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Disclosure Within Shopping Apps-Mobile Based: Usage Determination Factors

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ABSTRACT

Although Indonesia is recorded as the third-largest country in terms of mobile shopping application installations globally, the level of mobile shopping activity remains low. This study employs a quantitative research design to analyze the roles of personalization, direct marketing, and hedonic value in shaping behavioral intentions and their impact on the usage behavior of mobile shopping applications. Data were collected through a survey using a purposive sampling technique, involving 282 Gen Z respondents in Indonesia. The questionnaire underwent measurement model testing through Outer Loading, Construct Reliability and Validity, and Discriminant Validity to ensure reliable results, followed by hypothesis testing using SEM-PLS data analysis techniques. The analysis reveals that direct marketing, personalization, and hedonic value have a significant direct influence on behavioral intentions, explaining 93.2% of the variance. Additionally, behavioral intention is found to directly affect usage behavior, although this model accounts for only 37.4% of the variance. Most importantly, behavioral intention mediates the influence of direct marketing, personalization, and hedonic value on usage behavior. These findings suggest that personalization, direct marketing, and hedonic value are crucial factors in fostering behavioral intentions among Gen Z in Indonesia, thereby enhancing the usage of mobile shopping applications.

Keywords: Behavioral Intention, Direct Marketing, Personalization, Usage Behavior, Value.

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INTRODUCTION

Indonesia represents one of the largest and fastest-growing markets for mobile technology, particularly in the adoption of mobile shopping applications. As the third-largest global market for Android e-commerce apps, Indonesia accounted for 8% of total worldwide e-commerce app installations in 2021 (CNN, 2021). Despite this considerable level of adoption, there exists a notable discrepancy between the high volume of app downloads and their actual usage for transactional purposes. For example, while Indonesians spent over 5.56 billion hours using shopping apps in 2021, only 3% of internet users utilized these applications for conducting buying and selling transactions (Rizaty, 2021). This discrepancy highlights a critical issue: behavioral intention does not consistently lead to actual usage behavior..

Behavioral intention, defined as the motivational factor that drives individuals to engage with a particular technology (Chen et al., 2019), is crucial in explaining the gap between app installations and actual usage. Although mobile shopping applications are widely downloaded, the limited active engagement in transactional activities indicates a shortfall in users' behavioral intention to utilize these apps for shopping. Consequently, identifying the factors that influence behavioral intention is essential to bridging this usage gap.

Several studies have been conducted, the majority of which have developed adoption models grounded in the Technology Acceptance Model (TAM). These studies have extended TAM by incorporating additional variables to better explain technology adoption. Research (Agrebi & Jallais, 2015; Chong, 2013; Kah-Boon Lim et al., 2021; Lavuri et al., 2023; Madan & Yadav, 2018) has demonstrated that perceived enjoyment, usefulness, ease of use, trust, and social influence are significantly related to the intention to use mobile shopping applications.

Research by Chopdar and Sivakumar (2019) found that behavioral intention to use mobile shopping applications is associated with performance expectations, effort expectations, facilitating conditions, hedonic motivation, habits, and impulsivity (Chopdar & Sivakumar, 2019). Furthermore, behavioral intention, along with habits and impulsivity, were shown to significantly influence the actual usage of mobile shopping apps. Specifically, studies by (Kim et al., 2015; Lavuri et al., 2023; Madan & Yadav, 2018) identified value, comprising both hedonic and utilitarian value, as the most critical and significant predictor of consumers' behavioral intention to adopt mobile shopping applications. Chang et al. (2023) further argued that utilitarian flow elements directly influence purchasing decisions, whereas hedonic elements may drive internet usage but do not necessarily result in online purchases (Chang et al., 2023).

On the other hand, direct marketing involves targeting users with personalized promotions, discounts, and advertisements (Ningsih et al., 2023). This approach serves as a powerful tool that can shape users' perceptions of value and urgency (Tripathi et al., 2023), potentially driving both behavioral intention and actual usage behavior. However, limited research has been conducted in Indonesia to investigate how direct marketing strategies, particularly the use of personalization in mobile shopping applications, influence users' intention to shop and, ultimately, their actual usage behavior.

Given this background, the central issue addressed in this study is the discrepancy between the high download rates of mobile shopping applications and their relatively low transactional usage. While mobile shopping (m-shopping) has emerged as one of the most popular methods for shopping in tandem with the growth of mobile IT technology (Cheng et al., 2020), there remains a scarcity of studies that examine the role of shopping value within the context of m-shopping applications. Several studies have provided evidence of the influence of shopping value on consumer behaviors, including satisfaction, purchase intention, and loyalty. Therefore, this study explores mobile shopping value, databases, and direct marketing in the context of m-shopping usage, with a focus on both behavioral intention and actual usage behavior, to determine critical theoretical and practical implications. The findings from this research will offer valuable insights to enhance the effectiveness of mobile shopping apps in engaging users and increasing transaction volumes.

LITERATURE REVIEW

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is a framework that investigates the determinants of consumer behavioral intention to use technology, including mobile applications Unified Theory of Acceptance and Use of Technology (UTAUT) is a theory of information technology acceptance (IT acceptance) developed by Venkatesh et al (2003). The purpose of this theory is to provide criteria or variables that affect IT acceptance by users. UTAUT is confirmed to have higher relevance than TAM in measuring intentions in technology acceptance (Venkatesh Thong and Xu, 2016). UTAUT explains 70% prediction of behavioral intention, higher than the previous theory which only predicts 40% of behavioral intention (Bawack and Kala Kamdjoug, 2018). UTAUT is also appropriate as a technology measurement tool in marketing (Lok et. al., 2015). Consists of *performance expectancy, effort expectancy, social influence and facilitating conditions, behavioral intention* and *use behavior*. In various modified studies, Venkatesh et. al. in William, Rana and Dwivedi (2015, p. 461) explain the partial direct relationship of UTAUT from the four predictor factors, namely *performance expectancy*, *effort expectancy, social influence* and *facilitating conditions* to *behavioral intention*.

Email marketing can have an impact on behavioral intentions in technology, such as mobile apps. Behavioral intention refers to an individual's readiness to engage in a particular behavior, in this case using a mobile app. Several studies have examined the impact of email marketing on behavioral intentions and purchase decisions, which may provide insight into its influence on mobile app usage. A study of Lazada Indonesia customers found a strong influence between email marketing permission and purchase intention and purchase decision. This suggests that email marketing, when done with the recipient's permission, can positively impact a user's intention to engage with a product or service. Trust is an important factor in the relationship between email marketing and purchase intention. A study of Althea Korea consumers in Indonesia and Malaysia found that trust significantly influenced email marketing permission and purchase intention. This suggests that email marketing can help build trust, which in turn influences users' intention to engage with a product or service, such as a mobile app.

Personalization involves providing customized content and services based on customer data (Shen, 2014) and adapting offerings to meet customer needs (Sunikka & Bragge, 2012). Personalization aims to offer the most suitable product at the optimal time and in the best place to delight the customer (Sunikka & Bragge, 2012). This provides benefits to both retailers and customers as individualized products, services and interactions appeal to consumers (Bock et al., 2016). Personalization also offers transaction flexibility, more targeted banner and website ads, and product recommendations (Chandra et al., 2022). Chu et al (2022) proposed that personalization and customization are essential for selling products in *m-commerce* applications (Chu et al., 2022). (Park, 2014) stated that personalization directly affects the intention to use social networking sites (SNS) continuously . This was also stated by (Wang et al., 2017), where the direct relationship between personalization and continuous use intention was found to be significant.

Personalization is able to offer the desired information in the right form to the intended user (Cheng et al., 2020). Research (Bleier & Eisenbeiss, 2015), found personalized messages to be more relevant and informative than non-personalized communications. Later, (Barbosa et al., 2023) found *content personalization* influences user behavior and encourages real action *online*. Research (Cheng et al., 2020) also found personalization directly affects continual use intentions for mobile news apps. In healthcare, personalization can also have a positive effect on individual judgment and behavioral intentions (Liu et al., 2022). In addition, the quality and benefits of personalization have been shown to increase purchase intentions (Ampadu et al., 2022).

Shopping value refers to the evaluation of relative value based on qualitative and quantitative as well as subjective and objective shopping experiences (Cai & Xu, 2011; Carpenter, 2008; S.-H. Chen & Lee, 2008). Utilitarian value occurs through the conscious pursuit of desired outcomes, and hedonic value is associated with ecstatic reactions (Hu et al., 2023). Therefore, in the context of m-shopping, shopping value can be divided into utilitarian value and hedonic value. The former relates to the efficient and timely purchase of products through m- shopping, while the latter is about emotional benefits such as enjoyment experienced through shopping in addition to product purchases (Akdim et al., 2022; Vayghan et al., 2022). Utilitarian value means a purchase that is intentional and related to the purchase task and derives from rational purchasing (Kim et al., 2012; Lee et al., 2009). Utilitarian value may arise as a result of information gathered from different consumer needs (Jones et al., 2006; Teller et al., 2008).

Specifically (Kim et al., 2015; Lavuri et al., 2023; Madan & Yadav, 2018) found value consisting of hedonic and utilitarian value to be the most important and significant predictor of consumers' behavioral intention to adopt it. In addition, consumers are more likely to experience utilitarian value when shopping if they buy what they want and find what they are looking for (Carpenter & Moore, 2009; Nysveen et al., 2005). Utilitarian value is positively related to customer loyalty, and empirical research shows the importance of utilitarian value to customer loyalty in mobile phone services (Yen, 2012). Some studies (Yang, 2010; Yen, 2012)) suggest that the utilitarian aspect of mobile internet services is a key determinant of consumer attitudes towards service use because consumers use their mobile phones to obtain information. (Kleijnen et al., 2007) investigated the relationship between mobile channels and m-shopping usage intentions, and for this channel value, they focused on the perceived utilitarian value of m-shopping and examined how consumers derive utilitarian value from mobile services.

As discussed earlier, for consumers, shopping means not only the rational purchase of products but also shopping behavior where the experience itself is enjoyed as well as the associated recreational benefits. During such hedonic shopping, consumers emphasize their leisure time (Cai & Xu, 2011; Kim et al., 2012; Lee et al., 2009). In fact, shopping behavior provides hedonic value to consumers in a variety of ways regardless of the actual purchase of products (Ottar Olsen & Skallerud, 2011). A growing number of researchers consider hedonic value and argue that hedonic value is as important as another dimension of shopping, namely utilitarian value (Ashraf et al., 2019; Hu et al., 2023; Jones et al., 2006; Kim et al., 2015). The hedonic aspect of a technology can be an important determinant in predicting technology acceptance by consumers, and therefore the role of fun-oriented hedonic factors can be important in predicting consumer adoption of m- shopping services.

Based on the theoretical framework and previous empirical studies, the research hypothesis developed in this research is:

H1 : Direct Marketing (DM) has an effect on Behavioral Intention (BI)
H2 : Hedonic Value (HV) affects Behavioral Intention (BI).
H3 : Personalization (PL) affects Behavioral Intention (BI).
H4 : Utilitarian Value (UV) affects Behavioral Intention (BI).
H5 : Behavioral Intention (BI) affects Usage Behavior (UB)
H6 : Behavioral Intention (BI) mediates the effect of Direct Marketing (DM) on Usage Behavior (UB).
H7 : Behavioral Intention (BI) mediates the effect of Hedonic Value on Usage Behavior (UB).
H8 : Behavioral Intention (BI) mediates the effect of Personalization (PL) on Usage Behavior (UB).
H9 : Behavioral Intention (BI) mediates the effect of Utilitarian Value (UV) on Usage Behavior (UB).

The following Figure 1 presents the research framework of this study:

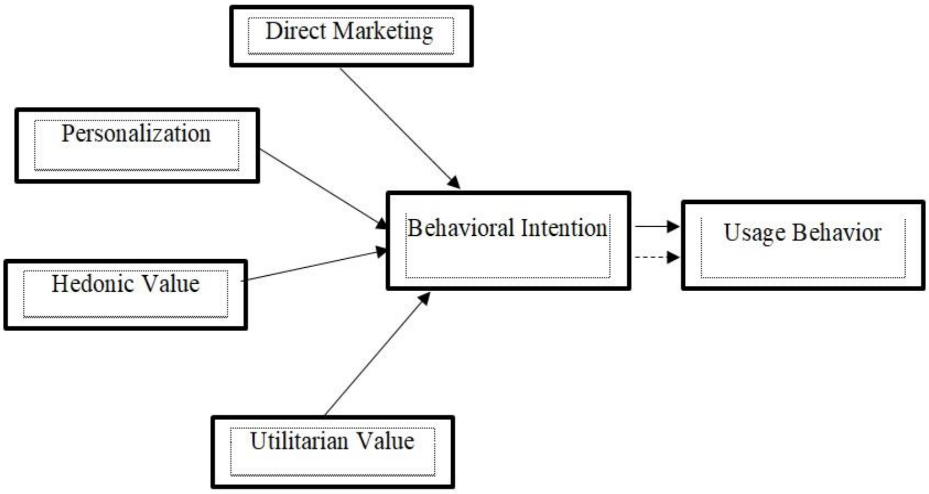

Figure 1 Conceptual Framework
Source: (Agrebi & Jallais, 2015; Akdim et al., 2022; Cheng et al., 2020; Chopdar & Sivakumar, 2019; Chu et al., 2022) (data processed, 2023)

METHODS

This study is an explanatory survey research with a quantitative approach. Data were collected through the distribution of questionnaires to the general public, with the target population being Gen Z in Indonesia. Generation Z in this study is based on the 2020 census data from the Central Statistics Agency (BPS) in Indonesia, referring to the age group born between 1997 and 2012, with a total population of approximately 74.93 million people.

The sampling technique used was purposive sampling, with the sample criteria including ownership of a smartphone, installation of a marketplace app on the smartphone, age between 11-27 years, and prior experience using mobile shopping applications. In determining the sample size, this study referred to empirical standards from previous research using Structural Equation Modeling (SEM). According to Hair et al. (2014), for SEM analysis, the recommended minimum sample size is 5 to 10 times the number of indicators in the model. Considering the number of latent variables and indicators used in this study, a minimum sample size of 250 respondents was established.

Out of the 337 respondents who completed the questionnaire, screening questions were used at the beginning of the survey to ensure that the respondents owned a mobile shopping app, had used it, and fit the targeted age category. After adjusting for the required sample criteria, 282 valid respondents were obtained for analysis in this study. Data were analyzed using Structural Equation Modeling (SEM) - Partial Least Square (PLS) with the SmartPLS 3.2 application. Measurement was conducted in two stages: model measurement and structural measurement. In the model measurement stage, the questionnaire had to meet and pass the Outer Loading, Construct Reliability and Validity, and Discriminant Validity tests to ensure reliable results.

Table 1 Questionnaire Measurements

Factors	Measurement	Reference Source
Personalization	1. Mobile shopping Apps know what I need 2. Mobile shopping Apps provide information/services tailored to	(Ampadu et al., 2022; Cheng et al., 2020; Chu et al., 2022)

	my needs 3. Mobile shopping Apps give me personalized information. 4. In general, most of the products recommended on the Mobile shopping app match my preferences 5. I can order products that suit my needs through mobile shopping.	
Direct Marketing	1. Direct Mail/E-mail Marketing 2. Online Channels (Text message from app) 3. Digital marketing (Social Media)	(Ningsih et al., 2023; Tripathi et al., 2023)
Utilitarian Value	1. I can browse through a wide range of products in a short period of time. 2. I can browse through a wide range of products in a short period of time. 3. Mobile shopping gives me important and valuable information	(Akdim et al., 2022; Ottar Olsen & Skallerud, 2011; Vayghan et al., 2022)
Hedonic Value	1. I use mobile shopping more for fun than for buyingproducts. 2. I feel happy and enjoy during mobile shopping 3. I can experience an exciting shopping atmospherethrough mobile shopping	(Akdim et al., 2022; Ottar Olsen & Skallerud, 2011; Vayghan et al., 2022)
Behavioral Intention	1. I intend to continue using this mobile shopping appin the future. 2. I have a strong desire to continue using this mobileshopping app. 3. I plan to make more purchases using this mobileshopping app. 4. I predict that I will use this mobile shopping appfrequently in the next few months. 5. I will always try to use mobile shopping apps in mydaily life 6. I will continue to use mobile shopping apps as oftenas I do now 7. I have already planned certain purchases that I wantto make through this mobile shopping app. 8. I have made a plan on how to optimize the use ofthe features in the mobile shopping app.	(Agrebi & Jallais, 2015; Ashraf et al., 2019; Chopdar & Sivakumar, 2019)
Usage Behavior	1. I often buy products through mobile shopping. 2. I always use mobile shopping. 3. I use mobile shopping all the time. 4. I use mobile shopping regularly	(Chopdar et al., 2022; Kim et al., 2015; Madan & Yadav, 2018)

RESULTS AND DISCUSSION

This study examined a total of 282 respondents whose answers were suitable for further analysis. Table 1 below presents a summary of the respondents' demographics including gender, age, education, occupation, domicile, monthly pocket money, shopping frequency, average payment when mobile shopping, number of marketplace applications, market place applications used:

Table 2. Respondent Profile

Item	Respondent	
	n	Persentase (%)
Gender		
Female	171	60.64
Male	111	39.36
	282	100
Age (Generation Z)		
20-24 Years	199	70.57
25-27 Years	54	19.15
16-19 Years	28	9.93
11-15 Years	1	0.35
	282	100
Education		
Undergraduate Student	164	58.16
Bachelor's Degree	77	27.3
High school students	19	6.74
Master's student	10	3.55
Master's Degree	6	2.13
Vocational Program Graduates	4	1.42
PhD Student	1	0.35
Vocational Program Students	1	0.35
	282	100
Jobs		
Not Working	143	50.71
Private Employee	53	18.79
Freelance	45	15.96
Entrepreneur	25	8.87
Permanent non-ASN/Civil Servants in Government Agencies	9	3.19
SOE Employee	4	1.42
ASN/Civil Servants	3	1.06
	282	100
Domicile (Province)		
West Java	198	70.21
West Sumatra	24	8.51
Central Java	13	4.61
DKI Jakarta	10	3.55
North Sumatra	7	2.48
West Kalimantan	6	2.13
Banten	5	1.77
IN Aceh	3	1.06
Lampung	3	1.06

East Java	2	0.71
Riau	2	0.71
South Sumatra	2	0.71
DI Yogyakarta	1	0.35
Central Kalimantan	1	0.35
North Kalimantan	1	0.35
Riau Islands	1	0.35
NTB	1	0.35
North Sulawesi	1	0.35
Central Sulawesi	1	0.35
	282	100
Monthly Allowance		
IDR 550,000-850,000	60	21.28
IDR 850,000 -1,000,000	54	19.15
Less than IDR 500,000	52	18.44
IDR 1,050,000-1,500,000	43	15.25
IDR 1,550,000-2,000,000	32	11.35
IDR 2,000,000-2,500,000	17	6.03
more than IDR 3,000,000	16	5.67
IDR 2,550,000-3,000,000	8	2.84
	282	100
Shopping Frequency		
Less than once per month	73	25.89
Less than 3 times per month	108	38.3
Less than 5 times per month	70	24.82
Less than 10 times per month	27	9.57
More than 21 times per month	4	1.42
	282	100
Average Payment during Mobile Shopping		
IDR 50,000-100,000	103	36.52
IDR 100,000-150,000	67	23.76
IDR 150,000-200,000	48	17.02
More than IDR 200,000	33	11.7
Less than IDR 50,000	31	10.99
	282	100
Number of Marketplace Applications used		
One App	164	58.36
Two Apps	100	35.59
Three Apps	15	5.34
Four applications	3	0.71
	282	100
Marketplace applications used		
Shopee	155	54.96
Shopee, Tokopedia	46	16.31
Shopee, Lazada	32	11.35
Shopee, Tiktok Shop	11	3.9
Shopee, Zalora	9	3.19
Shopee, Lazada, Tokopedia	7	2.48
Tokopedia	6	2.13

Shopee, Lazada, Tiktok shop	3	1.06
Shopee, Tokopedia, Zalora	3	1.06
Lazada	2	0.71
Shopee, Blibli, Tokopedia	2	0.71
Shopee, Blibli	1	0.35
Shopee, Blibli, Tokopedia, TikTok Shop	1	0.35
Shopee, Lazada, Tokopedia, Bukalapak	1	0.35
Shopee, Lazada, Tokopedia, Zalora	1	0.35
Shopee, MarketPlace Facebook	1	0.35
Tiktok Shop	1	0.35
	282	100

Source: Questionnaire Results, 2023

The results showed that the respondents were female (60.64%) while male (39.36%). Most of the respondents are from West Java (70.21%), aged 20-24 years old (70.57%), the majority of education is currently pursuing a bachelor's degree (58.16%) and not working (50.71%), has a monthly allowance of Rp 550,000 - Rp 850,000 (21.28%). They admitted that most of them shop less than three times per month (38.30%), with an average payment of Rp50,000-Rp100,000 (36.52%). The Gen Zs who filled out the questionnaire mostly only installed one mobile shopping app (58.36%), and the most installed app was Shopee (54.96%).

Measurement Models

In the research method, all indicators of the variables used in this study have been explained, but based on the Measurement Model test, there are several adjustments because some indicators do not meet the measurement model provisions consisting of Outer Loading, Construct Reliability and Validity, Discriminant Validity.The retest results are obtained as shown in the figure and table below.

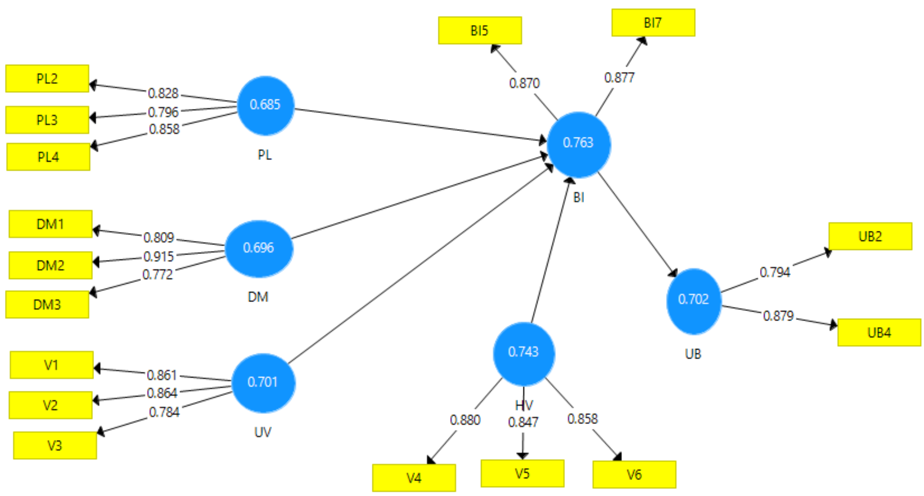

Figure 2 ***Measurement Model Ouput Outer Loading and AVE***
Source: Ouput PLS Algorithm SmartPLS 3.2

Table 3 Convergent Validity and Reliability of Measurement Models

Outer Model	**Indicators**	**Convergent Validity**		**Reliability**	
		Outer Loading	**AVE**	**Cronbach's Alpha**	**Composite Reliability**
		> 0.70	> 0.50	> 0.70	> 0.70
BI	I have a strong desire to	0.870	0.763	0.86	0.866

	continue using this mobile shopping application (BI5)				
	I have planned certain purchases that I want to makethrough this mobile shopping application (BI7)	0.877			
DM	E-mail Marketing (DM1)	0.809	0.696	0.78	0.872
	Online Channel (Text messagefrom app) (DM2)	0.915			
	Digital marketing (Social Media) (DM3)	0.772			
PL	Mobile shopping Apps give me personalized information (PL3)	0.828	0.685	0.773	0.867
	Mobile shopping Apps memberi saya informasi yang dipersonalisasi (PL3)	0.796			
	In general, most of the products recommended in the Mobile shopping app match my preferences (PL4)	0.858			
UB	I always use mobile shopping(UB2)	0.794	0.702	0.808	0.824
	I use mobile shopping regularly (UB4)	0.879			
UV	I can browse a wide range of products in a short time (V1)	0.861	0.701	0.788	0.875
	I can browse a wide range of products in a short time (V2)	0.864			
	Mobile shopping gives me important and valuable information (V3)	0.784			
HV	I use mobile shopping more for fun than for buying products (V4)	0.880	0.743	0.829	0.897
	I feel happy and enjoy duringmobile shopping (V5)	0.847			
	I can feel the exciting shopping atmosphere through mobile shopping (V6)	0.858			

Source: Ouput PLS Algorithm SmartPLS 3.2

Referring to table 3, objective information is obtained, all indicators are significant in measuring their latent variables, and have factor weight coefficients above the minimum required value of 0.70. Judging from the AVE statistic, the test results show that the six measurement models provide an AVE value greater than 0.50. This means that all indicators used to measure the latent variables under study have sufficient convergent validity. In addition, from Cronbach's Alpha and Composite Reliability, the statistical test results show that the value of Cronbach's Alpha and Composite Reliability for the six measurement models provides a value above the minimum required value of 0.70. This indicates that the six measurement models have adequate internal reliability.

The next step to test Discriminant Validity is to use the Cross Loading test. The Cross Loading test itself is a test of the Outer Loading value that a variable construct has to have a greater value for its own variable than for other variables.

Tabel 4 Cross Loadings

	BI	DM	HV	PL	UB	UV
BI5	**0.870**	0.561	0.580	0.819	0.541	0.758
BI7	**0.877**	0.734	0.723	0.858	0.528	0.601
DM1	0.524	**0.809**	0.624	0.641	0.773	0.732
DM2	0.738	**0.915**	0.862	0.746	0.651	0.745
DM3	0.569	**0.772**	0.820	0.548	0.462	0.598
PL2	0.863	0.568	0.587	**0.828**	0.554	0.768
PL3	0.620	0.641	0.529	**0.796**	0.734	0.649
PL4	0.861	0.730	0.719	**0.858**	0.518	0.597
UB2	0.446	0.479	0.501	0.454	**0.794**	0.634
UB4	0.569	0.745	0.605	0.708	**0.879**	0.749
V1	0.613	0.660	0.705	0.627	0.697	**0.861**
V2	0.754	0.639	0.636	0.719	0.588	**0.864**
V3	0.557	0.810	0.671	0.690	0.844	**0.784**
V4	0.759	0.913	**0.880**	0.766	0.668	0.765
V5	0.591	0.770	**0.847**	0.574	0.494	0.622
V6	0.545	0.685	**0.858**	0.552	0.530	0.648

Source: Ouput PLS Algorithm SmartPLS 3.2

Table 4 provides information that seen from the results of cross loading analysis, all indicators used to measure the six measurement models provide a weight factor coefficient value greater than the cross loading value. This indicates that the six measurement models have sufficient discriminant validity.

Furthermore, the validity of the research was followed by Discriminant Validity testing through the Fornell-Larker Criterion test.

Tabel 5 Discriminant Validity

	BI	DM	HV	PL	UB	UV
BI	**0.874**					
DM	0.743	**0.834**				
HV	0.747	0.830	**0.862**			
PL	0.860	0.779	0.746	**0.828**		
UB	0.612	0.746	0.664	0.708	**0.838**	
UV	0.776	0.828	0.795	0.811	0.830	**0.837**

Source: Ouput PLS Algorithm SmartPLS 3.2

Based on table 5 above, it shows that from the Fornell-laker Criterion criteria, the six measurement models have an AVE square root value that is greater than the correlation coefficient between the measured constructs and other constructs. This means that the six measurement models are indicated to have sufficient discriminant validity.

Hypothesis Testing

The proposed hypotheses were tested for data analysis and to verify the relationships in the proposed model. The results of direct effect hypothesis testing can be seen in the following figure:

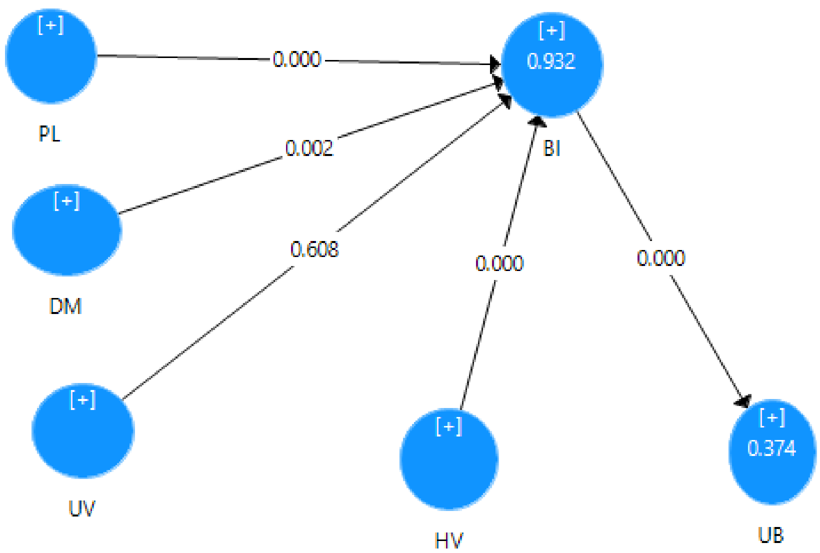

Figure 3 Direct Effect P-Value and R-Square Results
Source: Ouput Boostraping SmartPLS 3.2

The regression value shows the magnitude of the coefficient of direct influence between variables as shown in Table 5 below

Table 6 Direct Effect (Path Coefficient, p Value, R2 , and Q2)

Model	Koefisien Jalur	Nilai *p*	Hasil Uji	R^2	Q^2
Model BI					
H1 : DM in effect to BI **DM -> BI**	0.236	0.002	H0 is rejected H_1 accepted	0.932	0.695
H_2: HV in effect to BI **HV -> BI**	0.263	0.000	H0 is rejected H_2 accepted		
H_3: PL effect to BI **PL -> BI**	0.963	0.000	H0 is rejected H_3 accepted		
H_4: UV effect to BI **UV -> BI**	-0.018	0.608	H0 accepted H_4 rejected		
Model UB					
H_5: BI effect to UB **BI -> UB**	0.612	0.000	H0 is rejected H_5 accepted	0.374	0.254

Source: Ouput Boostraping SmartPLS 3.2

Source Referring to table 5, the following information is obtained

a. For the BI model, the test results show that the path coefficient of UV to BI is not significant. ($\gamma 1 = -0.018$, $p = 0.608 > 0.05$) H0 is accepted. This means that UV has no direct effect on BI. For the path coefficient of DM to BI ($\gamma 1 = 0.236$), HV to BI ($\gamma 1 = 0.263$), PL to BI ($\gamma 1 = 0.963$), all three have a significant effect on BI (H0 is rejected). This means that the null hypothesis that the *direct effect* coefficient is equal to zero is rejected. Thus, it can be concluded that DM, HV, and PL have a direct effect on UB. The coefficient of determination for the BI model is 0.932 (strong). This means that 93.2% of the variation that occurs in BI can be explained by this model. The remaining 6.8% is explained by other variables not explained by the model. The Q statistic^2 for the BI model is 0.695. This means that the model has sufficient predictive validity or relevance in predicting variations in the BI latent variable.

b. For the UB model, the results show the path coefficient of BI to UB ($\gamma 1$ = 0.612, p = 0.000 < 0.05) (H0 rejected), is highly significant. This means that the null hypothesis that the *direct effect* coefficient is equal to zero is rejected. Thus it can be concluded, BI directly affects UB. The coefficient of determination for the UB model is 0.374 (weak). This means that 37.4% of the variation that occurs in UB can be explained by this model. The remaining 62.6% is explained by other variables not explained by the model. The Q statistic^2 for the UB model is 0.254. This means that the model has sufficient predictive validity or relevance in predicting variations in the UB latent variable.

The primary objective of this study is to validate the key determinants influencing the intention to use mobile shopping applications and assess their implications for actual usage behavior among Gen Z in Indonesia. This study applied the UTAUT2 model, integrated with additional explanatory variables, including utilitarian value, hedonic value, personalization, and direct marketing as determinants of mobile shopping app usage. The results presented in Table 5 indicate that in the behavioral intention model, direct marketing, personalization, and hedonic value are the primary determinants that positively influence behavioral intention towards mobile shopping apps (H1, H2, H3 – accepted). Similarly, the usage behavior model is directly influenced by behavioral intention (H5 accepted).

Furthermore, the study demonstrates that direct marketing and personalization significantly influence Gen Z's behavioral intention to use mobile shopping applications. This finding is particularly relevant in the Indonesian context, where the majority of the population, especially Gen Z, is highly engaged with mobile devices and digital platforms, yet there remains a gap between app downloads and actual transactional use. Direct marketing can deliver personalized messages to potential users, increasing their interest and intention to use the app. In Indonesia, the widespread use of social media and mobile platforms presents a unique opportunity for businesses to capitalize on direct marketing strategies tailored to the preferences and behaviors of Gen Z, who are highly responsive to digital content that feels relevant and personalized.

Personalized messages, which are tailored to users' preferences, needs, and interests, have the potential to make mobile shopping apps more attractive to Indonesian Gen Z consumers. In a culturally diverse country like Indonesia, where purchasing behaviors and preferences can vary widely across regions and social groups, personalization becomes even more crucial. By addressing the cultural nuances and preferences of Indonesian users, personalized messages can drive higher engagement and adoption rates for mobile shopping apps. This is consistent with findings from previous research, which shows that consumers in Indonesia, as in other markets, perceive personalized messages as more relevant and informative than generic communications (Chu et al., 2022). However, the Indonesian market presents unique challenges and opportunities in terms of personalization, given the country's large population, diversity, and evolving digital economy.

Moreover, the study highlights the role of intrusiveness in direct marketing within the Indonesian context. Specifically, intrusiveness refers to how an advertisement disrupts a consumer's ongoing cognitive processes (Truong & Simmons, 2010). While personalized ads can capture Indonesian consumers' attention more effectively, there is a fine line between engaging and overwhelming them with overly intrusive messages. In Indonesia, where mobile advertising is prevalent, especially on social media platforms like Instagram and TikTok, advertisers need to strike a balance between personalization and intrusiveness. Ads that are perceived as too intrusive may lead to negative consumer reactions, particularly among Gen Z, who are known for being highly selective and sensitive to overly aggressive marketing tactics.

This reasoning aligns with existing literature on consumer responses to persuasive advertising, which suggests that ads stimulating increased cognitive processing can lead to more thorough consumer engagement (Dessart & Pitardi, 2019). For Indonesian Gen Z, who are constantly bombarded with digital content, personalized ads that are thoughtfully crafted can stand out and positively influence their intention to use mobile shopping apps. This underscores the importance of developing culturally relevant, non-intrusive marketing strategies that resonate with the unique social and economic dynamics of Indonesia.

Next, the hedonic value aspect of mobile shopping apps was found to be a significant predictor of Gen Z's behavioral intention to adopt these apps. Previous research (Hu et al., 2023) explains that hedonic value is closely related to enjoyment, and enjoyment plays an important role in consumers' perceived value of mobile shopping, which is consistent with the results of this study. However, to understand why and how hedonic value influences behavioral intention, we need to examine the psychological role of enjoyment in the user experience.

The enjoyment derived from mobile shopping activities provides a strong intrinsic motivation for users. This intrinsic motivation leads users to feel satisfied and encouraged to continue using mobile shopping apps. When users experience enjoyment while browsing products or making purchases through the app, they are more likely to develop an emotional attachment to the platform (Meena & Sarabhai, 2023). This increases the likelihood of repeat usage, as positive experiences tend to reinforce recurring behavior. Intrinsic motivation theory suggests that behaviors driven by enjoyment are more sustainable than those driven by external incentives alone (Lu et al., 2017). Therefore, the more enjoyable the experience of using the app, the higher the likelihood of adopting the technology.

Additionally, hedonic value is often associated with activities such as browsing and exploration. In the context of mobile shopping, users who enjoy exploring product offerings, discovering new items, and finding the shopping experience enjoyable are more likely to continue using the app (Akdim et al., 2022). This process involves both cognitive and emotional aspects, where the enjoyment felt during app usage not only fosters deeper engagement but also indirectly increases the likelihood of making a purchase. Users who feel comfortable and entertained by their interactions with a shopping app tend to view the experience as entertainment, and enjoyable experiences can drive the intention to continue using the app.

Previous research supports these findings, demonstrating a positive and direct relationship between hedonic value and behavioral intention to adopt new technology (Akdim et al., 2022; Hubert et al., 2017). Hedonic value creates a deeper affective experience, transforming mobile shopping apps from merely functional tools into a pleasurable experience for consumers (J. H. Chen & Fu, 2018). Thus, when consumers feel a sense of enjoyment while shopping through mobile devices, it has a strong motivational influence on their behavior (Čvirik et al., 2023; Yang, 2010). This enjoyment strengthens user engagement and encourages them to adopt the app as part of their regular shopping routine.

Moreover, in the context of Gen Z in Indonesia, hedonic value becomes even more relevant given that this generation is highly accustomed to digital technology and seeks interactive and enjoyable experiences. A satisfying user experience can encourage them to use mobile shopping apps more frequently as part of their digital lifestyle. This factor is crucial in attracting and retaining Gen Z users, who have high expectations for engaging and rewarding user experiences that include elements of exploration and discovery.

The above presentation explains the results of testing the *path coefficient* (*direct effect and path coefficient*) for the six models tested. The following is reported on the *specific indirect effect* test results.

Table 7. *Specific Indirect Effect*

Model	*Specific Indirect Effect*	*P Values*	95%CIBC*)		Test Results
			2.5%	97.5%	
H_6= BI memediasi pengaruh DM terhadap UB **DM -> BI -> UB**	0.145	0.001	0.061	0.242	H_0 rejected H_6 accepted
H_7= BI memediasi pengaruh HV terhadap UB **HV -> BI -> UB**	0.161	0.000	0.078	0.237	H_0 rejected H_7 accepted
H_8= BI memediasi pengaruh PL terhadap UB **PL -> BI -> UB**	0.589	0.000	0.469	0.681	H_0 rejected H_8 accepted
H_9= BI memediasi pengaruh UV terhadap UB **UV -> BI -> UB**	-0.011	0.617	-0.056	0.035	H_0 accepted H_9 rejected

Source: Ouput Boostraping SmartPLS 3.2

Based on the information obtained from table 6, the 95% CIBC estimation results for the three specific indirect effect coefficients all give zero. This means that the null hypothesis stating that the three specific indirect effect coefficients are equal to zero is rejected. Thus, hypotheses 6 to 8 can be accepted. In other words, the effect of DM, HV, and PL on UB is indirect, which is mediated through BI. The statistical results also show that UV still does not affect UB even though it is mediated by BI.

Research hypotheses 6 to 8 can be accepted. In other words, the influence of DM, HV, and PL on UB occurs indirectly, which is mediated by BI. Referring to the research findings, judging from the magnitude of the specific indirect effect coefficient estimate, the BI variable tends to have a relatively stronger role in mediating the effect of PL on BI. Then followed by the HV variable, and finally the DM variable.

Meanwhile, table 7 presents the results of testing the mediation effect on the research model. The results show that behavioral intention mediates the effect of direct marketing on usage behavior, so H_6 is accepted. Next, behavioral intention mediates the effect of hedonic value on usage behavior, so H_7 is accepted. Finally, behavioral intention mediates the effect of personalization on usage behavior, so H_8 is accepted. H_6 and H_8 also prove that through behavioral intention, direct marketing and personalization can also affect the usage behavior of Gen Z in Indonesia on mobile shopping applications.

Goodness of Fit Test

Furthermore, it is necessary to test the fit model, which is a global test or test of the suitability of the measurement model and structural model as a whole. The following is a summary of the model fit test results.

Table 8. Model Fit Testing

Model	SRMR	95% CI	d_ULS	95% CI	d_G	95% CI
Saturated Model	0.068	0.077	0.786	0.802	0.801	0.902
Estimed Model	0.071	0.086	0.890	1.012	0.932	1.322

Source: Ouput Boostraping SmartPLS 3.2

Based on information from table 8, the results of testing the fit model, the statistical values of SRMR, d_ULS, d_G for the estimated model are 0.071, 0.890, and 0.932, respectively. When compared with the 95% CI estimation value, the estimated statistical results of SRMR, d_UL, d_G are 0.086, 1.012, 1.322, respectively. This means that the three statistics SRMS, d_ULS, and d_G have smaller values than the 95% CI estimate. Thus it can be concluded that the results of the *behavioral intention* and *usage behavior* model parameter estimates fit the data. The results of this model estimation can be generalized to the population.

The findings from this study provide concrete insights that can be utilized by e-commerce companies and app developers to increase the adoption of mobile shopping apps among Gen Z consumers in Indonesia. First, companies must prioritize creating a highly enjoyable and immersive user experience that leverages the hedonic value identified in this study. This means investing in user interface (UI) and user experience (UX) design that promotes exploration, discovery, and ease of navigation, which are key drivers of user satisfaction and engagement.

To effectively engage Gen Z, gamification elements could be introduced within the app to make the shopping process more interactive and fun. For example, incorporating features such as reward-based systems, product discovery challenges, or personalized shopping recommendations can enhance the enjoyment users experience while browsing, making them more likely to return and use the app frequently.

Additionally, personalized content based on user behavior and preferences can strengthen the emotional attachment of users to the app. This might include personalized product suggestions, targeted promotions, and customized notifications that align with the user's shopping habits. Ensuring that these personalized messages are not overly intrusive is crucial to maintaining a positive user experience. By balancing personalization with non-intrusive notifications, companies can foster engagement without overwhelming users.

Another key takeaway from this study is the importance of leveraging social media integration to further enhance the hedonic value of mobile shopping apps. Given that Gen Z in Indonesia is highly active on social platforms, integrating features such as social sharing, influencer collaborations, or live shopping events within the app can create a sense of community and entertainment, motivating users to spend more time on the platform.

Lastly, app developers should consider conducting regular user experience testing to continuously refine the app and ensure that it meets the evolving needs and preferences of Gen Z. Offering in-app feedback systems where users can provide real-time suggestions and reviews will help developers maintain a high level of user satisfaction and address potential issues before they negatively impact the user experience.

CONCLUSION

Behavioral Intention is very important to improve the usage behavior of Gen Z Indonesia on mobile shopping apps, therefore it is necessary to study the factors that increase behavioral intention on these mobile shopping apps. In the behavioral intention model, the first, second and third hypotheses of this study prove that direct marketing, hedonic value and personalized marketing have an effect on behavioral intention. Only the fourth hypothesis is rejected, utilitarian value has no effect on behavioral intention. Then in the usage behavior model, the fifth hypothesis proves that increased behavioral intention affects the usage behavior of Gen Z Indonesia on mobile shopping apps. While testing the mediation effect proves that behavioral intention mediates the effect of direct marketing, hedonic value, and personalization on usage behavior, this proves hypotheses six, seven and eight. In contrast, behavioral intention does not mediate the effect of utilitarian value on usage behavior, and this rejects hypothesis nine.

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The results of this study imply marketplace strategies in targeted marketing, creating a pleasant shopping experience, and personalization efforts can help increase Gen Z's behavioral intention towards mobile shopping apps. It also indicates practical benefits, such as time saving and cost effectiveness are not the main factors that drive Gen Z's interest in using mobile shopping apps. Thus, increasing Gen Z's behavioral intention on mobile shopping apps using targeted marketing, pleasant shopping experiences, and personalized marketing efforts will encourage Gen Z to use these apps more frequently and engage in more online shopping activities. Therefore, marketplaces should apply direct marketing and personalization to their users, whether they are actively using or not actively using, in order to form usage behavior.

This research has limitations. From a theoretical point of view, it is very difficult to find research and direct marketing theories that affect behavioral intention. While in terms of sample size, this study has a small number of respondents to generalize to the total Gen Z in Indonesia. Respondents who filled in were spread across 19 provinces, but were still centered in West Java which filled in the most. In addition, some indicators were discarded because they did not meet the validity and reliability criteria, so further research should add indicators from other sources. Future research is recommended to include more respondents with a broader demographic profile to increase the generalizability of the research findings. Future research, in order to develop this research, because there is still very little empirical literature related to personalization and direct marketing in the context of behavioral intention. Researchers can use different sample groups to test their influence. This will be useful for marketers to develop marketing strategies based on direct and database marketing.

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