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Towards Sustainable E-Commerce: Understanding Post-Pandemic Online Shopping Intentions in Indonesia

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Abstract. This study investigated the online shopping intentions of 350 consumers in post-pandemic Indonesia using an integrated TAM-TPB-TTF framework. Stratified random sampling focused on the Jabodetabek region. PLS-SEM analysis validated the hybrid model, explaining 70% of the variance in intentions. Task Technology Fit and attitudes were the strongest drivers. The findings imply optimizing website design to match user tasks and emphasizing benefits to improve attitudes would promote continued online shopping adoption. However, expanding demographic factors and geographic scope in future research can enrich insights. This timely study provides theoretical and practical implications to encourage the sustainable growth of e-commerce in developing economies.

Keywords: Shop Online, Technology Acceptance Model, Theory Planned Behavior, Task Technology Fit, Post Pandemic

1. Introduction

The coronavirus disease (COVID-19) broke out in China at the end of 2019. The virus spread rapidly to the rest of the world and was declared a global pandemic by the World Health Organization (WHO) on 12 March 2020 (Ciotti et al., 2020). The first countries to proclaim lockdown were China and Italy (Ren, 2020). During the lockdown in March 2020, people were required to stay home. Those infected with the virus were required to self-quarantine in order to stop the spread of COVID-19 (Fanelli & Piazza, 2020). Since many were forced to work from home, people spent most of their time online. The global outbreak of the COVID-19 virus has had a significant and far-reaching influence on multiple facets of society, encompassing the realm of electronic commerce (e-commerce). This lifestyle change helped e-commerce platforms skyrocket. People had to buy clothing, food, and other necessities through e-commerce platforms (Hasanat et al., 2020). The total number of e-commerce users increased from 75 million people before the pandemic to 85 million people during the COVID-19 outbreak (Kaplan, 2022).

Through the use of internet technology and related infrastructure, e-commerce allows customers to buy goods and services over the internet (Olson, J. S., & Olson, 2000). According to Soleimani (2022), building trust and effective communication between e-commerce platform management and end users is critical to creating long-term customer connections. According to Zhuang and Lederer (2003) and Abou-Shouk et al. (2012), e-commerce can help retail companies by increasing back-end efficiency, market expansion, inventory management, cost reduction, and customer service benefits. It can also improve intra- and inter-organizational communication, which is crucial in developing countries. However, the population's lack of e-readiness prevented potential customers from using e-commerce platforms to buy goods and services (Holland & Gutiérrez-Leefmans, 2018; Molla & Heeks, 2007).

A substantial amount of research has explored customer acceptability in purchasing intention in reaction to these developments (Bhatti et al., 2020; Gao et al., 2020; Hashem, 2020; Kawasaki et al., 2022). These studies have produced significant evidence on whether purchases were made through online shopping platforms and consumer's purchasing intentions. Indonesia's population is estimated at 276.8 million people (BPPN, 2013). It is the fourth largest country in the world and the most populous developing country in Southeast Asia (Worlddata.info, 2023). During the global pandemic, the number of online shoppers in Indonesia increased by about 10 million (Kaplan, 2022). The high population and widespread internet access has positioned Indonesia as the ninth-largest e-commerce country in the world, with projected sales of USD $59 billion.

During the global pandemic, the implementation of social limitations and apprehensions regarding the transmission of the virus have instigated Indonesian consumers to embrace electronic commerce platforms as a means of fulfilling their shopping requirements. This transition towards conducting transactions online has evolved into a novel pastime or interest for numerous individuals, with the internet playing an essential role in satisfying their daily necessities. Consequently, the e-commerce sector in Indonesia has encountered exponential expansion, as millions of fresh users have joined online platforms amidst the pandemic. In view of these changes, it is anticipated that the e-commerce sector in Indonesia will likewise observe a transformation in consumer conduct and intentions in post-pandemic. With the gradual relaxation of societal constraints and the ongoing endeavors in vaccination, the post-pandemic era in Indonesia offers an occasion for the e-commerce sector to further expand and consolidate its existence in the market. The amplified reliance on internet-based shopping during the pandemic has not solely altered consumer conduct but has also accentuated the convenience and accessibility of e-commerce platforms.

Recent research has revealed that a significant proportion, namely 67%, of individuals surveyed expressed their concurrence with the notion that customer contentment serves as a pivotal determinant in the perpetuation of electronic commerce adoption. It should be noted, however, that this study was confined to the demographic groups of baby boomers, those who were born between the years 1946 and 1964, as well as the X generation, encompassing individuals born between the years 1980 and 1984, within the country of Indonesia (Santosa & Taufik, 2023). Another study shows that the habit of Indonesians to use online shopping platform was found to be the strongest predictor of influencing consumer behavior towards m-commerce applications, but this study was conducted during the pandemic (Ashoer et al., 2022).

Theory of Task-Technology Fit (TTF) is used to examine the determinant factors that affect the continued usage of e-health applications and concerns regarding these applications among people living in Jakarta and its surrounding areas (Wijaya et al., 2023). The Technology Acceptance Model (TAM) is a widely used theoretical framework in the information systems and technology adoption field. In the study of online shopping intent in post-pandemic, TAM can provide valuable insights into users' acceptance and adoption of online shopping platforms (Qiu & Li, 2008). This model has been widely used to study the acceptance and behaviors of customers in the e-commerce, banking, and medical sectors (Al-Emran & Granić, 2021).

The study of customer behaviors in electronic commerce provides a comprehensive overview of the motives and intentions of customers. These motives and intentions can serve as guidelines for business operators to improve and implement new strategies in online commerce. In particular, during the unpredictable pandemic outbreak in developing countries. To address this research gap, this study aims to use the TAM-TPB-TTF model to provide a comprehensive understanding of acceptance and behavioral change in online shopping platforms in post-pandemic. This study investigates e-commerce purchase intention and ease of use using a combination of qualitative research approaches such as the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), and Task-Technology Fit (TTF). It contributes to the long-term viability of the e-commerce platform by identifying the shortcomings of the platform, the marketing strategies, and the logistic chains of the online business.

2. Literature Review

The behavioral model used in this study has been modified to consider the benefits of each model. In recent studies on e-commerce usage, TPB and TAM were both favorable models used in predicting the acceptance behavior of the platform (Aldammagh et al., 2021; C. Nguyen & Do, 2019; Tusyanah et al., 2021). Different from previous studies that focus only on the acceptance of platform usage, the aim of this paper is to understand that the acceptance of the online shopping platform led to behavioral change among shoppers.

2.1. Technology Acceptance Model (TAM)

Davis (1989) introduced the Technology Acceptance Model (TAM), and it has since been extensively used in the field of information systems. TAM has been tested to reduce the potential measurement biases to ensure the accuracy of the model (Davis & Venkatesh, 1996). TAM has been applied in many research contexts and has contributed significantly to our comprehension of technology adoption and utilization behavior (Gefen et al., 2000). In our study, TAM is being utilized to understand the behavioral intention to shop online through e-commerce in the post-pandemic period.

TAM comprises two primary constructs: perceived usefulness and perceived ease of use. Perceived Usefulness (PU) refers to the degree to which individuals believe that using a specific technology will enhance their performance or benefit them. In the context of online shopping, individuals may perceive usefulness in various ways:

Convenience: Online shopping offers the convenience of browsing and purchasing products from the comfort of one's home.

Safety: Consumers may perceive online shopping as a safer alternative to in-person shopping post-pandemic. It minimizes the risk of exposure to viruses in a crowded environment.

Product Variety: Online platforms often offer users access to a more extensive selection of products and brands compared to physical stores.

Price Comparison and Discounts: Consumers can compare prices, read reviews, and find discounts more easily through online shopping.

2.2. Theory Reasoned Action (TRA)

Fishbein & Ajzen, (1975) created the Theory of Reasoned Action (TRA) in the late 1970s. According to TRA, a person's behavioral intention is determined by their attitude toward a behavior and one’s subjective norms. Both factors are predictors of an individual's intention to engage in a particular behavior, such as online shopping (Copeland & Zhao, 2020; Raman, 2019; Xi et al., 2020).

2.3. Theory Planned Behavior (TPB)

Ajzen (1991) developed the Theory of Planned Behavior (TPB) as an extension of Theory Reasoned Action (TRA). TPB proposes that attitudes, subjective norms, and perceived behavioral control (PBC) influence behavioral intention. Individuals are more likely to engage in a behavior if they have a favorable attitude toward it, perceived social pressure to perform it, and believe they have control over their capacity to engage. TPB includes constructs associated with control-related beliefs and self-efficacy (Ajzen, 1991). Implementing TPB in this study will make the investigation of behavioral intention more precise and accurate.

2.4. A combination of TAM, TRA and TPB

These models provide a theoretical basis for the study of factors that influence technology acceptability. It has been implemented in various domains. For example: e-commerce, mobile technology, and educational technology. In a study by Rouibah et al. (2009), the 3 competing models of behaviors (TAM, TRA and TPB) have been used to study the acceptance of internet banking. Further, a model for e-commerce adoption has previously been studied and applied several models together with other theories, including DOI, UTAUT and PERM. In this study, we focus on the usage of Theory Reasoned Action (TRA), Theory Reasoned Action (TRA), and Theory of Planned Behavior (TPB) to understand the perceived use of the users and their behavioral intentions.

2.5. Task Technology-Fit (TTF)

Goodhue and Thompson (1995) created a measure of Task-Technology Fit (TTF) which includes eight criteria: quality, location, authorization, compatibility, simplicity of use/training, production timeliness, systems reliability, and relationship with users. The term task-technology fit is used to describe the relationship between an individual (a technology user), technology (e.g., data, hardware, software tools, and the services they provide), and task features (individuals' activities carried out to create the required output). Task-Technology Fit (TTF) has been used in studies to identify aspects that affect the continued use of many online services such as e-health applications (Wijaya et al., 2023), and online banking (Tam & Oliveira, 2016).

2.6. Perceived Ease of Use, Usefulness, and Subjective Norms

Consumers are driven to make online purchases because of multiple factors. First, it allows for faster payment transactions and saves time compared to going to a physical store (Charm, T., et.al., 2020; Shanthi & Desti, 2015). Second, consumers can get goods at a cheaper price point than shopping in traditional retail stores because e-commerce stores are able to offer more competitive pricing (Lo et al., 2014; Mokhtar et al., 2020). Compared to traditional store owners, e-commerce sellers can reduce overhead costs (e.g., rent, utilities, and monthly maintenance fees) of running their business. Third, 45% of consumers in Indonesia research and compare price and reviews before making an online purchase (Katrina B. & Benedict L., 2018). Many consumers expect online prices to be 8-10% lower than store-based retailers (Jensen et al., 2003). Last, a survey found that 52.3% of online shopping platforms users were drawn to the ability to use coupons for additional discounts (eCommerce Market, 2023).

Another factor that needs to be considered is the subjective norms of one’s culture. Subjective norms are defined as the belief about whether most people approve or disapprove of behavior (Ajzen, 1991). Indonesian culture is more collectivist compared to people from western societies (Cultural Atlas, 2016). Indonesians tend to make decisions based on other's opinions, especially from friends and family. Indonesians are more likely to use the same e-commerce platforms used by their friends and family and perceive the e-commerce platforms as having a positive impact. However, they are more likely to be deterred from using the e-commerce platforms if people in their surroundings are not interested in it.

2.6.1 Attitude, Perceived Behavior Control, and Behavioral Intention

Attitude is defined as the degree to which a person has a favorable or unfavorable evaluation of the behavior of interest (Ajzen, 2020). If a person perceives e-commerce as beneficial, they will have a positive attitude and be more likely to use e-commerce. However, if they deemed it to be not beneficial, they would have less intention to use it. Perceived behavioral control refers to a person's perception of the ease or difficulty of utilizing the e-commerce website and services (Ajzen, 1991). People in Indonesia has a lack of technological knowledge. There is a 600,000 labor gap yearly between technology talent and demand from the technology sector (Bhwana, P., 2021; Putera, 2021).

Behavioral intention refers to the motivational factors that influence a behavior. The more vital the intention to perform the behavior, the more likely the behavior will be performed (Ajzen, 1991). In the current post-pandemic era, studies have shown a decline in e-commerce revenue in the first quarter of 2023 (eCommerce Market, 2023). Multiple factors could cause this phenomenon. For example, working adults have returned to the office and have less time to spend on online purchases. Consumers also have more options to do other activities, such as going on a vacation rather than online shopping. As the economy shifted post-pandemic, consumers prefer going to physical stores, visiting food markets, and going to public events.

In addition, Indonesia's inflation rate was low during the pandemic outbreak and has since increased to its highest point in 2023 (Trading Economics, 2023). People are more careful with their purchases because of the decrease in spending power and the increase in prices of goods. There has also been a shift in items that people purchased through e-commerce platform compared to those in physical stores. For example, data from the Statista Research Department (2023) showed that consumers are twice as likely to purchase fashion goods and electric devices online versus through a physical store. However, consumers are 50% more likely to purchase fresh fruits and vegetables in a physical store than online. All these factors combined have affected how consumers interact with e-commerce.

To sum up, there are many factors that can influence consumer's behavioral intention to shop online through e-commerce in the post-pandemic period. There are internal factors such as poor reviews or unfriendly e-commerce platforms which deter someone from utilizing e-commerce. There are external factors such as more access to public events and other forms of social gathering which may reduce one's spending on online shopping. There is also the economic factor of the country itself that influences one's spending power. Currently, there is a lack of study that investigates how these factors influence consumer's behavioral intention to shop online. Hence, our study would like to further understand these changes and provide insights for e-commerce enterprises and marketers. The study aims to enhance their platforms and tactics to effectively meet the demands and expectations of customers.

3. Methodology

A quantitative research method was used to analyze the hypothesis testing and confirm the relationship posited in this study. For this study, we gathered a sample size of 350 participants to fill out an online survey questionnaire. 350 samples can provide sufficient statistical power to detect significant relationships and effects within the studied population (Creswell & Creswell, 2017). It enables more precise estimates of population parameters and decreases the margin of error in the findings.

The combination of stratified random sampling methods is a practical approach to ensure that specific groups within the target population are adequately represented (Elfil & Negida, 2017). In this study, we use this method to collect information regarding domicile and e-commerce platform utilization among the residents of Jakarta, Bogor, Depok, Tangerang, and Bekasi (Jabodetabek). The predetermined questionnaire seeks to collect data regarding the participants' use of various platforms, including WhatsApp, Instagram, and TikTok.

By including specific e-commerce platforms in the queries, the study seeks to understand the engagement and experiences of participants with these platforms. This data can shed light on the popularity, effectiveness, usefulness, and user behaviors of each platform based on the hypotheses stated in the context of online shopping.

3.1. Study Area

The study focused on the study area of Jabodetabek on Java Island, Indonesia. Jabodetabek refers to the metropolitan area encompassing Jakarta, the capital city, and its surrounding regions, including Bogor, Depok, Tangerang, and Bekasi. It is one of the most populous and heavily urbanized areas in Southeast Asia.

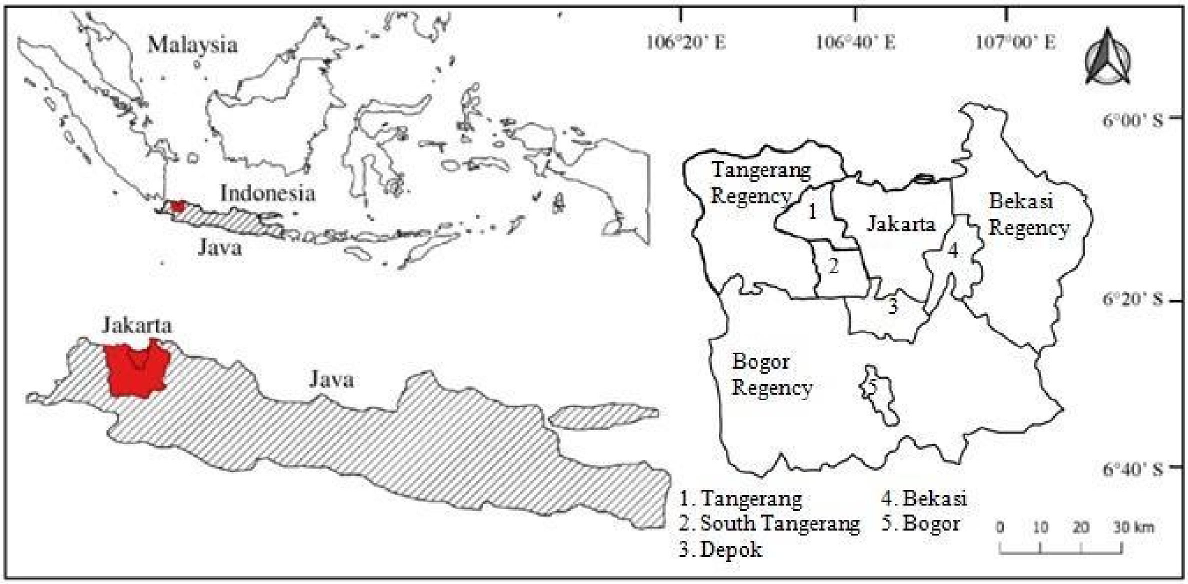

Fig. 1: Location of the big city clusters of Jabodetabek (generated using QGIS software).

According to Figure 1, survey questionnaires were distributed to the respondents from the big city clusters of Jabodetabek. The authors selected this mega metropolitan city for the case study because it is one of the most populated cities in Southeast Asia. It is estimated that 138 million Indonesians engage in e-commerce in this region, which reflects approximately 50% of the total population of Indonesia (Kaplan, 2022).

3.2. Analysis

The survey questionnaire will follow a systematic Path Modeling analysis method using SmartPLS. SmartPLS is a type of Structural Equation Modeling that simultaneously estimates and tests causal relationships between multiple dependent and independent variables. In this study, there were seven variables, namely Task-Technology Fit, Perceived Ease of Use, Perceived Usefulness, Subjective Norms, Attitude, Perceived Behavior Control, and Behavioral Intention. Each variable has five measurement items developed from previous research (Inthong et al., 2022; Kang & Namkung, 2019; Troise et al., 2021; Vanduhe, 2020). Each measurement item using 5-Likert scale ranges from strongly disagree to strongly agree.

Despite non-normality and small to medium sample sizes, latent constructs were modeled using SmartPLS 3.0 software, as Partial Least Squares (PLS) is a widely used technique for estimating path coefficients in structural models and had been used in several studies on the study of behavioral intentions. SPSS version 27.0 was used to perform descriptive statistics and reliability analysis on the post-survey questionnaire data, as shown in Table 1. The evaluation of the PLS path model employs the two-stage analytical procedures prescribed for SEM: outer model assessment (observation level) and inner model assessment (theoretical level). The convergent validity of the outer model was evaluated, then the validity and reliability of the measurement model, and last, the structural model. In contrast, the inner model evaluation consists of the variance of endogenous constructs, the magnitude of the effect, and the predictive significance (Hult et al., 2016). Using the bootstrap method (500 re-samples), the significance of path coefficients and loadings was determined. SEM requires data not to contravene the assumption of normality; therefore, a check on the normality of the data is required; a general rule of thumb for skewness states that if the number's skewness is less than or equal to 0.05, the data is normally distributed.

3.3. Measurement Items and Research Framework

Based on empirical data comprising 7 latent variables and 35 indicators, the statistical values were determined. Every indicator stated in Table 1 is tightly linked with earlier research.

Table 1: Measurement Items

Constructs	Measurement Items
Behavioral Intention (BI) (Cho et al., 2019; Inthong et al., 2022)	BI1: I intend to use e-commerce applications in the future. BI2: If I have the opportunity, I will buy necessities through e-commerce applications. BI3: I intend to continue making transactions via e-commerce applications. BI4: I will choose an e-commerce application to buy my needs. BI5: I would recommend the e-commerce app to others.
Attitude (ATT) (Cho et al., 2019; Inthong et al., 2022; Troise et al., 2021)	ATT1: Using e-commerce apps for shopping is useful. ATT2: I really like transacting e-commerce applications. ATT3: I want to use e-commerce applications. ATT4: I think using an e-commerce application is a good idea. ATT5: I recommend using e-commerce applications.
Subjective Norms (SN) (Roh & Park, 2019; Troise et al., 2021)	SN1: My friends suggested using an e-commerce application SN2: My family suggested using an e-commerce application SN3: The people closest to me suggested using an e-commerce application SN4: People whom I respect suggest using e-commerce applications SN5: People in my circle suggest using e-commerce applications
Perceived Behavior Control (PBC) (Hansen, 2008; Inthong et al., 2022; Troise et al., 2021)	PBC1: In general, buying necessities through e-commerce applications is not complicated. PBC2: Using e-commerce applications to buy necessities is fun. PBC3: Using e-commerce applications is very helpful in purchasing goods. PBC4: Using e-commerce applications is completely within my control. PBC5: I have the resources, knowledge, and ability to use e-commerce applications.
Perceived Ease of Use (PEOU) (Ajzen, 1991; Roh & Park, 2019)	PEOU1: I will feel the ease of using e-commerce applications. PEOU2: Operations on e-commerce applications are very clear and understandable. PEOU3: Using e-commerce applications does not require much effort. PEOU4: Learning to use e-commerce applications is easy. PEOU5: My experience is always satisfying when shopping through e-commerce applications.
Perceived Useful (PU) (Hagger et al., 2022; Roh & Park, 2019)	PU1: Using an e-commerce application will allow me to check the process of ordering and receiving delivery of goods effectively. PU2: Using e-commerce applications will make it more convenient.

	PU3: E-commerce applications will be useful for ordering goods PU4: My opinion, using an e-commerce application will allow me to buy goods faster. PU5: My opinion, using an e-commerce application will make it easier for me to buy the products that I want.
Task-Technology Fit (TTF) (Vanduhe et al., 2020; Zhao & Bacao, 2020)	TTF1: The functionality of the e-commerce application is enough for me. TTF2: The function of the e-commerce application is suitable to help manage ordering and receiving products. TTF3: The functionality of the e-commerce application fully meets my requirements for transactions. TTF4: It is effortless to understand the tools used in e-commerce applications. TTF5: E-commerce applications are suitable for helping me in completing shopping transactions.

Hypotheses developed:

H1 – H2: Task technology fit positively influences perceived ease of use and perceived usefulness among online shoppers
H3 – H4: Perceived ease of use positively influences perceived usefulness and attitude among online shoppers
H5: Perceived usefulness positively influences attitude among online shoppers
H6, H8: Subjective norm positively influences attitude and behavioral intention among online shoppers
H7, H9: Attitude positively influences perceived behavioral control and behavioral intention among online shoppers
H10 Perceived behavioral control positively influences behavioral intention among online shoppers.

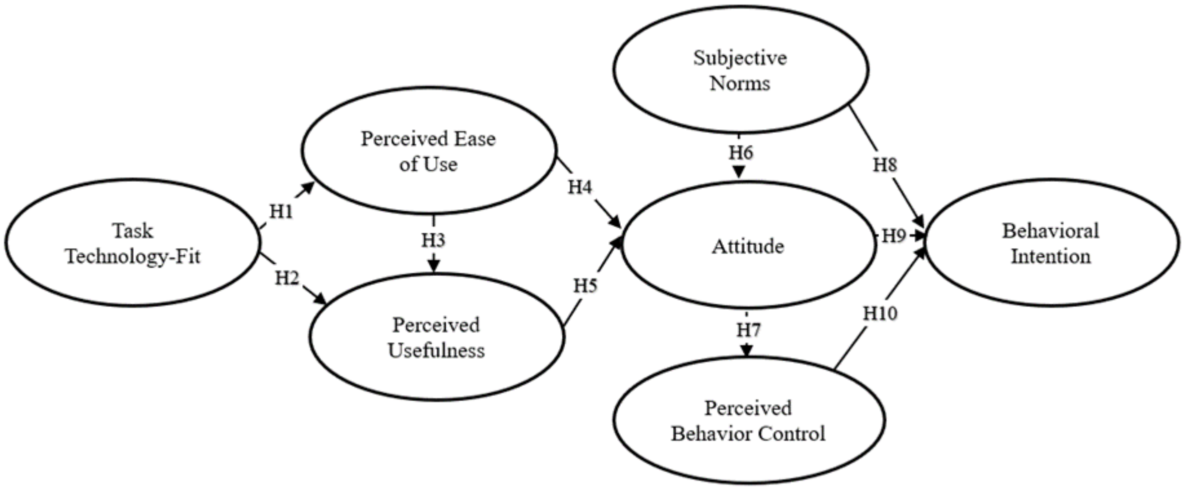

Fig. 2: Research Framework

4. Results

4.1. Descriptive Analysis

Table 2 provides descriptive statistics for respondents who completed researchers' electronic questionnaires. Most of the valid respondents were female (60.2%, n = 210). Most respondents were between the ages of 21 and 30 (n = 230, 65.71%), while 8.29% (n = 29) were under the age of 20, 10.29%

(n = 36) were between the ages of 31 and 40, and 15.71% (n = 55) were over the age of 41. In terms of educational attainment, 94% (n = 329) of the participants held a bachelor's degree or less, while only 6% (n = 21) were doctoral graduates.

Most participants (44.57%; n = 156) were in Jakarta, followed by Tangerang (27.14%; n = 95), Bekasi (15.43%; n = 54), Bogor (8%; n = 28), and Depok (4.86%; n = 17). The respondents held a variety of occupations, with private employees making up the largest group at 50% (n = 175), followed by housewives at 9.15% (n = 32), public servants at 3.43% (n = 12), and students and entrepreneurs. The maximum proportion of participants (38.57%; n = 135) reported using e-commerce platforms 3 to 5 times, followed by 2 times or fewer (32.86%; n = 115) and 6 times or more (28.57%; n = 100), showing that participants were moderate e-commerce users.

Most participants (42.72%, n = 153) spent less than Rp. 500,000 per month on e-commerce transactions, followed by Rp. 500,001 – Rp. 1,000,000 per month (27.43%, n = 96), Rp. 1,000,001 – Rp. 1,500,000 per month (11.71%, n = 41), and Rp. 1,500,001 – Rp. 2,000,000 per month (7.43%, n = 26). Shopee was the most popular e-commerce platform (56%, n = 196), followed by Tokopedia (30.29 %, n= 106), and Lazada and Blibli combined accounted for less than 15% of respondents.

Table 2: Demographic of Respondents

Profile	**N = 350**	**%**
Sex		
Male	140	40
Female	210	60
Age		
≤ 20 years old	29	8.29
21 – 30 years old	230	65.71
31 – 40 years old	36	10.29
≥ 41 years old	55	15.71
Most Advanced Education		
High School	81	23.14
Diploma	26	7.43
Undergraduate	222	63.43
Graduate-Doctor	21	6
Location		
Bekasi	54	15.43
Bogor	28	8
Depok	17	4.86
Jakarta	156	44.57
Tangerang	95	27.14
Occupations		
Students	55	15.71
Entrepreneurs	76	21.71
Private Employees	175	50
Public Servants	12	3.43
Housewife	32	9.15
Frequency of use e-commerce		
≤ 2 times per month	115	32.86
3 – 5 times per month	135	38.57
≥ 6 times per month	100	28.57

E-Commerce Transactions		
≤ Rp. 500,000 per month	153	42.72
Rp. 500,001 – Rp. 1,000,000 per month	96	27.43
Rp. 1,000,001 – Rp. 1,500,000 per month Rp.	41	11.71
1,500,001 – Rp. 2,000,000 per month	26	7.43
≥ Rp. 2,000,001 per month	34	9.71
Most used e-commerce application		
Blibli	4	1.14
Lazada	44	12.57
Shopee	196	56
Tokopedia	106	30.29

4.2. Outer Model Evaluation

The researcher initially investigates peripheral loadings and Average Variance Extracted (AVE) when evaluating convergent validity (Hult et al., 2016). In this study, factor loadings were used to measure variables including Attitude (ATT), Behavioral Intention (BI), Perceived Behavior Control (PBC), Perceived Ease of Use (PEOU), Subjective Norm (SN), Perceived Usefulness (PU), and Task Technology Fit (TTF). The research process involves a methodical approach to guaranteeing the accurate alignment of each variable within the broader context of the study, hence safeguarding the dependability and credibility of the measurements undertaken.

According to Hair et al., (2019) and Henseler et al., (2015), ideal factor loadings should be less than or equal to 0.70. For exploratory studies, however, a value of 0.50 is typically acceptable. As shown in Table 3, all item loadings exceed 0.6, satisfying the convergent validity criteria. In addition, the AVE values, which represent the proportion of variance explained by the latent construct, surpass the recommended cutoff value of 0.5 (Hair et al., 2019). The Cronbach's alpha (CA) values for all constructs are above 0.8, except for PU4 (0.786) and PEOU5 (0.67). However, it is crucial to note that a high alpha value may imply redundancy among items, as they may assess the same notion but in slightly different ways. Therefore, a maximum alpha value of 0.90 is commonly recommended (Streiner, 2003).Whereas only SN3 has a higher value of 0.905.

In terms of indicator reliability, all constructs have composite reliability (CR) values greater than 0.69, indicating a high level of indicator reliability. The researcher utilized the HTMT ratio, an alternative method based on the multi-trait-multi-method matrix (Henseler et al., 2015), to evaluate discriminant validity. In accordance with the HTMT criterion, discriminant validity is indicated when the value for two reflective constructs is less than 0.90. As shown in Table 4, the HTMT values for all constructs are less than 0.89, indicating adequate discriminant validity and diminishing the potential threat to the study's validity.

Table 3: Validity and Reliability of Constructs

Constructs/ Items	LF	CA	CR	AVE
Attitude (ATT)		0.909	0.933	0.735
ATT1	0.787			
ATT2	0.884			
ATT3	0.888			
ATT4	0.886			
ATT5	0.856			
Behavioral Intention (BI)		0.901	0.927	0.717
BI1	0.854			

BI2	0.866			
BI3	0.856			
BI4	0.839			
BI5	0.818			
Perceived Behavior Control (PBC)		0.892	0.921	0.699
PBC1	0.838			
PBC2	0.837			
PBC3	0.880			
PBC4	0.804			
PBC5	0.817			
Perceived Ease of USE (PEOU)		0.885	0.918	0.692
PEOU1	0.835			
PEOU2	0.882			
PEOU3	0.865			
PEOU4	0.889			
PEOU5	0.670			
Perceived Usefulness (PU)		0.908	0.932	0.733
PU1	0.849			
PU2	0.887			
PU3	0.879			
PU4	0.786			
PU5	0.875			
Subjective Norm		0.923	0.942	0.764
SN1	0.834			
SN2	0.843			
SN3	0.920			
SN4	0.890			
SN5	0.881			
Task Technology Fit		0.930	0.947	0.781
TTF1	0.883			
TTF2	0.905			
TTF3	0.850			
TTF4	0.884			
TTF5	0.897			

Note: All Loading Factors are significant

LF: Loading Factors, CA: Cronbach Alpha, CR: Composite Reliability, AVE: Average Variance Extracted

Table 4: Discriminant Validity using Fornell-Larcker Criterion

	ATT	BI	PBC	PEOU	PU	SN	TTF
Attitude	0.857						
Behavioral Intention	0.829	0.847					
Perceived Behavior Control	0.769	0/699	0.836				
Perceived Ease of Use	0.715	0.663	0.764	0.832			
Perceived Usefulness	0.685	0.659	0.732	0.780	0.856		
Subjective Norm	0.656	0.628	0.616	0.527	0.567	0.874	
Task Technology Fit	0.684	0.676	0.713	0.809	0.753	0.490	0.884

The Variance Inflation Factor (VIF) values for the variables in the model were examined to assess multicollinearity. The variance inflation factor is a way to quantify how multi-collinear the model terms are. A low correlation between that predictor and other predictors is indicated by a VIF of less than 5. VIF values greater than 10 are a symptom of strong, intolerable correlation of model predictors, while values between 5 and 10 indicate a moderate correlation (James et al., 2013). Table 5 shows the VIF values ranged from 1.000 to 2.891, indicating a low-to-moderate level of multicollinearity among the variables. Specifically, Variable Attitude had a VIF of 1.000, Behavioral Intention (BI) had a VIF of 2.816, Perceived Behavior Control (PBC) had a VIF of 2.586, Perceived Ease of Use (PEOU) had a VIF of 2.626, Perceived Usefulness (PU) had a VIF of 2.797, Subjective Norm (SN) had a VIF of 1.514, and Task-Technology Fit (TTF) had a VIF of 2.891. Results suggest the variables are reasonably independent from one another, making the results more trustworthy and easier to understand. Figure 3 presents the measurement model path diagram.

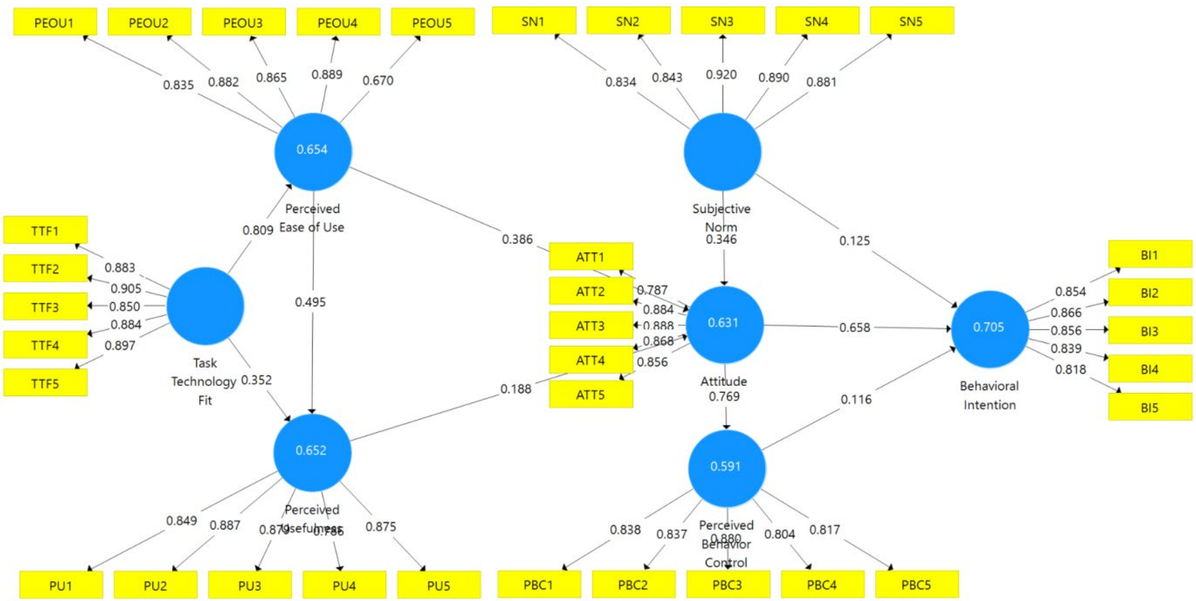

Fig. 3: Measurement Model Path Diagram

Table 5: Full Collinearity VIF

Constructs	VIF
Attitude	1.000
Behavioral Intention	2.816
Perceived Behavior Control	2.586
Perceived Ease of Use	2.626
Perceived Usefulness	2.797
Subjective Norm	1.514
Task Technology Fit	2.891

4.3. Inner Mode Evaluation

As shown in Table 6, the analysis of the inner model revealed several significant associations between the variables. Task-Technology Fit (TTF) had a large effect on Perceived Ease of Use (PEOU), indicating a significant influence. Nevertheless, the effect of TTF on Perceived Usefulness (PU) was relatively weak, with a small effect size. Perceived Ease of Use moderately influenced both Perceived Usefulness and Attitude. The Attitude was also moderately influenced by the Subjective Norm (SN).

However, the effects of Perceived Usefulness on Attitude and Subjective Norm on Behavioral Intention were comparatively modest. Attitude had a substantial influence on Perceived Behavior Control (PBC), indicating a significant relationship. Notably, Perceived Behavior Control did not significantly influence Behavioral Intention. These findings shed light on the relationships between the variables and their respective effect sizes.

4.4. Inner Model

Table 6: F-Square

Path	F-Square Value	Effect Size
TTF > PEOU	1.891	Large
TTF > PU	0.123	Small
PEOU > PU	0.244	Medium
PEOU > ATT	0.154	Medium
PU > ATT	0.034	Small
SN > ATT	0.214	Medium
ATT > PBC	1.448	Large
SN > BI	0.029	Small
ATT > BI	0.521	Large
PBC > BI	0.018	No Effect

Note: f-square is the effect size (Cohen, 2013) where 0.02 = small, 0.15 = medium, 0.35 = large

The coefficient of determination (R2), which assesses the amount of variation explained for each endogenous latent variable, is the most crucial criterion for assessing internal models (Hair et al., 2019). According to James et al., (2013), the R2 values of all constructs are greater than 0.26, indicating a large effect size, whereas 0.13 to 0.25 indicate a moderate effect size. This would suggest that the model is robust. Table 6 demonstrates that R square adjusted explains 63.1% of the variance in Attitude (R2 = 0.631), 70.5% of the variance in Behavioral Intention (R2 = 0.570), 59.1% of the variance in Perceived Behavior Control (R2 = 0.591), 65.4% in Perceived Ease of Use (R2 = 0.654) and 65.2% in Perceived Usefulness (R2 = 0.652) which are all large effect sizes.

Predictive relevance (Q2) is a predictive accuracy criterion evaluated by blindfolding, resampling, excluding endogenous variables, and estimating data for a complex model (Henseler et al., 2015). Table 7 also summarizes the Q2 values for Attitude (Q2 = 0.454), Behavioral Intention (Q2 = 0.497), and Perceived Behavior Control (Q2 = 0.397), Perceived Ease of Use (Q2 = 0.444), and Perceived Usefulness (Q2 = 0.465). If all Q2 values are larger than zero, then the model has predictive utility for the constructs (Hair et al., 2019). The model demonstrates strong explanatory and predictive capabilities in relation to user behavior and perceptions within the e-commerce domain, as seen by the high R2 values observed across all relevant constructs. The findings offer robust evidence for the model's dependability and efficacy in evaluating user attitudes and intentions within the realm of electronic commerce.

Table 7: R-Square & Q-Square

	R Square	R Square Adjusted	Q^2
Attitude	0.631	0.628	0.454
Behavioral Intention	0.705	0.703	0.497
Perceived Behavior Control	0.591	0.590	0.397
Perceived Ease of Use	0.654	0.653	0.444
Perceived Usefulness	0.652	0.650	0.465

4.5. Structural Estimates

In Table 8 shows the hypothesis testing results of the research. Task-Technology Fit (TTF) is found to be a significant predictor of the relationship of PEOU and PU, H1 ($\beta = 0.809$; $p < 0.01$) and H2 ($\beta = 0.352$; $p < 0.01$), PEOU is also a significant predictor for PU, H3 ($\beta = 0.495$; $p < 0.01$) and ATT, H4 ($\beta = 0.386$; $p < 0.01$). Besides, the significant predictor is also supported by PU with ATT H5 ($\beta = 0.188$; $p < 0.01$), SN with ATT H6 ($\beta = 0.346$; $p < 0.01$). ATT with PBC, H7 ($\beta = 0.769$; $p < 0.01$), and BI, H9 ($\beta = 0.658$; $p < 0.01$). SN is a significant predictor of BI, H8 ($\beta = 0.125$; $p < 0.01$) and PBC is also a significant predictor and BI, H10 ($\beta = 0.116$; $p < 0.05$).

Hypotheses 1 to 9 have obtained considerable support with a significant level of significance (p-value less than 0.01). H10 demonstrates a p-value below 0.05, which also has statistical significance, thereby emphasizing the consistency of the findings across the scrutinized hypotheses. In general, the majority of the hypotheses have received substantial support with a notable degree of statistical relevance, as indicated by p-values below 0.01. This highlights the robustness and reliability of the established associations. Figure 4 presents the structural modeling for this study.

Table 8: Hypotheses Testing

Path	Path Coefficient	t-statistic	p-value	Decision
H1: TTF > PEOU	0.809	27.536	0.000	Supported
H2: TTF > PU	0.352	3.384	0.000	Supported
H3: PEOU > PU	0.495	5.029	0.000	Supported
H4: PEOU > ATT	0.386	5.315	0.000	Supported
H5: PU > ATT	0.188	2.342	0.010	Supported
H6: SN > ATT	0.346	6.084	0.000	Supported
H7: ATT > PBC	0.769	25.577	0.000	Supported
H8: SN > BI	0.125	2.539	0.006	Supported
H9: ATT > BI	0.658	10.574	0.000	Supported
H10: PBC > BI	0.116	2.011	0.022	Supported

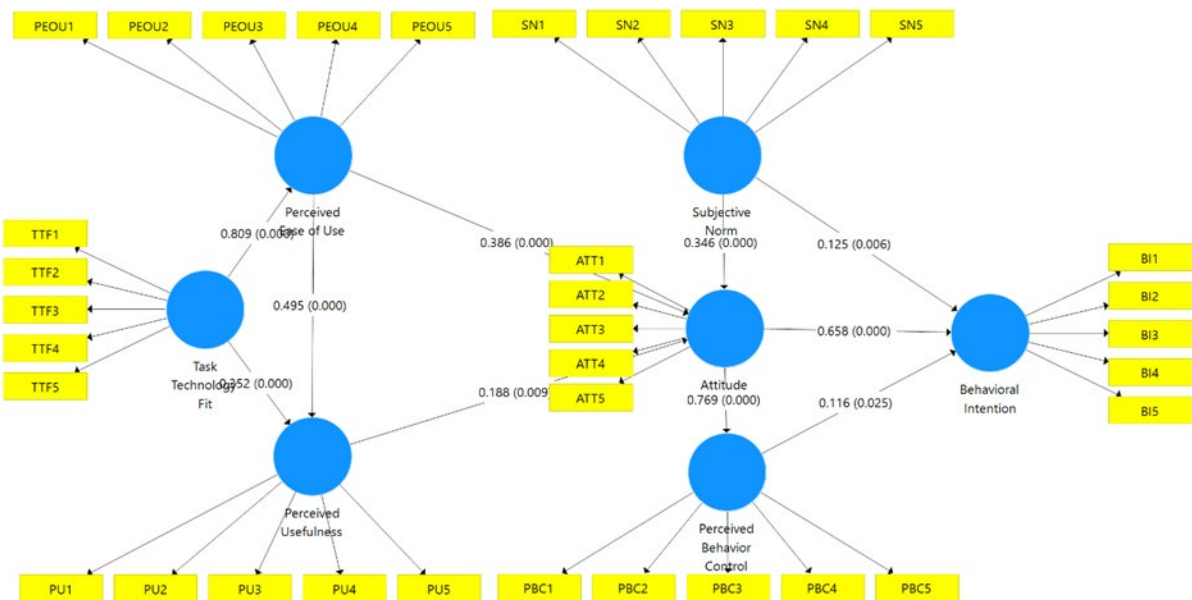

Fig. 4: Structural Model Path Diagram

5. Discussion

In H1 and H2, Task-Technology Fit (TTF) is a significant predictor of the relationship between Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). This hypothesis suggests that when the online shopping platform is well-aligned with users' duties, it will improve their perceptions of both usability and utility. This alignment has the potential to increase the platform's acceptability and subsequently influence consumers' behavior. When an online shopping platform is designed with a strong Task-Technology Fit, it indicates that the platform's features, functionalities, and capabilities are well-suited to satisfy the unique needs and tasks of online shoppers (Zeng et al., 2023). This alignment ensures that the platform provides a seamless and intuitive user interface, simple navigation, clear product descriptions, straightforward checkout processes, secure payment options, and other elements that make online purchasing convenient. In Shopee online shopping application, it would mean that users believe using the app makes their online shopping experience more useful or valuable (Priyatma, 2022).

Task-Technology Fit (TTF) is a significant predictor of the relationship between Perceived Ease of Use (PEOU) and Attitude (ATT). This suggests that the compatibility of the online purchasing platform with the users' tasks can influence their perception of the platform's usability, which influences their overall attitude toward the platform (Kasilingam, 2020; Suparno, 2020). Positive attitudes toward the platform may influence consumers' behavior. PEOU is a significant predictor of Perceived Usefulness (PU), in H3. This hypothesis suggests that users' perceptions of the platform's usability are influenced by their perceptions of its simplicity of use. If users find the platform to be user-friendly, they are more likely to perceive its utility, which can contribute to their adoption of the platform and subsequent behavior modification (Yousaf et al., 2021).

In H4, Perceived Ease of Use (PEOU) is also a significant predictor of Attitude (ATT). This suggests that the user's perception of the platform's usability influences their overall attitude toward it. If the platform is user-friendly, users are more likely to have a favorable attitude toward it, which can influence a behavior change (Al Enezi et al., 2022; Chawla & Joshi, 2019; Dogra & Kaushal, 2023). This finding is aligned with the previous studies by Priyatma, (2022), that PEOU has a positive and significant impact on repurchase intention among users of the Shopee online purchasing application in Indonesia.

In H5, perceived usefulness (PU) is a significant predictor of attitude (ATT). This hypothesis proposes that users' perceptions of the online shopping platform's utility influence their attitudes toward it. If users perceive the platform to be beneficial, they are more likely to develop a positive attitude, which can then result in a change in behavior (Chawla & Joshi, 2019; T. T. H. Nguyen et al., 2019). The study by Keni (2020) also reported the same results which both perceived usefulness (PU) and perceived ease of use (PEOU) play an important role in affecting consumers' intention to repurchase, both directly and indirectly toward customer satisfaction and trust.

In H6 posits that subjective norms (SN) are a significant predictor of attitude (ATT). SN refers to the social influences and conventions that shape the beliefs and actions of individuals. In the context of online shopping, this suggests that social factors, such as the opinions and expectations of others, can influence people's attitudes toward an online purchasing platform (Shirazi et al., 2022; Zhang et al., 2023). For example, if a person's peers and family all use the same online shopping platform, they are more likely to have a favorable opinion of that platform. This may then influence their behavior, such as their decision to purchase on the platform.

In H7, Attitude (ATT) is a significant predictor of Perceived Behavioral Control (PBC). In this instance, Attitude represents the overall evaluation and feelings of users toward the online purchasing platform. Perceived Behavioral Control refers to the confidence that users have in their ability to engage in the desired behavior, such as using an online purchasing platform. This hypothesis posits that a positive attitude toward the platform can increase users' perception of control over their own behavior, resulting in increased acceptance and behavioral change (Baikejuli et al., 2023).

In H8, Subjective Norms (SN) are a significant predictor of Behavioral Intention (BI). This suggests that social influences and norms play a role in shaping users' intentions to indulge online shopping platform-related behaviors. Positive subjective norms, such as recommendations from friends or family, can positively influence the behavioral intentions of users and increase the likelihood of platform adoption (La Barbera & Ajzen, 2020; Sun et al., 2020). If an individual perceives that their family, friends, or other important people in their life support and approve of online shopping, it can positively affect their Behavioral Intention to shop online. They may be more inclined to engage in online shopping because they want to conform to the social expectations and values of their reference group. Conversely, if the individual perceives that their social network disapproves of online shopping or believes it is risky or unfavorable, this may negatively influence their Behavioral Intention. They might be less motivated to shop online due to the perceived social pressure against it (La Barbera & Ajzen, 2020).

In H9, attitude is a significant predictor of Behavioral Intention. The users' attitudes toward the online purchasing platform influence their intentions to engage in specific platform-related behaviors. A positive attitude toward the platform increases the likelihood that users will intend to engage in the desired behaviors, ultimately resulting in a behavior change (Sharma et al., 2022). The result of this study aligned with another study suggests that purchasing attitude is influenced by the trust of customers to the online shopping platform quality, which includes aspects like website design, usability, speed, security, and reliability (Al-Debei et al., 2015).

In H10, Perceived Behavioral Control (PBC) is a significant predictor of Behavioral Intention (BI). Users' intentions to partake in particular behaviors are influenced by their perception of control over their own online shopping behavior. Higher levels of Perceived Behavioral Control (PBC) increase user adoption intentions and behavior modification (Hagger et al., 2022; La Barbera & Ajzen, 2020). This reflects a person's overall evaluation of the behavior. A positive attitude toward online shopping, for example, could increase the likelihood of forming a strong intention to shop online. When potential customer believes, they have a high level of control over their behavior (e.g., they believe they can quickly browse online businesses, make secure payments, etc.), their intention to engage in that behavior (BI) increases (La Barbera & Ajzen, 2020).

In conclusion, the hypotheses presented in this paragraph intend to investigate the relationships between Task-Technology Fit (TTF), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude (ATT), and behavioral change in the context of an online purchasing platform. These hypotheses suggest that the alignment of the platform with users' tasks, simplicity of use, perceived usefulness, and positive attitudes toward the platform can all influence shoppers' behavior. This study seeks to shed light on the factors that drive acceptance and subsequent behavioral change in the context of online shopping platforms by understanding and validating these relationships with investigating intentions using TAM-TPB-TTF model. In the current era of technological advancements and digitalization, online shopping platforms have become an integral part of consumers' lives. Many researchers have tried to understand the factors that influence consumers' acceptance and subsequent behavioral change towards online shopping platforms.

6. Implications

Indonesia is a multicultural nation with a broad variety of cultures. This variety may affect how individuals view and tolerate online shopping platforms. Some cultures may be more comfortable with online purchasing than others, for instance (Warganegara & Hendijani, 2022). Indonesia is a developing nation with an expanding middle class because of economic factors (Sibuea et al., 2022). This expanding middle class is more likely to have a disposable income for online shopping. The increasing availability of high-speed internet has also contributed to the growth of e-commerce in Indonesia.

The Indonesian government has supported the growth of e-commerce through its policies. This assistance has included initiatives to enhance the infrastructure for online purchasing, such as the creation of a national e-commerce platform. The availability of smartphones and other mobile devices has facilitated online shopping among the people of Indonesia. In addition, the growing popularity of social media has made it simpler for online retailers to reach prospective customers. This study's findings have implications for the attainment of multiple Sustainable Development Goals (SDGs). For instance, the SDGs related to economic growth (SDG 8) and reduced inequalities (SDG 10) could be advanced by increasing the adoption of online purchasing platforms, which could contribute to the creation of jobs and a reduction in the cost of living for consumers. In addition, the Sustainable Development Goals (SDGs) related to sustainable consumption and production (SDG 12) and climate action (SDG 13) could be advanced by encouraging consumers to shop online, which could reduce the environmental impact of transportation and consumption.

7. Limitation and Future Research

It is difficult to generalize study findings since the total respondents in Indonesia are not representative of the larger population in other areas of the country. Specific contextual factors frequently influence research outcomes, and these characteristics may not apply in other locations. Findings about online buying behavior in one location or country, for example, may not be readily transferable to a different cultural or economic setting. Moreover, the relevance of research findings can be limited by the timeframe in which the study was conducted. Technology, society, and behaviors grow over time, and what holds true today may not hold true in the future.

Additional research could investigate additional variables for the long term that could affect behavioral intent and acceptability of online purchasing platforms. For instance, research could investigate the influence of social media on consumer behavior or the role of government policies in promoting the adoption of online purchasing platforms. This study's findings have implications for consumers as well. Consequently, consumers who are aware of the factors that influence behavioral intention and acceptance of online purchasing platforms may be more likely to adopt these platforms and change their behavior.

The majority of our study’s respondents are people between the ages of 21 to 30 years old. While this working age group is the ones that engage the most in e-commerce, our study found that they tend to make small purchases (spent less than Rp. 500,000 per month on e-commerce transactions). Future studies can investigate whether the older population or those categorized in higher income groups are more likely to make e-commerce transactions and investigate how their engagement differs compared to the younger generations or those with lower socioeconomic status. The current study focuses on people living in Jakarta and its surrounding areas. Future study can look at e-commerce behavior of Indonesians that are living outside of Jakarta or Java Island where access to goods and services are more limited, slower, and tend to be more expensive compared to those in Jakarta and its surrounding areas.

8. Conclusion

This study provides an empirical analysis of post-pandemic online shopping intentions in Indonesia using a robust integrated TAM-TPB-TTF model. The results offer timely theoretical and practical insights into encouraging the continued adoption of e-commerce in developing economies recovering from pandemic disruptions. However, the limitations of focusing only on one metropolitan region and self-reported data suggest opportunities for additional research expanding the sample diversity and geographic coverage. Nonetheless, this study delivers strong initial evidence to guide e-commerce platforms in shaping their website design and promotional strategies to sustainably match evolving consumer needs and preferences.

E-commerce is very popular in Indonesia. It is the second-largest contributor of plastic waste in the world (Haryanti & Subriadi, 2022). This study highlights the significance of comprehending and mitigating the environmental ramifications associated with e-commerce in a nation such as Indonesia, which plays a substantial role in the generation of plastic trash. Future study should investigate the potential threat to the environment. It is important to investigate the circular economy, which allows the waste to be managed and not become a major influence on pollution. Adopting a circular economy strategy is essential for enhancing waste management and reducing e-commerce-related pollution, e.g., implementing Extended Producer Responsibility (EPR) policies and consumer awareness and participation in engaging activities (Cheng et al., 2022; Zaini et al., 2022).

In practical applications, it is possible to comprehend the importance of perceived behavior control and subjective norms as guiding factors for e-commerce enterprises in cultivating consumer engagement. Companies can enhance the favorable environment for their services by encouraging consumer engagement in online buying activities and increasing awareness regarding the advantages of e-commerce. Policymakers can use the findings of this study to inform the development of regulations and policies that promote the sustainability of e-commerce. One potential approach to fostering environmentally sustainable practices within the e-commerce industry is through implementing regulations that encourage Extended Producer Responsibility (EPR) and provide incentives for enterprises to embrace eco-friendly practices. These measures have the potential to mitigate the environmental consequences associated with the e-commerce industry.

This study investigated the post-pandemic antecedents of behavioral intention to purchase online via e-commerce. The study incorporated the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Task-Technology Fit (TTF) to comprehend the factors that influence shoppers' acceptance of online purchasing platforms and subsequent behavioral changes. In addition, this study enhances our comprehension of consumer behavior in the pandemic's aftermath. This observation highlights the enduring relevance of established behavioral theories in understanding consumer decision-making, particularly in a dynamic and developing environment. Such findings hold significant value for scholars and researchers investigating post-pandemic trends. All hypotheses were supported with a high level of statistical significance, showing that the integrated TAM, TPB, and TTF framework is a valuable instrument for understanding the factors that influence behavioral intention and acceptance of online purchasing platforms. E-commerce businesses can use this framework to design and implement platforms that are more likely to be accepted by consumers.

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