Analysis of Behavioral Intention Towards the Use of Smart Village Ogan Ilir (SVOI) Using Technology Acceptance Model (TAM) 3 Method

Riana Mayasari[1(✉)], Jovan Febriantoko[1], Rian Rahmanda Putra[4], Hendra Hadiwijaya[2], and Dedy Kurniawan[3]

[1] Accounting, Politeknik Negeri Sriwijaya, Palembang, Indonesia
{riana.mayasari,jovan.febriantoko}@polsri.ac.id
[2] Accounting, ITB Palcomtech, Palembang, Indonesia
hendra_hadi@palcomtech.ac.id
[3] Informatics Management, Universitas Sriwijaya, Palembang, Indonesia
dedykurniawan@unsri.ac.id
[4] Cumputer Engineering, Politeknik Negeri Sriwijaya, Palembang, Indonesia
rian.rahmanda@polsri.ac.id

Abstract. This study aimed to find What factors influence behavioral intention to use Smart Village Ogan Ilir (SVOI). Technology Acceptance Model 3 was employed in this investigation. The instance of this study were 200 respondents in 5 villages of Ogan Ilir Regency namely Tanjung Pinang I Village, Tanjung Pinang II Village, Limbang Jaya I Village, Limbang Jaya II Village, and Tanjung Laut Village as users of Smart Village Ogan Ilir (SVOI) application. The data were examined using the Variance or Component-Based Structural Equation Modeling (VB-SEM) approach. According to the findings, Perceived Usefulness had an impact on behavioral intention that was both positive and significant, at 0.521, and positive but not statistically significant, at 0.344. Perceived Utility had a positive but insignificant influence on Usage Behavior of 0.078, Usage behavior was positively and significantly influenced by perceived ease of use (0.421), While usage behavior was positively and significantly impacted by behavioral intention (0.374). In the use of Smart Village Ogan Ilir, Usage behavior was more affected by rather than perceived usefulness and behavioral intention (SVOI), perceived simplicity of use.

Keywords: Technology Acceptance Model · Smart Village · behavioral intention

1 Introduction

MSMEs must be resilient to survive the Industrial Revolution 4.0 and transition to society 5.0. This condition requires MSMEs in villages to be able to develop into startups. The resilience of MSMEs in villages must also be supported by environmental factors, security, supporting facilities, digital marketing technology, and adequate internet to be

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globally competitive with local wisdom. Environmental conditions indicate the need for technology in the management of MSMEs in Village. The local wisdom carried by MSMEs in Village becomes a strength in the competition for similar and substitute products in the market with innovation focused on the village. The such competition requires creative and visionary managers of MSMEs in Village.

In both the metropolis and the hamlet, information technology has advanced in every aspect of life. There is a shift from traditional habits to information technology-based modern habits. Therefore, a concept is needed to cover all the needs of these people by using the village as a role model to become a public service entity [1–3]. Villages are at the forefront of the government in determining policy directions, both in terms of economy and infrastructure development. Smart village is a concept of a smart city adoption on a smaller scale [1, 2, 4–6].

Tanjung Pinang I Village, Tanjung Pinang II Village, Limbang Jaya I Village, Limbang Jaya II Village, and Tanjung Laut Village are villages in South Sumatra Provinces that have various MSMEs. The five villages require a system to build a network consisting of digital correspondence, a marketplace for all MSMEs in the village to transact, digital security, an early warning system, an integrated multi-sector platform transportation system, and a geographic information system leading to the realization of the Smart Village Ogan Ilir (SVOI) to create synergy between MSMEs in Village and Village Government from various sectors. A smart town has four characteristics: smart people, smart administration, smart economics, and smart transportation [7–9]. The success of a smart village is measured by intensity, which can be seen from the usage behavior of system users [10–14].

Usage Behavior is a reflection of customer behavior which can be seen from their intention to use an information technology system. Customers will use the system if they believe that the system can help get the job done [10, 15–18]. Usage Behavior involves two dimensions: variations and frequency of use of a technology by users. The first dimension has to do with how extensively or frequently users use technology. The second component is called breadth of use, which refers to how much technology can help users become more knowledgeable and skilled. Factors that have an influence on the use of technology are conditions that provide ease of facilitation, habits, and behavioral intentions. [19].

Behavioral intention is the need for a consumer to do certain actions in order to possess, utilize, or get rid of a good or service. Customers can so perform informational searches, share their product experiences with others, purchase products, or access particular services [20–23]. Behavioral Intention has two aspects. The initial one is the determination to keep utilizing the system. The user's continuation, or how long they plan to use the technology, is the second element. Action is defined as a form of customer perception of the product. Customers with a good perception of the product will make the customer recommend the product to others and there is the possibility to use the product repeatedly.

Theory Reasoned Action (TRA) and Theory Planning Behavior (TPB) are modified by the Technology Acceptance Model (TAM) (TPB), which have succeeded in explaining the context of social psychological studies by connecting behavioral intention and behavioral action and successfully implemented in various kinds of human behavior.

[24]. Two fundamental constructs—perceived usefulness and perceived ease of use—make up the TAM model. TAM 3 is a development of TAM 1 where TAM 3 examines more deeply the determinants of perceived utility and perceived usability [24]. In its development, the TAM method is not only used to measure the level of application acceptance but can also be used to gauge how satisfied users are with a program. TAM 3 discusses the interrelationships of the nomological network to determine why individuals adopt and use Information Technology. Among the 17 interrelated variables Subjective Norm (SN), Experience, Voluntaries, Image, Job Relevancy (JR), Output Quality (OQ), Result Demonstrability (RD), Computer Self-Efficacy (CSE), Perception of External Control (PEC), Computer Anxiety (CA), Computer Playfulness (CP), Perceived Enjoyment (PE), Objective Usability (OU), and Perceived Ease of Use (PE) are the variables included in TAM 3. (UB), [25–29].

2 Research Method

The sample of this study were 200 respondents in 5 villages of Ogan Ilir Regency namely Tanjung Pinang I Village, Tanjung Pinang II Village, Limbang Jaya I Village, Limbang Jaya II Village, and Tanjung Laut Village as users of Smart Village Ogan Ilir (SVOI) application. Partial Least Squares (PLS) and the data were examined using Variance or Component-Based Structural Equation Modeling (VB-SEM), a type of SEM.

3 Results and Analysis

A. *Confirmatory Factor Analysis* (CFA)

The validity and dependability of latent concept indicators using a measurement model confirmatory factor analysis (CFA) can be seen in Model_1 CFA consisting of Exogenous (Perceived Usefulness, Perceived Usefulness) and Endogenous (Behavioral Intention, Usage Behavior) constructs.

Based on Fig. 1, after conducting CFA on the exogenous construct, There was a loading factor for perceived utility and perceived usability < 0.5 namely IMAGE, CP, and CSE. Meanwhile, after conducting CFA on the endogenous constructs the Behavioral Intention variable had a loading factor < 0.5, namely BI02. This means, these indicators were invalid and must be removed to then obtain Model_2.

Based on Fig. 2, after conducting CFA on Exogenous and Endogenous constructs, there was no loading factor < 0.5. Thus, all indicators on Exogenous and Endogenous constructs were valid. Composite Reliability of exogenous and endogenous constructs showed that all variables in the full model had good reliability.

Based on Table 1, all indicators of Exogenous and Endogenous constructs were valid. In addition, based on the Composite Reliability of exogenous Usage, Behavioral Intention, Perceived Usefulness, and Perceived Ease of Use Behavior across the entire model showed high dependability and can be further examined. Perceived utility, perceived usability, behavioral intention, and usage behavior all showed good dependability throughout the full model, warranting additional investigation.

B. *SEM-PLS Analysis*

The results of SEM-PLS in full model (without invalid indicators) is seen in Fig. 3.

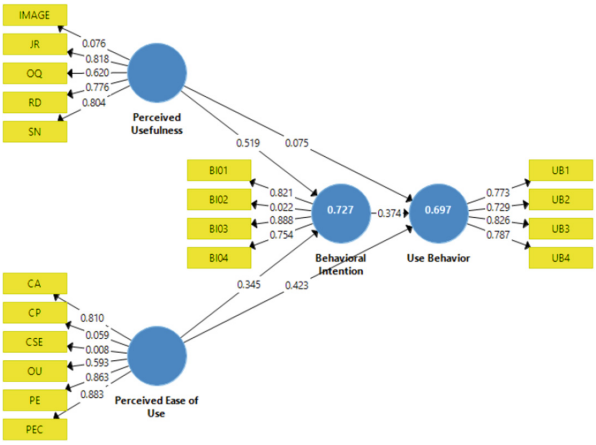

Fig. 1. CFA_1 of Exogenous and Endogenous Constructs

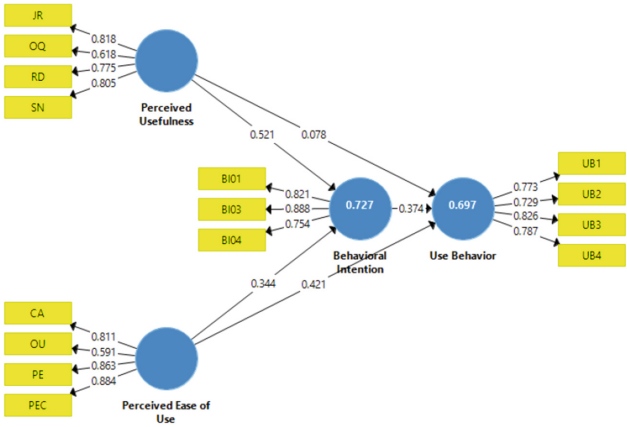

Fig. 2. CFA_2 of Exogenous and Endogenous Constructs

a. Goodness of Fit Index Test

The combined performance of the structural model and measurement model is meant to be assessed using the test for the Goodness of Fit (GoF) index. GoF is determined by multiplying the model's average R2 value by its square root of the average communalities index. The interpretations of the GoF numbers, which range from 0 to 1, are as follows: Low GoF: 0.1; mid GoF: 0.25; high GoF: 0.36. (high GoF) [30]

$$GoF = \sqrt{\overline{Com}x\overline{R}^2}$$

$$GoF = \sqrt{0.859x0.697}$$

$$GoF = 0.774$$

Table 1. Loading Factor and Composite Reliability of Exogenous Construct

Variable	Construct	*Loading factor* (> 0.5)	*Composite Reliability* (> 0.7)	Description
Perceived Usefulness **ξ1**	JR	0.818	0.843	Valid & Reliable
	OQ	0.618		Valid & Reliable
	RD	0.775		Valid & Reliable
	SN	0.805		Valid & Reliable
Perceived Ease of Use **ξ2**	CA	0.811	0.871	Valid & Reliable
	OU	0.591		Valid & Reliable
	PE	0.863		Valid & Reliable
	PEC	0.884		Valid & Reliable
Behavioral Intention **η1**	BI01	0.821	0.862	Valid & Reliable
	BI02	0.888		Valid & Reliable
	BI03	0.754		Valid & Reliable
Usage Behavior **η2**	UB1	0.773	0.861	Valid & Reliable
	UB2	0.729		Valid & Reliable
	UB3	0.826		Valid & Reliable
	UB4	0.787		Valid & Reliable

Source: Processed Data, 2022

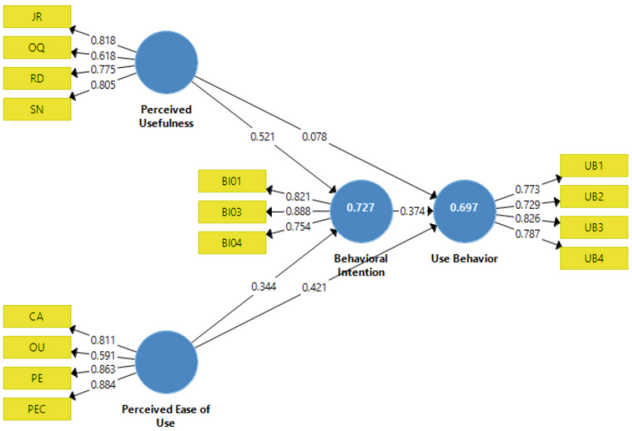

Fig. 3. SEM-PLS Models

The goodness of fit (GoF) index was 0,774 or in high category.

b. Resampling Bootstraping

The confidence level used was 95%, so the limit of error was (α) = 5% = 0.05, therefore t-table of 1.96, so:

Based on Table 2, the equations obained are:

1. Sub-Structural Equation:

$$\mathrm{BI} = 0.521 * \mathrm{PU} + 0,344 * \mathrm{PEU}$$

It can be explained using the sub-structural model that Behavioral Intention (BI) was directly influenced according to perceived utility (PU) and perceived usability (PEU). This demonstrates that PU affects the BI of 0.521 that was both favorable and meaningful and PEU had a positive but insignificant influence of 0.344 on BI.

2. Structural Equation:

$$\mathrm{UB} = 0.521 * \mathrm{PU} + 0.344 * \mathrm{PEU} + 0.374 * \mathrm{BI}$$

According to the structural model shown above, behavioral intention, perceived usefulness, and perceived ease of use all had a direct impact on usage behavior (UB). PEU had a substantial positive impact of 0.421, PU had a significant positive impact of 0.078, and BI had a significant positive impact of 0.374. All three compounds showed significant beneficial effects on UB. PEU had a greater impact on UB's use of Smart Village Ogan Ilir than PU and BI combined (SVOI) (Table 3).

3. Results of Direct and Indirect Effect

Table 2. Coefficient and t-value at 5% level

Variable	Coefficient	T-value (>1,96)	P Values	Description
Behavioral Intention → Usage Behavior	0.374	3.611	0.000	Significant
Perceived Usefulness → Usage Behavior	0.078	0.486	0.627	Not Significant
Perceived Ease of Use → Usage Behavior	0.421	2.107	0.036	Significant
Perceived Usefulness → Behavioral Intention	0.521	2.090	0.037	Significant
Perceived Ease of Use → Behavioral Intention	0.344	1.412	0.159	Not Significant

Source: Processed Data (2022)

Table 3. Direct and Indirect Effect

Variable	Effect
Behavioral Intention → Usage Behavior	0.374
Perceived Usefulness → Usage Behavior	0.078
Perceived Ease of Use → Usage Behavior	0.421
Perceived Usefulness → Behavioral Intention	0.521
Perceived Ease of Use → Behavioral Intention	0.344
Perceived Ease of Use → Behavioral Intention → Usage Behavior	0.128
Perceived Usefulness → Behavioral Intention → Usage Behavior	0.195

Source: Processed Data, 2022

4 Conclusion

Perceived usefulness (0.521) had a favorable and significant influence on behavioral intention, but perceived usability (0.344) had no such effect. Perceived Utility had a positive but insignificant influence on Usage Behavior of 0.078, Usage Behavior was considerably and favorably impacted Usage patterns were considerably and favorably influenced by behavioral intention (0.374) but not by perceived ease of use (0.421). When using Smart Village Ogan Ilir, reported simplicity of use had a stronger influence on usage behavior than perceived usefulness and behavioral intention. Perceived usability had a greater impact on using behavior in Smart Village Ogan Ilir than perceived usefulness and behavioral intention (SVOI).

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