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The Effects of Customer Participation Behavior and Customer Expertise on Behavioral Intention through Self-Efficacy in Using Self-Service Technology

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ABSTRACT

This study aims to analyze the effects of *Customer Participation Behavior* (CPB) and *Customer Expertise* (CE) on *Behavioral Intention* (BI) through *Self-Efficacy* (SE) in the use of *Self-Service Technology* (SST). The research employed the *Partial Least Squares Structural Equation Modeling* (PLS-SEM) approach, using an online questionnaire distributed to respondents who had used one or more forms of SST, such as vending machines, self-ordering kiosks, self-check-in counters, or self-service fuel stations. The results reveal that CPB and CE significantly influence SE and BI, while SE acts as a mediator between CPB and CE on BI. These findings provide theoretical and practical implications for improving customer adoption and the continued use of self-service technologies.

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INTRODUCTION

The advancement of information technology has been a key driver of service innovation, particularly through the implementation of *Self-Service Technology* (SST). This technology enables customers to access services independently, giving them freedom and control over their service experiences (Meuter et al., 2000). SST has significantly impacted various industries, such as retail, banking, and healthcare, by reshaping customer–provider interactions (Shahid Iqbal et al., 2018). Its implementation helps companies reduce operational costs while providing customers with convenience and accessibility anytime and anywhere (Meuter et al., 2000). Examples of SST include ATMs, mobile banking, airport self-check-in counters, vending machines, and self-ordering kiosks. For instance, airport self-check-in systems effectively reduce queues (Ardiansyah & Ahyudanari, 2017) and enhance operational efficiency (Jong-Hyeon & Jin-Woo, 2019). However, technical issues such as machine malfunctions, unstable internet connections, and lack of clear instructions still hinder users (Enjelika, 2024). Similarly, self-ordering kiosks in restaurants may cause discomfort among users due to limited technological knowledge, concerns about data security, and poor interface design (Ngelambong et al., 2023).

SST adoption at gas stations also faces challenges, such as low customer understanding leading to operational errors and long queues (Erdiyanti & Edriadi, 2024; Ottemusu et al., 2023). Likewise, while vending machine usage in Indonesia is increasing rapidly, users still encounter technical difficulties, including screen damage and payment failures (Wicaksono et al., 2019). These findings highlight that successful technology adoption depends not only on infrastructure availability but also on customers' readiness to interact with new systems. Hence, user education and clear guidance are essential to improve customers' comfort and confidence in using SST.

In this context, *Customer Participation Behavior* (CPB) plays an essential role in SST success. Active customer participation enables value co-creation between customers and service providers, which enhances both efficiency and satisfaction (Auh et al., 2007). However, not all customers possess the confidence or expertise required for active engagement. Some experience stress, anxiety, or discomfort when dealing with technology-based systems (Parasuraman, 2000; Meuter et al., 2005; Ugwuanyi et al., 2022), indicating that personal factors such as *Customer Expertise* (CE) and *Self-Efficacy* (SE) are crucial in determining SST adoption success.

Customer Expertise refers to a customer's technological knowledge and skills, while *Self-Efficacy* represents their belief in their ability to use technology effectively (Hsiao & Tang, 2015). Customers with higher expertise and confidence tend to adapt faster and handle technological barriers better (Hilton et al., 2013). Conversely, users with limited experience or high anxiety toward technology are more likely to avoid SST (Meuter et al., 2003). Therefore, self-efficacy acts as an essential motivator influencing behavioral intentions toward technology usage (Davis et al., 1989; Sheeran et al., 1999).

Based on these considerations, this study focuses on the lack of customer expertise and participatory behavior that may reduce *self-efficacy* and lower repeat usage intentions toward SST. The research scope is limited to four types of technologies—vending machines, self-ordering kiosks, airport self-check-in counters, and self-service fuel stations. This study aims to examine the effects of Customer Participation Behavior and Customer Expertise on Behavioral Intention through Self-Efficacy in SST usage, and to understand how these variables interact to encourage continuous technology adoption. Theoretically, this research contributes to the literature on consumer behavior in technology-based services, while practically, it offers insights for businesses to design more interactive and efficient self-service systems that enhance customer confidence, satisfaction, and loyalty (Revilla-Camacho et al., 2015)

LITERATURE REVIEW

This study integrates several theoretical foundations, including the Technology Acceptance Model (TAM) (Davis, 1989), which explains that users' behavioral intention toward technology is shaped by their perceived usefulness and perceived ease of use. In the context of SST, customers who perceive technology as both useful and easy to use tend to form positive attitudes toward adoption (Sukma, 2022). The Service-Dominant Logic (SDL) by Vargo and Lusch (2004) supports this view, suggesting that customers co-create value through active participation, which enhances service quality and recovery efficiency (Cheng & Xue, 2013). Furthermore, Social Cognitive Theory (Bandura, 1997) emphasizes that self-efficacy, or confidence in one's abilities, strongly determines behavioral outcomes. Finally, the Expectation-Confirmation Model (ECM) (Bhattacherjee, 2001) posits that satisfaction and confirmation of expectations after initial use foster continuance usage intention.

Active participation in service processes allows customers to gain hands-on experience, enhancing their knowledge and problem-solving abilities (Yi & Gong, 2011). Revilla-Camacho et al., (2015) found that customer engagement strengthens learning and competence. Similarly, Yang et al., (2014) showed that experiential interaction with technology increases user expertise. However, Koc and Kotsos (2017) cautioned that excessive system complexity can limit this effect. Despite these nuances, most empirical evidence supports a positive relationship between participation and expertise development.
H1: Customer Participation Behavior positively influences Customer Expertise.

According to Bandura's Social Cognitive Theory, active participation leads to mastery experiences that enhance self-efficacy. Users who successfully operate SST develop stronger confidence to repeat similar tasks (Compeau & Higgins, 1995; Wang et al., 2013). Parasuraman (2000), argued that high technology anxiety may inhibit this growth. More recent studies Ugwuanyi et al., (2022) reaffirm that user involvement improves confidence and reduces perceived technological barriers, reinforcing the expected positive link.
H2: Customer Participation Behavior positively influences Self-Efficacy.

Expertise reflects accumulated knowledge and technical capability, which directly strengthen self-efficacy (Hsiao & Tang, 2015; Jamal & Anastasiadou,

2009). Experienced users are better equipped to handle difficulties, thereby enhancing confidence (Hilton et al., 2013). Dennis (2008) also observed that self-efficacy improves as users gain familiarity with technology over time. Hence, customer expertise serves as a foundation for self-efficacy development.
H3: Customer Expertise positively influences Self-Efficacy.

Customer involvement fosters satisfaction, engagement, and emotional connection, which drive repeat usage intentions (Yim et al., 2012; Dong & Sivakumar, 2015). In SST contexts, hands-on interaction deepens user familiarity, reducing perceived risk. Nonetheless, Ugwuanyi et al. (2022) highlighted that excessive participation burden might dampen behavioral intention. On balance, empirical findings favor a positive association between CPB and BI.
H4: Customer Participation Behavior positively influences Behavioral Intention.

Technologically skilled customers exhibit higher efficiency and confidence, leading to stronger continuance intentions (Ding & Chai, 2012; Wang et al., 2013). Hilton et al. (2013) confirmed that expertise enhances sustained use by improving comfort and perceived control. However, Cheung & Limayem (2005) noted that contextual constraints such as service accessibility and changing needs can moderate this link. Despite this, the consensus in literature supports that expertise predicts repeat usage.
H5: Customer Expertise positively influences Behavioral Intention.

Self-efficacy has been widely identified as a strong predictor of intention and technology adoption (Bandura, 1997; Venkatesh et al., 2003). Confident users are more inclined to reuse and recommend technology (Kim & Park, 2019). Conversely, low self-efficacy individuals may avoid new systems due to anxiety or perceived difficulty (Meuter et al., 2003). Supporting this, X. Chen et al. (2022) found that self-efficacy exerts the strongest direct effect on behavioral intention among SST users, reinforcing its central role in technology acceptance.
H6: Self-Efficacy positively influences Behavioral Intention.

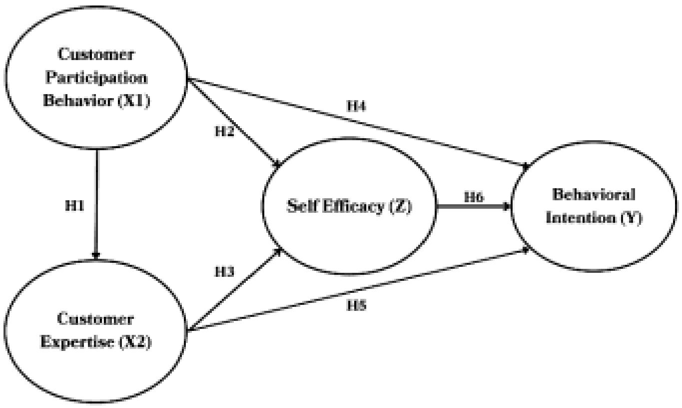

Figure 1. Research Model

METHODOLOGY

Sample and Population

The research population comprises individuals who have previously used SST services such as self-service fuel pumps at gas stations, self-ordering kiosks in fast-food restaurants, vending machines, and self-check-in counters at airports or train stations. These individuals represent users with direct experience in interacting with technology-based services (Priadana & Sunarsi, 2021). The sampling technique adopted in this study is *non-probability sampling* with a *purposive sampling* approach. This method was chosen because it allows the researcher to select respondents deemed most relevant and knowledgeable about the research topic (Etikan, 2017). The inclusion criteria include: (1) male or female respondents who have used SST, (2) aged between 17 and 65 years, and (3) intending to use another form of SST different from the one previously experienced.

Data Collection

The interval data in this research were collected using an *agree–disagree scale* format, where respondents were asked to indicate their level of agreement with a series of statements related to the research variables. A five-point Likert scale was applied, ranging from (1 = strongly disagree to 5 = strongly agree). This scaling approach was chosen because it effectively captures the intensity of respondents' attitudes and perceptions, providing a quantitative foundation for subsequent statistical analysis. Primary data were gathered via an online questionnaire distributed through Google Forms. The questionnaire consisted of two parts: (1) respondent characteristics and demographic profiles, and (2) measurement items using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Measurement

The operationalization of each variable was based on established literature. *Customer Participation Behavior* was measured using two dimensions—*information seeking* and *responsible behavior*—adapted from Yi and Gong (2011) and Yim et al. (2012). *Customer Expertise* was measured using indicators developed by Ding and Chai (2012), including knowledge, ability, and problem-identification capability during SST use. *Self-Efficacy* was measured using two items adapted from Sumartini et al. (2024), representing confidence in completing specific tasks and the ability to overcome difficulties. *Behavioral Intention* was adapted from Choi et al. (2004), focusing on consumers' intention to reuse SST in the near future. All constructs were modeled reflectively, as their indicators were considered manifestations of the latent variables.

RESEARCH RESULT

Data analysis

Respondent Data Characteristics

This study involved a total of 143 respondents, all of them were between 17 and 65 years old. Based on the data obtained, every respondent (100%) had prior experience using *Self-Service Technology* (SST), Most respondents (80.4%) were undergraduate students, followed by 13.3% who had completed senior high school, 3.5% with diploma-level education, and only a small proportion (1.4% each) holding master's or doctoral degrees. In terms of occupation, 81.8% of respondents were students, 12.6% were private employees, and 5.6% were homemakers. This distribution indicates that most respondents are within a productive age group that is generally familiar with technology and adaptive to innovations such as SST.

Regarding the frequency of SST usage, a large portion of respondents (79%) had used SST within the last six months, 13.9% within six months to one year, 4.9% within one to two years, and only 2.1% within two to three years. The most commonly used SST was self-service fuel dispensers (62.2%), followed by self-ordering kiosks in fast-food chains (60.8%), self-check-in counters at airports or train stations (57.3%), and vending machines (46.9%). Descriptive statistical analysis shows that all indicators across variables obtained mean scores above 3.4, indicating responses within the "Agree" to "Strongly Agree" categories. This suggests that respondents held a generally positive perception of all measured constructs. The *Customer Participation Behavior (CPB)* variable recorded the highest means on items related to fulfilling procedural and responsibility aspects (mean = 4.3), which fall into the "Strongly Agree" category. The *Customer Expertise (CE)* variable showed average scores ranging from 3.4 to 3.7. *Self-Efficacy (SE)* had mean scores between 3.8 and 4.0. Similarly, *Behavioral Intention (BI)* demonstrated means ranging from 3.7 to 4.0.

Convergent Validity

The next stage of analysis involved testing the measurement model (*outer model*) to ensure the validity and reliability of the constructs. The results of the *convergent validity* test revealed that all indicators achieved *loading factor* values above the recommended threshold of 0.7, except for one indicator (CPB1 = 0.642). The *Average Variance Extracted (AVE)* values for all constructs exceeded 0.5, confirming that the indicators were capable of explaining more than 50% of their respective construct variance. Moreover, the *Composite Reliability (CR)* values were above 0.86 for all constructs, indicating strong internal consistency and reliability across measurement items.

Table 1. Convergent Validity Result

Indicator	Loading	CR	AVE
Customer Participation Behavior (X1) (CA= 0,847)		0,888	0,570
I have searched for information about new Self-Service Technology besides the ones I have used before.	0,642		
I have searched for information about the service locations provided by Self-Service Technology (SST).	0,721		
I have carefully observed others' behavior in using this Self-Service Technology (SST).	0,715		

Indicator	Loading	CR	AVE
I follow all the necessary steps required by the system to obtain services from Self-Service Technology.	0,830		
I complete all the actions expected by Self-Service Technology (SST).	0,793		
I fulfill my responsibilities as a consumer in using Self-Service Technology (SST).	0,813		
Customer Expertise (X2) (CA= 0,756)		0,860	0,672
I know a lot about new Self-Service Technology besides the ones I have used before.	0,840		
When problems occur in using new Self-Service Technology besides the ones I have used before, I am able to identify the causes.	0,764		
I have the ability to use new Self-Service Technology besides the ones I have used before.	0,853		
Behavioral Intention (Y) (CA= 0,846)		0,907	0,765
I plan to use new Self-Service Technology besides the ones I have used before in the near future.	0,871		
Most likely, I will use new Self-Service Technology besides the ones I have used before in the near future.	0,879		
I hope to be able to use new Self-Service Technology besides the ones I have used before in the near future.	0,873		
Self Efficacy (Z) (CA= 0,732)		0,882	0,789
I am confident that I can use new Self-Service Technology besides the ones I have used before.	0,889		
I am confident that I can overcome difficulties in using new Self-Service Technology besides the ones I have used before.	0,887		

Composite Reliability

Furthermore, the results of the reliability assessment revealed that all *Composite Reliability (CR)* values were at an excellent level. According to Fornell and Larcker (1981) and Hair et al., (2017), the minimum acceptable threshold for CR is 0.7. In this study, all constructs recorded CR values above 0.860, indicating a very high degree of internal consistency across the measurement items.

Discriminant Validity

To further assess *discriminant validity*, both *cross-loading* and *Fornell–Larcker* criteria were employed. The *cross-loading* results indicated that each indicator loaded higher on its associated construct than on other constructs, confirming discriminant validity. The *Fornell–Larcker* criterion showed that the square root of AVE for each construct exceeded its correlations with other constructs. For example, the square root of AVE for *Behavioral Intention (0.874)* was higher than its correlations with *Customer Expertise (0.644)*, *Customer Participation Behavior (0.627)*, and *Self-Efficacy (0.672)*. Similar results were observed across all other constructs, thereby demonstrating that each variable was empirically distinct from the others.

Table 2. Cross Loading Result

	BI	CE	*CPB*	SE
CPB1	0,467	0,544	0,642	0,354
*CPB*2	0,451	0,516	0,721	0,503
CPB3	0,490	0,350	0,715	0,485
*CPB*4	0,489	0,439	0,830	0,493
*CPB*5	0,441	0,402	0,793	0,478
CPB6	0,492	0,406	0,813	0,516
CE1	0,588	0,840	0,464	0,500
CE2	0,406	0,764	0,419	0,512
CE3	0,573	0,853	0,555	0,600
SE1	0,613	0,586	0,531	0,889
SE2	0,580	0,581	0,583	0,887
BI1	0,871	0,587	0,567	0,586
BI2	0,879	0,580	0,515	0,604
BI3	0,873	0,520	0,563	0,572

Table 3. Fornell-Larcker Result

	BI	CE	*CPB*	SE
BI	0,874			
CE	0,644	0,820		
CPB	0,627	0,590	0,755	
SE	0,672	0,657	0,627	0,888

Heterotrait–Monotrait Ratio (HTMT)

The *Heterotrait–Monotrait Ratio (HTMT)* analysis further confirmed discriminant validity, with all values below the 0.90 threshold recommended by Hair et al. (2017). The highest HTMT values were observed between *Customer Expertise* and *Self-Efficacy* (0.881) and between *Behavioral Intention* and *Self-Efficacy* (0.854). These relatively high but acceptable values indicate strong relationships among the constructs, which are theoretically expected. Specifically, higher customer expertise tends to enhance self-efficacy, while greater self-efficacy often leads to stronger behavioral intentions to reuse SST. Therefore, all constructs in this study were found to be valid, reliable, and suitable for further analysis in the structural model.

Table 4. HTMT Result

	BI	CE	CPB	SE
BI				

CE	0,795			
CPB	0,741	0,729		
SE	0,854	0,881	0,796	

Path Coefficient

Customer Participation Behavior exhibited a strong and significant influence on Customer Expertise, with a coefficient value of 0.590 (p = 0.000). Customer Participation Behavior was also found to have a significant positive effect on Self-Efficacy, with a coefficient of 0.368 (p = 0.000). In a similar vein, Customer Expertise significantly influenced Self-Efficacy, with a coefficient of 0.441 (p = 0.000). Furthermore, Customer Participation Behavior was shown to positively influence Behavioral Intention, as evidenced by a coefficient of 0.258 (p = 0.003). Similarly, Customer Expertise exhibited a positive and significant effect on Behavioral Intention, with a coefficient of 0.275 (p = 0.002). Additionally, Self-Efficacy demonstrated a significant positive effect on Behavioral Intention, with a coefficient of 0.330 (p = 0.001).

Table 5. Path Coefficient Result

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	P Values	Statement
CE -> BI	0,275	0,279	0,090	0,002	Accepted
CE -> SE	0,441	0,431	0,087	0,000	Accepted
CPB -> BI	0,258	0,264	0,087	0,003	Accepted
CPB -> CE	0,590	0,595	0,067	0,000	Accepted
CPB -> SE	0,368	0,369	0,091	0,000	Accepted
SE -> BI	0,330	0,319	0,100	0,001	Accepted

Indirect Effects

The analysis of indirect effects further revealed that Self-Efficacy plays a significant mediating role in the model. The relationship between Customer Expertise and Behavioral Intention was found to be significantly mediated by Self-Efficacy (p = 0.004), indicating that customers' confidence in their technological ability amplifies the impact of expertise on behavioral intention. Likewise, the influence of Customer Participation Behavior on Behavioral Intention was significantly mediated by Self-Efficacy (p = 0.000), confirming that active participation fosters confidence, which subsequently enhances the intention to reuse SST. Moreover, Customer Participation Behavior influenced Self-Efficacy indirectly through Customer Expertise (p = 0.000). Together, these findings illustrate that both expertise and self-efficacy serve as psychological enablers that transform active engagement into sustainable behavioral intentions.

Table 6. Indirect Effect Result

Variabel	*Original Sample*	*Sample Mean*	STDEV	P Values
CE -> BI	0,145	0,051	2,856	**0,004**
CPB -> BI	0,369	0,363	0,068	**0,000**
CPB -> SE	0,260	0,264	0,057	**0,000**

Coefficient of Determination (R^2)

The coefficient of determination (R^2) values further supports the model's explanatory strength. Behavioral Intention ($R^2 = 0.560$) was explained by 56% of the variance in the model, influenced by Customer Participation Behavior, Customer Expertise, and Self-Efficacy. Customer Expertise ($R^2 = 0.348$) was explained by 34.8% of the variance, primarily driven by Customer Participation Behavior, while Self-Efficacy ($R^2 = 0.520$) was explained by 52% of the variance, influenced by both participation and expertise. These values fall within the moderate to strong range, indicating that the proposed model has satisfactory explanatory power for behavioral research in the context of technology adoption.

Table 7. R Square Result

	R Square	R Square Adjusted
BI	0,560	0,551
CE	0,348	0,343
SE	0,520	0,513

Effect size (f^2)

The evaluation of model fit through effect size (f^2) and predictive relevance (Q^2) also supports the robustness of the model. The effect size results indicate that Customer Participation Behavior exerts a large effect on Customer Expertise ($f^2 = 0.533$), while the effects on Self-Efficacy and Behavioral Intention are in the moderate range.

Table 8.Effect Size Result

		BI	**CE**	**CPB**	**SE**
BI					
CE		0,089			**0,264**
CPB		0,083	**0,533**		**0,184**
SE		0,119			

Q Square (Q^2)

Meanwhile, the Q^2 results for all endogenous variables—Behavioral Intention (0.410), Customer Expertise (0.217), and Self-Efficacy (0.397)—are positive, confirming that the model possesses good predictive relevance and is capable of accurately estimating observed data (Ghozali, 2016; Chin, 1998).

Table 9. Q Square Result

	Q^2 (=1-SSE/SSO)
BI	0,410
CE	0,217
CPB	
SE	0,397

Mediation Analysis

At the end, the mediation analysis results show that all indirect relationships exhibit partial mediation, in accordance with the criteria proposed by Baron and Kenny (1986). This means that while the mediating variables Self-Efficacy and Customer Expertise significantly strengthen the relationships among constructs, the direct effects remain substantial. In this context, Self-Efficacy and Customer Expertise not only serve as mediating mechanisms but also amplify the direct influence of customer participation on behavioral intention. Overall, the inner model results provide strong empirical evidence that active customer participation enhances expertise and self-efficacy, both of which are crucial determinants of customers' intention to reuse Self-Service Technologies in the future.

Table 10. Mediation Analysis Result

No.	Tested mediation	Criteria				Result
		k1	k2	k3	k4	
1.	The influence of CPB on SE is mediated by CE.	**s**	**s**	**s**	**s**	*Partially Mediated*
2.	The influence of CPB on BI is mediated by SE.	**s**	**s**	**s**	**s**	*Partially Mediated*
3.	The influence of CE on BI is mediated by SE.	**s**	**s**	**s**	**s**	*Partially Mediated*

DISCUSSION

Influence of Customer Participation Behavior on Customer Expertise

Value co-creation theory and Service-Dominant Logic (Vargo & Lusch) emphasize that active customer involvement in the process (customer participation) forms the foundation for developing customer expertise and understanding of the service or technology employed. Active engagement in seeking information, trying features, and participating naturally fosters experience and knowledge, thereby enhancing expertise. Thus, higher customer participation correlates with greater expertise in using SST. Customer interaction mode depends on experience, ability, and service knowledge (Meuter et al., 2005). Cheng & Xue, (2013) found that increasing customer expertise not only directly improves perceived service quality but also strengthens the positive effect of customer participation on service quality. Therefore, customer expertise acts as a key determinant and a moderating variable enhancing the relationship between participation and service quality perception. The stronger the customer expertise, the greater the positive impact of participation on service quality. Empirical and theoretical models support that increased interaction with SST builds deeper expertise and understanding, consistent with (Yang et al., 2014).

Influence of Customer Participation Behavior on Self Efficacy

Chen, (2018) agrees with previous studies (Bandura, 1986; Silver et al., 1995; Stajkovic & Sommer, 2000) that customers with high self-efficacy tend to attribute service failure responsibility to firms rather than themselves. This research argues that customer involvement enhances self-esteem maintenance, reflecting how belief in one's capabilities influences responses to negative situations. Active and frequent SST use increases consumer confidence in handling challenges, supported by the hypothesis that Customer Participation Behavior (CPB) significantly predicts SST user self-efficacy.

Influence of Customer Expertise on Self Efficacy

In technology usage behavior, experience and expertise reduce fear of failure and hesitation. Alves et al. (2016) demonstrated that customer expertise positively affects self-efficacy perception. Higher expertise leads to greater confidence in decision-making and situation management related to services. Expertise thus strengthens belief in one's ability to complete tasks or achieve goals. Bandura stresses that demonstrated success enhances self-confidence. Customers mastering SST technical aspects show greater confidence when trying new features or facing novel situations. This study confirms customer expertise positively and significantly influences self-efficacy, aligning with prior research.

Influence of Customer Participation Behavior on Behavioral Intention

Customer participation behavior shows a positive, significant effect. Actively engaged consumers move beyond initial hesitation and perceive tangible SST benefits, increasing intentions for reuse or habit formation. Chiang et al., (2020) utilized this variable to evaluate participation outcomes. Participative customers exhibit higher repeat purchase behavior (Hsieh & Yen, 2005; Hsieh et al., 2004). Participation empowers customer control over production and service delivery (Marzocchi & Zammit, 2006) and helps build sustained provider relationships (Ennew & Binks, 1996). Empirical findings confirm that direct SST participation enhances reuse intention, positively impacting adoption and loyalty.

Influence of Customer Expertise on Behavioral Intention

Some customers possess greater knowledge or expertise in self-service than others and may not show equal loyalty. TAM (Davis, 1989) and Dabholkar & Bagozzi, (2002) show expertise strengthens perceived usefulness and ease of use. Higher expertise lowers perceived risk or errors, increasing willingness and desire to reuse SST. Ghali, (2024) found customer expertise significantly moderates sustained usage intention in electronic contexts. Skilled users better understand service utilization, reinforcing continuous use intention. Technical knowledge enhances comfort and confidence, leading to repeated SST use or habit formation.

Influence of Self Efficacy on Behavioral Intention

Self-efficacy is a strong determinant of technology usage intention. Consumers confident in managing SST intend to continue or reuse it. Bandura (1977, 1986) emphasized self-efficacy as a key internal factor influencing intention to adopt innovations or technologies. TAM development integrates self-efficacy's role in strengthening adoption intention. Ariff et al., (2012) revealed significant effects of customer self-efficacy on behavioral intention to use systems, supporting prior studies. Individuals confident in their system skills are more likely to sustain usage. Similarly, Sheng & Zolfagharian (2014) demonstrated perceived usefulness, ease of use, and credibility significantly affect behavioral intention within an extended TAM. Hence, this study's hypothesis that self-efficacy influences behavioral intention aligns with existing research.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This study demonstrates that Customer Participation Behavior (CPB), Customer Expertise (CE), and self-efficacy (SE) positively and significantly influence Behavioral Intention (BI) to use self-service technology (SST). Active customer participation plays a crucial role in developing expertise and confidence, which ultimately strengthens customers' intention to continue using self-service. Furthermore, self-efficacy significantly mediates the effect of expertise and participation on behavioral intention. The developed model exhibits moderate to strong explanatory power regarding SST usage behavior, as evidenced by adequate R Square values.

Recommendations

Based on these findings, SST management and service providers are advised to intensify educational and support programs that enable active customer participation, learning, and expertise development in using self-service technologies, through direct training, digital guides, or interactive help features within SST systems. Services should be designed to be user-friendly, easily accessible, and provide safe exploration opportunities that encourage customers to try without fear of failure, thereby building self-efficacy and comfort during usage. Regular evaluation and incorporation of customer feedback are essential for service development, alongside fostering user communities or discussion forums to promote a culture of learning and experience-sharing. Future research should consider integrating external factors such as environmental influences, social norms, or technological barriers to develop a more comprehensive understanding of SST adoption and sustainability. Moreover, limitations regarding data collection techniques and respondent age diversity should be addressed and refined in subsequent studies. This research is thus expected to provide valuable evaluation material for future investigations.

ADVANCED RESEARCH

The study's data collection instruments showed limitations, with questionnaires insufficiently distributed and respondent backgrounds largely homogeneous, mostly students. This lack of variation limits the diversity of responses. The limited questionnaire distribution within the researcher's environment reduces response conclusiveness. Future research should distribute surveys within actual SST contexts, e.g., self-service fuel stations and fast-food self-order kiosks, to achieve greater respondent diversity and accuracy. Age range criteria for respondents also need refinement, as the current range was broad and insufficiently representative, resulting in uneven and limited data coverage.

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