COSTING: Journal of Economic, Business and Accounting
Volume 7 Nomor 6, Tahun 2024
e-ISSN : 2597-5234

THE EFFECT OF ONLINE FOOD DELIVERY SERVICES ON CONSUMER BEHAVIORAL INTENTIONS

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ABSTRACT
The research explored the Special Region of Yogyakarta towards online food delivery services, which had become a prominent trend within the food and beverage industry. Consumers were increasingly opting for the convenience of ordering food online rather than traditional dining out or takeout. This study aimed to develop an integrated model to examine the relationship between several antecedents (perceived ease of use, time-saving orientation, convenience motivation, privacy and security, and behavioral intention) and repurchase intention towards OFD services. The findings revealed that time-saving orientation, convenience motivation, and privacy and security positively influenced behavioral and repurchase intentions. These results offered valuable insights for OFD service providers and researchers, shedding light on the key factors driving urbanites to adopt and continue using these services.

Keywords: Online Food Delivery Services, Perceived Ease of Use, Time-Saving Orientation, Convenience Motivation, Behavioral Intention, Repurchase Intentions.

INTRODUCTION

Within the dynamic digital landscape, food delivery apps have emerged as a powerful force shaping consumer behavior in the culinary world (Liu, 2023). Supported by technological advancements and readily available online platforms, consumers can indulge in various dishes without leaving home (Li et al., 2020). This trend signifies a significant transformation in how people acquire and consume food.

Furthermore, online food delivery applications' affordability and ease of use make them highly appealing to consumers. These platforms offer instant access to menu options from popular restaurants and local vendors (Shafiee & Wahab, 2021). Users can enjoy high-quality meals from the comfort of their own homes, eliminating the need for cooking or venturing out (Tajvidi & Tajvidi, 2021). This convenience factor significantly contributes to the popularity of online food delivery services.

As the technological tide rises, online food delivery services have become a game-changer in the culinary world, dramatically altering how consumers interact with food (Vitsentzatou et al., 2022). The ubiquity of technological advancements and the convenience offered by online platforms have redefined how individual access and enjoy a diverse array of dishes without leaving the comfort of their homes (Buhalis et al., 2019). This shift in consumer habits signifies a pivotal moment in the food and beverage industry, with affordability and user-friendly interfaces providing instant access to an extensive range of menu options from favored restaurants and local stalls.

The surge in online food delivery services presents exciting opportunities for local restaurants and food vendors (Li et al., 2020). These platforms enable both merchants and consumers to thrive in the digital landscape. Restaurants gain wider market reach and compete more effectively, while consumers benefit from access to diverse culinary options beyond geographical limitations (Sgroi & Marino, 2022; Dasaklis & Malamas, 2023). Platforms with review and rating features empower consumers to make informed choices, fostering transparency and trust in their gastronomic experiences (Tian et al., 2021). This transparency, facilitated by user reviews, allows consumers to make more informed decisions about where to order food, ultimately leading to more satisfying culinary experiences.

The importance of online food delivery services has increasingly shaped the modern culinary landscape, facilitated changes in consumer behavior, and significantly impacted the food and beverage industry (Ahuja et al., 2021). These developments continue to play an essential role in defining how we enjoy food, creating convenience, and defining future culinary trends.

In facing the dynamic development of online food delivery services in the digital era, understanding its impact on consumer behavioral intentions is crucial (Muangmee et al., 2021). Consumer behavioral intentions in the context of online food delivery services include the decisions and actions consumers take regarding purchasing and consuming food via online platforms (Inthong et al., 2022). Several factors significantly influence consumer behavioral intentions: perceived ease of use, time-saving orientation, convenience motivation, and privacy and security.

Modern life's hectic pace has led many to dislike the time commitment of finding food and waiting at restaurants (Yeo et al., 2017). The appeal of online food delivery lies in its convenience – minimal effort is required, with food delivered directly to their doorstep as quickly as possible. This aligns with research by Sultan and Uddin (2011), who found that time-saving features positively influence the intention to use online shopping platforms. Online food delivery services cater to this desire for efficiency, offering a solution that minimizes time investment and maximizes convenience.

The topic of Perceived ease of use (PEOU) on behavioral intention is the first variable that refers to a user's perception of how effortless and intuitive it is to learn and experiment with a new technology (Consult, 2002). Research suggests that PEOU is critical in shaping user attitudes and influencing their willingness to adopt new technologies (Cho & Sagynov, 2015). In simpler terms, if people find a technology easy to use, they are more likely to embrace it. Studies have shown that developing user-friendly systems with high PEOU can encourage continued use, as demonstrated in the context of web-based learning by Chiu & Wang (2008). Jahangir & Begum (2008) also emphasized the importance of user-friendliness in promoting technology adoption.

The topic of time-saving orientation on behavioral intention is the second variable. The fast-paced nature of modern life fuels a dislike for the time commitment involved in finding food and waiting at restaurants (Yeo et al., 2017). This resonates with the concept of time-saving orientation, where consumers prioritize solutions that minimize wasted time (Settle & Alreck, 1991). Online food delivery thrives on convenience; it requires minimal effort and delivers food swiftly to customers' doorsteps.

Furthermore, the rapid pace of urbanization has created a significant challenge for many city dwellers: a need for more time for meal preparation or even dining out during weekdays (Botchway et al., 2015). This often leads to unhealthy choices like relying heavily on fast food or skipping meals. Online food delivery services offer a convenient alternative, allowing busy city dwellers to enjoy a wider variety of healthier options without sacrificing precious time.

The topic of convenience motivation on behavioral intention is the third variable. Fortunately, advancements in technology offer a solution. As Kimes (2011) points out, users are increasingly comfortable utilizing safe and user-friendly online platforms. Online food delivery services provide a multitude of benefits, including avoiding the potential for poor customer service at restaurants (Chen & Hung, 2015) and eliminating the hassle of crowded establishments (Katawetawaraks & Wang, 2011). Collier and Kimes (2013) highlighted that the convenience of saving time and effort is a crucial factor influencing consumer adoption of online food delivery services. With minimal time investment and the ability to avoid common frustrations, these services offer an attractive solution for busy urban residents struggling to maintain a healthy balance amidst their hectic lifestyles.

The topic of privacy and security on behavioral intention is the fourth variable. The security of personal information has become a significant concern for online shoppers, supported by frequent news of data breaches at large companies (Flavian & Guinaliu, 2006). Research by Zulkarnain et al. (2015) confirmed this anxiety, highlighting that privacy and security are top priorities for online shoppers, directly impacting their decision to purchase online.

In addition, building trust is paramount for online food delivery services. Research consistently shows a link between strong privacy and security practices and customers' openness to online shopping (Bashir et al., 2015; Sultan & Uddin, 2011). When online platforms prioritize data protection and user security, it builds trust and confidence, ultimately leading to more positive experiences with online food delivery (Miyazaki & Fernandez, 2000).

The topic of behavioral intention on online food delivery services is the fifth comparison. In the context of customer actions, behavioral intention refers to a conscious decision to perform or avoid a specific behavior in the future (Warshaw & Davis, 1985). However, intention can be multifaceted. Leong et al. (2013) suggested that it also encompasses the motivation and effort; thus, someone is willing to invest in a particular behavior. While interest might signal a person's initial curiosity, it does not necessarily translate into a long-term commitment, and they might even regret the behavior later.

The topic of repurchase intention on online food delivery services is the last comparison conducted by Hellier et al. (2003), who found that customer satisfaction and brand preference influence customers' likelihood of making repeat purchases. Repurchase intention reflects a company's ability to fulfill customer expectations and can be measured by a customer's decision to return to a specific food or service provider. The difference between the current study and the object under study is the cinema website and Online Food delivery services. The hypothesis research was tested using LISREL.

By understanding the complexity of these factors, service providers can design more effective strategies for improving Perceived ease of use, time-saving orientation, convenience motivation, and privacy and security. Overall, a deep understanding of the factors that influence consumer behavioral intentions is critical to optimizing operations and increasing the competitiveness of online food delivery services in an ever-growing market.

The main variables that are the focus of this research are online food delivery services as the independent variables and consumer behavioral intentions as the dependent variable. Additionally, perceived usefulness is a mediating variable that may influence the relationship between online food delivery services and consumer behavioral intentions. This research seeks to develop a unified model that explores how specific factors like perceived ease of use, time-saving orientation, convenience motivation, and privacy and security concerns influence urban residents' willingness to utilize online food delivery services in Yogyakarta, Indonesia.

METODE PENELITIAN

Procedure

This research used quantitative approach, utilizing a cross-sectional survey to gather data from online food delivery service users in the Special Region of Yogyakarta. A structured questionnaire, distributed online, collected data from a representative sample of respondents. The research used multiple linear regression analysis, a statistical technique, to examine the relationships between the factors influencing online food delivery usage (independent variables) and the outcome of interest (dependent variable). Additionally, descriptive statistics will likely used to summarize the characteristics of the respondents and the variables involved.

Research Location

This research gathered data reflecting a diverse range of users; the research recruited participants from the Special Region of Yogyakarta. An online survey platform was used allowing respondents to access the survey conveniently through a link distributed on social media, email, and other online channels. This online approach facilitated efficient data collection and ensured the participation of individuals with varied backgrounds and preferences.

Population and Sample Research

Population

According to Shukla's definition of the population (2016), a population is a collective or grouping of all the parts to whom the research findings will be applied. Put another way, a population is a grouping of all the units with variable characteristics being studied and for which research findings could be generalized (Satishprakash, 2020). The population in this research was people who have experienced ordering food using online delivery applications.

Sample

The sample was an apprehensive part of the research population. Therefore, any subset of the population represents all of the population's types of elements. Moreover, a sample is a small amount of information about the thing from which it was taken (Shukla, 2020). A sample is an entirely representative subset of a population. This means that the units selected as a sample of the population must reflect all of the criteria for the different units of the population (Satishprakash, 2016).

The non-probability sampling method was used in this research. According to Zikmund (2003), this method is unlimited, where the number and characteristics of the respondents are not known with certainty, and the selection depends on the researcher's judgment. The advantage of this sampling method is that it is more reliable (Sekaran & Bougie, 2016).

This research used a sample of 200 respondents. Referring to the provisions, it is argued that the number of representative samples is around 100-200, according to Ghozali (2017). Accordingly, the sample size used in this research met the assumptions required by the SEM test.

RESULT AND DISCUSSION

Model Evaluation

Outer Model Evaluation

The measurement model was evaluated using several indicators, including convergent validity, discriminant validity, and reliability. The measurement model was calculated using the PLS Algorithm.

Convergent Validity

An indicator was considered valid if

its loading factor was positive and greater than 0.7 and its Average Variance Extracted (AVE) was greater than 0.5. The loading factor indicated the weight of each indicator/item as a measure of each variable. An indicator with a high loading factor showed that the indicator is the strongest (dominant) measure of the variable. The loading factor values could be seen in Table 1 below.

Table 1. Convergent Validity Test

Variabel	Item	Loading Factor	AVE	Keterangan
Perceived Ease of Use	PE1	0.862	**0.775**	**Valid**
	PE2	0.857		**Valid**
	PE3	0.893		**Valid**
	PE4	0.909		**Valid**
Time Saving Orientation	TS1	0.914	**0.788**	**Valid**
	TS2	0.871		**Valid**
	TS3	0.881		**Valid**
	TS4	0.885		**Valid**
Convenience Motivation	CM1	0.884	**0.751**	**Valid**
	CM2	0.858		**Valid**
	CM3	0.852		**Valid**
	CM4	0.871		**Valid**
Privacy & Security	PS1	0.897	**0.816**	**Valid**
	PS2	0.906		**Valid**
	PS3	0.898		**Valid**
	PS4	0.911		**Valid**
Behavioral Intention	BI1	0.858	**0.805**	**Valid**
	BI2	0.919		**Valid**
	BI3	0.897		**Valid**
	BI4	0.915		**Valid**
Repurchase Intention	RI1	0.886	**0.765**	**Valid**
	RI2	0.875		**Valid**
	RI3	0.857		**Valid**
	RI4	0.880		**Valid**

Source: Primary Data Processed, 2024

Based on Table 1 above, it was known that the loading factor values of each indicator were more than 0.7 and the AVE values were more than 0.5. Thus, these indicators were declared valid as measures of their latent variables.

Discriminant Validity

Discriminant validity was used to test the validity of a model. Discriminant validity was assessed through cross-loading values and the Fornell-Larcker criterion, which indicated the magnitude of the correlation between a construct and its indicators, as well as with indicators of other constructs. The standard value used for cross-loading and the Fornell-Larcker criterion should be greater than 0.7 or by comparing each construct's square root of the average variance extracted (AVE) with the correlation between the constructs in the model. If the square root of the AVE of each construct was greater than the correlation between the constructs in the model, it was said to have good discriminant validity.

Table 2. Fornell-Larcker Criterion Value

Variabel	Behavioral Intention	Convenience Motivation	Perceived Ease of Use	Privacy & Security	Repurchase Intention	Time Saving Orientation
Behavioral Intention	**0.897**					
Convenience Motivation	0.726	**0.866**				
Perceived Ease of Use	0.620	0.605	**0.880**			
Privacy & Security	0.683	0.708	0.596	**0.903**		
Repurchase Intention	0.611	0.690	0.796	0.609	**0.875**	
Time Saving Orientation	0.646	0.662	0.605	0.647	0.708	**0.888**

Source: Primary Data Processed, 2024

Table 3. Cross-Loading Value

Item	Behavioral Intention	Convenience Motivation	Perceived Ease of Use	Privacy & Security	Repurchase Intention	Time Saving Orientation
BI1	**0.858**	0.599	0.514	0.566	0.458	0.512
BI2	**0.919**	0.640	0.565	0.615	0.577	0.555
BI3	**0.897**	0.660	0.516	0.616	0.533	0.595
BI4	**0.915**	0.701	0.621	0.649	0.610	0.646
CM1	0.652	**0.884**	0.476	0.619	0.585	0.620
CM2	0.600	**0.858**	0.520	0.629	0.549	0.479
CM3	0.617	**0.852**	0.527	0.605	0.606	0.606
CM4	0.647	**0.871**	0.575	0.602	0.647	0.586
PE1	0.537	0.521	**0.862**	0.497	0.668	0.480
PE2	0.501	0.535	**0.857**	0.526	0.677	0.527
PE3	0.587	0.552	**0.893**	0.562	0.725	0.566
PE4	0.552	0.523	**0.909**	0.514	0.731	0.555
Item	**Behavioral Intention**	**Convenience Motivation**	**Perceived Ease of Use**	**Privacy & Security**	**Repurchase Intention**	**Time Saving Orientation**
PS1	0.589	0.591	0.531	**0.897**	0.527	0.554
PS2	0.562	0.579	0.471	**0.906**	0.475	0.531
PS3	0.648	0.680	0.588	**0.898**	0.598	0.608
PS4	0.657	0.694	0.554	**0.911**	0.587	0.632
RI1	0.562	0.628	0.700	0.531	**0.886**	0.648
RI2	0.538	0.600	0.690	0.538	**0.875**	0.603
RI3	0.500	0.606	0.680	0.525	**0.857**	0.597
RI4	0.533	0.578	0.714	0.537	**0.880**	0.627
TS1	0.623	0.620	0.620	0.618	0.687	**0.914**
TS2	0.560	0.575	0.475	0.538	0.583	**0.871**
TS3	0.563	0.572	0.495	0.595	0.587	**0.881**
TS4	0.541	0.583	0.553	0.541	0.653	**0.885**

Source: Primary Data Processed, 2024

Based on Tables 2 and 3, the cross-loading values of each item were greater than 0.70 and each item had the highest value when linked to its latent variable compared to other latent variables. This indicated that each variable in this study had accurately explained its latent variable, proving that the discriminant validity of all items was valid.

Reliability

Reliability in PLS was measured using Cronbach's Alpha and Composite reliability. It was considered reliable if the Composite reliability value was above 0.7 and the Cronbach's alpha value was preferably above 0.7. The following table shows the Cronbach's Alpha and Composite reliability values:

Table 4. Reliability Result

Variabel	Cronbach's Alpha	Composite Reliability
Behavioral Intention	0.919	0.943
Convenience Motivation	0.889	0.923
Perceived Ease of Use	0.903	0.932
Privacy & Security	0.925	0.946
Repurchase Intention	0.898	0.929
Time Saving Orientation	0.910	0.937

Source: Primary Data Processed, 2024

Based on Table 4 above, it could be seen that the composite reliability values of all research variables were > 0.7 and Cronbach's Alpha was > 0.7. These results indicated that each variable had met the composite reliability and Cronbach's alpha criteria; thus, it could be concluded that all variables had a high level of reliability. Therefore, further analysis could be done by examining the model's goodness of fit by evaluating the inner model.

Inner Model Evaluation

After conducting the outer model test, the next step was to conduct the inner model test. The inner model or structural model test was done to examine the relationship between constructs, significance values, and R-square of the research model.

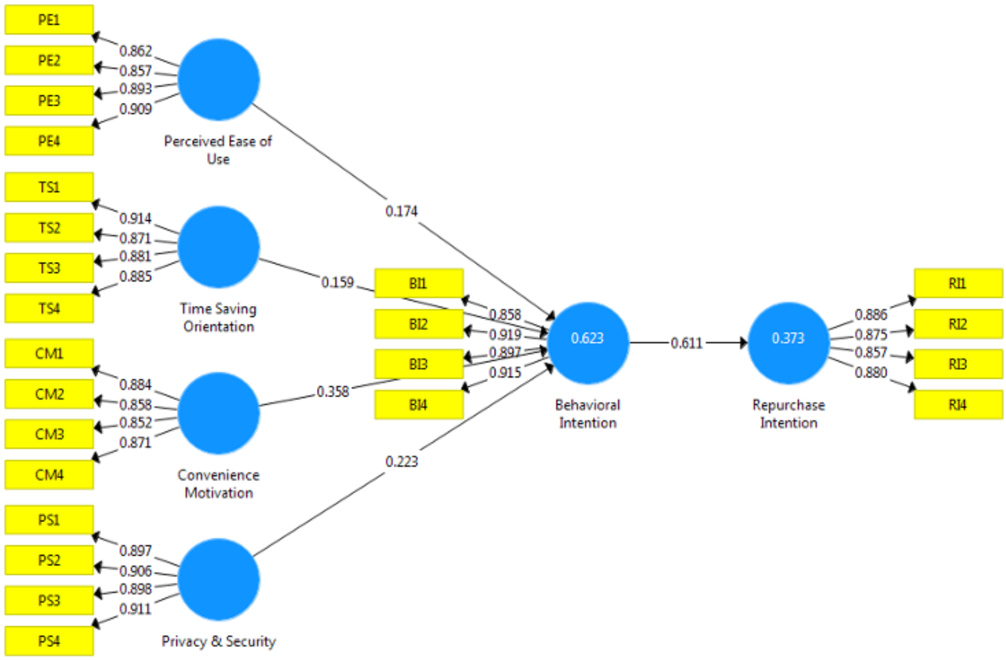

Figure 1. Structural Model
Source: Primary Data Processed, 2024

Evaluation of the PLS structural model began by looking at the R-square for each dependent latent variable. Table 5 presents the estimated R-square values using PLS.

R Square

Table 5. R Square Result

Variabel	R-Square	R-Square Adjusted
Behavioral Intention	0.623	0.615
Repurchase Intention	0.373	0.370

Source: Primary Data Processed, 2024

Table 5 above showed that the R-square value of the Behavioral Intention variable was 0.623. This value means that the Behavioral Intention variable can be explained by the independent variables by 62.3% and the remaining 37.7% could be explained by other variables not included in this research.

Meanwhile, the R-square value of the Repurchase Intention variable was 0.373. This value means that the Repurchase Intention variable could be explained by the independent variables by 37.3% and the remaining 62.7% can be explained by other variables not included in this research.

Predictive Relevance (Q Square)

Predictive relevance was a test conducted to show how well the observed values were produced using the blindfolding procedure by looking at the Q-square value. If the Q-square value was > 0, then it could be said to have good observed values, while if the Q-square value was < 0, then it could be stated that the observed values were not good. Q-Square predictive relevance for the structural model measures how well the observed values were produced by the model and its parameter estimated.

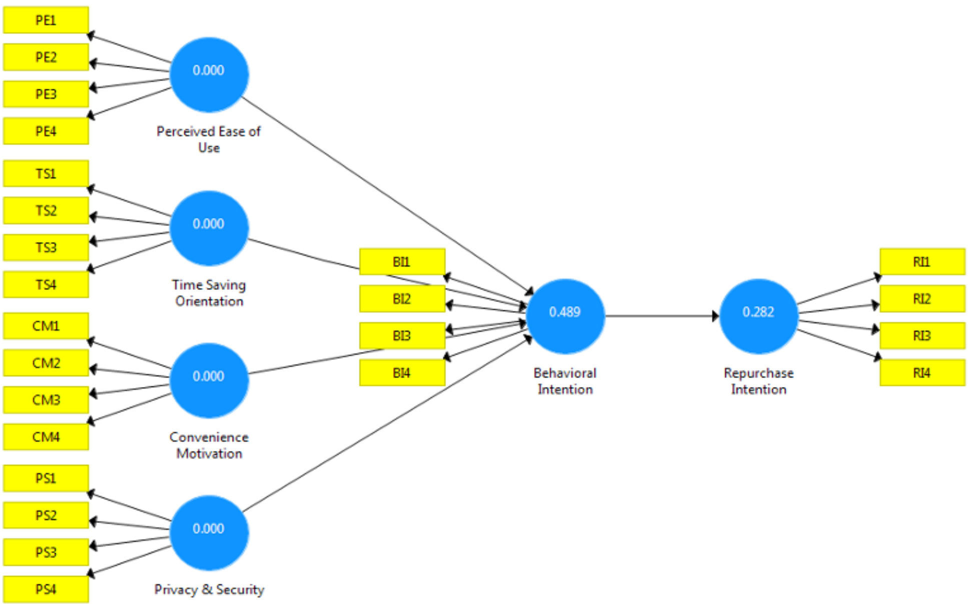

Figure 2. Predictive Relevance
Source: Primary Data Processed, 2024

Based on the figure above, it could be concluded that the following table summarized:

Table 6. Predictive Relevance

Variabel	Q² (=1-SSE/SSO)	Description
Behavioral Intention	0.489	Memiliki nilai predictive relevance
Repurchase Intention	0.282	Memiliki nilai predictive relevance

Source: Primary Data Processed, 2024

Based on the data presented in the table above, it could be seen that the Q-square value for the dependent variable was > 0. Considering this value, it could be concluded that this research had good observed values because the Q-square value was > 0 (zero).

Hypothesis Testing

Structural equation modeling explains the relationships between variables in a research. The structural model was tested using PLS software. The basis for directly testing hypotheses was the output image and the values in the path coefficient output. The basis for directly testing hypotheses was that if the p-value < 0.05 (significance level = 5%) and the t-statistic > 1.960, there was a significant influence of the exogenous variable on the endogenous variable. The following was a complete explanation of hypothesis testing:

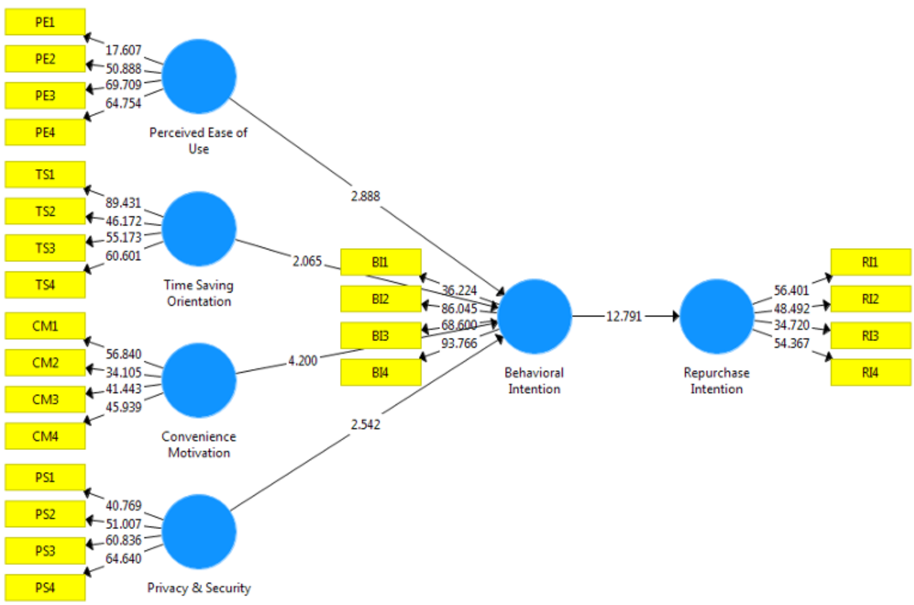

Figure 3. Hypothesis Testing
Source: Primary Data Processed, 2024

Based on the figure above, it could be concluded that the following table summarized:

Table 7. Hypothesis Testing

Variable	Original sample (O)	T Statistic (| O/STDEV |)	P Values
Behavioral Intention -> Repurchase Intention	0.611	12.791	0.000
Convenience Motivation -> Behavioral Intention	0.358	4.200	0.000
Perceived Ease of Use -> Behavioral Intention	0.174	2.888	0.004
Privacy & Security -> Behavioral Intention	0.223	2.542	0.011
Time Saving Orientation -> Behavioral Intention	0.159	2.065	0.039

Source: Primary Data Processed, 2024

In PLS, statistical testing of each hypothesized relationship was conducted using simulation. In this case, it was done using the bootstrapping method on the sample. The following were the results of the PLS bootstrapping analysis:

1. **Perceived Ease of Use to Behavioral Intention**
   The results of the hypothesis test for the first hypothesis, namely the Influence of Perceived Ease of Use on Behavioral Intention, showed a coefficient value of 0.174, a p-value of 0.004 < 0.05, and a t-statistic of 2.888 > 1.960. These results indicated that Perceived Ease of Use had an influence on Behavioral Intention. Therefore, the hypothesis stating that "Perceived Ease of Use has a positive and significant influence on Behavioral Intention" was

accepted.

2. **Time Saving Orientation to Behavioral Intention**
   The results of the hypothesis test for the second hypothesis, namely the Influence of Time Saving Orientation on Behavioral Intention, showed a coefficient value of 0.159, a p-value of 0.039 < 0.05, and a t-statistic of 2.065 > 1.960. These results indicated that Time Saving Orientation had an influence on Behavioral Intention. Therefore, the hypothesis stating that "Time Saving Orientation has a positive and significant influence on Behavioral Intention" was accepted.

3. **Convenience Motivation to Behavioral Intention**
   The results of the hypothesis test for the third hypothesis, namely the Influence of Convenience Motivation on Behavioral Intention, showed a coefficient value of 0.358, a p-value of 0.000 < 0.05, and a t-statistic of 4.200 > 1.960. These results indicated that Convenience Motivation had an influence on Behavioral Intention. Therefore, the hypothesis stating that "Convenience Motivation has a positive and significant influence on Behavioral Intention" was accepted.

4. **Privacy & Security to Behavioral Intention**
   The results of the hypothesis test for the fourth hypothesis, namely the Influence of Privacy & Security on Behavioral Intention, showed a coefficient value of 0.223, a p-value of 0.011 < 0.05, and a t-statistic of 2.542 > 1.960. These results indicated that Privacy & Security had an influence on Behavioral Intention. Therefore, the hypothesis stating that "Privacy & Security has a positive and significant influence on Behavioral Intention" was accepted.

5. **Behavioral Intention to Repurchase Intention**
   The results of the hypothesis test for the fifth hypothesis, namely the Influence of Behavioral Intention on Repurchase Intention, showed a coefficient value of 0.611, a p-value of 0.000 < 0.05, and a t-statistic of 12.791 > 1.960. These results indicated that Behavioral Intention had an influence on Repurchase Intention. Therefore, the hypothesis stating that "Behavioral Intention has a positive and significant influence on Repurchase Intention" was accepted.

Discussion

1. **Perceived Ease of Use**
   The result of this research was supported by Venkatesh et al. (2003), who observed that perceived ease of use initially influenced the adoption of new applications but that this effect diminished over time. This finding aligned with previous research (Teo et al., 1999; Childers et al., 2001; Chan & Lu, 2004; Pikkarainen et al., 2004; Cheng et al., 2006) which suggested that perceived ease of use may not be a long-term motivator for using web services.
   In conclusion, hypothesis one which stated "Perceived ease of use significantly influences behavioral intention of online food delivery services" was accepted.

2. **Time-Saving Orientation**
   The result of this research was supported by Sultan and Uddin (2011), which emphasized the time-saving benefits of online food delivery services. Customers can avoid the hassle of finding a restaurant and waiting for their food, making these services a convenient option. Additionally, Yeo et al. (2017) highlight the ability of online food delivery platforms to facilitate easy comparison of food options and prices. This time-

saving factor was a significant motivator for customers to utilize these services.

In conclusion, hypothesis one which stated "Time-saving orientation significantly influences behavioral intention of online food delivery services" was accepted.

3. **Convenience Motivation**

The result of this research was supported by previous studies (Cho & Sagynov, 2015; Jiang et al., 2011) which have similarly found that convenience was a key factor influencing the adoption of online food delivery services. User-friendly websites that provide clear instructions can further motivate customers to use these services, as they could easily understand and navigate the platform. When customers perceive the OFD service as convenient and meets their expectations, they were more likely to continue using it.

In conclusion, hypothesis one which stated "convenience motivation significantly influences behavioral intention of online food delivery services" was accepted.

4. **Privacy & Security**

The result of this research was supported by Bashir et al. (2015), which highlighted the growing importance of privacy and security concerns in online shopping. Customers were more likely to adopt OFD services if they trusted the platform to protect their personal information. Zulkarnain et al. (2015) further emphasized the positive impact of trust on customers' online purchasing intentions.

In conclusion, hypothesis one which stated "Privacy & security significantly influences behavioral intention of online food delivery services" was accepted.

5. **Behavioral Intentions**

The result of this research was supported by Jackson (1985). Repurchase intention was the likelihood of a customer using a service again, which was defined as a consumer's inclination to continue or increase their use of a service from a particular provider. Surveys of current customers were often used to measure repurchase intention by assessing their likelihood of making repeat purchases.

In conclusion, hypothesis one which stated "Behavioral Intention significantly influences repurchase intention of online food delivery services" was accepted.

CONCLUSION

The purpose of this research was to examine and analyze the influence and relationship of several variables, namely perceived ease of use, time-saving orientation, convenience motivation, privacy and security, behavioral intention, and repurchase intention. The findings from the hypothesis tests conducted in the previous chapter were used to formulate the conclusions of this research.

1. Perceived ease of use significantly influenced customers' decisions to utilize online food delivery services. This suggested that when consumers perceive a food delivery platform as user-friendly, they were more likely to adopt and continue using the service.
2. The study found a positive relationship between customers' time-saving orientation and their intention to use online food delivery services. This suggested that the perception of saving time through these platforms significantly influenced customers' decisions to utilize them.
3. Convenience motivation significantly influenced customers' intention to use online food delivery services. The desire for ease and efficiency in

ordering food positively impacted customers' decisions to utilize these platforms.
4. The research found a positive correlation between customers' perception of privacy and security and their intention to use online food delivery services. This indicated that customers were more likely to use these services when they felt their personal information and data were protected.
5. A strong positive relationship was found between customers' behavioral intentions and their subsequent repurchase intentions for online food delivery services. This indicated that customers who expressed a higher intention to use these services were more likely to become repeat customers.

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