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Predicting Agricultural Product E-Commerce Usage Behavior In Indonesia With Machine Learning Algorithms

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ABSTRACT

This study aims to identify factors that predict the usage behavior of agricultural product e-commerce platform in Indonesia with a comprehensive approach using machine learning algorithms. The research model uses the theory of technology acceptance and use (UTAUT), which consists of variables of social influence, supporting conditions, usage behavior, performance expectancy, effort expectancy, behavioral intention, and supporting conditions. The data in this study were collected throuh an online survey. Model analysis uses a partial least square-structural equation model (PLS-SEM) approach. Furthermore, machine learning algorithms were used to analyze the relationship between elements in the research model. The results showed that behavioral intentions were predicted by performance expectations, effort expectations, social influence, and supporting factors. Agricultural product e-commerce usage behavior is influenced by these behavioral intentions. This study also emphasizes the importance of further research on the application of machine learning algorithms in predicting agricultural e-commerce consumption behavior.

Abstrak

Penelitian ini bertujuan untuk mengidentifikasi faktor-faktor yang memprediksi perilaku penggunaan platform e-commerce produk pertanian di Indonesia dengan pendekatan komprehensif menggunakan algoritma machine learning. Model penelitian menggunakan teori penerimaan dan penggunaan teknologi (UTAUT), yang terdiri dari variabel pengaruh sosial, kondisi pendukung, perilaku penggunaan, harapan kinerja, harapan usaha, niat perilaku, dan kondisi pendukung. Data dalam penelitian ini diperoleh melalui survei online. Analisis model menggunakan pendekatan partial partial least square-structural equation model (PLS-SEM). Lebih lanjut, algoritma *machine learning* digunakan untuk menganalisis hubungan antar elemen dalam model penelitian. Hasil penelitian menunjukkan bahwa niat perilaku diprediksi oleh ekspektasi kinerja, ekspektasi usaha, pengaruh sosial, dan faktor pendukung. Perilaku penggunaan platform e-commerce produk pertanian dipengaruhi oleh niat perilaku tersebut. Penelitian ini juga menekankan pentingnya penelitian lebih lanjut mengenai penerapan algoritma machine learning dalam memprediksi perilaku konsumsi e-commerce pertanian.

1. Introduction

The digital transformation has led to significant advancements in mobile information technology, particularly with the widespread use of smartphones. The delivery of goods and services is among the many digitally based services that have developed and are rapidly growing. This rapid growth underscores the urgency for businesses and individuals to adapt to digital transformation. The growth of digital services has made the use of e-commerce platforms for fulfilling needs more convenient. Certainly, the expansion of e-commerce will assist Indonesia in becoming the largest contributor to the digital economy by Google, Temasek, and Bain & Company (2023) noted that the e-commerce sector in Indonesia's digital economy generated a gross merchandise value (GMV) of US$62 billion, or 75.6% of the overall GMV of US$82 billion for the sector. E-commerce has also altered people's lives and lifestyles and created new business options for the community (BPS, 2022). An e-commerce study by BPS in 2023 found that the number of e-commerce enterprises increased by 4.46% in 2022, reaching 2,995,986.

Developing the e-commerce business in Indonesia provides a variety of conveniences for people to get daily products from the agricultural sector without having to interact directly with farmers. People can shop more efficiently by accessing online stores. With the opening of SeroyaMart, Sukamart, and Honestbee in Indonesia in 2013, the trend of online retailers began. Even though Honestbee and Sukamart perished, other online stores such as HappyFresh, KeSupermarket, GoMart, GrabFresh, and Sayurbox are now growing (Shalihati et al., 2023). The trend continues to rise with the increased use of online shopping services during the Covid-19 pandemic.

The user experience has drastically changed as technology and people's habits change (Pollák et al., 2022). Service providers like Sayurbox must continually strive to maintain platform utilization. Sayurbox is an appropriate research object for several important reasons. First, the platform is very popular in Indonesia, particularly in the food e-commerce sector, with a large and diverse user base. This makes it relevant to study e-commerce usage behavior in the context of an emerging Indonesian market. Secondly, Sayurbox operates in the food industry which has different consumption patterns compared to other e-commerce sectors such as fashion or electronics, providing a unique perspective in studying technology adoption in the basic needs sector. Third, Sayurbox leverages technology to create an efficient and convenient user experience, making it ideal for exploring factors such as ease of use, trust, and customer satisfaction that influence platform usage. Fourthly, with its rich user data, Sayurbox offers the potential to apply machine learning algorithms to predict user behavior, providing insights that can be used to improve user engagement and retention. Finally, Sayurbox lends itself to testing the Unified Theory of Acceptance and Use of Technology (UTAUT), which can provide a deeper understanding of the factors that influence technology adoption and use in the context of the Indonesian market. Overall, Sayurbox is an ideal research object to explore user behavior in the food e-commerce sector in Indonesia, and contribute to the development of digital strategies in the local market.To this end, ongoing research into how users utilize the Sayurbox e-commerce platform is crucial. By leveraging existing research and the Unified Theory of Acceptance and Use of Technology (UTAUT) paradigm, we can identify the elements that influence platform usage, providing valuable insights for technology research (Venkatesh et al., 2012).

This study aims to examine how Sayurbox e-commerce usage patterns in Indonesian society relate to the UTAUT framework model's elements. The UTAUT (Unified Theory of Acceptance and Use of Technology) model was chosen in this study because this model was developed to predict and explain the factors that influence the adoption and use of technology by individuals. The use of the UTAUT (Unified Theory of Acceptance and Use of Technology) model in studying Sayurbox e-commerce usage patterns in Indonesian society is very relevant for several reasons: a) Comprehensive framework: UTAUT combines elements from various technology acceptance models (e.g., TAM, TRA, and TPB), providing a more holistic approach to understanding the factors that influence technology adoption. UTAUT takes into account variables such as performance expectancy, effort expectancy, social influence, and facilitating conditions, which are particularly important when evaluating the adoption of e-commerce platforms such as Sayurbox. b) Contextual Relevance: The UTAUT model is designed to measure technology acceptance across different contexts and user groups. As Sayurbox operates in the fast-growing e-commerce sector in Indonesia, UTAUT can help identify the key drivers behind consumers' decisions to use or not use the platform.

This is particularly important to understand how Indonesians interact with digital platforms, which may differ from global trends. c) Behavioral Insights: The UTAUT model highlights the role of social influence and facilitating conditions in technology adoption. Given that Indonesia has a diverse culture and varying levels of digital literacy, these factors may significantly influence consumers' willingness to engage with e-commerce platforms such as Sayurbox. d) Predictive Power: Research shows that UTAUT is an effective model for predicting user behavior regarding technology acceptance. By applying this model to Sayurbox, this research can not only explore current usage patterns, but also predict future trends and challenges that the platform may face as it develops. Indonesia is one of the largest and fastest growing e-commerce markets in Southeast Asia. By looking at Sayurbox through the lens of UTAUT, you can better understand how Indonesian consumers view and adopt online shopping, which can provide valuable insights for academic research and practical business strategies. In short, the UTAUT model provides a powerful and adaptable framework for understanding how individual and contextual factors influence the adoption and use of e-commerce platforms like Sayurbox in Indonesia.

This study aims to answer the question What elements influence Sayurbox e-commerce consumption behavior using the UTAUT framework? This study employs machine learning techniques and statistical analysis to find variables that predict Sayurbox usage behavior. Research on the application of machine learning in the context of agricultural technology platforms such as Sayurbox is still very limited. Most of the existing research focuses on machine learning applications in large e-commerce platforms or general software applications, with little attention to the agricultural sector or local product-based platforms. In addition, the utilization of user data in the agriculture sector in machine learning is still limited. While platforms such as Sayurbox collect a lot of data on user behavior, this data is often not analyzed to its full potential. Therefore, the use of machine learning techniques in predicting consumer behavior on agricultural platforms must take into account the unique characteristics of agricultural products, which are very different from products in other e-commerce sectors. There is a significant research gap in the utilization of machine learning to predict the continued use of agriculture-based e-commerce platforms such as Sayurbox. More specific research on the variables that influence user behavior as well as more optimal utilization of user data is needed to improve understanding of the factors that influence consumer decisions and the sustainability of using the platform.

Machine learning algorithms have been frequently utilized to evaluate technological products and forecast their continued use by customers (Arpaci et al., 2021). However, machine learning methods are still rarely used to anticipate the Sayurbox platform's sustainability. Guided by relevant studies (Almaiah et al., 2021; Arpaci et al., 2021; Kuadey et al, 2022), this paper will use several algorithms, such as a rule-learner (OneR), decision tree (RandomForest), Bayesian classifier (NaiveBayes), lazy classifier (IBk), meta-classifier (AdaBoostM1), and linear logistic regression classifier (SMO) to predict people's Sayurbox usage behavior. This research contributes by applying the UTAUT model to analyze e-commerce consumption behavior on the Sayurbox platform in the Indonesian agricultural sector. In addition, this research fills a gap in the literature by using machine learning techniques to predict user behavior, as well as optimizing the utilization of user data in agricultural e-commerce platforms. The findings of this study are expected to provide new insights for the development of effective digital strategies in the agriculture sector and improve the understanding of the factors that influence the adoption of local product-based platforms.

2. Literature Review

2.1. UTAUT Model

Out of all the models that are now accessible, the Technology Acceptance Model (TAM) is the one that is used by users the most to adopt technology (Wahyu & Anwar, 2020). Despite the fact that research has been done to confirm its capacity to forecast information system usage (Handayani & Sudiana, 2017). TAM has limitations as summarised by Lee et al. According to Taiwo & Downe (2013), TAM is lacking because it ignores a crucial component, namely society's role in how new technologies are used and adapted. Additionally, TAM ignores the obstacles that keep people from utilizing specific technologies they would otherwise like to Aprianto (2022).

UTAUT is the basis for TAM development. UTAUT is a successful synthesis of eight of the most well-known theories of technological adoption, named Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), Combination TAM and TPB, Model of PC Utilization (MPTU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). Compared to the other eight theories, UTAUT demonstrated greater efficacy in accounting for up to 70% of user variance (Venkatesh et al., 2003). Seven factors seemed to be important drivers of behavioral intention or use behavior in one or more of the eight models evaluated. These constructs are self-efficacy, performance expectancy, effort expectancy, social influence, and conducive situations. Further investigation showed that behavioral intention and use behavior were significantly influenced by four main constructs: performance expectancy, effort expectancy, social influence, and facilitating factors. The primary objective of UTAUT research is to assist organizations in comprehending how usage responds to the introduction of new technologies (Indah & Agustin, 2019). First created in 2003, UTAUT was derived from the TAM and included four dimensions: performance expectancy, effort expectancy, social impact, and facilitating conditions. These concepts affect how people behave when deciding to use technology (Chen et al., 2021).

The Sayurbox e-commerce industry can benefit from the implementation of the UTAUT model for behavioral intention prediction. This model is used to comprehend the variables that affect how technology is accepted and employed. There are four primary components of the UTAUT (Hormati, 2012).

1. Performance expectancy: this aspect has to do with how much technology can enhance user productivity. Performance expectations in Sayurbox e-commerce can be gauged by how simple it is for customers to locate what they're looking for, how simple it is for them to make payments, and how promptly their orders are delivered.
2. Effort expectancy: this factor has to do with how user-friendly people think technology is. Sayurbox e-commerce users' ease of use in navigating the website or application, locating the information they require, and completing payments are all indicators of their effort expectations.
3. Social influence: this component has to do with how other people use technology and their effect. Social influence in Sayurbox e-commerce is quantified by counting the number of users who promote the service to others and whose friends or family also use it.
4. Facilitating conditions: This aspect has to do with how much the surrounding conditions and available resources facilitate technology adoption. When it comes to Sayurbox e-commerce, the ease with which customers may obtain the equipment required to utilize the service, the internet, and technical help in the event of an issue are all indicators of facilitating conditions.

In the context of Sayurbox e-commerce, technology adoption can be predicted through the relationship between performance expectations, effort expectations, social influence, and facilitating conditions.

2.2. Performance Expectancy and Behavioral Intention

Many literature claimed that performance expectancy significanty affect behavioral intention (Alalwan, 2020; Naruetharadhol et al., 2023). In the context of adopting digital platforms such as Sayurbox, the greater the user's belief that the platform offers tangible benefit, such as time efficiency, increased sales outcomes, or ease in product distribution, the stronger their intention to use the platform sustainably. Belief in performance improvement serves as a key driver in shaping a positive attitude toward new technologies, which in turn fosters behavioral intention to adopt them. So, the first hypothesis can be formulated as follows.
H1: Performance expectancy (PE) has a positive effect on behavioral intention (BI)

2.3. Effort Expectancy and Behavioral Intention

Tsai et al. (2013) state that the ease of use a digital platform will increase behavioral intention to use the technology. An individu will be more likely to adopt new technology if the it is easy to operate (Venkatesh et al., 2012). In the context of using Sayurbox, the perception that the platform features

an intuitive interface, simple transaction processes, and easily accessible functionalities enhances user comfort in operating it. Effort expectancy plays a critical role in reducing both psychological and technical barriers that often hinder the acceptance of new technologies. When users perceive that minimal effort is required to learn or operate the platform, their intention to use it regularly is likely to increase. So, the second hypothesis can be formulated as follows.
H2: Effort expectancy (EE) has a positive effect on behavioral intention (BI)

2.4. Social Influence and Behavioral Intention

Users of agricultural products often enhance their skills and knowledge through discussions with peers and colleagues. Social influence plays a significant role in facilitating information acquisition and knowledge sharing among individuals during the process of technology adaptation (Slade et al., 2015). The exchange of information and knowledge among users of agricultural products can further strengthen an individual's intention to adopt the Sayurbox e-commerce platform. Therefore, the third hypothesis can be formulated as follows.
H3: Social influence (SI) has a positive effect on behavioral intention (BI)

2.5. Facilitating Conditions and Usage Behavior

Facilitating conditions refer to the extent to which an individual believes that adequate resources and support are available to use a particular technology (Venkatesh et al., 2003). Previous research found that facilitating conditions positively and significantly affect use behavior (Octaviani et al., 2023; Fatihanisya & Purnamasari, 2021; Musakwa & Petersen, 2023) In the context of using digital platforms such as Sayurbox, the availability of supporting infrastructure, such as a stable internet connection, compatible technological devices, and access to technical assistance or user training can significantly ease the process of adopting and continuously using the technology. When users perceive that they have sufficient access to the necessary facilities and resources, they are more likely to feel confident and motivated to engage with the platform in their daily activities. Therefore, the fourth hypothesis can be formulated as follows.
H4: Facilitating conditions (FC) has a positive effect on usage behavior (UB)

2.6. Behavioral Intention and Usage Behavior

Behavioral intention refers to the extent to which an individual has the intention or tendency to use a particular technology in the near future (Venkatesh et al., 2003). Several literatures such as Giandi & Irawan (2020), Samila & Shabrina (2022), and Zhang & Gong (2023) mentioned that behavioral intention significantly and positively influences use behavioral. In the context of using Sayurbox, the stronger the individual's intention to use the platform, the greater the likelihood that they will actually engage with it in their daily activities. Intention serves as a primary predictor of actual behavior, as it reflects the individual's mental commitment and motivation toward technology usage. When individuals form a positive intention based on perceived usefulness, ease of use, and available support, actual usage behavior is likely to follow. Therefore, the last hypothesis can be formulated as follows.
H5: Behavioral intention (BI) has a positive effect on usage behavior (UB)

3. Research Methods

This research uses quantitative methodology with a causal relationship approach to test the existence of a cause-and-effect relationship between the variables studied. The quantitative approach was chosen because this research aims to measure and analyze the relationship between variables through numerical data. In this context, the research focuses on identifying whether a variable can affect other variables, where changes in one variable are expected to cause changes in other variables (Dhika, 2012; Samsu, 2017). For data collection, an online questionnaire containing closed-ended questions with a Likert scale of 1-5 was used. This scale allows respondents to choose their level of agreement with each statement posed, with answer options ranging from "strongly disagree" to "strongly agree". The questionnaire was distributed to 34 respondents, all of whom were Sayurbox e-commerce users, in the hope of obtaining a representative view of their experiences and perceptions of the application. The indicators shown in Table 1. The data collected is then processed quantitatively, using statistical analysis techniques to see if there is a significant relationship between the variables under study.

The analysis used SEM PLS and machine learning to explore and verify the causal relationship between the variables of interest. By using numerical data collected through questionnaires, researchers can draw conclusions regarding how one variable might affect another in the context of E-commerce application usage. The findings of this study are expected to provide deeper insights into the factors that influence user satisfaction and consumer behavior on E-commerce platforms, and help develop strategies to improve the quality of services provided.

This study merges primary data gathered via questionnaire distribution with secondary data gathered from publications, journals, and pertinent references. Descriptive analysis is the type of data analysis employed, and it displays information on the socioeconomic and demographic traits of the respondents as tables, charts, or diagrams. While the influence analysis uses SEM (Structural Equation Model), PLS, and machine algorithm analysis. Researchers can evaluate and quantify the link between numerous exogenous and endogenous variables with numerous indicators simultaneously by using SEM PLS, a multivariate methodology that combines factor analysis and path analysis (Sholihin & Ratmono, 2020). According to Haryono (2017), SEM PLS is one of the statistical studies available in research where the independent and response variables are unmeasured or relative.

The UTAUT model can be used to predict behavioral intention in Sayurbox e-commerce. The factors that most affect users' behavioral intention can be found in this investigation. In conclusion, by examining the variables that affect people's adoption and usage of technology, the UTAUT model can be utilized to forecast behavioral intention in Sayurbox e-commerce. SVM sentiment analysis on user reviews and PLS-based SEM are two possible methods for the analysis. To further understand customers' behavioral intentions, the impact of product quality and pricing on their intention to purchase can also be examined. With this analysis, Sayurbox e-commerce can enhance its services to meet users' requirements and preferences. Performance expectancy, effort expectancy, social influence, and facilitating conditions are the exogenous variables in this study. Behavioral intention is the endogenous variable, though. An explanation of research indicators and operational definitions is provided below. Based on this table, the study assumes that performance expectancy, effort expectancy, social influence, and facilitating conditions positively and significantly influence behavioral intention and use behavior.

This machine learning research method aims to separate user classes using the Support Vector Machine (SVM) algorithm. The first step in this research is data collection that includes various user information, such as demographic data (age, gender, location), user behavior (frequency of visits, interactions with the app), and transaction history (number of purchases, products purchased). Class labels to be predicted or separated, such as user categories (e.g. active vs. passive users) or product preferences, are also included in the dataset.

Once the data is collected, a pre-processing stage is performed which includes data cleaning to remove missing or invalid data, as well as handling outliers. Next, the numerical data was normalized and standardized to be on the same scale, as SVM is sensitive to feature scale. For categorical data, encoding techniques such as one-hot encoding or label encoding are used. After pre-processing, the dataset is divided into two parts, namely training data (80%) and test data (20%), which will be used to train and test the SVM model. The k-fold cross-validation technique is also used to ensure the model does not experience overfitting and provide a more accurate estimate of the model's performance.

In the modeling stage, the selection of the SVM kernel is very important. Depending on the characteristics of the data, a linear kernel can be chosen for relatively simple data or a non-linear kernel (such as RBF) if the relationship between features is more complex. After selecting an appropriate kernel, important parameters such as C (for regularization) and gamma (for kernel parameters) are adjusted using parameter search techniques such as grid search or randomized search. Model training is done by utilizing the training data to find a hyperplane that separates the user classes with maximum margin, which is a basic principle in the SVM algorithm.

Once the model is trained, the performance of the model is evaluated using evaluation metrics such as accuracy, precision, recall, and F1-score, which give an idea of how well the model predicts the user class. In addition, the confusion matrix is used to analyze classification errors and evaluate correct and incorrect predictions. The results of this evaluation will give a clear picture of the quality of the model and how well the SVM algorithm can separate user classes based on the available data. Furthermore, further analysis is conducted to understand which features affect the classification process the most, which can provide further insights into user behavior that can be used for future marketing strategies or product development.

Table 1. Operational definition of variables and research indicators

No	Variables	Indicators
1	Performance Expectancy (X1)	X1.1 Sayurbox can help me understand my vegetable and fruit shopping needs.
		X1.2 Using Sayurbox allows me to shop for vegetables and fruits more quickly
2	Effort Expectancy (X2)	X2.1 Sayurbox is clear and easy to understand
		X2.2 Easy for me to learn Sayurbox
		X2.3 I can easily access Sayurbox
3	Social Influence (X3)	X3.1 my family advised me to shop at Sayurbox
		X3.2 Friends and peers recommend shopping at Sayurbox
		X3.3. Work environment suggests shopping at Sayurbox
4	Facilitating Conditions (X4)	X4.1 I have a smartphone
		X4.2 I have an internet quota to access Sayurbox
5.	Behavioral Intention (Z1)	Z1.1. I intend to shop at Sayurbox
		Z1.2. I plan to use Sayurbox to shop for groceries
6	Use Behavioral (Y)	Y1.1. I noticed the features in Sayurbox
		Y1.2 I understand and actively use Sayurbox

4. Results and Discussion

4.1. Respondents Characteristics

Multiple criteria are utilized to determine the diversity of the respondents. These requirements include age, occupation, education level, and gender. This should clearly depict the respondents' circumstances and how they relate to the study's subject. Table 2 presents the respondents' characteristics.

Table 2. Characteristics of the respondents

Characteristics	Description	Number of Respondents	%
Gender	Man	16	47 %
	Woman	18	53 %
	Total	**34**	**100.00 %**
Age	<19	2	6 %
	20-21	3	9%
	22-23	15	44 %
	24-25	10	29 %
	>25	4	12 %
	Total	**34**	**100.00 %**
Income	<IDR 1,000,000	**11**	32 %
	IDR 1,000,000-IDR 2,000,000	**5**	15 %
	> IDR 2,000,000	**18**	53 %
	Total	**34**	**100.00 %**
Education	Master	2	6 %
	Bachelor	27	79 %
	Senior High School	5	15 %
	Total	**34**	**100.00 %**

Several factors are used to evaluate respondent characteristics to determine respondents' diversity. These factors consist of income, age, education level, and gender. This should clearly depict the respondent's condition and how it relates to the study question. 34 persons in total responded, with a gender distribution of 53% female and 47% male, according to the statistics in the table above. There were sixteen male respondents and eighteen female respondents in all. Analysis of age characteristics is just as significant as gender features. We measured the respondents' age in terms of the years this research was conducted. According to this table, 15 responders, or 44% of the total, were between the ages of 22 and 23. One of the things that affects a person's degree of happiness with the good or service they have acquired is their age. It will undoubtedly be simpler for a productive adult to think about the current offerings in goods and services. People of productive age are more likely to be active and sensitive to changes in their surroundings. Even though their experience may be considered to be very limited, people who are still in their productive age tend to be braver in taking chances in the choices they make or the activities they are pursuing. Age plays a significant role when it comes to a person's capacity to choose and gauge their degree of self-satisfaction. Existing self-satisfaction influences how one thinks when performing tasks since it is strongly linked to one's physical, mental, and decision-making abilities (Rustandi et al., 2020; Sa'adah et al., 2021)

The income element also reveals another factor that affects customer pleasure. According to this table, 18 consumers, or 53% of the total, earn less than Rp 2,000,000, which accounts for the largest income. This is because consumers are dominated by students who think that the vegetable box makes it easier for students to buy vegetables without needing to go to the market. Income data is income obtained by a person from sales of goods or services carried out to obtain profits and salaries as wages. Income categorization is crucial to this study's analysis of the impact of income levels on Sayurbox application users' satisfaction. Undoubtedly, a person's income plays a significant part in meeting their demands in relation to the judgments they will make about purchases. In addition to income, education is a crucial factor in determining (Andrian et al., 2019). The education a person has undergone is certainly not the same from one individual to another, so instilling a different way of thinking can influence a person's behavior in purchasing. Undergraduate education is in the largest position with 27 respondents. This fact must be taken into consideration by policymakers, specifically regarding the use of the Sayurbox application so that in conveying information about consumers, it is necessary to target students as targets in market segmentation.

4.2. SEM-PLS Analysis

Outer Loading Testing

This indicator's convergent validity testing aims to demonstrate each indicator's validity in relation to its latent variable. The first step in the validity test procedure is the convergent validity test. Convergent validity is demonstrated at the indicator level by the factor loading value. An indication is considered valid if its factor loading value exceeds 0.7 (Hair et al., 2011; Hair et al., 2017; Hair et al., 2013). The Average Variance Extracted (AVE) value determines convergent validity at the variable level. A variable is deemed legitimate when the AVE value is more than 0.5 (Chin, 2010). The test results for the 20 distributed questionnaire question items indicate that the AVE value is over 0.5 and the outer loading value is above 0.7.

Table 3. Outer Loading dan Cross loading

Variables	PE	EE	SI	FC	BI	UB
X1.1	**0.849**	0.577	0.467	0.672	0.373	0.660
X1.2	**0.895**	0.706	0.280	0.390	0.443	0.476
X2.1	0.449	**0.764**	0.129	0.417	0.368	0.573
X2.2	0.682	**0.851**	0.233	0.477	0.382	0.511
X2.3	0.682	**0.857**	0.343	0.381	0.482	0.292
X3.1	0.489	0.384	**0.934**	0.536	0.525	0.454
X3.2	0.375	0.221	**0.937**	0.558	0.505	0.416
X3.3	0.323	0.233	**0.958**	0.548	0.557	0.359
X4.1	0.412	0.453	0.478	**0.885**	0.389	0.663
X4.2	0.624	0.409	0.514	**0.810**	0.502	0.526
Z1.1	0.436	0.509	0.563	0.475	**0.959**	0.551
Z1.2	0.465	0.453	0.510	0.512	**0.953**	0.532
Y1.1	0.591	0.497	0.267	0.642	0.464	**0.877**
Y1.2	0.529	0.442	0.494	0.596	0.529	**0.873**

Table 3 shows that the indicator's correlation value with other variables is smaller than the outer loading value between the indicator and the desired variable. By stating that the hidden variable can predict its indications more accurately than the indicators in other variables, it can be said that the indicator is deemed legitimate. The Validity Test is followed by a Reliability Test, which looks at the lower and higher limits of reliability consistency, respectively, using Cronbach's alpha value and Composite Reliability.

Table 4. Reliability Testing

Variables	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Performance Expectancy (PE)	0.688	0.702	0.864	0.761
Effort Expectancy (EE)	0.766	0.784	0.865	0,681
Social Influence (SI)	0.938	0.940	0.960	0.889
Facilitating Conditions (FC)	0.614	0.635	0.836	0.719
Behavioral Intention (BI)	0.906	0.910	0.955	0.914
Use Behavioral (UB)	0.694	0.694	0.867	0.766

The Cronbach's Alpha value for the total variable is more than equal to 0.6, as can be seen in the Table 4. Therefore, it can be said that the questionnaire is reliable for assessing the suggested phenomena and that the variables have excellent reliability values.

Inner Model Testing

Internal Model Utilizing the SmartPLS program, assess the inner model following the exterior model's testing. This inner model test aims to comprehend how the study's latent variables are correlated. To demonstrate how much the exogenous factors influence the endogenous variables, the R square calculation is utilized (Sholihin & Ratmono, 2020) provide criteria for measuring the strength of the model based on the R Square value to be weak (R2 = 0.19), moderate (R2 = 0.33), and substantial (R2 = 0.67). Based on these criteria, the model presented in this study falls into the moderate group, which is closer to substantial. The R square value falls within the medium category according to Table 5's findings.

Table 5. R square value

Variabel	R Square	Adjusted R Square
Behavioral Intention (BI)	0.441	0.379
Use Behavioral (UB)	0.556	0.525

In hypothesis testing, the Path Coefficient value is used to determine whether a variable has a positive or negative effect with a value range of -1 to 1. Furthermore, the T-statistics and p-values are used to determine the significance of each path in the research model. If the p-value is less than 0.1 and the T-statistics value is greater than 1.64, the path is considered significant (Hair et al., 2018). The results of the hypothesis testing in this study, along with the information, are shown in Figure 1.

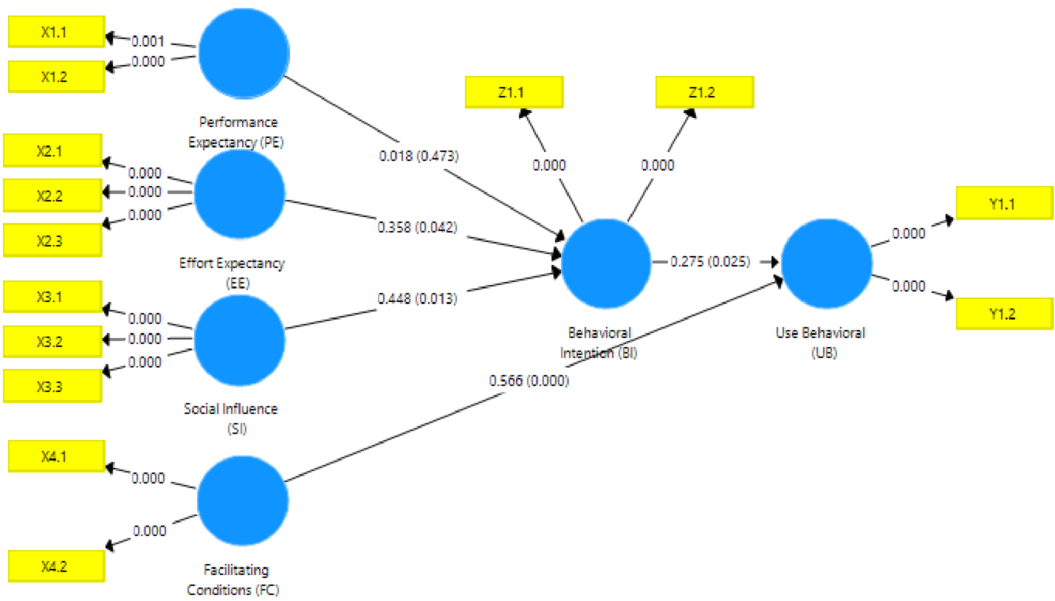

Figure 1. SEM-PLS Model

A hypothesis testing that has been analyzed as shown in Table 6.

Table 6. Hypothesis Testing

Hypotheses	Path Coefficient	T-Statistic	P-Value	Results
H1 : PE → BI	0.018	0.069	0.473	Positive and Not significant
H2 : EE → BI	0.358	1.733	0.042	Positive and Significant
H3 : SI → BI	0.448	2.214	0.013	Positive and Significant
H4 : FC → UB	0.566	4.213	0.000	Positive and Significant
H5 : BI → UB	0.275	1.967	0.025	Positive and Significant

The Effect of Performance Expectancy (PE) on Behavioral Intention (BI)

According to the hypothesis testing, the statistical t value was 0.069, or less than 1.96, and the P value was 0.473, or more than 0.05. Concurrently, the path coefficient was 0.018. The performance expectancy positively and marginally impacts behavioral intention, indicating that $H1$ is rejected. This research is aligned with previous research (Fatihanisya & Purnamasari, 2021; Mustaqim et al., 2018; Setiyani et al., 2023) which states that performance expectancy has no significant effect on behavioral intention. However, this contrasts with Naruetharadhol et al. (2023) and Alalwan (2020) indicates that performance expectancy significantly affects behavioral intention. Through a digital platform, a person can save time, generate greater productivity, and believe that using technology can increase efficiency in activities (Venkatesh et al., 2003). According to Oliveira et al. (2016), high technological awareness can motivate behavioral intention to use a digital platform. In this case, the Sayurbox application in circulation has not been able to encourage behavioral intention to use the application. The advanced features offered in the Sayurbox application could not increase a person's effectiveness in making purchase transactions. Here, it indicates the possible role of mediating factors, which causes consumers to tend not to depend on using the Sayurbox application.

The Effect of Effort Expectancy (EE) on Behavioral Intention (BI)

According to the results, the statistical t value was 1.733 or less than 1.96, P value was 0.042 or less than 0.05, and path coefficient was 0.358. It means that behavioral intention is impacted by the effort expectation positively and significantly, indicating that $H2$ is acceptable. This research is in line with (Alalwan, 2020; Naruetharadhol et al., 2023), which say that effort expectancy positively and significantly influences behavioral intention. This is supported by Tsai et al. (2013) which states that the easier it is to use a digital platform, the higher the percentage of a person's behavioral intention to adopt the technology. According to Pitchay (2023), a person will feel difficulties at the beginning in using technology and after getting used to using the technology, a person's perception of ease of use will increase. A person will be more likely to accept new technology if the technology is easy to operate (Venkatesh et al., 2012). In this case, effort expectancy can be described as a person's ability to complete a purchase transaction with little effort through the Sayurbox application. This situation will make someone comfortable using the Sayurbox application, in contrast to Morosan & DeFranco (2016), which failed to find the effect of effort expectation on behavioral intention on the adoption of mobile technology. Effort Expectancy has been demonstrated to influence an individual's behavioral intention to use the Sayurbox application. Hence, this could be the result of disparities in research that compares online shopping applications with other mobile technologies.

The Effect of Social Influence (SI) on Behavioral Intention (BI)

According to the results, the statistical t value was 2.214 or greater than 1.96, and the P value was 0.013 less than 0.05. The path coefficient was 0.448. In summary, the social influence positively and significantly impacts behavioral intention, indicating that $H3$ is acceptable. This research is in line with Alalwan (2020); Duan et al. (2022); Mustaqim et al., (2018); Zhou & Lu (2010) that social influence positively and significantly affects behavioral intention. This is supported by Fatihanisya & Purnamasari (2021) and Naruetharadhol et al. (2023) in their research, social influence significantly affects behavioral intention on vegetable e-commerce platforms in Thailand. Social influence has proven to be very important in influencing a person's behavioral intention in using technology (Liu et al., 2022). This study shows that the existence of social influence from family, colleagues, and friends regarding the knowledge of using the Sayurbox application can allow a person to gain the ability to operate the application more quickly. So that this can encourage a person's intention to use the Sayurbox application. Furthermore, research in South Africa conducted by Verkijika (2018), social influence plays a role in predicting e-commerce applications intention to use.

The Effect of Facilitating Conditions (FC) on Use Behavioral (UB)

The results showed that the statistical t-value was 4.213 or greater than 1.96, and the P-value was 0.000, less than 0.05. Meanwhile, the path coefficient value is 0.566. It shows that the facilitating conditions positively and significantly affects use behavioral, meaning that *H*4 is accepted. This research is in line with Octaviani et al., (2023) and Musakwa & Petersen (2023) which states that facilitating conditions positively and significantly affect use behavior. Meanwhile, research conducted (Zhang & Hassan, 2023) contradicts the results of the study and says that facilitating conditions have no significant effect on Use Behavioral. Conceptually, UTAUT considers facilitating conditions to be influencing user behavior only. However, Venkatesh (2012) refutes this in his research, which shows that facilitating conditions also affect a person's behavioral intention to adopt certain technologies and research. Although the results of the research are very diverse, facilitating conditions are an important factor that influences a person's behavior using the Sayurbox application. Facilitating conditions can be seen as a person's perception of the facilities or obstacles available to use the application. In this case, the cost or availability of internet services in an area can facilitate or inhibit someone from using the Sayurbox application for shopping. The availability of internet services greatly affects e-commerce, because every e-commerce transaction requires internet services

The Effect of Behavioral Intention (BI) on Use Behavioral (UB)

The findings indicated that the P value was 0.000 less than 0.05, and the statistical t value was 4.213 exceeding the threshold of 1.96. Additionally, the path coefficient was 0.566 during the interim analysis. We may conclude that use behavioral is positively and significantly impacted by the social influence variable, indicating that *H*5 is acceptable. This research is in line with Giandi & Irawan (2020); Samila & Shabrina (2022); Zhang & Gong (2023) which indicate that behavioral intention significantly and positively influences use behavioral. The findings imply that the greater an intention to utilize the Sayurbox, the more likely they are to incorporate the application in their behavior. The outcomes demonstrated how frequently daily needs transactions have been completed using the Sayurbox program. This is consistent with the fact that the majority of responders were in the 20–25 age range and had prior familiarity with digital technologies.

4.3. Predicting Model Using Machine Learning Algorithms

Classification is used to evaluate how constructs in predictive models relate to one another (Arpaci et al., 2021). While there are many categorization methods, the following are the main ones that this study looks at as has been done in prior works, a rule learner (OneR), a decision tree (RandomForest), a Bayesian classifier (NaiveBayes), a lazy classifier (IBk), a meta-classifier (AdaBoostM1), a Bayesian classifier (SMO), and a lazy-classifier (IBk) (Almaiah et al., 2021; Arpaci et al., 2021)

To analyze the connections between dimensions in the proposed research model, this study applies 10-fold cross-validation and utilizes Weka software version 3.8.6. Weka employs various classification algorithms to examine data. Performance measures used to evaluate classification algorithms include correctly classified instances (CCI), true positive (TP) rate, false positive (FP) rate, precision, recall, F-measure, and receiver operating characteristic (ROC) area (Witten, 2005). CCI is an important performance indicator that assesses classification algorithms' success rate in producing accurate predictions. The ratio of accurate classifications to total classifications is known as the CCI.

Table 7 shows that SMO and OneR outperform other algorithms in predicting BI with PE, with an accuracy of 96.87%. Furthermore, this approach outperforms earlier methods in terms of F-measure (0.968) and precision (0.970). Thus, *H*1 is endorsed.

Table 7. Predicting the BI by PE

Classification algorithms	CCI (%)	TP Rate	FR rate	Precision	Recall	F-measure	ROC area
NaiveBayes	87.50	0.875	0.542	0.892	0.875	0.848	0.972
SMO	96.87	0.969	0.135	0.970	0.969	0.968	0.597
AdaBoostM1	93.75	0.938	0.271	0.942	0.938	0.932	0.871
IBk	84.37	0.844	0.677	0.869	0.844	0.795	0.883
OneR	96.87	0.969	0.135	0.970	0.969	0.968	0.906
RandomForest	93.75	0.938	0.271	0.942	0.938	0.932	0.968

Table 8. Predicting the BI by EE

Classification algorithms	CCI (%)	TP Rate	FR rate	Precision	Recall	F-measure	ROC area
NaiveBayes	90.62	0.906	0.232	0.903	0.906	0.904	0.919
SMO	93.75	0.938	0.223	0.942	0.938	0.933	0.596
AdaBoostM1	87.50	0.875	0.446	0.892	0.875	0.855	0.850
IBk	84.37	0.844	0.558	0.870	0.844	0.807	0.836
OneR	93.75	0.938	0.223	0.942	0.938	0.933	0.596
RandomForest	87.50	0.875	0.446	0.892	0.875	0.855	1.000

Table 8 indicates that SMO and OneR outperform all other algorithms in predicting BI with EE, with an accuracy of 93.75%. Additionally, these two methods perform best in terms of F-measure (0.933) and precision (0.942). Therefore, we can say that *H*2 is supported.

Table 9. Predicting the BI by SI

Classification algorithms	Correctly classified instances (CCI) (%)	TP Rate	FR rate	Precision	Recall	F-measure	Receiver operating characteristic (ROC) area
NaiveBayes	93.75	0.938	0.063	0.944	0.938	0.937	0.946
SMO	96.87	0.969	0.031	0.971	0.969	0.969	0.767
AdaBoostM1	78.12	0.781	0.219	0.791	0.781	0.779	0.727
IBk	100.00	1.000	0.000	1.000	1.000	1.000	0.989
OneR	93.75	0.938	0.063	0.944	0.938	0.937	0.749
RandomForest	93.75	0.938	0.063	0.944	0.938	0.937	0.935

With a 100% accuracy rate, Table 9 demonstrates that IBk performs better than others in predicting BI with SI. Based on precision (value of 1) and F-measure (value of 1), IBk performs the best. Therefore, one may claim that *H*3 is validated.

Table 10. Predicting the UB by FC

Classification algorithms	Correctly classified instances (CCI) (%)	TP Rate	FR rate	Precision	Recall	F-measure	Receiver operating characteristic (ROC) area
NaiveBayes	93.75	0.938	0.119	0.943	0.938	0.936	0.974
SMO	100.00	1.000	0.000	1.000	1.000	1.000	0.704
AdaBoostM1	100.00	1.000	0.000	1.000	1.000	1.000	0.864
IBk	87.50	0.875	0.195	0.876	0.875	0.872	0.893
OneR	100.00	1.000	0.000	1.000	1.000	1.000	0.858
RandomForest	100.00	1.000	0.000	1.000	1.000	1.000	1.000

Table 10 reveals that SMO, AdaBoostM1, OneR, and RandomForest outperform other algorithms in predicting UB with FC, achieving 100% accuracy. Additionally, these four approaches perform the best in terms of F-measure (value 1) and accuracy (value 1). So we can conclude that *H*4 is supported.

Table 11. Predicting the UB by BI

Classification algorithms	Correctly classified instances (CCI) (%)	TP Rate	FR rate	Precision	Recall	F-measure	Receiver operating characteristic (ROC) area
NaiveBayes	93.75	0.938	0.104	0.943	0.938	0.936	0.944
SMO	96.87	0.969	0.052	0.970	0.969	0.968	0.703
AdaBoostM1	93.75	0.938	0.104	0.943	0.938	0.936	0.766
IBk	84.37	0.844	0.260	0.875	0.844	0.832	0.898
OneR	96.87	0.969	0.052	0.970	0.969	0.968	0.825
RandomForest	96.87	0.969	0.052	0.970	0.969	0.968	0.971

With an accuracy of 96.87%, Table 11 demonstrates that SMO, OneR, and RandomForest beat other classification methods in UB prediction using BI. The third has the best performance based on accuracy (0.970) and F-measure (0.968). As a result, we can conclude that *H*5 is supported.

Based on the classification results using various machine learning algorithms, this study aims to evaluate the factors that influence Behavioral Intention (BI) and Use Behavior (UB) in the use of a technology. The main factors analyzed include Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and the relationship between BI and UB. The classification algorithms used in this study include NaiveBayes, SMO, AdaBoostM1, IBk, OneR, and RandomForest, with evaluation performed based on various performance metrics such as Correctly Classified Instances (CCI), True Positive Rate (TP Rate), False Positive Rate (FP Rate), Precision, Recall, F-measure, and Receiver Operating Characteristic (ROC) Area.

From the classification results obtained, it can be concluded that SMO and OneR show superior performance in predicting BI based on PE and EE, with accuracy rates of 96.87% and 93.75%, respectively. The superiority of these algorithms is also evident from the high precision and F-measure values, which are 0.970 and 0.968 for BI prediction based on PE and 0.942 and 0.933 for BI prediction based on EE. This shows that expectations of technology performance and ease of use have a significant impact on one's intention to adopt a system. Users tend to be more interested in using an application if they believe that the technology can help them complete tasks more quickly and efficiently. Conversely, if an application is difficult to use or requires more effort to understand its functionality, users will be more reluctant to adopt it.

In addition, social influence (SI) was also shown to play a large role in shaping user intent, with the IBk algorithm showing a perfect accuracy of 100% in predicting BI based on SI. This indicates that external factors such as recommendations from friends, influencers, communities, or social media contribute significantly to a user's decision to use a service. In the context of technology-based platforms, such as e-commerce and vegetable marketplaces like Sayur Box, community-based marketing strategies can be a key driving factor for service adoption. Users are more likely to trust and adopt a service if they see positive testimonials from people around them.

Meanwhile, in terms of predicting usage behavior (UB) based on external factors, the classification results show that SMO, AdaBoostM1, OneR, and RandomForest have a perfect accuracy of 100% in predicting UB based on FC. Supporting facilities, such as technological infrastructure reliability, transaction processing speed, ease of payment, and good customer service support, play a crucial role in ensuring that users actually use the app. If a platform has many technical glitches, limitations in payment methods, or inefficient logistics, then users will tend to abandon it and switch to other platforms that are more convenient to use.

Furthermore, the study also shows that BI has a very close correlation with UB, meaning that the higher a user's intention to use a service, the more likely they are to actually use it. SMO, OneR, and RandomForest again showed the best performance with 96.87% accuracy in predicting UB based on BI, with a precision value of 0.970 and F-measure of 0.968. This finding confirms that while various external factors can drive user intentions, ultimately the internal commitment and motivation of the users themselves is the main factor in determining whether they will actually use the service consistently.

The results of this analysis have significant implications for the Sayur Box business, a digital platform that provides fresh vegetables and groceries online. To increase technology adoption and encourage more consistent usage behavior, Sayur Box can implement various strategies based on the classification results that have been carried out.

First, in the aspect of Performance Expectancy (PE), Sayur Box needs to ensure that the platform they offer functions quickly, stably, and reliably in meeting the needs of its users. This can be done by optimizing the application infrastructure, such as increasing order processing speed, strengthening server capacity to prevent downtime, and implementing a more responsive system in displaying products to customers. Users will be more likely to use this service repeatedly if they feel that this platform can provide real benefits in their lives, both in terms of time efficiency and the quality of the products offered.

Second, in terms of Effort Expectancy (EE), Sayur Box needs to prioritize ease of use and an intuitive user experience (UX). Applications that are complicated and difficult to use will hinder service adoption. Therefore, Sayur Box can simplify the ordering process, provide a "favorites" feature to make repeat purchases easier, and provide interactive guides for new users. In addition, the automatic recommendation feature based on purchase history can also increase customer convenience in finding the products they need. Third, in the aspect of Social Influence (SI), Sayur Box can utilize community-based marketing strategies to increase service adoption. Encouraging users to share their experiences on social media, providing incentives for referral programs, as well as working with relevant influencers in the healthy food and lifestyle industry, are steps that can build a strong ecosystem. With recommendations from trusted people, users will more easily trust and adopt the service.

Fourth, Facilitating Conditions (FC) should also be continuously improved to ensure a seamless and barrier-free user experience. Sayur Box needs to ensure that its logistics system runs smoothly, offer flexible payment methods (such as through e-wallets, bank transfers, or COD), and provide responsive customer service in dealing with user issues. With a strong infrastructure and good service, users will feel more comfortable and confident to continue using the platform in the long run. Finally, since the classification results show that Behavioral Intention (BI) is closely related to Use Behavior (UB), Sayur Box can implement retargeting, loyalty programs, and discounts based on user behavior. For example, if a user has added products to the cart but has not completed the payment, Sayur Box can send a notification or email reminder to complete the transaction. Loyalty programs, such as cashback for repeat transactions or exclusive promos for loyal customers, can also improve user retention and ensure that usage intentions lead to actual consumption behavior.

Overall, by implementing these analytics-based strategies, Sayur Box can strengthen its position in the market and encourage more consistent usage, thereby expanding adoption and creating long-term customer loyalty.

5. Conclusion

The analysis shows that behavioral intention and usage behavior are positively and significantly impacted by effort expectation, social influence, enabling conditions, and performance expediency. In contrast, performance expediency has an insignificant influence on behavioral intention. A machine learning system was developed to forecast the variables of performance expectancy, effort expectancy, social impact, and facilitating conditions on behavioral intention. Furthermore, behavioral intention predicts Sayurbox's behavioral use in e-commerce. However, this study has limitations, including excluding additional variables that might affect behavioral intention and usage behavior. The potential impact of future research in exploring these omitted variables and incorporating a more diverse set of predictors to enhance the model's accuracy is significant. Additionally, expanding the study to different e-commerce platforms could provide a broader understanding of the factors influencing behavioral intention and usage behavior.

As for managerial implications, Sayurbox is expected to increase the use of their e-commerce platform with several strategic steps. First, simplify processes such as registration, product search, and payment to improve user experience. Second, strengthen social influence through collaboration with influencers to increase trust and market reach. Third, ensuring supporting services such as on-time delivery and responsive customer service. Fourth, although performance efficiency is not significant, maintaining delivery efficiency and product quality remains important. In addition, the use of data-driven systems to personalize user experience can improve customer retention.

For other researchers in the future, further research with additional variables such as price and product quality is also important to improve the strategy. Lastly, extending the research to other platforms will provide greater insight into consumer behavior. These steps can help Sayurbox design more effective strategies and expand its customer base.

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