



Bridging the Intention–Behavior Gap in Digital Marketing Usage: Evidence from MSMEs Using the UTAUT3 Model

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ABSTRACT

This study aims to analyze the determinants of digital marketing usage among micro, small, and medium enterprises (MSMEs) by applying the Unified Theory of Acceptance and Use of Technology (UTAUT3) framework, with a particular focus on examining the relationship between behavioral intention and actual use behavior. A quantitative research approach was employed using a cross-sectional survey design. Data were collected from 300 MSME actors in Pontianak, Indonesia, through structured questionnaires distributed both online and offline. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the assistance of SmartPLS software to evaluate both the measurement and structural models. The results indicate that behavioral intention has a positive and significant effect on use behavior, confirming its central role in driving digital marketing implementation. Furthermore, performance expectancy, effort expectancy, social influence, hedonic motivation, and facilitating conditions significantly influence behavioral intention, while facilitating conditions and habit directly affect use behavior. Most variables influence use behavior indirectly through behavioral intention, highlighting the presence of an intention–behavior gap. The findings contribute to the extension of the UTAUT3 model in the MSME context and provide practical implications for policymakers and practitioners to enhance digital marketing usage behavior through infrastructure support, training, and sustained usage strategies.

Keywords: digital marketing usage behavior; UTAUT3; behavioral intention; MSMEs; PLS-SEM.

INTRODUCTION

The utilization of digital marketing has become a crucial determinant in enhancing the competitiveness of micro, small, and medium enterprises (MSMEs), particularly amid the shift in consumer behaviour toward digital platforms. The development of social media, marketplaces, and various internet-based communication channels enables MSMEs to expand market reach, enhance customer interaction, and improve marketing performance more effectively and efficiently despite limited resources (Eid et al., 2019); (Cao & Weerawardena, 2023). Furthermore, the use and continued utilization of digital marketing has been shown to contribute to the sustainable growth of MSMEs through increased visibility and operational efficiency (Bruce et al., 2023). Competitive pressures and the dynamics of digital markets encourage MSMEs not only to adopt technology partially but also to integrate it into sustainable business strategies (Su et al., 2023). In the context of developing countries such as Indonesia,

where MSMEs serve as the backbone of the economy, digital transformation has become a strategic necessity to ensure business continuity while fostering economic growth.

According to the Ministry of Communication and Digital of Indonesia, the government targeted 30 million MSMEs to adopt digital technology by 2024 (Ministry of Communication and Digital of Indonesia, 2024). Despite this rapid digital expansion, many MSMEs still utilize digital platforms only for basic promotional activities and have not strategically integrated digital marketing into broader business operations. In Pontianak City, which has more than 28,000 MSMEs, digital marketing utilization remains largely concentrated on basic social media exposure rather than sustainable digital business management. Many MSMEs use social media merely to upload product information without implementing structured content planning, customer engagement strategies, or digital performance evaluation. As a result, the benefits of digital marketing are often not fully optimized, and several MSMEs tend to use digital platforms inconsistently after initial adoption.

Furthermore, many MSMEs exhibit a tendency to discontinue or inconsistently use digital marketing tools after initial adoption. This indicates that while the intention to adopt digital marketing exists, it is not always translated into sustained usage behavior. Such conditions reflect the existence of an intention–behavior gap, namely a discrepancy between behavioral intention and actual technology usage behavior, particularly among MSMEs in developing regions such as Pontianak.

However, the adoption of digital marketing among MSMEs does not always proceed optimally. Several studies indicate that digital transformation in MSMEs is often uneven and faces various challenges, particularly in the post-adoption stage, where initial intentions to use technology are not always followed by consistent actual usage (Khurana et al., 2022); (Kraus et al., 2022). Additionally, limitations in digital capabilities and organizational readiness are key factors that slow down the digital transformation process in MSMEs (Verhoef et al., 2021). Many MSMEs only engage in limited digitalization without integrating technology into core business processes, resulting in suboptimal impacts on business performance (Wessel et al., 2021). This phenomenon is known as the intention–behavior gap, which refers to the discrepancy between intention and actual behavior in technology usage. This gap indicates that the success of digital transformation is not solely determined by adoption intention but also by the sustainability of technology use in operational activities. This condition raises an important question: why do MSMEs with high intention to adopt digital marketing fail to consistently implement it in practice?

To explain technology usage behavior, particularly in the post-adoption stage, the Unified Theory of Acceptance and Use of Technology (UTAUT) model has been widely employed as a primary theoretical framework. This model posits that intention and usage behavior are influenced by factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions, with the strength of relationships among these variables varying depending on research contexts such as sample size and culture (Jadil et al., 2021); (Dwivedi et al., 2020); (Tamilmani, Rana, & Dwivedi, 2021). The development of the model through UTAUT2 and UTAUT3 extends its analytical scope by incorporating variables such as habit, hedonic motivation, and personal innovativeness in information technology, which are more relevant in the context of dynamic digital technologies. Empirical studies suggest that integrating psychological and behavioral factors into technology usage and post-adoption behavior models enhances their ability to explain and predict digital technology usage (Venkatesh et al., 2012); (Tamilmani, Rana, Wamba, et al., 2021); (Dwivedi et al., 2019). Thus, UTAUT3 provides a more comprehensive framework for understanding technology usage behavior, particularly in the context of MSMEs.

In this study, the UTAUT3 framework is operationalized using seven key constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic

motivation, habit, and personal innovativeness in information technology. These constructs are selected because they represent a comprehensive combination of cognitive (performance expectancy, effort expectancy), social (social influence), facilitating (facilitating conditions), and psychological factors (hedonic motivation, habit, and personal innovativeness), which are particularly relevant in explaining both the adoption and post-adoption behavior of digital marketing among MSMEs. The inclusion of habit and personal innovativeness is especially important, as these variables capture behavioral consistency and individual readiness to adopt technology, which are critical in understanding the intention–behavior gap.

In this study, the intention–behavior gap is conceptualized as the discrepancy between behavioral intention and actual use behavior, where high intention does not necessarily lead to consistent usage. This gap is empirically examined by analyzing the direct effect of behavioral intention on use behavior, as well as the indirect effects of UTAUT3 constructs through behavioral intention. By modeling both direct and mediated relationships, this study provides a more precise explanation of how intention is translated into actual digital marketing usage, where the intention–behavior gap is reflected in the strength and significance of the relationship between behavioral intention and actual use behavior.

Although previous studies have extensively examined the determinants of digital marketing adoption, most of them focus primarily on behavioral intention rather than actual use behavior. Moreover, limited studies explicitly investigate the mechanism underlying the intention–behavior gap (Jenkins et al., 2021); (Khurana et al., 2022), particularly by integrating psychological variables such as habit and personal innovativeness within the UTAUT3 framework. This gap is even more evident in the context of MSMEs in developing countries, where structural and behavioral challenges coexist.

Based on this gap, this study aims to analyze the influence of variables within the UTAUT3 framework on behavioral intention and actual usage behavior in the post-adoption context among MSMEs in Indonesia, as well as to examine the effect of behavioral intention on actual use behavior. Building upon the identified research gap and theoretical framework, a conceptual model is developed to explain the relationships between UTAUT3 constructs, behavioral intention, and use behavior, which subsequently forms the basis for hypothesis development.

This study offers several novelties. First, unlike prior studies that mainly focus on behavioral intention, this research explicitly examines the intention–behavior gap by analyzing both behavioral intention and actual use behavior simultaneously. Second, this study integrates the extended UTAUT3 model with a specific focus on post-adoption behavior, which remains underexplored in digital marketing research. Third, this study provides empirical evidence from MSMEs in a developing city context (Pontianak), where digital adoption challenges are more complex and context-dependent compared to developed countries.

Literature Review

Digital marketing has become a strategic tool for MSMEs to enhance competitiveness and sustain business growth in increasingly digitalized markets. In recent years, the focus of research has shifted from initial technology adoption to post-adoption behavior, emphasizing how and why users continue to use digital technologies after initial acceptance. This shift is particularly relevant in the context of MSMEs, where the sustainability of digital technology usage determines the actual benefits gained from digital transformation (Kraus et al., 2022).

The Unified Theory of Acceptance and Use of Technology (UTAUT) and its extensions have been widely used to explain technology adoption and usage behavior. The extended versions, such as UTAUT2 and UTAUT3, incorporate additional psychological and behavioral constructs, including hedonic motivation, habit, and personal innovativeness, which enhance the explanatory power of the model in dynamic digital environments (Tamilmani, Rana, Wamba, et al., 2021). These constructs are particularly important in understanding post-

adoption behavior, as they capture not only cognitive evaluations but also habitual and affective aspects of technology use.

Recent studies highlight that behavioral intention alone is insufficient to explain actual technology usage, as a significant gap often exists between intention and behavior. This phenomenon, commonly referred to as the intention–behavior gap, indicates that individuals may express strong intentions to use technology but fail to translate these intentions into consistent usage (Jenkins et al., 2021). In the context of MSMEs, this gap is often influenced by practical constraints such as limited resources, lack of digital skills, and organizational readiness (Khurana et al., 2022).

Furthermore, research on digital transformation in SMEs suggests that post-adoption challenges are more complex than initial adoption decisions. While factors such as performance expectancy and effort expectancy influence intention, the actual implementation of digital technologies depends on facilitating conditions, habit formation, and continuous engagement with the technology (Verhoef et al., 2021). This indicates that usage behavior is shaped by both intentional and non-intentional mechanisms, making it essential to integrate behavioral and psychological constructs in explaining technology use.

In addition, empirical studies emphasize the importance of social and environmental influences in shaping digital technology usage among MSMEs. Social influence and external support systems, such as training and infrastructure, play a crucial role in sustaining technology usage beyond initial adoption (Cao & Weerawardena, 2023). These findings suggest that digital marketing usage behavior is not solely an individual decision but is also embedded within a broader socio-technical context.

To bridge the intention–behavior gap, it is essential to identify the mechanisms that enable the translation of behavioral intention into actual usage behavior. Prior studies suggest that facilitating conditions and habit play a critical role in supporting consistent technology use by reducing operational barriers and reinforcing repeated behavior (Verhoef et al., 2021); (Khurana et al., 2022). In addition, behavioral intention functions as a mediating mechanism that connects cognitive and social determinants with actual behavior. Therefore, bridging the gap requires not only strong intention but also supporting conditions and behavioral reinforcement mechanisms that ensure sustained digital marketing usage among MSMEs.

Based on the existing literature, it can be concluded that while prior studies have extensively examined technology adoption, there remains limited understanding of the mechanisms underlying post-adoption behavior, particularly in relation to the intention–behavior gap. Therefore, integrating UTAUT3 constructs provides a more comprehensive framework to explain how behavioral intention is translated into actual usage behavior in the context of digital marketing among MSMEs.

Hypothesis Development

Behavioral intention has been widely recognized as a key predictor of actual technology usage behavior. In the context of digital marketing, MSME actors who have a strong intention to use digital platforms are more likely to implement them consistently in their business operations. Previous studies confirm that behavioral intention significantly influences actual use behavior in various digital technology contexts (Tamilmani, Rana, Wamba, et al., 2021). Therefore, the following hypothesis is proposed:

H₁: Behavioral intention positively influences use behavior.

Effort expectancy reflects the perceived ease of using digital marketing technologies. When MSME actors perceive digital tools as easy to use, they are more likely to develop a positive intention to adopt them. However, ease of use does not always directly translate into actual usage behavior without strong intention (Tamilmani, Rana, Wamba, et al., 2021). Therefore:

H₂: Effort expectancy positively influences behavioral intention.

H₃: Effort expectancy positively influences use behavior.

Facilitating conditions describe the availability of resources and support required to use digital marketing technologies. Adequate infrastructure, technical support, and access to digital tools not only enhance intention but also directly enable actual usage behavior (Verhoef et al., 2021). Therefore:

H₄: Facilitating conditions positively influence behavioral intention.

H₅: Facilitating conditions positively influence use behavior.

Habit reflects the extent to which individuals perform behaviors automatically due to prior experience. In the context of digital marketing, repeated use can form habits that directly influence actual usage behavior, even without conscious intention (Cai et al., 2021). Therefore:

H₆: Habit positively influences behavioral intention.

H₇: Habit positively influences use behavior.

Hedonic motivation refers to the enjoyment or pleasure derived from using digital technologies. Positive user experience can encourage MSME actors to develop stronger intention to use digital marketing, although its direct influence on actual behavior is often limited (Tamilmani, Rana, Wamba, et al., 2021). Therefore:

H₈: Hedonic motivation positively influences behavioral intention.

H₉: Hedonic motivation positively influences use behavior.

Performance expectancy refers to the degree to which individuals believe that using digital marketing will enhance business performance. In MSMEs, perceived benefits such as increased sales, customer reach, and efficiency play an important role in shaping intention to use digital technologies (Cao & Weerawardena, 2023). However, its direct effect on actual usage behavior is often indirect through behavioral intention (Kraus et al., 2022). Therefore:

H₁₀: Performance expectancy positively influences behavioral intention.

H₁₁: Performance expectancy positively influences use behavior.

Personal innovativeness in information technology refers to an individual's willingness to try new technologies. Individuals with high innovativeness are generally more open to adopting digital marketing tools, although its influence may vary depending on contextual factors in MSMEs (Al-Adwan & Al-Debei, 2024). Therefore:

H₁₂: Personal innovativeness positively influences behavioral intention.

H₁₃: Personal innovativeness positively influences use behavior.

Social influence refers to the extent to which individuals perceive that important others believe they should use digital marketing. In MSMEs, peer influence, customer expectations, and competitive pressure can significantly shape intention to adopt digital technologies (Cao & Weerawardena, 2023). However, its direct impact on usage behavior may be limited. Therefore:

H₁₄: Social influence positively influences behavioral intention.

H₁₅: Social influence positively influences use behavior.

METHOD

This study employs a quantitative approach with a cross-sectional survey design to analyze the determinants of behavioral intention and use behavior in the use of digital marketing among MSME actors. Data were collected at a single point in time without intervention, allowing for the examination of relationships among variables within one observation period. The research model was developed based on the Unified Theory of Acceptance and Use of Technology (UTAUT3) framework, emphasizing causal relationships among constructs and examining the mediating role of behavioral intention on use behavior. This approach is considered appropriate for explaining the gap between intention and actual behavior (intention-behavior gap) in technology usage behavior (Shah & Zhongjun, 2021).

The population of this study consists of MSME actors in Pontianak City, with the unit of analysis being business owners or managers who are directly involved in digital marketing decision-making. Based on data from the Department of Cooperatives and MSMEs and supported by previous studies, the number of MSMEs in Pontianak City is approximately 28,128 units (Dinas Koperasi, Usaha Mikro dan Perdagangan Kota Pontianak, 2025). The sampling technique used is non-probability sampling with a purposive sampling method, where respondents are selected based on specific criteria, namely having operated a business for at least one year and having utilized digital channels (such as social media, marketplaces, or digital advertising) in their marketing activities. This study focuses on post-adoption behavior, as all respondents have prior experience using digital marketing technologies. Therefore, the analysis emphasizes factors influencing continued usage and the translation of intention into actual behavior. A total of 300 respondents were included in this study. This sample size is considered adequate for PLS-SEM analysis because the method is suitable for complex models with multiple constructs and indicators. Following the recommendation of Hair et al. (2021), the minimum sample size in PLS-SEM should be at least ten times the largest number of structural paths directed at a particular construct. In this study, the construct Behavioral Intention receives seven direct paths, indicating a minimum requirement of 70 samples. Therefore, the use of 300 respondents substantially exceeds the minimum threshold and enhances the statistical power and stability of the model estimation.

Primary data were collected through structured questionnaires distributed both online and offline. Respondents were provided with information regarding the purpose of the study, data confidentiality assurance, and informed consent. This study also adheres to research ethics principles by ensuring that all respondent data are anonymous and used solely for academic purposes. To minimize potential common method bias, several procedures were implemented, such as maintaining respondent anonymity, designing clear and simple questionnaire items, and randomizing the order of items across constructs in the instrument (Kock et al., 2021).

The research instrument consists of two parts: respondent profiles and measurement items for latent constructs. All constructs were measured using a six-point Likert scale to reduce the tendency toward neutral responses. Measurement items were adapted from previous studies relevant to the context of digital technology usage behavior, particularly in the use of social media and digital technologies in business activities (Puriwat & Tripopsakul, 2021); (Al-Adwan & Al-Debei, 2024). Conceptually, the constructs include performance expectancy, effort expectancy, social influence, facilitating conditions, habit, hedonic motivation, and personal innovativeness in information technology as determinants of behavioral intention, as well as use behavior as the dependent variable. These constructs reflect cognitive, social, and psychological dimensions in explaining technology usage behavior (Tamilmani, Rana, Wamba, et al., 2021); (Cai et al., 2021).

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the assistance of SmartPLS 3.0 software. This method was chosen because it is prediction-oriented, suitable for exploratory research, and capable of handling complex models with multiple latent constructs without requiring normally distributed data (Dash & Paul, 2021). Model evaluation was carried out in two stages: measurement model (outer model) evaluation and structural model (inner model) evaluation (Hair et al., 2020); (Guenther et al., 2023).

The evaluation of the measurement model for reflective constructs was conducted by testing indicator reliability using the criterion of outer loading ≥ 0.70 , internal consistency reliability using Cronbach's alpha and composite reliability ≥ 0.70 , convergent validity through Average Variance Extracted (AVE ≥ 0.50), and discriminant validity using the Heterotrait-Monotrait ratio (HTMT < 0.85 – 0.90). Additionally, the potential for common method bias was

assessed using a collinearity approach by examining the Variance Inflation Factor (VIF) values (Kock et al., 2021).

Subsequently, the structural model evaluation was conducted by examining the coefficient of determination (R^2) to assess the model's predictive capability. The significance of relationships among constructs was tested using the bootstrapping technique with 5,000 subsamples. Mediation testing was performed by evaluating the significance of indirect effects and comparing direct and total effects within the tested paths.

Through this approach, the study is expected to produce valid and reliable model estimations in explaining digital marketing usage behavior among MSMEs.

RESULTS AND DISCUSSION

Results

Measurement Model Evaluation (Outer Model)

Validity Test

Construct validity was assessed using the PLS-SEM measurement model evaluation, including indicator loadings and Average Variance Extracted (AVE). The results indicate that all indicators have outer loading values above 0.70, thus meeting the criteria for convergent validity. In addition, the Average Variance Extracted (AVE) values for each construct are above 0.50, indicating that the constructs adequately explain the variance of their indicators. Therefore, as shown in Table 1, all constructs in this study are considered to have satisfactory convergent validity and are suitable for further analysis.

Table 1. Validity Test Results

Construct	AVE	Lowest Loading	Number of Indicators	Indicators Loading ≥ 0.70	Decision
Behavioral Intention (Z)	0.781	0.874	3	3	Convergent validity achieved
Effort Expectancy (X_2)	0.765	0.864	3	3	Convergent validity achieved
Facilitating Conditions (X_6)	0.758	0.828	3	3	Convergent validity achieved
Habit (X_5)	0.751	0.832	3	3	Convergent validity achieved
Hedonic Motivation (X_4)	0.748	0.857	3	3	Convergent validity achieved
Performance Expectancy (X_1)	0.754	0.824	3	3	Convergent validity achieved
Personal Innovativeness (X_7)	0.723	0.830	3	3	Convergent validity achieved
Social Influence (X_3)	0.750	0.859	3	3	Convergent validity achieved
Use Behavior (Y)	0.775	0.854	3	3	Convergent validity achieved

Source: Data processed by the author, 2026.

Reliability Test

Construct reliability was evaluated to ensure internal consistency. Reliability was measured using Cronbach's alpha, rho_A, and composite reliability. The results show that all

constructs have Cronbach's alpha and composite reliability values above 0.70, indicating good reliability. Therefore, as shown in Table 2, all constructs are considered reliable and suitable for further analysis.

Table 2. Reliability Test Results

Construct	Cronbach's Alpha	rho_A	Composite Reliability	Decision
Behavioral Intention (Z)	0.860	0.862	0.914	Reliable
Effort Expectancy (X ₂)	0.847	0.852	0.907	Reliable
Facilitating Conditions (X ₆)	0.840	0.856	0.904	Reliable
Habit (X ₅)	0.834	0.839	0.901	Reliable
Hedonic Motivation (X ₄)	0.833	0.857	0.899	Reliable
Performance Expectancy (X ₁)	0.837	0.840	0.902	Reliable
Personal Innovativeness (X ₇)	0.809	0.821	0.887	Reliable
Social Influence (X ₃)	0.834	0.834	0.900	Reliable
Use Behavior (Y)	0.855	0.856	0.912	Reliable

Source: Data processed by the author, 2026.

Discriminant Validity

Discriminant validity was further assessed using the Heterotrait–Monotrait Ratio (HTMT). All HTMT values are below the threshold of 0.90, confirming that the constructs are empirically distinct and free from discriminant validity issues.

Table 3. HTMT Results

	BI (Z)	EE (X ₂)	FC (X ₆)	HB (X ₅)	HM (X ₄)	PE (X ₁)	PI (X ₇)	SI (X ₃)	UB (Y)
BI (Z)									
EE (X ₂)	0,503								
FC (X ₆)	0,454	0,204							
HB (X ₅)	0,341	0,19	0,39						
HM (X ₄)	0,514	0,201	0,282	0,189					
PE (X ₁)	0,555	0,372	0,274	0,244	0,293				
PI (X ₇)	0,202	0,208	0,238	0,265	0,253	0,31			
SI (X ₃)	0,517	0,192	0,21	0,319	0,368	0,335	0,198		
UB (Y)	0,818	0,433	0,523	0,478	0,431	0,493	0,304	0,474	

Source: Data processed by the author, 2026.

Note: BI = Behavioral Intention, EE = Effort Expectancy, FC = Facilitating Conditions, HB = Habit, HM = Hedonic Motivation, PE = Performance Expectancy, PI = Personal Innovativeness, SI = Social Influence, UB = Use Behavior.

All HTMT values are below the recommended threshold of 0.90, indicating that discriminant validity is established for all constructs.

Structural Model Testing (Inner Model)

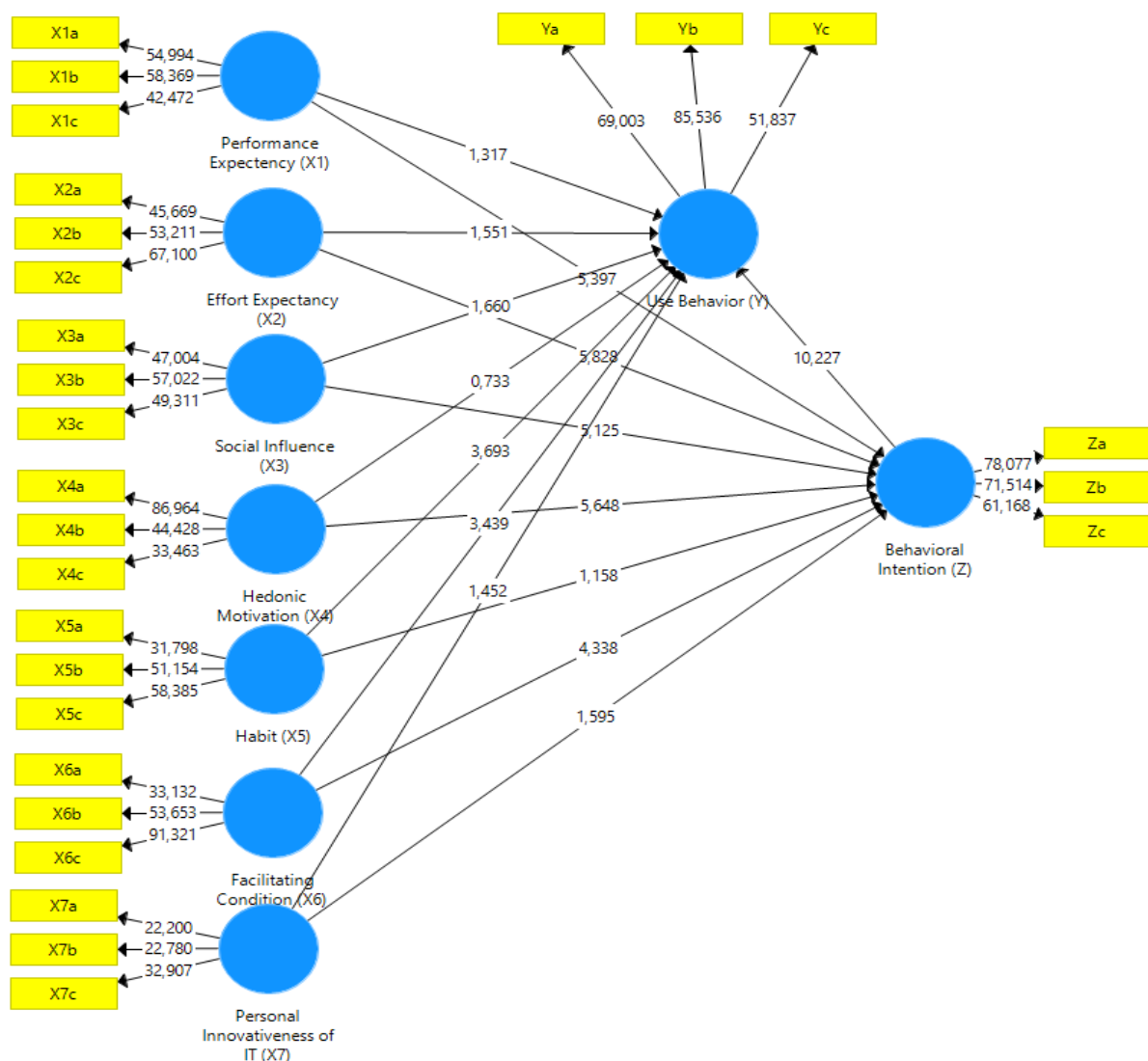
Before evaluating the structural relationships, collinearity among the predictor constructs was assessed to ensure that the estimation of the model is not biased by multicollinearity. This assessment was conducted using the Variance Inflation Factor (VIF), and the results are presented in Table 4.

Table 4. Inner VIF Values

Predictor → Endogenous	VIF
BI → UB	1.999
EE → BI	1.144
FC → BI	1.204
HB → BI	1.214
HM → BI	1.192
PE → BI	1.264
PI → BI	1.140
SI → BI	1.214

Source: Data processed by the author, 2026.

As shown in Table 4, all VIF values range from 1.140 to 1.999, which are below the recommended threshold of 3.3. This indicates that multicollinearity is not a concern in the model, and each predictor construct contributes uniquely to the explanation of the endogenous variables. Furthermore, these results suggest that common method bias is unlikely to affect the findings of this study.



Source: Data processed by the author, 2026.

Figure 1. Bootstrapping Results of the Structural Model

Figure 1 presents the bootstrapping results of the structural model generated using SmartPLS with 5,000 bootstrap resamples. The figure illustrates the significance of the relationships among constructs based on the t-statistics values. The results indicate that Behavioral Intention has a significant positive effect on Use Behavior, while several UTAUT3 constructs significantly influence Behavioral Intention and Use Behavior.

The structural model was evaluated by examining the relationships among variables using path coefficients, t-statistics, and p-values based on bootstrapping results. A hypothesis is considered significant if t-statistics > 1.96 and p-values < 0.05.

Table 5. Path Coefficient Results

Code	Path	O	M	STDEV	T	P	Direction	Significance	Decision
H ₁	BI → UB	0.488	0.488	0.048	10.102	0.000	Positive	Significant	Accepted
H ₂	X ₂ → BI	0.251	0.251	0.043	5.860	0.000	Positive	Significant	Accepted
H ₃	X ₂ → UB	0.061	0.062	0.040	1.529	0.126	Positive	Not significant	Rejected
H ₄	X ₆ → BI	0.192	0.192	0.043	4.453	0.000	Positive	Significant	Accepted
H ₅	X ₆ → UB	0.148	0.149	0.044	3.390	0.001	Positive	Significant	Accepted
H ₆	X ₅ → BI	0.057	0.057	0.048	1.189	0.234	Positive	Not significant	Rejected
H ₇	X ₅ → UB	0.155	0.154	0.042	3.641	0.000	Positive	Significant	Accepted
H ₈	X ₄ → BI	0.232	0.234	0.041	5.678	0.000	Positive	Significant	Accepted
H ₉	X ₄ → UB	0.032	0.030	0.044	0.737	0.461	Positive	Not significant	Rejected
H ₁₀	X ₁ → BI	0.236	0.236	0.044	5.378	0.000	Positive	Significant	Accepted
H ₁₁	X ₁ → UB	0.057	0.057	0.043	1.322	0.186	Positive	Not significant	Rejected
H ₁₂	X ₇ → BI	-0.069	-0.065	0.043	1.607	0.108	Negative	Not significant	Rejected
H ₁₃	X ₇ → UB	0.064	0.065	0.044	1.448	0.148	Positive	Not significant	Rejected
H ₁₄	X ₃ → BI	0.222	0.220	0.044	5.078	0.000	Positive	Significant	Accepted
H ₁₅	X ₃ → UB	0.073	0.073	0.044	1.644	0.100	Positive	Not significant	Rejected

Source: Data processed by the author, 2026.

Based on the Table 5, significant relationships include Behavioral Intention → Use Behavior; Effort Expectancy, Facilitating Conditions, Hedonic Motivation, Performance Expectancy, and Social Influence → Behavioral Intention; and Facilitating Conditions and Habit → Use Behavior. Meanwhile, several relationships are not significant, particularly the direct effects on Use Behavior and Personal Innovativeness. These findings indicate that most variables influence behavior indirectly through behavioral intention. This suggests that behavioral intention plays a central role in translating determinants into actual usage behavior, although the existence of an intention–behavior gap depends on the strength of the relationship between intention and behavior.

3. Testing of Specific Indirect Effects

The testing of specific indirect effects was conducted to analyze the mediating role of the behavioral intention variable in the relationship between independent variables and use behavior. This testing uses path coefficient values, t-statistics, and p-values obtained from bootstrapping results. A hypothesis is considered significant if the t-statistics value is greater than 1.96 and the p-values are less than 0.05.

Table 6. Specific Indirect Effects (Mean, STDEV, T-Value, P-Values)

Code	Path	O	M	STDEV	T	P	Direction	Significance	Decision
M1	Effort Expectancy → BI → UB	0.122	0.123	0.025	4.941	0.000	Positive	Significant	Accepted
M2	Facilitating Conditions → BI → UB	0.094	0.093	0.023	4.167	0.000	Positive	Significant	Accepted
M3	Habit → BI → UB	0.028	0.028	0.023	1.187	0.235	Positive	Not significant	Rejected
M4	Hedonic Motivation → BI → UB	0.114	0.114	0.024	4.753	0.000	Positive	Significant	Accepted
M5	Performance Expectancy → BI → UB	0.115	0.115	0.025	4.542	0.000	Positive	Significant	Accepted
M6	Personal Innovativeness → BI → UB	-0.034	-0.032	0.021	1.582	0.114	Negative	Not significant	Rejected
M7	Social Influence → BI → UB	0.108	0.107	0.023	4.729	0.000	Positive	Significant	Accepted

Source: Data processed by the author, 2026.

Based on the Table 6, the accepted mediation hypotheses are M1, M2, M4, M5, and M7 because they have t-statistics values greater than 1.96 and p-values less than 0.05. These results indicate that behavioral intention acts as a significant mediator in the relationships between effort expectancy, facilitating conditions, hedonic motivation, performance expectancy, and social influence on use behavior. Meanwhile, hypotheses M3 and M6 are rejected because they are not significant, indicating that habit and personal innovativeness are not significantly mediated by behavioral intention in influencing use behavior.

4. Testing of Total Effects

The total effects testing was conducted to determine the total influence (direct and indirect) of independent variables on the dependent variable. This testing uses path coefficient values, t-statistics, and p-values from bootstrapping results. A hypothesis is considered significant if the t-statistics value is greater than 1.96 and the p-values are less than 0.05.

Table 7. Total Effects (Mean, STDEV, T-Value, P-Values)

Code	Path	O	M	STDEV	T	P	Direction	Significance	Decision
T1	BI → UB	0.488	0.488	0.048	10.102	0.000	Positive	Significant	Accepted
T2	X ₂ → BI	0.251	0.251	0.043	5.860	0.000	Positive	Significant	Accepted
T3	X ₂ → UB	0.184	0.185	0.044	4.209	0.000	Positive	Significant	Accepted
T4	X ₆ → BI	0.192	0.192	0.043	4.453	0.000	Positive	Significant	Accepted
T5	X ₆ → UB	0.242	0.243	0.045	5.320	0.000	Positive	Significant	Accepted
T6	X ₅ → BI	0.057	0.057	0.048	1.189	0.234	Positive	Not significant	Rejected
T7	X ₅ → UB	0.182	0.182	0.051	3.546	0.000	Positive	Significant	Accepted
T8	X ₄ → BI	0.232	0.234	0.041	5.678	0.000	Positive	Significant	Accepted
T9	X ₄ → UB	0.146	0.145	0.044	3.301	0.001	Positive	Significant	Accepted
T10	X ₁ → BI	0.236	0.236	0.044	5.378	0.000	Positive	Significant	Accepted
T11	X ₁ → UB	0.173	0.173	0.047	3.653	0.000	Positive	Significant	Accepted
T12	X ₇ → BI	-0.069	-0.065	0.043	1.607	0.108	Negative	Not significant	Rejected

Code	Path	O	M	STDEV	T	P	Direction	Significance	Decision
T13	$X_7 \rightarrow UB$	0.030	0.033	0.048	0.618	0.537	Positive	Not significant	Rejected
T14	$X_3 \rightarrow BI$	0.222	0.220	0.044	5.078	0.000	Positive	Significant	Accepted
T15	$X_3 \rightarrow UB$	0.181	0.180	0.047	3.866	0.000	Positive	Significant	Accepted

Source: Data processed by the author, 2026.

Based on the Table 7, most hypotheses are accepted because they have significant effects on the dependent variable. Accepted hypotheses include the effect of behavioral intention on use behavior, as well as the effects of effort expectancy, facilitating conditions, hedonic motivation, performance expectancy, and social influence on behavioral intention and use behavior. Meanwhile, rejected hypotheses include the effect of habit on behavioral intention and the effect of personal innovativeness on behavioral intention and use behavior because they are not significant. These findings indicate that the total influence of independent variables on usage behavior becomes stronger when considering the mediating effect of behavioral intention.

5. R-Square (R^2)

The evaluation of the inner model was conducted by analyzing the coefficient of determination (R-square or R^2) for each endogenous variable. The R^2 value reflects the extent to which exogenous variables explain the variability of endogenous constructs in the research model.

Table 8. R Square

Variabel	R Square	R Square Adjusted
Behavioral Intention (Z)	0.500	0.488
Use Behavior (Y)	0.576	0.564

Source: Data processed by the author, 2026.

Based on the table 8, the R^2 value for Behavioral Intention is 0.500, indicating that 50% of the variance in Behavioral Intention can be explained by the independent variables in the model, while the remaining 50% is influenced by other factors outside the model. Based on general SEM criteria, this value is categorized as moderate.

Furthermore, the R^2 value for Use Behavior (Y) is 0.576, indicating that 57.6% of the variance in usage behavior can be explained by the constructs in the model, while the remaining 42.4% is influenced by other variables not included in this study. This value is also categorized as moderate, but with a higher explanatory power than Behavioral Intention.

6. Hypothesis Testing

Hypothesis testing in this study was conducted using the bootstrapping approach in the Partial Least Squares Structural Equation Modeling (PLS-SEM) model. This testing aims to determine the significance of the relationships among variables in the research model. The criteria for hypothesis testing are based on t-statistics and p-values, where a hypothesis is accepted if the t-statistics value is greater than 1.96 and the p-values are less than 0.05 at a 5% significance level.

The results indicate that not all proposed hypotheses in this study are accepted. In general, relationships among variables leading to behavioral intention show more dominant significant results compared to direct relationships with use behavior.

First, the effect of behavioral intention on use behavior is proven to be positive and significant. This indicates that the higher the intention of MSME actors to use digital marketing, the greater the likelihood that they will actually implement it in their business activities. Thus, the hypothesis stating that behavioral intention influences use behavior is accepted.

Furthermore, the performance expectancy variable is found to have a positive and significant effect on behavioral intention, but not a significant effect on use behavior. This indicates that the perceived usefulness of technology can encourage intention to use, but does not directly drive actual behavior. Therefore, the hypothesis regarding its effect on behavioral intention is accepted, while its effect on use behavior is rejected.

The effort expectancy variable shows a similar pattern, where its effect on behavioral intention is positive and significant, but not significant on use behavior. This suggests that ease of use plays a greater role in shaping intention than actual behavior. Thus, the hypothesis regarding behavioral intention is accepted, while that regarding use behavior is rejected.

Furthermore, facilitating conditions are found to have a positive and significant effect on both behavioral intention and use behavior. This indicates that the availability of infrastructure, technical support, and resources plays an important role not only in forming intention but also in encouraging actual usage. Therefore, both hypotheses related to this variable are accepted.

The social influence variable also shows a positive and significant effect on behavioral intention, but not on use behavior. This suggests that social environmental influence is more effective in shaping intention than directly influencing behavior. Thus, the hypothesis regarding behavioral intention is accepted, while that regarding use behavior is rejected.

Similarly, hedonic motivation is found to have a positive and significant effect on behavioral intention, but not on use behavior. This indicates that the enjoyment or comfort in using technology plays a greater role in increasing intention than actual behavior. Therefore, the hypothesis regarding behavioral intention is accepted, while that regarding use behavior is rejected.

The habit variable shows a different result, where it does not have a significant effect on behavioral intention but has a positive and significant effect on use behavior. This indicates that habits do not always form intention but can directly influence usage behavior. Thus, the hypothesis regarding behavioral intention is rejected, while that regarding use behavior is accepted.

Finally, the personal innovativeness in information technology variable does not show a significant effect on either behavioral intention or use behavior. This indicates that the level of individual innovativeness is not a primary factor in driving the usage of digital marketing in the MSME context. Therefore, all hypotheses related to this variable are rejected.

Overall, the results of hypothesis testing indicate that most variables in the UTAUT3 model play a greater role in shaping behavioral intention rather than directly influencing use behavior. In addition, behavioral intention is proven to be a key variable that bridges the relationship between determinant factors and actual usage behavior.

Discussion

The results of this study indicate that the UTAUT3 model used has good measurement quality and is able to adequately explain digital marketing usage behavior among MSMEs. Specifically, these findings reinforce the argument that cognitive, social, and facilitating factors play an important role in shaping behavioral intention, which subsequently becomes the main determinant of use behavior. These results are consistent with the development of the UTAUT model, which emphasizes the central role of intention in mediating the relationship between technology determinants and usage behavior (Dwivedi et al., 2020); (Tamilmani, Rana, Wamba, et al., 2021).

The main finding of this study shows that behavioral intention has a positive and significant effect on use behavior. This confirms that intention is a key mechanism in driving the implementation of digital marketing usage among MSMEs. In the context of digital transformation, this result is in line with previous studies indicating that the success of technology usage behavior is not only determined by access or technical capability, but also by

the psychological readiness of business actors to integrate technology into their business activities.

Furthermore, the variables of performance expectancy, effort expectancy, social influence, hedonic motivation, and facilitating conditions are proven to have a significant effect on behavioral intention. This indicates that perceived usefulness, ease of use, social pressure, enjoyable user experience, and infrastructure support are important determinants in shaping the intention to use digital marketing. These findings support previous studies emphasizing that a combination of cognitive and social factors is the main driver in the early stage of digital technology usage behavior (Cao & Weerawardena, 2023); (Al-Adwan & Al-Debei, 2024).

However, this study also reveals that most of these variables do not have a direct effect on use behavior. This finding indicates the presence of an intention–behavior gap, namely the discrepancy between intention and actual behavior in technology usage. This condition suggests that although MSME actors have a high intention to use digital marketing, actual implementation is still influenced by other factors such as limited resources, digital literacy, and changes in operational routines. This finding is consistent with previous studies highlighting that the conversion of intention into behavior is a critical stage in the technology usage behavior process that is often overlooked (Jenkins et al., 2021); (Khurana et al., 2022).

Interestingly, the facilitating conditions variable is found to have a significant effect on both behavioral intention and use behavior. This indicates that the availability of resources, technical support, and infrastructure plays a dual role, both as a driver of intention and as an enabler of implementation. This finding strengthens the view that the success of digital transformation in MSMEs depends not only on psychological aspects but also on the readiness of supporting systems (Verhoef et al., 2021).

In addition, the habit variable shows a significant effect on use behavior but not on behavioral intention. This indicates that technology usage in the MSME context can develop into automatic behavior that is not always based on conscious intention. This finding expands the understanding of technology usage dynamics, where habit can function as an alternative mechanism in driving usage behavior, particularly in the context of repeated use.

Conversely, the personal innovativeness in information technology variable does not show a significant effect on either behavioral intention or use behavior. This finding indicates that in the context of MSMEs in developing countries, individual characteristics such as innovativeness are not the main factors in determining technology usage behavior. This may be due to the dominance of external factors such as resource constraints and environmental pressures compared to personal factors.

The mediation analysis results show that behavioral intention acts as a significant mediator in the relationship between most independent variables and use behavior. This indicates that the influence of these variables on usage behavior is largely indirect through the formation of intention. This finding reinforces the central role of behavioral intention as the main mechanism bridging technology determinants and actual behavior.

Furthermore, the total effects results indicate that when considering both direct and indirect effects simultaneously, most variables have a significant influence on use behavior. This suggests that the influence of independent variables becomes stronger when mediation pathways are considered, highlighting the importance of a comprehensive approach in analyzing technology usage behavior.

In terms of model capability, the coefficient of determination values indicate that the model is able to explain variations in behavioral intention and use behavior at a moderate level, with high predictive capability. This shows that the UTAUT3 model used has strong empirical relevance in explaining digital marketing usage behavior among MSMEs, particularly in the context of developing countries.

Theoretically, this study contributes by extending the application of the UTAUT3 model in the context of digital marketing among MSMEs, particularly in explaining the mechanism of converting behavioral intention into use behavior. This study also confirms that the relationship between intention and behavior is not always linear, but is influenced by contextual factors such as infrastructure support and usage habits. Thus, this study enriches the technology usage behavior literature by highlighting the importance of integrating psychological and operational factors in explaining technology usage behavior.

Practically, the findings of this study provide important implications for MSME actors and policymakers. First, efforts to increase digital marketing usage should focus not only on enhancing intention but also on facilitating implementation through the provision of infrastructure, training, and technical assistance. Second, intervention strategies need to be designed to encourage sustained technology usage, for example through the formation of usage habits and the integration of technology into daily operational activities. Third, MSME development policies should consider an ecosystem-based approach that supports comprehensive digital transformation.

CONCLUSION

This study aims to analyze the factors influencing the usage of digital marketing by MSMEs using the UTAUT3 model approach. Based on the analysis results, it can be concluded that the model used has good measurement and structural quality and is able to adequately explain technology usage behavior.

The findings indicate that behavioral intention is the main determinant that significantly influences use behavior. In addition, the variables of performance expectancy, effort expectancy, social influence, hedonic motivation, and facilitating conditions are proven to have a significant effect on behavioral intention. These findings confirm that cognitive, social, and facilitating factors play an important role in shaping technology usage intentions among MSMEs.

However, most of these variables do not have a direct effect on use behavior, except for facilitating conditions and habit. This indicates the existence of an intention–behavior gap, where high intention is not always followed by actual technology usage. On the other hand, the personal innovativeness variable does not show a significant effect on either intention or behavior, suggesting that individual characteristics are not the main factors in the MSME context.

Furthermore, the analysis results show that behavioral intention acts as a significant mediator in the relationship between most independent variables and use behavior. This reinforces the strategic role of intention as the main mechanism in bridging the influence of determinant factors on technology usage behavior.

In terms of model capability, the coefficient of determination values indicate that the model is able to explain variations in behavioral intention and use behavior at a moderate level and has very good predictive capability. This shows that the UTAUT3 model is relevant and applicable in explaining digital marketing usage behavior among MSMEs.

This study contributes to the literature by contextualizing the UTAUT3 framework in the domain of digital marketing usage among MSMEs, with a specific focus on post-adoption behavior and the intention–behavior relationship. It also highlights the role of behavioral intention as a key mechanism in translating technological perceptions into sustained usage. In addition, this study provides practical implications for stakeholders, such as government and business actors, to enhance infrastructure support, digital training, and strategic initiatives that can strengthen behavioral intention and promote sustained digital marketing usage.

Despite these contributions, this study has several limitations that open opportunities for future research. Future research is encouraged to employ longitudinal designs to examine the

dynamic nature of digital marketing usage over time. Additionally, comparative analyses between adopters and non-adopters of digital marketing could provide deeper insights into the mechanisms underlying the intention–behavior gap. Overall, this study highlights the importance of behavioral intention as a key mechanism in bridging the intention–behavior gap in digital marketing usage among MSMEs.

Author Contribution

The author is solely responsible for all aspects of this research and manuscript preparation. The author contributed to the conceptualization of the study, research design, data collection, data analysis, interpretation of results, and manuscript writing. The author has read and approved the final version of the manuscript.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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