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Analysis Of Factors That Affect Consumer Behavioral Intentions On E-Commerce Platforms Using The Utaut2 Model

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ABSTRACT
The research aims to formulate an empirical model to identify factors that influence consumer behavior in the use of technology. In addition, the research seeks to broaden the understanding of the adaptation of technology use with contextual variables. The research is supported by sample data from 115 respondents who use e-commerce platforms. Empirical analysis uses a Partial Least Square Structural with an Equation Modelling (PLS-SEM). Data processing with the Smart-PLS software application. The results of the reflective measurement model test show the loading factor value (>0.70), cross loading (>0.70), average variance (AVE>0.50). While the reliability of Cronbach's alpha, reliability rho-A and rho-C (>0.70). The structural equation model test can be proven that the determination factors can influence consumer behavior in the use of technology. Meanwhile, related to moderation and interaction effects, the results of the research prove that there is no significant difference between gender and income level on the behavior of e-commerce platform users. The same thing is also related to the interaction effect, there is no significant difference. The increase in technology use behavior is only determined directly and non-moderation

Keywords : E-commerce, behavioral intention, use behavior, UTAUT2.

1. INTRODUCTION:

Over the past twenty years, there has been an exponential development in the world of mobile and wireless communications that has provided new business opportunities that can be implemented in everyday life. This can be seen as more and more users using mobile as a means of business activities, one of which is online sales and purchases of products or digital marketing. This has resulted in a shift in the way products and services are marketed by utilizing technology from previously using conventional marketing methods.

With this change, many smartphone users who were previously only for phone calls and messages, are now more than that, which allows them to make transactions such as in digital payments, online shopping, transfers, marketing services through mobile phones and so on. The phenomenon of using mobile devices for business affairs is generally known as mobile commerce or e-commerce.

E-commerce applications as a service mechanism, allow to improve competence, provide new opportunities to sell goods and services and increase the efficiency and effectiveness of the supply chain [1]. E-commerce businesses introduce opportunities to compete in the global market with innovative information technology and furthermore, through relationships with partners and customers.

E-commerce is basically defined as a business model that provides consumers with the opportunity to make transactions through mobile devices [2], [3]. Given the ever-evolving variety of e-commerce platforms, many definitions of e-commerce emerge covering the specific context of various applications. Therefore, this study will mainly focus on e-commerce that supports product transactions through mobile devices referring to some previous studies [3], [4], [5].

Clear e-Commerce has a number of advantages today especially in terms of providing local, universal and Customized [2], [5]. Today, many researchers see E-commerce is one of the fastest-growing business models, although a few years ago, e-commerce was seen as still in its infancy with little results in various places. In addition, the pace of e-commerce adoption and growth varies across countries, with very low rates especially in developing countries [2]. According to Laudon and Traver (2016), e-commerce is one of the important pillars in business. Rapid transition to an e-commerce-based economy driven by internet companies: Google, Amazon, Apple, Facebook, Yahoo, Twitter, and YouTube.

In general, e-commerce refers to transactions that are done digitally and includes all types of transactions that are powered by digital technology. This means that any commercial interaction that takes place on the internet will always involve the transfer of value, such as money, that takes place between organizations or individuals to purchase goods and services. Value transfer is essential to understand the limitations of the platform. Without value transfer, online trading would not happen. According to Laudon and Traver (2016). Progress E-commerce is acquired thanks to the advancement of internet technology. Without internet technology, e-commerce businesses would be almost impossible. Internet technology facilitates advances in security and payment aspects, marketing and advertising strategies, financial applications, media distribution, and commerce-to-business and retail. Technological adaptation has revolutionized traditional business rules (from offline-to-online) and created new ways in business competition. Therefore, the digital transformation of the economy should be used as an alternative solution as an engine of new economic growth [7].

The study of the acceptance and use of technology has attracted the attention of researchers for decades. User acceptance of new innovative technologies is often described as one of the most prevalent areas of research in the contemporary technology literature. Studies in this field produce various models that can explain a person's desires and intentions using information system technology innovations.

In connection with this explanation, an evaluation approach is needed as a solution. Because of its emphasis on evaluating user acceptance of e-commerce, the integrated model of technology use and acceptance is considered the most appropriate. One of the widely used models to understand the acceptance of technology is UTAUT (Unified Theory of Acceptance And Use of Technology) developed by Venkatesh et al. (2003) To give an understanding of the acceptance of technology, Venkatesh et al. (2003) Setting the goal of developing the theory of technology acceptance by integrating the main constructs: performance expectacy, Effort expectancy, social influence and facilitating conditions which predicts bhavioral intentions. UTAUT is applied to e-commerce platforms using four main constructs and additional trust perceptions and cost perceptions [9]. Other studies also sought to identify structural models related to the implementation of e-commerce in Tanzanian SMEs [10]. While Sim et al. (2021) extends the UTAUT model by adding two variables: the level of trust in the vendor (TIV) and the perception of the effectiveness of the e-commerce institutional mechanism (PEEIM) [7].

UTAUT's theoretical model in the acceptance and use of technology is actually determined by behavioral intentions. The perceived possibilities of adapting to technology depend on the direct effects of four main constructs, namely performance expectations, effort expectations, social influences, and supportive conditions. The predictor effect was moderated by age, gender, experience, and voluntariness of use [8].

Next, we adopted the UTAUT2 model which is an extension of the UTAUT which Involve the moderation variables: gender and income to measure how these moderation variables affect the relationship between other variables. We discuss the research objectives of the UTAUT2 model as well as previous studies on the use of technology in various contexts such as the use of mobile devices [2], [3], [4], [5], mobile payments [12], [13], e-invoicing services [14], online insurance [15], online banking [12].

The rest of this study is arranged as follows: the second part is literature review and hypothesis development; methodology is given in the third part; the fourth part is the results of empirical studies; the fifth is the discussion and the sixth is the conclusion and implications. The analysis method used Partial Least Squares Structural Equations Modeling (PLS-SEM) application Smart-PLS 4.1.0.9.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Literature Review

Technology acceptance research has yielded a wealth of evidence on user behavior related to technology adoption. Many theories have been introduced to understand the acceptance of technology, which cumulatively explains the 40 percent variance in technological use behavior intentions [16], [17]. The integrated model of the acceptance and use of technology is one of the most superior streams of information systems research. Several theoretical models have been developed from the theories of psychology and sociology.

The UTAUT integrated model is a combination of eight theories of understanding the adoption and use of technology such as Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivation Model (MM), Theory of Planned Behavior (TPB), Combined (C-TAM-TPB), Model of PC Utilization (MPTU), Innovation Diffusion Theory (IDT) and Social Cognitive Theory (SCT).

These models are rooted in different disciplines, which limit the application of these theories to specific contexts [8], [18]. For example Theory of Planned Behavior (TPB) and Theory of Reasoned Action (TRA), both offer a psychological perspective on human behavior by examining variables such as behavioral control, attitudes, and subjective norms [19]. Instead Innovation Diffusion Theory (IDT) Focusing on the innovation factors that determine behavior in technology adoption [20]. In addition, the models have different perspectives that reflect the types of variables such as subjective norms, motivations, attitudinal factors related to technological performance, experience, and supportive conditions [8] [19].

The MPCU has very narrow implications, since the model only includes the factors underlying the use of PC computers on job suitability, complexity, long-term consequences, facilitating conditions and social factors [21]. The perspective of the psychology of technology acceptance behavior is represented by the Motivation Model (MM) which suggests that technology adoption and use behavior can be explored through user motivation [22].

Type UTAUT has the ability to achieve 70 percent variance in behavioral intent [8], which offers more powerful predictive power compared to other models. The interactive effects of some constructs with personal and demographic factors show the complexity of the technology acceptance process, which depends on the individual's age, gender, and experience [8].

Venkatesh, Thong, and Xu (2012) combines the relationship of UTAUT with a new construct that expands the application of UTAUT to the consumer context. Through a two-stage online survey of 1,512 mobile Internet consumers, the research results showed the intention to behavioral (74 percent) and use technology (52 percent). The proposed expansion is critical to making the predictive validity of UTAUT.

Conducting research on the application of mobile banking, which measures how motivated customers are to adopt technology. In the context of Jordan, the adoption rate of mobile banking is very low and very little research has examined issues related to mobile banking. The results of the study showed that behavioral intentions were significantly and positively influenced by performance expectations, business expectations, hedonistic motivation, price values, and trust. The research also aims to provide guidelines for banks in Jordan [12].

The same thing is done [23] who analyzes Internet Banking Acceptance Dimensions. Empirical findings prove a significant positive contribution of hedonistic motivation (HM) and trust (T). Along with this, hedonistic motivation (HM), trust (T), self-efficacy (SE) and habit (H) showed a positive impact on behavioral intentions (BI). Finally, the results of the study revealed that habits (H) and behavioral intentions (BI) have a significant positive impact on users' intentions to adopt internet banking.

The study conducted Kabra et al. (2017) seeks to integrate personal innovations specific to the IT domain with the UTAUT model [7]. This study investigated the impact of business expectations, supportive conditions, social influences, performance expectations, and trust in technology on behavioral intentions, with personal innovation as a moderator in the context of HSCM. UTAUT constructs, performance expectations and business expectations have a positive and significant effect on behavioral intentions to adopt information technology.

Empirical studies conducted Chen et al. (2021) showing performance expectations and social influence have a positive effect on the purchase intention of an e-commerce platform [7]. The study contributes by providing a better explanation among consumers in Mainland China in adopting e-commerce platforms to buy fresh food. This study is useful for e-commerce platform developers and fresh food retailers in helping to structure online platform promotions.

Some of the limitations of the above studies, then Venkatesh et al. (2012) expanding UTAUT, named UTAUT2 (Unified Theory of Acceptance and Use of Technology 2). The purpose of the UTAUT2 model is first, to represent a comprehensive framework for examining the acceptance of the technology. It is designed to provide greater precision in explaining user behavior [18]. The second proposes a model of consumer technology acceptance behavior, in contrast to UTAUT, which was developed to examine technology in organizational settings.

To meet these goals, Venkatesh et al. (2012) extending the UTAUT model with new construction into the original model to adapt to the context of technology use. This kind of approach, theoretically to predict the acceptance of technology, is driven and supported by previous research [8], [26]. In addition to advancing the technology acceptance literature, UTAUT2 aims to achieve a broader generalization by addressing the private user segment.

As explained at the beginning, some of the construct variables used in the Unified Theory of Acceptance and Use of Technology (UTAUT2) study are described as follows:

Performance expectancy in the sense that So far where one believes that the use of the system helps to achieve improved performance Venkatesh et al. (2003). These performance expectations are based on the construct of the acceptance model (TAM), combination (C-TAMTPB), motivation (MM), PC utilization (MPCU), diffusion of innovation (IDT) and social cognitive (SCT). Performance expectations are a strong predictor of behavioral intentions in technology acceptance [27].

Effort expectancy in the sense that convenience associated with use technology. Business expectations are built from the perception of ease of use and complexity, driven by the influence of TAM, MPCU, IDT theories which have similarities in measurement scales [8].

Social Influence, in the sense that A person or individual feels that others will believe that he or she should use new technology. These social influences are similar to the subjective norms used in TRA, TPB, CTAMTPB, MPCU and IDT, suggesting that one's behavioral intentions will be adjusted to other people's perceptions of them. The effect of this social influence is significant when using technology [8].

Facilitating conditions an individual's belief that infrastructure is available in support of the use of technology. These facilitating conditions are formed from compatibility, perceived behavioral control and facilitating condition constructs from the influence of TPB, C-TAMTPB, MPCU and IDT theories. Facilitating conditions have a direct effect on the behavioral intention of technology acceptance [8].

The UTAUT2 model postulates the use of individual technology supported by three additional constructs, hedonistic motivation, habits and price values, perceived and habits, which are moderated by gender, age and experience. The three additions are:

Hedonic motivation as a pleasure derived from the use of technology and proven to play an important role in determining the use of technology [18]. The inclusion of this hedonistic construct is justified by the findings of previous research in the domain of information systems and marketing that found that hedonists are perceived as a significant predictor of the use of technology.

Habits asto what extent people tend to behave automatically. This construct is operated based on previous research that has brought the perspective of automation. Habits are hypothesized to have direct and indirect effects on actual use through behavioral intent [18].

Perceived Value in the sense of a consumer compromise between the perceived benefits of the application and the cost of using it [18]. The relationship between perceived value and intention to use suggests that users consider the benefits of using technology to be more important than monetary costs.

Hypothesis Development

Referring to the theoretical foundation of Sub-chapter 2.1. it can be shown that the integrated model of the use and acceptance of UTAUT2 technology is influenced by determination and moderation factors. However, the signs of a (positive/negative) relationship between determination and moderation to behavioral intentions cannot be predicted in advance, so empirical testing is necessary.

1. *Performance Expectancy* (PE)

Technology users believe that in the use of information technology will help achieve gains in performance [8]. In this case, the expectations Performance is the level of benefit obtained in a particular activity due to the use of technology. Performance expectations refer to consumers' confidence that their purchases from new e-commerce platforms improve shopping efficiency. Several studies have proven that performance expectations have consistently been found to have a significant effect on behavior using technology [8], [28], [29].

Deep In the context of online shopping consumers, performance expectations reveal the benefits consumers get when using technology such as the ability to search for product information, compare prices and track orders for packages shipped [30]. Performance expectations are considered to be the dominant predictor of behavioral intention in using technology as referred to by the UTAUT2 model. The greater the increase in efficiency of using e-commerce platforms, tends to make consumers use the platform. Therefore, we propose the following hypothesis:

H-1: *Performance expectations have a significant effect on the behavioral intentions of using e-commerce platforms.*

2. *Effort Expectancy* (EE)

The ease of use of technology was initially introduced by Davis (1989) in the technology acceptance model as the main factor of technology acceptance and is evidenced in several UTAUT2 models which show that business expectations are a significant predictor [8], [18]. The UTAUT model defines business expectations as convenience related to the use of technology. Customers tend to choose technologies that require little effort to use efficiently.

Several studies have consistently found that business expectations have a significant effect on technology user behavior [12], [31]. Studies in banking confirm that business expectations are a positive indicator of behavioral intentions for consumers in using mobile banking [32]. Business expectation factors shows that there are benefits that mobile banking users feel, more specifically, speeding up banking transactions. The convenience felt because of the availability of financial services can be done remotely 24/7 through internet banking. Next, the following hypotheses are proposed:

H-2: *Business expectations have a significant effect on the behavioral intent of using e-commerce platforms.*

3. *Social Influence* (SI)

Social influence is defined as the extent to which an individual feels that others are using a new technological system [8]. Social influences have a more pronounced impact on behavior in the early stages of technology adoption. This has to do with the extent to which other people think that users should try online services [33]. The concept of social influence refers to the following ideas: the subjective norms of the Theory of Reasoned Action TRA (Fishbein and Ajzen, 1975) and the Theory of Planned Behavior TPB [34], social factors of MPCU [21].

In many studies using the UTAUT2 model, social influencing factors have been shown to have a significant impact on behavior. Social influence expresses consumer adoption in the use of technology that is strongly influenced by the people around (family and friends). In the current context, social influence refers to whether family members (friends) are more likely to buy goods or products on e-commerce platforms. Therefore, we propose the following hypothesis:

H-3: *Social influence have a significant effect on the behavioral intentions of using e-commerce platforms.*

4. *Facilitating Conditions* (FC)

The condition that facilitates is a person's perception of the assistance of the equipment needed to carry out the intention behavior [18]. Previous research has shown that the condition of facilities in banking to build a positive attitude towards banking [35]. Dwivedi et al. (2019) estimating the conditions that facilitate influencing attitudes to technology positively. The facilities provided can correlate with performance expectations that have the potential to lead to a positive attitude. Banking and third-party applications provide the advanced architecture needed to provide a seamless experience on m-payment users [37]. Thusi and Maduku (2020) finding facilitates conditions can improve behavior [33]. The use of online retail banking is positive, a finding that can be extended to the context of m-payment. From transfers to digital payments, the m-payment application has integrated features to build a positive attitude towards the m-payment system. Thus, this hypothesis states:

H-4a: *Facilitating conditions have a significant effect on the behavioral intention of using e-commerce platforms.*

Furthermore, online banking and m-payment applications will be able to generate a series of related terms under various headings such as SI technology infrastructure, IT architecture, IT archetypes and information technology functions [33]. Overall all this is to facilitate which can provide greater benefits to the users. Kabra et al. (2017)

proving that by facilitating technology can build acceptance of positive behavior. This can be considered applicable in all cases of m-payment, as the m-payment banking application is more dynamic and can provide better facilities. Therefore, this hypothesis is proposed as follows:

H-4b: *Facilitating conditions have a significant effect on the actual usage behavior of the e-commerce platform.*

5. *Hedonic Motivation* (HM)

Hedonistic motivation (conceptualized as a form of perceived pleasure) is defined as pleasure or pleasure derived from the use of technology, and has been shown to play an important role in determining the acceptance and use of technology [39].

Hedonistic motivation is an intrinsic value that cognitively absorbs users to online platforms. A pleasant experience and inherent fun and motivating for users to continue using technology-based services [23]. They highlight that clients' trust in car banking is determined by hedonistic motivational factors. The client's feelings and emotions are the main prerequisites for the view of technology use. Therefore, we add hedonistic motivation as a predictor of consumer behavior intent to use a technology. Thus, the following hypotheses are proposed:

H-5: *Hedonic motivation has a significant effect on the behavioral intentions of using e-commerce platforms.*

6. *Habits* (HA)

Habits as conceptualized in the research model Kim and Malhotra (2005) and Venkatesh et al. (2003) reflects the opportunities for the use of technology and is usually operationalized as an experience from the initial use of a technology [8] [40]. Habits are automated behaviors that are observed following learning accumulated after the use of technology. In other words, habits are behaviors learned in response to subconscious stimuli that lead to pleasurable outcomes.

Yen and Wu (2016) proposes a model that combines three external variables, namely: perceived pleasure, perceived mobility and personal habits. Technology acceptance model (TAM) to assess antecedent influencing behavioral intent in the continuous use of MFS (mobile Financial Services). Their findings reveal that habits are the main antecedent that affects the intention to behave in the use of technology.

H-6: *Habits have a significant effect on the behavioral intentions of using e-commerce platforms.*

7. *Perceived Value* (PV)

The price value may have an influence on the use of technology. In marketing research, (monetary) price is usually conceptualized along with the quality of the product or service in determining the product [42]. Mobile banking-related costs are generally due to the need for a mobile phone, internet connection, and any additional costs in the use of technology applications.

We follow the definition that a price value is the consumer's cognitive exchange between the perceived benefits of the platform's application and the monetary value. Empirical evidence confirms that consumers are more likely to adopt services of comparable value [43]. In their paper, they anticipate the possibility of higher adoption of mobile banking for consumers with the price value of the service. Therefore, here are the proposed hypotheses:

H-7: *Perceived value has a significant effect on the behavioral intention of using e-commerce platforms.*

3. METHOD

Participants

The survey is distributed through a Google Form questionnaire. All participants who participated in the study were volunteers. In face-to-face contact, participants are informed of their right to participate in or withdraw from the survey at any time during the study orally and by reading and understanding the research ethics and the primary objectives of the study. The online survey explains the purpose of the study and the participants' right to participate.

The distribution of survey questionnaire answers is calculated based on the type of questions of each indicator. The recapitulation of the distribution of participants shows several indicators with many participant assessments on a Likert scale from 1 to 5 where the answer items are combined to form a score that presents the attitudes, opinions and perceptions of participants in the use and acceptance of technology. After filtering out missing data and duplicate responses, we gathered 115 participants.

Table 1. Demographic Data.

Information	Man			Woman	
	Frequency	Frequency (%)		Frequency	Frequency (%)
Gender	52	45,5%		63	54,8%
Tokopedia Shopee Income:	24 28	46,15% 53,85%		27 36	42.86% 57,14%
< 10 million	19	16,5%		96	83,5%
10 – 25 million	19	16,5%		96	83,5%
25 > million	14	12,2%		101	87,8%

Research Variables

Exogenous variables of the integrated model of acceptance of the use of technology include performance expectations, business expectations, social factors and facilitation conditions are adapted [8]. Based on the literature review, we developed the UTAUT2 model as an adaptive synthesis in the context of the acceptance and use of technology. Furthermore, additional constructs such as hedonic motivation [39], [40] and Clothes. Lastly, the price value is adapted from [42] used as an exogenous variable. The pricing structure may have a significant impact. Empirical evidence of short messaging services in China, cheaper prices [44].

The behavioral intention in the UTAUT2 model is one of the main variables of technology acceptance and use. In the UTAUT2 model, it is shown that behavioral intention and use behavior are influenced by several determinant factors.

For moderation variables What was observed were gender and income. Gender as a dummy variable (1/0) to see if there is a significant difference from gender moderation (female and male) in technology acceptance [8]. Furthermore, income is also used to see if there is a difference in technology acceptance based on the user's consumer income

4. RESULT AND DISCUSSION

RESULT

As shown in Table 2, the average indicator is 4.122 and ranges between 4 and 5. These findings show that the majority of respondents expressed very positive responses to the questions. Further the normal range of skewness-kurtosis values is ±1.96 (significance 0.05). Therefore, all indicator items are distributed normally (< ± 1.96). Specifically, the mean values of kurtosis are 0.0196 or range -0.935 and 1.915 and skewness -0.5253 or range -1.340 to -1.002. However, this method is not based on assumptions or conditions such as normal distribution and is free of symptoms of multicollinearity.

Table 2. Descriptive Statistics.

Indicators	Mean	Median	Min	Max	Standard Deviation	Kurtosis	Skewness
PE1	4.113	4.000	2.000	5.000	0.832	-0.139	-0.676
PE2	4.452	5.000	3.000	5.000	0.636	-0.445	-0.744
PE3	4.243	4.000	3.000	5.000	0.641	-0.667	-0.272
PE4	4.061	4.000	1.000	5.000	0.761	1.205	-0.704
EE1	4.209	4.000	2.000	5.000	0.692	-0.220	-0.466
EE2	4.217	4.000	1.000	5.000	0.755	1.915	-1.002
EE3	4.061	4.000	1.000	5.000	0.761	1.205	-0.704
SI1	4.209	4.000	2.000	5.000	0.692	-0.220	-0.466
SI2	4.452	5.000	3.000	5.000	0.636	-0.445	-0.744
SI3	4.235	4.000	2.000	5.000	0.677	-0.059	-0.500
FC1	4.113	4.000	2.000	5.000	0.832	-0.139	-0.676
FC2	4.130	4.000	2.000	5.000	0.764	-0.451	-0.465
FC3	4.243	4.000	3.000	5.000	0.641	-0.667	-0.272
FC4	4.200	4.000	1.000	5.000	0.771	1.100	-0.825
HM1	3.974	4.000	2.000	5.000	0.728	-0.003	-0.371
HM2	3.739	4.000	1.000	5.000	0.970	-0.010	-0.669
HM3	3.496	4.000	1.000	5.000	0.810	-0.660	-0.298
HA1	4.243	4.000	3.000	5.000	0.641	-0.667	-0.272
HA2	4.200	4.000	3.000	5.000	0.635	-0.609	-0.198
HA3	4.243	4.000	3.000	5.000	0.641	-0.667	-0.272

Indicators	Mean	Median	Min	Max	Standard Deviation	Kurtosis	Skewness
PV1	4.235	4.000	2.000	5.000	0.677	-0.059	-0.500
PV2	4.113	4.000	2.000	5.000	0.832	-0.139	-0.676
PV3	4.130	4.000	2.000	5.000	0.764	-0.451	-0.465
BI1	4.243	4.000	3.000	5.000	0.641	-0.667	-0.272
BI2	4.209	4.000	2.000	5.000	0.692	-0.220	-0.466
BI3	4.061	4.000	1.000	5.000	0.761	1.205	-0.704
USE1	4.061	4.000	1.000	5.000	0.761	1.570	-0.824
USE2	3.826	4.000	2.000	5.000	0.826	-0.402	-0.319
USE3	3.861	4.000	2.000	5.000	0.768	-0.367	-0.222
Observation, *N*	115						
Mean	4.122						

Measurement Model

After the PLS-SEM algorithm was carried out, the research design was tested by evaluating validity and reliability [45]. Convergent validity confirms whether each construct can be reflected by its own indicators to ensure the unidimensionality of the multi-item factor and eliminate unreliable indicators. In addition to the loading factor, the measurement must report validity and reliability. Table 3. Reporting on the loading factor, AVE and composite relation.

Composite reliability aims to see the consistency and stability of respondents in answering the questions contained in the questionnaire. The construct variable in this study is declared reliable if it has a composite reliability greater than 0.70 and Cronbach's alpha value of more than 0.60 [45], [46]. The main measurement criteria include reliability consistency (Cronbach's alpha, rho-A reliability, and rho-C reliability).

Table 3. Loading Factor, AVE and CR.

Construct	Items	Load Factor	AVE	Cronbach's Alpha	CR (rho-A)	CR (rho-C)
Performance Expectancy	PE1	0.729				
	PE2	0.732				
	PE3	0.873				
	PE4	0.790	0.614	0.793	0.830	0.863
Effort Expectancy	EE1	0.839				
	EE2	0.748				
	EE3	0.810	0.639	0.723	0.746	0.841
Social Influence	SI1	0.846				
	SI2	0.803				
	SI3	0.751	0.642	0.734	0.787	0.843
Facilitating Condition	FC1	0.818				
	FC2	0.768				
	FC3	0.766				
	FC4	0.809	0.625	0.802	0.814	0.870
Hedonic Motivation	HM1	0.811				
	HM2	0.724				
	HM3	0.873	0.648	0.751	0.864	0.846
Clothes	HA1	0.978				
	HA2	0.759				

Construct	Items	Load Factor	AVE	Cronbach's Alpha	CR (rho-A)	CR (rho-C)
	HA3	0.978	0.830	0.894	0.951	0.935
Perceived Value	PV1	0.841				
	PV2	0.864				
	PV3	0.851	0.726	0.813	0.824	0.888
Behavioral Intention	BI1	0.897				
	BI2	0.835				
	BI3	0.789	0.708	0.793	0.805	0.879
Use Behavior	USE1	0.835				
	USE2	0.818				
	USE3	0.837	0.689	0.777	0.790	0.869

The reliability of rho-C composites measures internal consistency by accounting for shared variances among items and errors in measurements. A high Rho-C indicates that the construct items are closely related to each other and measure the same basic construct. Meanwhile, the correlation between rho-A items is a measure of the average correlation between the items of a construct. This correlation gives an indication of how closely the items are related to each other. A low average inter-item correlation can indicate that the item is not strongly correlated and may not measure one basic construct.

Furthermore, AVE describes the magnitude of the diversity of the indicator variables contained in the construct. The evaluation then measures the validity of the convergence by calculating the AVE which is statistically if the one is greater than 0.5. This ratio illustrates that more than 50 percent of the variation of reflective indicators has been accommodated by the construct. In addition, AVE of 0.50 will also be better if the value is larger. If the total reliability value of the indicator is more than 0.70, then the results can be interpreted as having consistency or accuracy in the indicator so that the entire construct is declared valid.

Structural Equation Model

UTAUT2 Model (No Moderation)

We ran two separate models to test the integrated model of UTAUT2 (**without moderation**) and to test the model of UTAUT2 (**with moderation**). Figure 1., is the design structure of the UTAUT2 model without moderation; while the results of the UTAUT2 model estimation in the acceptance and use of technology are reported in Table 4.

Empirical research within the framework of the UTAUT model shows the following findings. Performance expectancy had a significant effect on the behavioral intention of using technology (β = 0.137; p-value 0.046). Effort expectancy had a significant effect (β = 0.537; p-value 0.000); Social influence had a positive effect (β = 0.082; p-value 0.069) and facilitating conditions had a significant effect (β = 0.039; p-value 0.046) to behavioral intention.

While the other three constructs, hedonic motivation had a significant effect (β = 0.325; p-value 0.007), habits with (β = 0.224; p-value 0.000) and perceived value had a significant negative effect (β = -0.357; p-value 0.000). Facilitating conditions for technology users (use behavior) had a positive effect (β = 0.412; p-value 0.000) and behavioural intention on technology user behavior had a positive effect (β = 0.360; p-value 0.000).

Table 4. UTAUT2 Hypothetical Path Coefficient (**Without Moderation**)

Path	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p Values	Confidence level	
					2.5%	97.5%
PE > BI	0.137**	0.069	1.999	0.046	0.004	0.275
EE > BI	0.537***	0.035	15.489	0.000	0.478	0.612
SI > BI	0.082*	0.045	1.816	0.069	0.011	0.165
FC > BI	0.039**	0.020	1.997	0.046	0.002	0.075
FC > USE	0.412***	0.091	4.497	0.000	0.228	0.587
HM > BI	0.325***	0.120	2.720	0.007	0.088	0.552
HA > BI	0.224***	0.058	3.896	0.000	0.116	0.341
PV > BI	-0.357***	0.068	5.268	0.000	-0.492	-0.221

BI > USE	0.360 ***	0.094	3.847	0.000	0.172	0.539
R-square	= 0.979	Behavioral intention				
R-square Adj.	= 0.977					
R-square	= 0.476	Use behavior				
R-square Adj	= 0.467					

Remarks: Bootstrapping path analysis on 5000 resample iterations. Significance level ***$p < 0.01$ ** $p < 0.05$ and * $p < 0.10$.

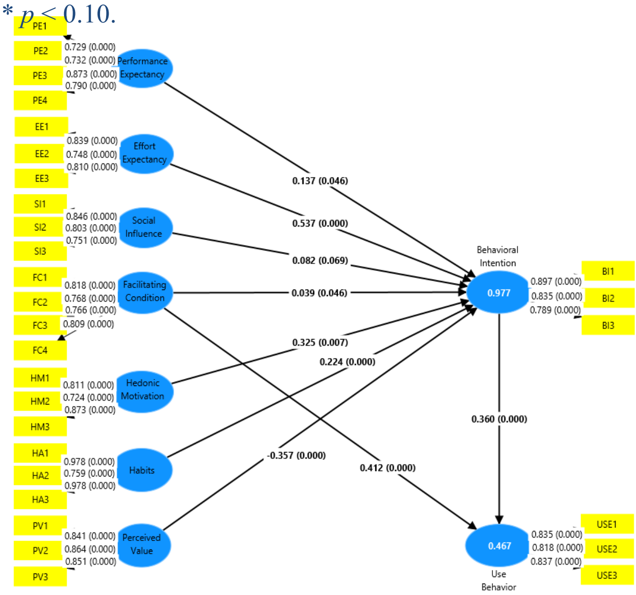

Figure 1. UTAUT2 Model Research Design (**Without Moderation**)

UTAUT2 Model (With Moderation)

The intervening variables described above are assumed to influence or moderate the relationship between constructs separated in the chain of cause and effect. It is possible to model interactions with other constructs where the hypothesis includes a direct (indirect) relationship with moderation and interaction. Figure 2. the research design of the UTAUT2 model (with moderation) and the estimated results are reported in Table 5.

Table 5. UTAUT2 Hypothesis Path Coefficient (**With Moderation**)

Hypothesis	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p values	Confidence level	
					2,5 %	97,5 %
PE > BI	0.106	0.254	0.416	0.678	-0.309	0.645
EE > BI	0.518 ***	0.152	3.413	0.001	0.201	0.779
SI > BI	0.214	0.185	1.157	0.248	-0.195	0.497
FC > BI	0.035	0.066	0.536	0.592	-0.071	0.176
HM > BI	0.479	0.360	1.331	0.183	-0.468	0.960
HA > BI	0.114	0.213	0.534	0.593	-0.130	0.647
PV > BI	-0.478 **	0.194	2.466	0.014	-0.773	-0.029
FC > USE	0.412 ***	0.091	4.502	0.000	0.235	0.597
BI > USE	0.360 ***	0.096	3.761	0.000	0.155	0.530
GENDER > BI	-0.047	0.146	0.321	0.748	-0.340	0.195
GENDER x PE > BI	0.437	0.574	0.761	0.447	-1.213	1.243
GENDER x EE > BI	0.124	0.336	0.370	0.711	-0.517	0.791
GENDER x SI > BI	-0.797 *	0.453	1.759	0.079	-1.142	0.551
GENDER x FC > BI	0.149	0.167	0.893	0.372	-0.235	0.422

Hypothesis	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p values	Confidence level	
					2,5 %	97,5 %
GENDER x HM > BI	-1.287	0.846	1.520	0.129	-2.024	1.359
GENDER x HA > BI	0.607	0.451	1.347	0.178	-0.814	1.015
GENDER x PV > BI	0.880 *	0.511	1.723	0.085	-0.750	1.259
INCOME > BI	-0.017	0.144	0.120	0.905	-0.245	0.265
INCOME x PE > BI	0.279	0.636	0.439	0.660	-1.226	1.220
INCOME x EE > BI	0.088	0.366	0.242	0.809	-0.746	0.771
INCOME x SI > BI	-0.376	0.574	0.656	0.512	-1.129	1.032
INCOME x FC > BI	0.133	0.205	0.646	0.518	-0.362	0.430
INCOME x HM > BI	-0.671	0.996	0.673	0.501	-2.128	1.744
INCOME x HA > BI	0.248	0.572	0.433	0.665	-0.922	1.015
INCOME x PV > BI	0.389	0.609	0.640	0.523	-1.060	1.270
GENDER x INCOME > BI	-0.031	0.298	0.105	0.916	-0.586	0.531
GENDER x INCOME x PE > BI	-0.952	1.231	0.773	0.440	-2.596	2.495
GENDER x INCOME x EE > BI	-0.214	0.715	0.299	0.765	-1.583	1.247
GENDER x INCOME x SI > BI	1.543	1.038	1.487	0.137	-1.512	2.261
GENDER x INCOME x FC > BI	-0.279	0.336	0.831	0.406	-0.819	0.497
GENDER x INCOME x HM > BI	2.742	1.840	1.490	0.136	-3.253	3.834
GENDER x INCOME x HA > BI	-1.371	1.022	1.342	0.180	-2.105	1.721
GENDER x INCOME x PV > BI	-1.649	1.118	1.475	0.140	-2.422	1.756
R-square = 0.985	Behavioral intention					
R-square Adj. = 0.476						

Hypothesis	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	p values	Confidence level 2,5 %	Confidence level 97,5 %
R-square = 0.979	Use behavior					
R-square Adj. = 0.467						

Remarks: Bootstrapping path analysis on 5000 resample iterations.

Significance level ***p < 0.01 ** p < 0.05 and * p < 0.10.

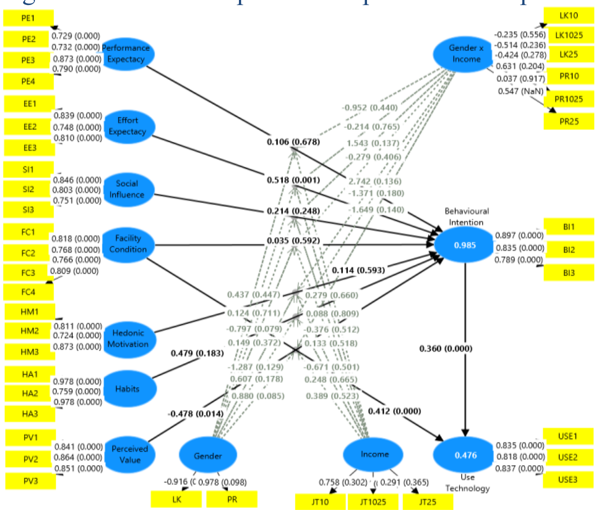

Figure 2. UTAUT2 Model Research Design (**With Moderation**)

5. DISCUSSION

Referring to the development of the hypothesis, it can be seen that behavioral intentions in the use of actual technology (use behavior) can be caused by the influence of determinative factors. However, the signs of the relationship between behavioural intention and technology use cannot be predicted in advance, so empirical testing is needed.

Related Table 4. results of the UTAUT model research (**without moderation**) The use of technology shows the following findings. **Performance expectancy** has an important positive influence on behavioural intention and technology use (β = 0.137; p-value 0.046) which is in line with most of the previous literature [40][8] [36]. Some research using the UTAUT2 model, the Performance Expectacy has been proven to have a significant impact on behavior using technology. Zhou, Lu, and Wang (2010) testing TTF and UTAUT models that explain adoption in mobile banking users. By integrating the two, the results of the study found that performance expectations, task technology suitability, social factors and facilitating conditions had a significant effect on user adoption. In addition, studies have found a significant effect of technological suitability on performance expectations.

In the scope of research, performance expectations mean that users prefer e-commerce platforms because they can improve shopping efficiency and the shopping process is more effective. The huge increase in efficiency on e-commerce platforms makes users more likely to use the platform. Thus, the H-1 hypothesis, which states that performance expectations have a significant effect on the technology usage behavior of e-commerce platforms, is proven to be a strong indicator in predicting technology acceptance models.

Related effort expectancy has an important positive influence (*β* = 0.537; p-value 0.000). The results of this study are supported by several previous studies that show that business expectations as a predictor are very significant [8], [18]. Several studies have also consistently proven that business expectations have a significant positive influence on the use of technology [12], [31]. In the study Tarhini et al. (2016) in the sector Banking also confirmed that business expectations are a positive indicator in the use of mobile banking. This statement built from the perception of ease and complexity influenced by the TAM theory model, MPCU which has the same measurement scale [8].

The ease of shopping apps and websites will have a significant impact on shopping behavior. So, platform vendors need to consider the design and ease of use of the application. They need to figure out how to increase trust to make customers feel comfortable. This will attract more consumers to e-commerce shopping as a way to get the goods they need. Thus, the H-2 hypothesis that business expectations have a significant effect on technology use behavior is proven to be important in the technology acceptance model.

Factor Social influence Within the framework of an integrated model, expressing shopping behavior on the platform is influenced by the people around them who trust and encourage consumers to use technology. Social influence refers to the idea of subjective norms of TRA action theory (Fishbein and Ajzen, 1975) and TPB behavior theory [34] which states that a person's behavior will be adjusted to the perception of others. Social influence reflects the behavioral influence of the opinions of friends, relatives and family. Result Empirical evidence shows that social factors have a positive and significant effect (β = 0.082; p-value 0.069). These results are in line with the study [24] which seeks to integrate personal innovations specific to the technology domain on the influence of social factors, along with other variables. The results of the study show that performance expectations, business expectations and social factors have a positive effect on information system technology adoption behavior. Thus, the H-3 hypothesis states that social factors affect the intention to behave in using technology.

Regarding facilitating conditions, it is empirically identified as a direct determinant of technology adoption. Empirical results showed that supporting facilities had a positive effect (β = 0.039; p-value = 0.046) on behavioral intentions. The effect of the condition of the supporting facilities on the use of actual technology (use behavior) produced an important positive effect (β = 0.412; p-value 0.000). The same thing is shown in the research of Dwivedi et al. (2019) which estimates that facilitation conditions affect attitudes towards technology positively.

Furthermore, supporting facilities can help increase consumer confidence. Thus, the H-4a hypothesis that the facility is conditioned to have a significant positive effect on behavioral intentions. The same thing is also shown by the H-4b hypothesis where the condition of the facility has a significant positive effect. This proves that conditioned facilities can be an important variable in the technology acceptance model.

Related hedonic motivation has been shown to play an important role in determining behavioral intentions. Empirical research shows that hedonistic motivation has a significant positive effect (β = 0.325; p-value = 0.007). The same findings were given [32] related to the hedonistic motivation of adoption on mobile services. The same thing is stated Sharif and Raza (2017), in Pakistan, client trust in banking is heavily influenced by hedonistic motivational factors. The results of this study support the findings Hwang and Kim (2007) and Akhlaq (2013) which proves that consumer feelings and emotions are the main prerequisites of user trust. They highlight the hedonistic motivation for mobile use to be seen as an entertainment gadget. Thus, the H-5 hypothesis states that hedonistic motivation has a positive effect on behavior has been proven to be an important factor in the acceptance of technology.

Related habits, hypothesized to have an important influence on the use of technology [18]. The results of the estimation showed that habits had a significant positive effect (β = 0.224; p-value 0.000) on behavioral intentions. The same research was put forward Yen and Wu (2016) and Limayem and Hirt (2003) stating the behavior of using technology in many studies, proving habits is one of the determining factors. Thus the hypothesis H-6 which states that habits affect consumer behavior and have proven to be an important factor in the technology acceptance model.

Related perceived value, this study verifies that price values significantly influence the behavioral intentions of online shopping. However, these findings are not supported by the study [8], [18]. The results of the empirical estimation of the price value had a significant negative effect (β = -0.357; p-value 0.000). The argument of this study is due to respondents' responses to the question of cost structure and the imposition of expensive fees that have a negative impact on online shopping. Thus the hypothesis D-7 which states that the price value has a direct effect on behavior Consumers proved to be important in the model.

Meanwhile, the hypothesis testing of the UTAUT2 model (with moderation) as shown in Table 5. presents the results of the gender and income moderation coefficients on behavioral intentions and indirect influences on the use of actual technology. In Table 5. The moderation variable produced a coefficient of behavioral intentions such as (gender > BI) of (β = -0.047 p-value 0.748), coefficient (income > BI) of (β= -0.017 p-value 0.905) and interaction coefficient (gender x income > BI) of (β = -0.031 p-value 0.916). However, the influence of the three moderations was not significant on behavioral intentions. This means that there is no significant difference between male and female consumers in the use of transaction technology on e-commerce platforms.

Similarly, when viewed from the level of income, there is no significant difference from the level of consumer income to behavioral intentions. The same is also shown by the moderation variables of gender and income interaction which do not provide significant difference values. The presence of an insignificant coefficient indicates that it is not possible to ascertain the effect of the moderation variable.

Furthermore, the evaluation is for example gender-moderated construct variables (EE) and (BI). The moderation effect (gender x EE > BI) produced a non-significant effect (β = 0.124 and p-value 0.711). These results show that the influence of (EE) on (BI) remains strong and is not influenced by gender moderation. Thus, the construct (EE) remains an important predictor of behavioral intent (BI) without considering the influence of gender moderation.

The relationship between (EE) and (BI) that was moderated by income (income x EE > BI) also had a insignificant effect (β = 0.088 and p-value 0.809). This shows that the influence of (EE) on (BI) is not influenced by income moderation. Thus, (EE) remains an important predictor without the need to consider the influence of consumer income moderation.

Furthermore, the interaction (gender x income >BI) resulted in a coefficient (β = -0.031 p-value 0.916). Interaction-moderated (EE) and (BI) relationships (gender x income x EE > BI) resulted in coefficients (β = -0.214 and p-value 0.765) or insignificant. This reality shows that behavior in using the platform is not influenced by gender or consumer income. Thus, this coefficient estimation ensures that the influence (EE) on behavioral intention (BI) is not supported by the moderation interaction variable. If the indirect effect (gender x income) is not significant, while the coefficient (EE > BI) has a significant effect, then the moderation interaction variable has no effect. The negative (minus sign) indicates that the effect of the combination of two moderations weakens the relationship between (EE) and (BI). However, because the influence of interaction is not significant, the increase in behavioral intent (BI) in the use of technology is only directly determined by (EE). This indicates a direct and non-moderating influence or effect.

6. CONCLUSION

This study formulates and empirically tests an extended integrated model of UTAUT2 to explain the factors that influence the behavioral intentions of using e-commerce platform technology. This study seeks to expand the understanding of the adaptation of the acceptance model and the use of technology with contextual variables. The theoretical foundation combines the variables of performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation, habits and perceived value.

The study adopts a two-step approach, investigating the relationship in a conceptual framework with the partial least square approach of the PLS-SEM structural equation for model analysis. Reflective measurement model testing, factor load values (>0.70) and mean variance (AVE>0.50). reliability of Cronbach's alpha (>0.70), rho-A (>0.70) and rho-C (>0.70). From the evaluation of the measurement model and the structural equation model, it can be interpreted that all constructs have consistency or accuracy.

Specifically, the empirical conclusions of the study are as follows: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habits and perceived value have a significant positive effect on behavioral intention in the acceptance and use of technology. In the end, the variables of gender moderation and income level did not have a significant influence on behavioral intention. This means that there is no difference between male and female users in using platform applications. Similarly, the income level showed no significant difference in behavioral intent. The same is also proven that the effect of moderation interactions does not show a significant difference. Therefore, there is an increase in the intention of technology use behavior only directly and non-moderately.

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