PARAMETER
JURNAL MATEMATIKA, STATISTIKA DAN TERAPANNYA

e-ISSN. 2829-6303
Vol. 05 No. 1, April 2026
Pages 29-44

Exploring the Determinants of Behavioral Intention and Use Behavior Toward TikTok Shop Based on the UTAUT 2 Model

Rizki Fitriani Muin [1*], Bambang Widjanarko Otok [2]

[1]Information Technology Management, Interdisciplinary School of Management and Technology, Institut Teknologi Sepuluh Nopember, Kampus ITS-Cokroaminoto, Surabaya 60264, Indonesia
[2]Department of Statistics, Faculty of Science and Data Analytics, Institut Teknologi Sepuluh Nopember, Kampus ITS-Sukolilo, Surabaya 60111, Indonesia

E-mail Correspondence Author: **Bambang_wo@its.ac.id*

Abstract
The rapid growth of social commerce through TikTok Shop has opened new opportunities for businesses and consumers in Indonesia, including in the city of Ambon. This study aims to analyze the factors influencing consumers' behavioral intention and use behavior in shopping on TikTok Shop by applying the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model. The respondents of this research were TikTok Shop users in Ambon who had made at least one transaction, with a minimum sample size of 200 participants. The results show that all UTAUT 2 constructs, except for facilitating conditions on use behavior, have a significant effect on consumers' intention and usage behavior. The variable behavioral intention was found to be the most dominant factor driving actual usage behavior, with R^2 *values of 0.753 for behavioral intention and 0.817 for use behavior, indicating a strong predictive capability of the model. These findings affirm the relevance of the UTAUT 2 model in explaining technology adoption in the context of social commerce and provide practical implications for platform developers and digital business practitioners to design marketing strategies that align with the characteristics of consumers in eastern Indonesia.*

Keywords: *Behavioral intention, PLS-SEM, social commerce, tiktok shop, use behavior, UTAUT2.*

: https://doi.org/10.30598/parameterv4i1pp29-44

1. INTRODUCTION

The presence of TikTok Shop has further strengthened TikTok's position as a social commerce platform by integrating entertainment and shopping activities within a single application. A study by McKinsey revealed that the live-streaming-based shopping model can generate conversion rates of up to 30%, significantly higher than those of conventional e-commerce platforms [1]. McKinsey's projection also positions Indonesia as one of the largest e-commerce markets in Southeast Asia, with an estimated market value expected to exceed USD 40 billion within the next five years [2]. This phenomenon has also begun to emerge in Ambon City, which is known as the center of trade and services in Maluku. The younger generation in Ambon particularly students, university learners, and young professionals has shown a high level of adoption of digital applications and social media [3].

A latent variable is an abstract concept that cannot be directly observed but must be constructed from a set of indicators [4]. Latent variables cannot be measured directly; instead, they are assessed through their indicators, which consist of several manifest variables. Meanwhile, manifest variables (or indicator variables) are the observable variables used to measure the corresponding latent variables [5].

Partial Least Square (PLS) is a regression-based method introduced by Herman O. A. Wold in 1975 for the development of models and methods in the social sciences using a prediction-oriented approach [6]. PLS is employed to analyze the complex relationships between latent variables as well as the relationships between a latent variable and its indicators [7]. PLS is defined by two main equations: the inner model and the outer model [8]. The inner model specifies the relationships among latent variables, while The outer model specifies the relationships between latent variables and their indicators [9].

There are various models used to measure user acceptance, one of which is the UTAUT 2 (Unified Theory of Acceptance and Use of Technology 2) model. Developed by Venkatesh, Thong, and Xu in 2012, UTAUT 2 is an extension of the original UTAUT model that focuses on understanding technology acceptance and usage in the consumer context [10]. The main objective of the UTAUT 2 model is to identify three important constructs in studies of technology acceptance and usage both in general and consumer settings modify several existing relationships found in the original UTAUT model, and introduce new relationships to enhance its explanatory power [11].

To understand the phenomenon of TikTok Shop adoption in Ambon, a comprehensive theoretical framework is required. One relevant model is UTAUT 2 [12]. This model includes seven key constructs, namely: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. A meta-analysis study by Tamilmani, Rana, and Dwivedi [13] emphasized that the pathway from behavioral intention (BI) to use behavior (UB) is the most consistent relationship in explaining digital technology adoption.

Several studies support the relevance of the UTAUT 2 model in the context of social commerce. Maulida, Sari, and Rohmah [14] found that hedonic motivation, price value, and electronic word of mouth (e-WOM) have a significant effect on purchase intention in TikTok Shop. Putri et al. [15] emphasized that trust and privacy concern influence Generation Z's purchasing behavior on TikTok Shop. Meanwhile, Pradnyamitha and Maradona [16] revealed that actual purchasing behavior in TikTok live-streaming sessions is influenced by parasocial relationships and utilitarian shopping value.

The study conducted by Aprianto [17] adopted the UTAUT 2 theoretical framework to explain the factors influencing behavioral intention in TikTok Shop. The findings indicate that several key constructs of UTAUT 2 namely performance expectancy (PE), social influence (SI), price value (PV), hedonic motivation (HM), and habit (HT) have a significant influence on consumers' purchase intention.

However, there remains a research gap. The majority of TikTok Shop studies in Indonesia have focused on behavioral intention, while use behavior has been relatively underexplored particularly in regional contexts such as Ambon. Furthermore, the role of moderating variables such as gender, age, and experience, which according to [18] can influence the strength of relationships between variables, has not been specifically examined in the context of Ambon City. Considering the cultural and social diversity of Ambon's community, these moderating factors have the potential to yield distinct findings compared to studies conducted in larger urban areas of Indonesia. Therefore, this study is important to examine the influence of UTAUT 2 constructs on behavioral intention and use behavior in shopping through TikTok Shop in Ambon City.

2. RESEARCH METHODOLOGY

2.1 Data and Sources

The sampling technique used in this study is purposive sampling, with the following respondent criteria: residing in Ambon City, having made at least one purchase on TikTok Shop, and being 17 years old or older (productive age). The minimum sample size is 200 respondents, determined based on the 10 times the number of indicators rule for SEM-PLS analysis as suggested by Hair [19]. With a total of 32 indicators, the recommended minimum number of respondents is 320; however, in social research practice, a range of 200 to 400 respondents is generally considered adequate for analysis using SEM-PLS. This study is grounded in the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model.

2.2 Unified Theory of Acceptance and Use of Technology 2

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) model was developed by Venkatesh, Thong, and Xu in 2012 as an extension of the original UTAUT model. This model is used to explain individuals acceptance and use of technology in a consumer context. UTAUT 2 comprises seven main constructs that influence technology usage intention and behavior, namely: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit [20]. The model also takes into account moderating variables such as age, gender, and experience. Thus, UTAUT 2 provides a comprehensive framework for understanding the factors that affect technology adoption and usage behavior, including in the context of online shopping behavior through platforms such as TikTok Shop.

2.3 Structural Equation Model Partial Least Squares

Partial Least Squares (PLS) was first developed by Herman Wold. This approach was introduced as an alternative when the underlying theory for model specification is relatively weak. PLS is considered a powerful analytical technique because it can be applied to various types of measurement scales and offers more flexible distributional assumptions. Estimation using the PLS algorithm is conducted in three stages. The first stage consists of an iterative procedure based on simple or multiple regressions that accounts for the relationships among the structural model (inner model), the measurement model (outer model), and the estimation of weights (weight relations). The resulting set of weights is then used to compute latent variable scores, which are linear combinations of the observed (manifest) indicators. After the latent variable scores are obtained, the second and third stages involve estimating the path coefficients of the structural model (inner model) and the parameters of each measurement model (outer model). Essentially, the PLS algorithm comprises a series of simple and multiple regression analyses estimated using ordinary least squares (OLS) **[21]**.

The structural model (inner model) in PLS describes the relationships among latent variables. The model can be expressed in a linear form as follows:

$$\xi_j = \sum_i \beta_{ji}\xi_i + \zeta_j \tag{1}$$

where β_{ji} denotes the coefficient describing the relationship between the *i*-th latent variable and the *j*-th latent variable (path coefficient) with $\mathrm{E}(\zeta_j) = 0, \mathrm{E}(\xi_i\zeta_j) = 0$. The measurement model (outer model) in PLS can be defined such that each block of indicators is associated with its corresponding latent variable. For reflective indicator blocks, the measurement equations can be written as the following simple regression forms:

$$x_{jk} = \lambda_{jk}\xi_j + \varepsilon_{jk} \tag{2}$$

where λ_{jk} denotes the loading coefficient of the relationship between the *j*-th (ξ_j) latent variable and its *k*-th indicator (x_{jk}), ε_{jk} represents the residual (measurement error) for each measurement variable and $E(\varepsilon_{jk}) = E(\xi_j\varepsilon_{jk}) = 0$.

Data analysis in this study was conducted using the Structural Equation Model Partial Least Squares (SEM-PLS) method. The stages of analysis include:

1. Developing a conceptual framework.
   The conceptual research model is a theoretical framework used to guide a study by linking relevant key constructs. The purpose of this model is to clearly identify the relationships among variables and indicators being examined, thereby explaining the factors that influence consumer acceptance and behavior in using TikTok Shop. This research model is developed based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) framework proposed by Venkatesh et al. in 2012 and integrates findings from previous studies by Maulida and Sari **[14]**, Putri et al. **[15]**, Aprianto et al. **[22]**, Sawitri et al. **[23]**, Pradnyamitha and Maradona **[16]**, Nguyen and Nguyen **[24]**, Riadi et al. **[25]**, Razafinandrasana and Tamara **[18]**. The conceptual framework designed for this research is illustrated in **Figure 1**.

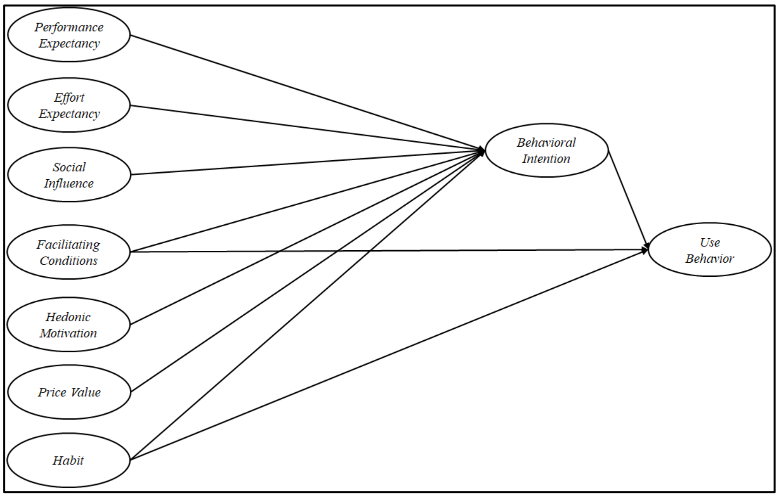

Figure 1. **Conceptual Framework**

2. The outer model testing explains the relationship between latent variables and their indicators within the measurement model. There are two types of measurement models in the outer model, namely the reflective model and the formative model. In the reflective model, indicators are considered manifestations of the latent variable, meaning that changes in the latent construct are reflected in its indicators. Meanwhile, in the formative model, indicators act as components that collectively form or define the latent variable. The measurement model can therefore be expressed through several forms of equations that represent these relationships mathematically[26]:

$$x_p = \lambda_p \xi + \delta_p \tag{3}$$

Next, the outer model (measurement model) test is used to assess the validity and reliability of the constructs within the measurement model, referring to the criteria recommended by Hair. These criteria include a loading factor greater than 0.70 to measure convergent validity, an Average Variance Extracted (AVE) value greater than 0.50 to ensure discriminant validity, a Composite Reliability (CR) value greater than 0.70, and a Cronbach's Alpha value greater than 0.70 to test internal consistency.

3. The inner model testing, also known as the structural model, is used to describe and predict the causal relationships among latent variables within a study. This model serves to test the influence between constructs that have been established in the conceptual framework. Mathematically, the general equation of the structural model can be expressed as follows:

$$\eta_j = \beta_{j0} + \sum_{i=1}^{I} \beta_{ji}\eta_i + \sum_{k=1}^{K} \gamma_{jk}\xi_i + \varsigma_j \tag{4}$$

In general, it can be written as follows:

$$\eta = \beta_0 + \beta\eta + \Gamma\xi + \varsigma \tag{5}$$

The inner model (structural model) test aims to evaluate the relationships among latent variables within the structural model. This evaluation is carried out by examining the R^2 value, which indicates the strength of the dependent variable in explaining the variance influenced by the independent variables.

4. Research Hypotheses
   H1: Performance Expectancy has a significant effect on Behavioral Intention.
   H2: Effort Expectancy has a significant effect on Behavioral Intention.
   H3: Social Influence has a significant effect on Behavioral Intention.
   H4: Facilitating Conditions have a significant effect on Behavioral Intention.
   H5: Hedonic Motivation has a significant effect on Behavioral Intention.
   H6: Price Value has a significant effect on Behavioral Intention.
   H7: Habit has a significant effect on Behavioral Intention.
   H8: Behavioral Intention has a significant effect on Use Behavior.
   H9: Facilitating Conditions have a significant effect on Use Behavior.
   H10: Habit has a significant effect on Use Behavior.

3. RESULTS AND DISCUSSION

Based on the descriptive analysis of respondent characteristics, it was found that, in terms of gender, the majority of respondents were female, totaling 150 people (63.68%), while male respondents numbered 70 people (36.32%). This indicates that female respondents were more involved in this study than their male counterparts. Meanwhile, based on age groups, the majority of respondents belonged to Generation Z, with 198 individuals (81.13%), followed by Millennials with 39 individuals (17.45%), and Generation X with 3 individuals (1.42%). These results suggest that TikTok Shop users in Ambon City are predominantly from the younger generation, particularly Generation Z, who are known for their high level of digital literacy and their active use of social media platforms as a medium for online shopping. Furthermore, based on the path diagram construction presented in **Figure 1**, the next step is to convert the model into mathematical equations, consisting of both the measurement model equations and the structural model equations.

3.1. Measurement Model (outer model)

By using SmartPLS software, the parameter coefficients of the measurement model (λ) and the structural model (γ) were obtained. The λ coefficient or factor loading is used to assess the accuracy of each indicator in explaining both exogenous and endogenous constructs within the model. Indicators with factor loading values below 0.5 should be removed from the model, followed by a re-estimation process to ensure the model's validity and reliability. For a clearer overview, the factor loading values for each indicator are presented in **Table 1**.

Tabel 1. Loading Factor Values

Latent Variable	Manifest Variable	Loading Factor
Performance Expectancy	$X_{1.1}$	0.894
	$X_{1.2}$	0.861
	$X_{1.3}$	0.870
	$X_{1.4}$	0.888
Effort Expectancy	$X_{2.1}$	0.873
	$X_{2.2}$	0.892
	$X_{2.3}$	0.843
Social Influence	$X_{3.1}$	0.888
	$X_{3.2}$	0.904
	$X_{3.3}$	0.891
	$X_{3.4}$	0.820
Facilitating Conditions	$X_{4.1}$	0.860
	$X_{4.2}$	0.903
	$X_{4.3}$	0.888
Hedonic Motivation	$X_{5.1}$	0.862
	$X_{5.2}$	0.883
	$X_{5.3}$	0.875
	$X_{5.4}$	0.901
Price Value	$X_{6.1}$	0.874
	$X_{6.2}$	0.887
	$X_{6.3}$	0.890
Habit	$X_{7.1}$	0.895
	$X_{7.2}$	0.867
	$X_{7.3}$	0.885
	$X_{7.4}$	0.870
Behavioral Intention	$Y_{1.1}$	0.912
	$Y_{1.2}$	0.920
	$Y_{1.3}$	0.907
Use Behavior	$Y_{2.1}$	0.881
	$Y_{2.2}$	0.898
	$Y_{2.3}$	0.883
	$Y_{2.4}$	0.876

***Data source**: processed results from smartPLS*

3.2. Evaluation of the Measurement Model (Outer Model)

3.2.1 Validity

Validity describes the correlation relationship between indicators and latent variables. This evaluation examines the loading factor values of each indicator with its corresponding latent variable. If the loading factor value meets the specified threshold, the indicator is considered valid. However, if the loading factor value is below the threshold, the indicator is considered invalid and must be removed from the model, followed by re-estimation. This indicates that the indicator is not sufficiently reliable in measuring the latent variable.

The structural equation path diagram with indicators that have met the validity requirement (loading factor values above the threshold) is presented in Figure 2.

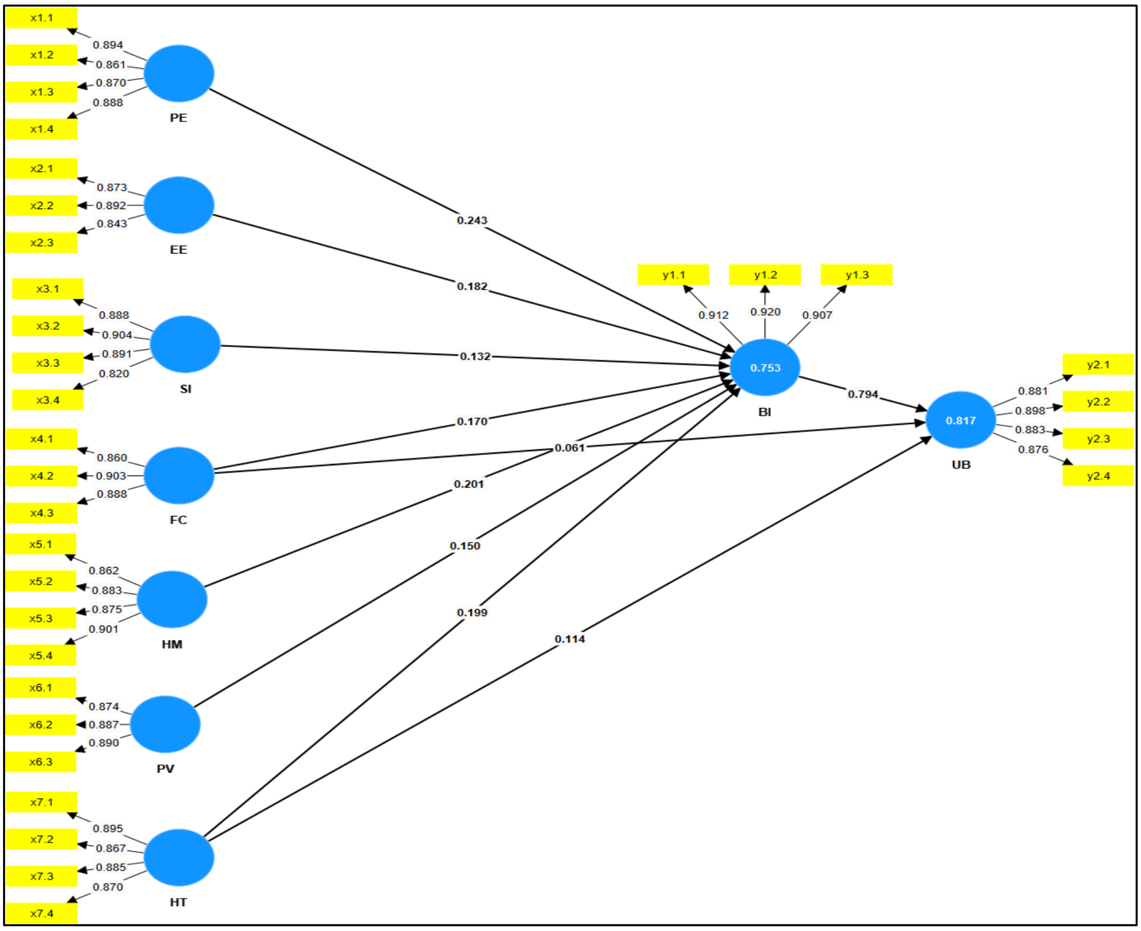

Figure 2. Loading Factor Values Using Path Diagram

(Source: Processed results from smartPLS)

Based on Figure 2, it is shown that all indicators for each construct have outer loading values above 0.70. This indicates that each indicator has a strong contribution to its respective construct. Therefore, all indicators in this model meet the criteria for convergent validity, as recommended by Hair, who specifies that the loading factor value should exceed 0.70.

In addition, there are no indicators with loading values below the minimum threshold, meaning that no indicators need to be eliminated from the model. These results confirm that the research instrument demonstrates good validity and is capable of measuring latent constructs consistently. Hence, the measurement model (outer model) can be considered valid and suitable for use in the subsequent stages of analysis.

3.2.2 Reliability

The reliability of a latent variable refers to the stability and consistency of its measurement. A variable is considered to have good composite reliability if it has a composite reliability (CR) value ≥ 0.7, and its Cronbach's alpha value ≥ 0.5. These values indicate that the indicators consistently measure the same construct.

The SmartPLS output results, which include the Composite Reliability (CR), Cronbach's Alpha, and Average Variance Extracted (AVE) values for each variable, are presented in Table 2.

Table 2. Composite Reliability (CR) and AVE Values for Each Latent Variable

Latent Variable	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Behavioral Intention	0.901	0.901	0.834
Effort Expectancy	0.838	0.842	0.756
Facilitating Conditions	0.860	0.863	0.782
Hedonic Motivation	0.903	0.906	0.775
Habit	0.902	0.904	0.774
Performance Expectancy	0.901	0.906	0.771
Price Value	0.860	0.860	0.781
Social Influence	0.899	0.908	0.768
Use Behavior	0.907	0.908	0.783

Data source: processed results from smartPLS

Based on Table 2, the results of the reliability and convergent validity tests indicate that all constructs in the model meet the established criteria. The Cronbach's Alpha values for all latent variables are above 0.70, ranging from 0.838 to 0.907, demonstrating that each construct possesses a high level of internal consistency. This means that the indicators for each variable are reliable in measuring the same underlying concept.

Furthermore, the Composite Reliability (CR) values for all constructs also exceed the minimum threshold of 0.70, ranging from 0.842 to 0.908, confirming that each construct has strong reliability. Meanwhile, the Average Variance Extracted (AVE) values for all variables are above 0.50, ranging between 0.756 and 0.834. This shows that more than 50% of the variance of the indicators can be explained by their respective constructs, indicating that all variables meet the convergent validity criteria.

Overall, these results demonstrate that all latent variables in this study possess good levels of validity and reliability. In other words, the research instrument used in this study has been proven to be valid and reliable for measuring the constructs within the UTAUT 2 model in the context of TikTok Shop usage in Ambon City.

3.3. Structural Model (inner model)

Based on the estimation results presented in Table 1, all factor loading values for each indicator are ≥ 0.5, indicating that all indicators for each latent variable are valid. The parameter coefficients (γ), which represent the relationships between latent variables in the structural model, can be seen in Table 3.

Tabel 3. Parameter Coefficients (γ)

Latent Variable	Path coefficients
BI -> UB	0.794
EE -> BI	0.182
FC -> BI	0.170
FC -> UB	0.061
HM -> BI	0.201
HT -> BI	0.199
HT -> UB	0.114
PE -> BI	0.243
PV -> BI	0.150
SI -> BI	0.132

Data source: processed results from smartPLS

3.3. Evaluation of the Structural Model (inner model)

The R-square (R^2) value represents the coefficient of determination for endogenous latent variables and the path parameter coefficients in the model. The R^2 value for the latent variable Behavioral Intention is 0.753, which means that Behavioral Intention can be explained by the variables Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit by 75.30%, while the remaining 24.70% is explained by other variables outside the model. Furthermore, the R^2 value for the latent variable Use Behavior is 0.817, indicating that Use Behavior can be explained by Behavioral Intention, Facilitating Conditions, and Habit by 81.70%, while the remaining 18.30% is explained by other external variables. Therefore, it can be concluded that the structural model in this study demonstrates a strong predictive relevance, as both R^2 values indicate that a substantial proportion of the variance in the endogenous variables is explained by the proposed model.

3.4. Hypothesis Testing

Hypothesis testing includes the examination of the λ parameters and γ parameters. The statistical test used in SmartPLS is the t-test, which determines the significance of the relationships among variables in the model.

3.4.1. Hypothesis Testing of the Measurement Model (Outer Model)

The results of the outer model hypothesis testing using SmartPLS show the t-statistics and p-values for each indicator to determine their significance in measuring the corresponding latent variables. Indicators are considered significant if the t-statistic > 1.96 and the p-value < 0.05. The detailed results of this analysis are presented in **Table 4** below:

Tabel 4. Results of Hypothesis Testing for the Measurement Model

Latent Variable	Variabel Manifest	Standard deviation	t-statistics	p-values
Performance Expectancy	$X_{1.1}$	0.015	60.459	0.000
	$X_{1.2}$	0.022	38.585	0.000
	$X_{1.3}$	0.018	49.324	0.000
	$X_{1.4}$	0.018	49.683	0.000
Effort Expectancy	$X_{2.1}$	0.022	40.313	0.000
	$X_{2.2}$	0.017	53.517	0.000
	$X_{2.3}$	0.028	29.930	0.000
Social Influence	$X_{3.1}$	0.016	54.687	0.000
	$X_{3.2}$	0.013	71.348	0.000
	$X_{3.3}$	0.011	77.739	0.000
	$X_{3.4}$	0.025	32.498	0.000
Facilitating Conditions	$X_{4.1}$	0.026	33.180	0.000
	$X_{4.2}$	0.016	56.746	0.000
	$X_{4.3}$	0.016	57.024	0.000
Hedonic Motivation	$X_{5.1}$	0.018	47.492	0.000
	$X_{5.2}$	0.015	60.650	0.000
	$X_{5.3}$	0.015	57.145	0.000
	$X_{5.4}$	0.013	71.972	0.000
Price Value	$X_{6.1}$	0.018	49.677	0.000
	$X_{6.2}$	0.017	51.979	0.000
	$X_{6.3}$	0.014	63.040	0.000
Habit	$X_{7.1}$	0.013	69.894	0.000
	$X_{7.2}$	0.017	50.971	0.000
	$X_{7.3}$	0.017	53.466	0.000
	$X_{7.4}$	0.014	64.177	0.000
Behavioral Intention	$Y_{1.1}$	0.011	83.120	0.000
	$Y_{1.2}$	0.009	99.481	0.000
	$Y_{1.3}$	0.012	73.314	0.000
Use Behavior	$Y_{2.1}$	0.013	70.395	0.000
	$Y_{2.2}$	0.011	79.651	0.000
	$Y_{2.3}$	0.016	56.896	0.000
	$Y_{2.4}$	0.013	64.970	0.000

Data source: processed results from smartPLS

Based on Table 4, the results of the indicator significance test (outer loading) show that all indicators for each latent variable have T-statistics values much greater than the critical value of 1.96 and p-values = 0.000 (less than 0.05). This indicates that all indicators used in this study have a significant effect on their respective latent constructs. In addition, the standard deviation values for each indicator are relatively small (ranging from 0.011 to 0.028), suggesting that the estimation results are stable and there are no major deviations in the measurement model. Thus, these results reinforce the findings of the convergent validity test, where all indicators are proven to be statistically valid, having significant outer loading values, t-statistics > 1.96, and p-values < 0.05. This confirms that all items in the research instrument are capable of consistently and accurately measuring their respective latent variables.

3.2.2. Hypothesis Testing of the Structural Model (Inner Model)

The results of the structural model hypothesis testing (inner model) using the bootstrapping technique in SmartPLS provide the t-statistics and p-values for each hypothesized relationship between latent variables. These values are used to determine whether the proposed hypotheses are statistically significant, with the criteria of t-statistic > 1.96 and p-value < 0.05 indicating a significant relationship. The detailed results of this analysis are presented in Table 5 below.

Table 5. Results of Hypothesis Testing for the Structural Model

Latent Variable	Standard deviation	t-statistics	p- values
BI -> UB	0.035	22.414	0.000
EE -> BI	0.040	4.562	0.000
FC -> BI	0.037	4.650	0.000
FC -> UB	0.038	1.583	0.114
HM -> BI	0.039	5.096	0.000
HT -> BI	0.037	5.318	0.000
HT -> UB	0.026	4.346	0.000
PE -> BI	0.040	6.123	0.000
PV -> BI	0.044	3.406	0.001
SI -> BI	0.038	3.477	0.001

Data source: processed results from smartPLS

Based on Table 5, the results of the structural model (inner model) testing indicate that most of the relationships among constructs in the UTAUT 2 model show significant effects, as reflected by t-statistics values greater than 1.96 and p-values less than 0.05. Specifically, the variable Behavioral Intention (BI) has a significant effect on Use Behavior (UB), with t-statistics = 22.414 and p-values = 0.000, meaning that the higher an individual's behavioral intention, the greater their tendency to actually use TikTok Shop. Furthermore, the variables Effort Expectancy (EE), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HT), Performance Expectancy (PE), Price Value (PV), and Social Influence (SI) all have significant effects on Behavioral Intention (BI), with T-statistics values exceeding 1.96 and P-values < 0.05.

However, there is one non-significant relationship, namely Facilitating Conditions (FC) → Use Behavior (UB), with t-statistics = 1.583 and p-value = 0.114, indicating that facilitating conditions do not have a direct influence on the actual use behavior of TikTok Shop. This suggests that while technological support and infrastructure are important, their influence on usage behavior is indirect, primarily mediated through behavioral intention.

Overall, these results demonstrate that the structural model developed in this study has strong empirical support. Factors such as effort expectancy (EE), performance expectancy (PE), hedonic motivation (HM), habit (HT), price value (PV), and social influence (SI) play crucial roles in shaping behavioral intention (BI), which in turn drives use behavior (UB) of TikTok Shop users in Ambon City.

These results are broadly consistent with prior empirical applications of UTAUT2 in consumer technology and social commerce settings, where performance expectancy and effort expectancy typically emerge as core utilitarian beliefs that strengthen behavioral intention, while social influence captures normative pressures that are especially salient in highly networked platforms. The significant roles of hedonic motivation and habit also align with UTAUT2-based evidence showing that enjoyment-driven consumption and repeated prior use are central in entertainment-oriented, mobile-first environments, often making intention and usage more affective and routine than purely instrumental. Likewise, the effect of price value reflects findings from digital commerce studies indicating that users' intention increases when the perceived benefits of convenience, deals, and transaction efficiency outweigh perceived costs. Taken together, the strong BI → UB linkage mirrors the dominant pattern reported across technology acceptance and social commerce research, reinforcing the view that, for platforms such as TikTok Shop, actual usage is primarily channeled through intention shaped by perceived usefulness, ease of use, social cues, enjoyment, habitual tendencies, and value considerations.

4. CONCLUSION

Based on the analysis using the UTAUT 2 model with the SEM-PLS approach, this study successfully identified the factors influencing behavioral intention and use behavior in the use of TikTok Shop in Ambon City. The results indicate that most of the relationships among constructs in the model are significant. The variables performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit were found to have positive and significant effects on behavioral intention. This means that the higher the users perceptions of usefulness, ease of use, social influence, facilitating conditions, enjoyment, price value, and habit, the stronger their intention to shop on TikTok Shop. Furthermore, behavioral intention has a significant effect on use behavior, indicating that behavioral intention serves as the primary driver of actual usage of TikTok Shop among users in Ambon City. The variable habit also has a direct effect on use behavior, while facilitating conditions do not have a significant direct effect on actual use behavior. This suggests that technical support and infrastructure factors play an indirect role, primarily by enhancing behavioral intention rather than directly influencing usage. The R^2 value of 0.753 for behavioral intention and 0.817 for use behavior demonstrates that the model possesses strong predictive capability, indicating that the UTAUT 2 constructs effectively explain user behavior in the context of social commerce. Overall, the findings strengthen the relevance of the UTAUT 2 model in explaining technology acceptance on social media–based shopping platforms, while also providing practical implications for digital business practitioners to optimize user experience and marketing strategies tailored to the characteristics of consumers in eastern Indonesia, particularly Ambon City.

Acknowledgments

The authors would like to express their sincere gratitude to the respondents in Ambon City who participated in this research and to the academic community of Institut Teknologi Sepuluh Nopember (ITS) for their valuable support throughout the completion of this study. Special thanks are extended to the Interdisciplinary School of Management and Technology and the

Faculty of Science and Data Analytics, ITS, for providing academic guidance and access to research facilities.

Funding Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. Funding statement: The authors state no funding involved.

Author Contributions Statement

Rizki Fitriani Muin contributed to the conceptualization, methodology, data curation, formal analysis, software implementation, original draft writing, and visualization of the research. Bambang Widjanarko Otok provided supervision, validation, project administration, resources, and contributed to the review and editing of the manuscript. Both authors discussed the results, collaborated throughout the research process, and approved the final version of the manuscript.

Conflict of Interest Statement

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

Informed Consent

All participants involved in this study were informed about the objectives and procedures of the research prior to their participation. Informed consent was obtained from all individuals included in the study, ensuring their voluntary participation and the confidentiality of their responses throughout the research process.

Ethical Approval

The research involving human participants was conducted in accordance with relevant national regulations and institutional policies, following the principles of the Helsinki Declaration. The study protocol was reviewed and approved by the Institutional Review Board of Institut Teknologi Sepuluh Nopember (ITS). All participants provided informed consent prior to participation.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data contain information that could compromise the privacy of research participants and are therefore not publicly available.

REFERENCES

[1] F. Ayu, C. Kamila, and R. D. Utomo, "Exploring Live Selling in Social Commerce: A Systematic Review of Engagement Metrics and Sales Methods," *JDBIM (Journal of Digital Business and Innovation Management*, vol. 4, no. 1, pp. 1–21, 2025, doi: 10.26740/jdbim.v4i1.66683.

[2] N. Huda, Dyah, A. Rani, S. E. Bhima, and Y. Adhinegara, "Digital Economy Outlook 2025," 2024. [Online]. Available: www.celios.co.id

[3] 2020 5, "Renewable Energy INVESTMENT OPPORTUNITIES IN KOREA Ringkasan Eksekutif."

[4] G. Dash and J. Paul, "CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting," *Technol Forecast Soc Change*, vol. 173, Dec. 2021, doi: 10.1016/j.techfore.2021.121092.

[5] M. A. Ashraf and H. Ahmed, "Approaches to Quality Education in Tertiary Sector: An Empirical Study Using PLS-SEM," *Educ Res Int*, vol. 2022, 2022, doi: 10.1155/2022/5491496.

[6] W. Zhang, B. Wang, and L. Zhou, "Evaluation and Improvement of English-Speaking Instruction Based on PLS-SEM and Intelligent Speech System," *Mobile Information Systems*, vol. 2022, 2022, doi: 10.1155/2022/1081327.

[7] D. J. Lee, "Bootstrap tests for structural breaks when the regressors and the serially correlated error term are unstable," *Bull Econ Res*, vol. 73, no. 2, pp. 212–229, 2021, doi: 10.1111/boer.12243.

[8] F. Magno, F. Cassia, and C. M. Ringle, "A brief review of partial least squares structural equation modeling (PLS-SEM) use in quality management studies," *TQM Journal*, vol. 36, no. 5, pp. 1242–1251, 2024, doi: 10.1108/TQM-06-2022-0197.

[9] S. Demir and M. Uşak, "Analyzing the Implementation of PLS-SEM in Educational Technology Research: A Review of the Past 10 Years," *Sage Open*, vol. 15, no. 2, pp. 1–23, 2025, doi: 10.1177/21582440251345950.

[10] A. S. Al-Adwan and R. M. S. Jafar, "Breaking into the black box of consumers' perceptions on metaverse commerce: An integrated model of UTAUT 2 and dual-factor theory," *Asia Pacific Management Review*, vol. 29, no. 4, pp. 477–498, Dec. 2024, doi: 10.1016/j.apmrv.2024.09.004.

[11] R. Farhat, Q. Yang, M. A. O. Ahmed, and G. Hasan, "E-Commerce for a Sustainable Future: Integrating Trust, Product Quality Perception, and Online-Shopping Satisfaction," *Sustainability (Switzerland)*, vol. 17, no. 4, Feb. 2025, doi: 10.3390/su17041431.

[12] O. Carvache-Franco, J. Loaiza-Torres, C. Soto-Montenegro, M. Carvache-Franco, and W. Carvache-Franco, "The risks perceived by the consumer in the acceptance of electronic commerce. A study of Bolivia," *PLoS One*, vol. 17, no. 11 November, Nov. 2022, doi: 10.1371/journal.pone.0276853.

[13] K. Tamilmani, N. P. Rana, and Y. K. Dwivedi, "Consumer Acceptance and Use of Information Technology: A Meta-Analytic Evaluation of UTAUT2," *Information Systems Frontiers*, vol. 23, no. 4, pp. 987–1005, Aug. 2021, doi: 10.1007/s10796-020-10007-6.

[14] M. Maulida, Y. Sari, and S. Rohmah, "Influence of Electronic Word Of Mouth (e-WOM), Hedonic Motivation, and Price Value On Consumer's Purchase Intention Using Social Commerce 'TikTok Shop,'" in *2022 7th International Conference on Informatics and Computing, ICIC 2022*, Institute of Electrical and Electronics Engineers Inc., 2022. doi: 10.1109/ICIC56845.2022.10007012.

[15] N. Putri, Y. Prasetya, P. W. Handayani, and H. Fitriani, "TikTok Shop: How trust and privacy influence generation Z's purchasing behaviors," *Cogent Soc Sci*, vol. 10, no. 1, 2023, doi: 10.1080/23311886.2023.2292759.

[16] D. P. Pradnyamitha and A. F. Maradona, "Actual Purchase on TikTok Live Streaming Commerce: An Analysis of Utilitarian Shopping Value and Attitude Toward Electronic Live Streaming," 2024. [Online]. Available: http://ijsoc.goacademica.com

[17] R. Aprianto, N. E. Retno Wuryandari, and . R. I., "The UTAUT 2 to Explains How Tiktok Shop Application Affects Consumers' Behavior," KnE Social Sciences, Jul. 2023, doi: 10.18502/kss.v8i12.13698.

[18] C. Razafinandrasana and D. Tamara, "Exploring The Factors Which Impact Impulse Purchase Intention in TikTok Live Streaming Shopping in Indonesia," *International Journal of Electronic Commerce Studies*, vol. 15, no. 2, pp. 21–62, 2024, doi: 10.7903/ijecs.2279.

[19] F. Schuberth, Y. Rosseel, M. Rönkkö, L. Trinchera, R. B. Kline, and J. Henseler, "Structural Parameters under Partial Least Squares and Covariance-Based Structural Equation Modeling: A Comment on Yuan and Deng (2021)," *Structural Equation Modeling*, vol. 30, no. 3, pp. 339–345, 2023, doi: 10.1080/10705511.2022.2134140.

[20] R. Aprianto, N. E. Retno Wuryandari, and . R. I., "The UTAUT2 to Explains How Tiktok Shop Application Affects Consumers' Behavior," *KnE Social Sciences*, vol. 2023, no. January 2022, pp. 493–508, 2023, doi: 10.18502/kss.v8i12.13698.

[21] M. Sarstedt and O. I. Moisescu, "Quantifying uncertainty in PLS-SEM-based mediation analyses," *Journal of Marketing Analytics*, vol. 12, no. 1, pp. 87–96, 2024, doi: 10.1057/s41270-023-00231-9.

[22] R. Aprianto, N. E. Retno Wuryandari, and . R. I., "The UTAUT2 to Explains How Tiktok Shop Application Affects Consumers' Behavior," *KnE Social Sciences*, Jul. 2023, doi: 10.18502/kss.v8i12.13698.

[23] "Tampilan Analisis Faktor Penerimaan TikTok Shop berdasarkan Model UTAUT2 dan SCC".

[24] T. T. Nguyen and L. T. T. Nguyen, "E-commerce applications: A study of customers' behavioral intentions and behaviors of using these applications towards online shopping," *Journal of Infrastructure, Policy and Development*, vol. 8, no. 10, 2024, doi: 10.24294/jipd.v8i10.8032.

[25] Akhmad Riadi, Michelle Angelina Halim, Shafa Raissalya Khairunnisa, and Bunyaworakul Chanya, "An empirical study of the impact of live streaming quality on purchase intention in Indonesia," *International Journal of Management & Entrepreneurship Research*, vol. 7, no. 8, pp. 581–592, Aug. 2025, doi: 10.51594/ijmer.v7i8.1979.

[26] M. Sarstedt, J. F. Hair, M. Pick, B. D. Liengaard, L. Radomir, and C. M. Ringle, "Progress in partial least squares structural equation modeling use in marketing research in the last decade," *Psychol Mark*, vol. 39, no. 5, pp. 1035–1064, 2022, doi: 10.1002/mar.21640.