levene's test conducted using the SPSS application for the control variable of gender, it can be concluded that a higher level of impulsive buying occurs among males, with a mean of 5.459. Based on the results of the ANOVA test and Levene's test conducted using the SPSS application for the control variable of income, it can be concluded that the level of impulsive buying occurs in the second category, which ranges from IDR 5,000,000 to IDR 10,000,000, compared to other income categories. For the control variable of smartphone usage time, it can be concluded that the level of impulsive buying occurs in the first category, which is 1 to 3-hours, with a mean of 5.571. However, it should be noted that the population in the first category is still relatively small ($n=28$). These results need to be interpreted with caution.

4.1. Theoretical implications

This research contributes to the development of consumer behavior theory in OIB using the LST theory to identify the relationships between SP, advertisement attractiveness, MDPS, HSM, impulsive behavior, and SA towards OIB. The research findings indicate that consumer addiction to smartphones can lead to increased dependency on electronic devices and a tendency to make impulsive purchases. These insights provide valuable guidance for marketers and policymakers in designing strategies to manage and influence consumer impulsive buying behavior in the evolving digital marketplace.

4.2. Practical implications

In practical implications, this research is valuable for all marketers, especially sellers in mobile commerce, vendors, and m-commerce shopping applications (e.g., Shopee, Amazon, Tokopedia, Taobao, and Lazada). Marketers can focus on creating content that provides beneficial or useful information about specific products, unique and engaging content to capture consumers' attention, thereby motivating them to make impulsive purchases, particularly consumers with high impulsive behavior. Based on the findings of this study, advertisement attractiveness EA is the most critical and influential factor.

Additionally, marketers can start planning and devising new marketing strategies using other impulsive factors to persuade consumers to make impulsive purchases, especially SPs. This is because, as

indicated by the data analysis results presented in this research, consumers may have doubts about the SPs offered, both online and offline. This research is also beneficial for consumers to avoid making impulsive online purchases by providing information, knowledge, and insights into SA, impulsive behavior, and other impulsive buying factors through m-commerce. Moreover, consumers can protect themselves from companies' strategies that exploit impulsive consumers to make decisions and impulsive purchases for maximum profit.

5. CONCLUSION

This study provides empirical evidence that advertising appeal, MDPS, HSM, impulsive behavior, and SA significantly influence OIB, while SP does not. These findings highlight that ease of digital transactions and behavioral engagement are stronger predictors of impulsive purchases in m-commerce than traditional promotional methods. The use of t-SNE for consumer clustering also presents a novel methodological contribution, demonstrating its effectiveness in capturing complex consumer behavior patterns compared to ISomap and PCA. From a practical standpoint, marketers are advised to focus on personalized and emotionally engaging advertising strategies, supported by seamless mobile payment systems, to effectively trigger impulse purchases. The study also extends consumer behavior theory by applying the LST framework to explain the interaction between situational, motivational, and personal traits. However, the study is limited by its focus on Indonesian consumers, which may restrict the generalizability of findings across different cultural settings. Future research should examine cross-cultural differences, integrate AI-driven recommendation systems, and explore the influence of social media engagement to further understand impulsive buying behavior in digital commerce.

FUNDING INFORMATION

We extend our heartfelt gratitude to Universitas Pelita Harapan (UPH) and the Institute of Research and Community Services (LPPM) UPH for their support towards this research, with research number P-022-M/SISTech/IX/2023, as well as to all parties involved in the writing of this research.

AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : **O**riting - **O**riginal Draft

E : **E**riting - **R**eview & **E**editing

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author.

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APPENDIX

Table 1. Demographic statistics table





No.	Question	N=449	
		#	%
1.	Gender		
	Man	144	32.1
	Woman	305	67.9
2.	Age		
	17-25 years old	396	88.2
	26-35 years old	25	5.6
	36-45 years old	17	3.8
	46-55 years old	10	2.2
	>55 years	1	0.2
3.	Profession		
	Student/students	360	80.2
	Employee	56	12.5
	Self-employed	26	5.8
	Other	7	1.6
4.	Income per month		
	<IDR 5,000,000	329	73.3
	IDR 5,000,000-IDR 10,000,000	88	19.6
	IDR 10,000,000-IDR 15,000,000	20	4.5
	>IDR 15,000,000	12	2.7

Table 1. Demographic statistics table (*Continued*)





No.	Question	N=49	
		#	%
5.	Number of hours of use of your smartphone per day:		
	1-3 hours	28	6.2
	4-5 hours	86	19.2
	6-8 hours	145	32.3
	>8 hours	190	42.3
6.	How long have you been using smartphone shopping apps for online purchases?		
	<1 year	48	10.7
	1-2 years	104	23.2
	3- 4 years	130	29
	>4 years	167	37.2
7.	How many purchase transactions have you made on online shopping applications in 1 month?		
	1-2 times	174	38.8
	3-5 times	160	35.6
	6-10 times	72	16
	>10 times	43	9.6
8.	What is the total amount of your purchases in all online shopping applications for 1 month?		
	<IDR 1,000,000	295	65.7
	IDR 1,000,000-IDR 5,000,000	128	28.5
	IDR 5,000,000-IDR 10,000,000	22	4.9
	>IDR 10,000,000	4	0.9
9.	What types of product categories do you buy most often?		
	Stationery & office supplies (e.g., pens, paper, scissors, and printers)	7	1.6
	Babies and children (e.g., baby diapers, and baby equipment)	1	0.2
	Digital (for example, game vouchers, e-books, electricity tokens, and credit)	30	6.7
	Fashion (e.g., clothing, shoes, accessories, and purses)	137	30.5
	Gadgets & electronics (e.g., cameras, laptops, and charging cables)	36	8
	Pets (e.g., pet toys, and pet food)	8	1.8
	Beauty & cosmetics (e.g., perfume, and lipstick)	96	21.4
	Health (e.g., masks, hand sanitizer, vitamins, and medicine)	6	1.3
	Toys and hobbies (e.g., merchandise, dolls, and action figures)	33	7.3
	Food and drinks (e.g., snacks, and cooking oil)	89	19.8
	Household/interior (e.g., houseplants, and lamps)	6	1.3
10.	What factors made you choose to buy products online?		
	Can read positive customer comments	21	4.7
	Can compare prices or product quality	61	13.6
	Can choose from a variety of available products	16	3.6
	Detailed product description	5	1.1
	Cheaper product prices	94	20.9
	Get gifts, coupons, promotional items (e.g., buy 1 get 1 free)	28	6.2
	Easy payment method	12	2.7
	Free shipping or cheaper shipping prices	180	40.1
	There is a shopping cart feature	3	0.7
	No hassle returns and refund policy	9	2
	Not limited by time and shopping area (including abroad)	20	4.5
11.	I use my smartphone most for:		
	Entertainment and lifestyle (e.g., watching movies, playing games, and listening to music)	224	49.9
	Social connections (e.g., communicating with others, and building relationships)	149	33.2
	Productivity and work (e.g., studying, working, and shopping)	76	16.9
12.	Types of applications you use most often on your smartphone:		
	Shopping (for example, Shopee, Tokopedia, and Lazada)	124	27.6
	Browser (e.g., Chrome, and Firefox)	18	4
	Social media (for example, WA, Line, Facebook, IG, and Tiktok)	261	58.1
	Education support (e.g., Zoom, Teams, and Gmeets)	3	0.7
	Banking or payments (e.g., Gopay, OVO, and Dana)	16	3.6
	Games (e.g., Genshin Impact, Mobile Legends, and PUBG)	20	4.5
	Transportation (e.g., Grab, and Gojek)	7	1.6
13.	One day when I was on my way to work but realized that I left my smartphone at home, what I would do was		
	Returning home to get the smartphone and being late for work.	123	27.4
	Go to work on time and ask someone to bring your smartphone to your workplace.	251	55.9
	Go to work, leave your smartphone at home and pick it up later after work.	75	16.7
14.	The reason you use digital payments when making transactions on online purchasing applications (for example, ShopeePay, GoPayLater, OVO, BCA KlikPay, and LinkAja)		
	Cheaper transaction/shipping fees	44	9.8
	Payment security	5	1.1
	Faster, easier and more convenient to use	332	73.9
	Get cashback or points	53	11.8
	There is a digital record of transactions	15	3.3

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