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The Effects of Characteristics of In-Store Retail Technology on Customer Citizenship Behavior

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KEYWORDS

Customer citizenship behavior (CCB), Customer engagement, In-store retail technology characteristics, Sustainable development goals, Work demands-resources (JD-R) theory.

ABSTRACT

This study explores the effects of in-store retail technology features on customer citizenship behavior (CCB) through the lens of the job demands-resources (JD-R) theory. Based on a survey of 153 retail customers, the research identifies key technology characteristics—perceived advantage, compatibility, complexity, and risk—that influence customer engagement and fatigue, which in turn affect CCB. The results show that perceived advantage and compatibility enhance customer engagement, fostering pro-social behaviors such as feedback and brand advocacy, while perceived complexity and risk lead to customer exhaustion, diminishing CCB. Customer education was found to moderate these relationships, alleviating the negative impact of complexity and risk. Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), effectively handling complex constructs and non-normal data. The findings offer actionable insights for retailers seeking to optimize in-store technology to enhance customer engagement, promote sustainable consumption, and drive the green transformation of retail systems. This research contributes to the understanding of how technology can support sustainable development goals within the retail sector, and it also advances the understanding of consumer citizenship behavior (CCB) by investigating technical variables such as interactivity, convenience of use, and compatibility, as well as how these elements influence customer involvement. This emphasizes the relationship between technology and consumer loyalty in contemporary retail.

1. Introduction

The retail sector is rapidly evolving through interconnected technologies, transforming both consumer experiences and business operations (Daunt & Harris, 2017). Retailers are increasingly adopting in-store innovations, such as mobile apps, handheld POS devices, inventory management systems, and mobile payment solutions, to enhance the shopping experience and influence consumer behavior (Yaseen et al., 2017; Seethamraju & Diatha, 2018). These technologies are critical for maintaining a competitive edge, with successful adoption contributing to market positioning (Renko & Druzijanic, 2014). Technologies like self-service systems improve customer satisfaction and loyalty by streamlining processes, while mobile devices and e-commerce platforms enable deeper customer engagement (Pantano & Priporas, 2016; Grewal et al., 2017).

However, customer adoption of retail technologies can be hindered by discomfort or anxiety, affecting

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willingness to interact with these systems (Roy et al., 2017). Perceptions of technology, particularly privacy concerns with tools like facial recognition, can limit engagement (Roy et al., 2017). Retailers' effective communication of technology benefits can alleviate these concerns and foster trust and satisfaction (Blut & Wang, 2020).

This study examines how in-store technologies influence consumer behavior, especially loyalty and engagement, with a focus on how technology features interact with customer needs. It explores whether factors like interactivity or complexity impact behavior and loyalty (Pizzi & Scarpi, 2020). It also investigates the role of customer exhaustion and engagement in the stability of retailer-consumer relationships (Gong & Yi, 2021).

By exploring these dynamics, the study aims to provide insights into how retailers can leverage technological innovations to enhance customer loyalty and engagement while managing barriers to adoption. Specifically, it will assess how technology characteristics influence customer citizenship behaviors, which can offer a competitive advantage and improve relational dynamics (Gong & Yi, 2021). Additionally, the research will consider the impact of perceived risks, such as privacy concerns, on customer engagement (Roy et al., 2017). While prior research has focused on technology elements affecting consumer behavior, this study broadens the scope by extending the Job Demands-Resources (JD-R) theory to the in-store retail scenario, which has received less attention. Specifically, the study not only evaluates technology qualities such as perceived advantages, compatibility, complexity, and perceived risk, but it also investigates how these aspects influence consumer citizenship behavior (CCB), an essential but understudied aspect of previous research.

2. Literature review - Hypotheses development - Research model

2.1. Job demands-resources theory

This research applies the Job Demands-Resources (JD-R) theory to examine the impact of in-store retail technologies. Originally developed to understand work engagement and employee exhaustion, JD-R theory posits that both job demands and resources affect well-being and performance (Bowen, 1986). In retail, this theory can be extended to explore how customer engagement and exhaustion are influenced by in-store technologies. Bowen (1986) suggested that customers, like employees, are vital to service delivery, especially when technology is integrated into the service process. Customers are a valuable resource due to their active role in facilitating service provision, particularly with the introduction of in-store technologies (Halbesleben & Buckley, 2004).

Tat Keh and Wei Teo (2001) argued that technologies like self-checkout reduce costs for retailers by allowing customers to act as supplementary employees in the service process. Groth (2005) expanded on this, noting that consumers often perform tasks traditionally handled by staff. For example, self-checkout systems enable consumers to independently complete transactions that were once managed by store employees. This shift highlights the growing role of customers in the co-creation of services (Barnard, 1948). In this context, customers are integral to the service environment, and service organizations are considered open systems, incorporating customers as key stakeholders (Yi et al., 2011).

In recent years, the retail industry has been characterized by rapid growth and technological advancements. Many experts believe that this industry will not be able to meet the needs of the people. Gong et al. (2022) conducted a study on JD-R and found that some factors might have a significant impact on it. According to Gong et al. (2022), education, training, and leisure activities may increase motivation and quality of life. According to Pham Thi & Ho's (2023) research, using e-commerce may improve customer satisfaction and loyalty. According to Murad et al., (2024), the quality of education, training, and teaching cannot be compared to other industries. Drawing from employee citizenship behavior, which is linked to engagement and discretionary effort (Bakker, 2018), we argue that in-store retail technologies have a dual effect on customers. These technologies can increase engagement by offering control and convenience, but they may also lead to customer exhaustion due to additional cognitive and emotional demands. Thus, customer behavior, including engagement and stress, is shaped by the interplay between technological demands and the resources provided by these innovations, ultimately influencing customer citizenship behaviors in retail.

Although the JD-R theory has been extensively employed in employee and organizational studies, this study provides a novel viewpoint by applying it to the retail setting, specifically in self-service outlets. This is particularly essential in the context of developing-country retail marketplaces, such as Vietnam, where technology adoption confronts several hurdles but also offers substantial opportunity to boost consumer interaction and optimize the shopping experience.

2.2. Hypotheses development and Research model

2.2.1. Perceived complexity (PCC)

Perceived complexity (PCC) refers to the degree to which consumers perceive in-store retail technology as complex and difficult to use (Kapoor et al., 2014).

According to the Job Demands-Resources (JD-R) theory, greater complexity increases cognitive demands, potentially leading to consumer fatigue during interactions (Adapa et al., 2020). Research by Mani and Chouk (2018) supports this by demonstrating that complexity can deplete consumers' cognitive resources, resulting in feelings of exhaustion. Therefore, we argue that perceived complexity exacerbates customer fatigue by demanding more cognitive effort during technology interactions.

H1: PCC positively influences customer exhaustion.

2.2.2.Perceived risk (PCR)

Perceived risk (PCR) refers to consumers' concerns about potential dangers or negative outcomes associated with using in-store retail technology (Rogers, 2003). These concerns increase cognitive load as consumers invest additional effort to assess and mitigate perceived risks, leading to greater fatigue (Roy et al., 2017). Martin et al. (2015) further emphasized that the possibility of technical failures in such technologies heightens consumer stress, ultimately contributing to fatigue. Thus, we contend that perceived risk amplifies consumer fatigue by requiring additional cognitive resources to manage these concerns.

H2: PCR positively influences customer exhaustion.

2.2.3. Perceived advantage (PCA)

Perceived advantage (PCA) refers to the positive emotional state consumers experience when they perceive enhanced performance using in-store retail technology (Gao & Bai, 2014). This technology improves efficiency, enhances service quality, and provides a more convenient shopping experience (Renko & Druzijanic, 2014). Consequently, consumers tend to show higher levels of engagement and greater comfort in using such technology.

H3: PCA positively influences customer engagement.

2.2.4. Perceived compatibility (PCB)

Perceived compatibility (PCB) refers to the degree to which consumers perceive in-store retail technology as aligning with their needs, lifestyles, and values (Lin et al., 2011). When consumers recognize this alignment, their engagement with both the technology and the brand increases, leading to more favorable behaviors.

H4: PCB positively influences customer engagement.

2.2.5. Customer Exhaustion (CEH)

Customer exhaustion (CEH) refers to the psychological fatigue caused by the perceived complexities and risks associated with using technology. Consumers experiencing exhaustion are less likely to engage in civic behaviors, such as helping others or supporting technology-related initiatives (Petrou et al., 2015).

H5: CEH negatively influences customer citizenship behavior.

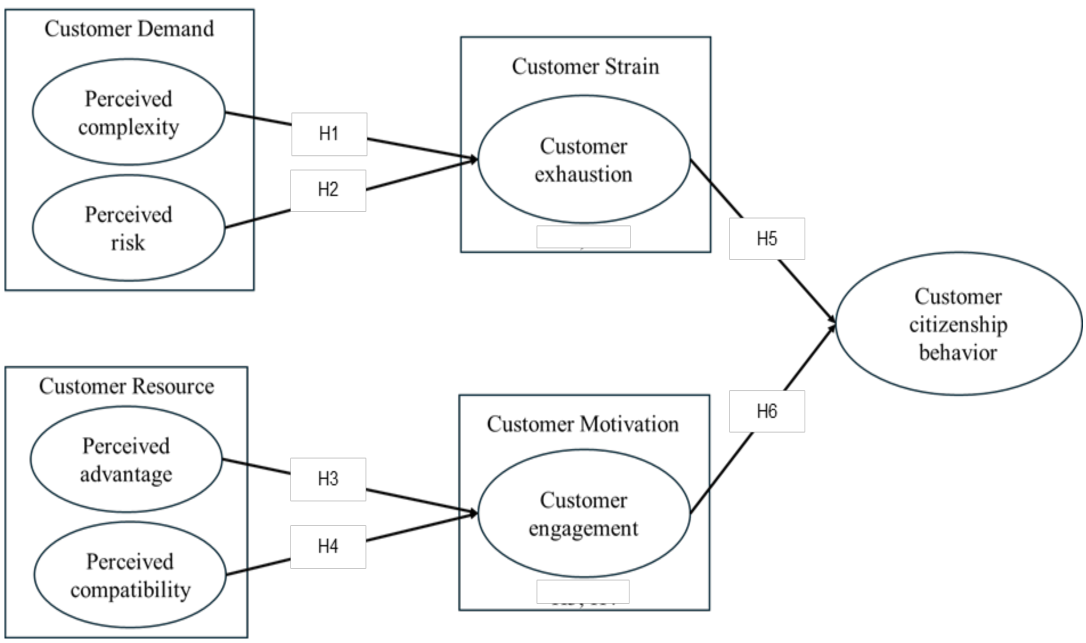

Figure 1. Conceptual framework

2.2.6. Customer Engagement (CEG)

Customer engagement (CEG) refers to the active participation of customers in using in-store retail technology. When customers perceive clear benefits and compatibility with the technology, their engagement increases, which in turn positively impacts their behavior toward the company (Bakker & Demerouti, 2007).

H6: CEG positively influences customer citizenship behavior.

3. Methodology

3.1. Sampling method

To achieve the research objective, a survey method was employed, which is a widely recognized approach for collecting primary data (Ranjit, 2019). Google's platform was utilized as the survey tool for this study. The sample consisted of retail customers with prior experience using self-checkout technology. Invitations were sent via email and text to experienced users, requesting their participation in an online survey. A non-probability sampling method was adopted since no customer list or sample frame was available. In line with previous research, a judgmental sampling approach was used to select participants.

3.2. Sample size

To determine an appropriate sample size for the Partial Least Squares-Structural Equation Modeling (PLS-SEM) analysis, the "10 times rule" proposed by Christopher Westland (2010) was applied, which suggests that the sample size should be at least 10 times the number of predictors. Based on this rule, a minimum of 20 responses was required. Additionally, the sample size was calculated using G*Power version 3, considering four predictors, a 0.05 margin of error, 0.8 statistical power, and an effect size of 0.15. The results indicated that a sample of 98 respondents would be sufficient. It is important to note that the term "minimum" refers to the smallest sample size necessary for structural equation modeling (SEMs) to maintain adequate significance and power. However, larger sample sizes are preferable as they offer a more accurate representation of the target population. With 153 respondents, the sample for this PLS-SEM analysis surpassed the minimum requirement, justifying further analysis.

3.3. Questionnaire designs

The questionnaire consisted of two sections: demographic questions and key inquiries related to customer demand and resources, customer strain,

Table 1. Questionnaire structures

Constructs	Items	References
Perceived complexity (PCC)	PCC1. The use of self-checkout is complicated.	(Adapa et al., 2020) (Kleijnen et al., 2007)
	PCC2. The use of self-checkout takes a lot of effort.	
	PCC3: It is difficult to learn how to use self-checkout.	
Perceived risk (PCR)	PCR1: The use of self-checkout makes me nervous.	(Demoulin & Djelassi, 2016)
	PCR2: I am uncomfortable using self-checkout.	
Perceived advantage (PCA)	PCA1: The use of self-checkout enables me to save time.	(Kleijnen et al., 2007) (Demoulin & Djelassi, 2016) (Adapa et al., 2020)
	PCA2: The use of self-checkout is convenient.	
	PCA3: The use of self-checkout is useful.	
	PCA4: I find using self-checkout to be advantageous in performing my shopping.	
Perceived compatibility (PCB)	PCB1: The use of self-checkout is compatible with my lifestyle.	(Meuter et al., 2005) (Kleijnen et al., 2007)
	PCB2: The use of self-checkout is completely compatible with my needs.	
	PCB3: The use of self-checkout is in line with my service preferences.	
Customer exhaustion (CEH)	CEH1: I feel tired from the use of self-checkout.	(Babakus et al., 1999)
	CEH2: I feel frustrated by the use of self-checkout.	
Customer engagement (CEG)	CEG1: I am passionate about using self-checkout.	(Yen et al., 2020)
	CEG2: I feel excited about using self-checkout.	
	CEG3: The use of self-checkout grabs my attention	
	CEG4: I become immersed in the use of self-checkout.	
Customer citizenship behavior (CCB)	CCB1: If I had a useful idea on how to improve service, I informed the employee.	(Yi & Gong, 2013)
	CCB2: I said positive things about this store and the employee to others.	
	CCB3: I helped other customers if they seem to have problems.	

customer motivation, and customer citizenship behavior. Minor adjustments were made to the original questionnaire before it was distributed. Subsequently, the questionnaire was translated into Vietnamese to ensure that respondents could complete it accurately and comfortably. The survey was adapted from previous research and was based on reliable and validated measurement scales found in the literature. A seven-point Likert scale, ranging from (1) strongly disagree to (7) strongly agree, was used to assess each item. The measurement items and their corresponding sources are provided in Table 1 below.

3.4. Profile of respondents

The data collected for this study included responses from 153 participants. Table 2 provides a detailed demographic breakdown of the respondents. Of the total, 78.4% were female, while 21.6% were male. The age distribution was as follows: 14.4% were under 20 years old, 84.3% were between 20 and 35 years old, 0.7% were between 35 and 50 years old, and 0.7% were older than 50 years. The highest educational attainment among respondents was college or university level, with 82.4% reporting this qualification. In terms of occupation, the majority (85%) were students. Regarding monthly income, the largest group (74.5%) earned less than 5 million VND per month, followed by 18.3% earning between 5 million and 10 million VND. A smaller proportion (7.2%) reported a monthly income of over 10 million VND.

3.5. Data analysis

A confirmatory meta-analysis was conducted using SmartPLS version 4.1.0.4 to validate the measurement model (Ringle, 2015). Confirmatory meta-analysis offers several advantages over confirmatory factor analysis (CFA) in terms of enhancing construct validity because confirmatory meta-analysis is an advanced statistical approach that builds on classic confirmatory factor analysis (CFA) by merging numerous datasets to improve construct validity. Unlike CFA, which is mainly concerned with evaluating a preset factor structure, confirmatory meta-analysis incorporates data from several studies or datasets to give a more robust validation of the measurement model. This strategy is very useful when dealing with complicated datasets or when researching non-normality or heterogeneity in the data. The use of confirmatory meta-analysis in this work guarantees that the measurement model is more properly verified, increasing the results' reliability and generalizability (J. F. Hair et al., 2020). Schuberth et al. (2018) note that CFA has certain limitations, which meta-factor analysis overcomes by alleviating these constraints, thus facilitating the operationalization and evaluation of design concepts.

4. Results and Discussion

4.1. Results

4.1.1. Measurement assessment

Table 2. Respondents Profile (N=153)

Demographic characteristic		Frequency	Percentage (%)
Age	< 20	22	14.4%
	20–35	129	84.3%
	35–50	1	0.7%
	> 50	1	0.7%
Gender	Male	33	21.6%
	Female	120	78.4%
Education level	Have not graduated from high school	2	1.3%
	High school graduation	17	11.1%
	College/University	126	82.4%
	After university	8	5.2%
Employment status	Student	130	85%
	Office staff	13	8.5%
	Worker	2	1.3%
	Part–time job	8	5.2%
Monthly Income (in VND)	Below 5.000.000	114	7.5%
	5.000.000–10.000.000	28	18.3%
	Above 10.000.000	11	7.2%

The measurement model was evaluated following the guidelines of J. F. Hair, Risher, et al. (2019). As shown in Table 3, the t-statistics, loadings, composite reliability, and Cronbach's alpha values all exceed the required threshold of 0.710 (V.-H. Lee et al., 2021), indicating strong internal consistency and reliability (J. F. Hair, Risher et al., 2019). Additionally, discriminant validity was assessed using both cross-loading methods and the Fornell-Larcker criterion, as illustrated in Table 4 (Tan et al., 2018; Wong et al., 2020). As shown in Table 3, the correlation coefficients between constructs are lower than the square root of the average variance extracted (AVE) for each construct on the diagonal, confirming discriminant validity. Furthermore, the cross-loading values for each factor are higher than those for other factors, as demonstrated in Table 5, satisfying the cross-loading requirements outlined by J. F. Hair et al. (2017). Therefore, discriminant validity was confirmed.

4.1.2. Hypotheses testing

The structural model was evaluated following the guidelines by J. F. Hair, Risher, et al. (2019). First, variance inflation factor (VIF) values for all constructs and predictor items were below 3.0, indicating no multicollinearity issues. Second, R^2 values for customer exhaustion, customer engagement, and customer

Table 3. Reliability and convergent validity

Construct	Items	Outer loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
CCB	CCB1	0.870	0.799	0.800	0.882	0.713
	CCB2	0.832				
	CCB3	0.831				
CEG	CEG1	0.816	0.775	0.779	0.856	0.599
	CEG2	0.822				
	CEG3	0.710				
	CEG4	0.742				
CEH	CEH1	0.914	0.796	0.797	0.908	0.831
	CEH4	0.909				
PCA	PCA1	0.791	0.842	0.847	0.894	0.680
	PCA2	0.888				
	PCA3	0.843				
	PCA4	0.772				
PCB	PCB1	0.840	0.806	0.816	0.885	0.720
	PCB2	0.837				
	PCB3	0.868				
PCC	PCC1	0.872	0.875	0.887	0.923	0.800
	PCC2	0.919				
	PCC3	0.892				
PCR	PCR1	0.848	0.759	0.856	0.888	0.799
	PCR2	0.938				

Table 4. Fornell - Lacker's Criterion

	CCB	CEG	CEH	PCA	PCB	PCC	PCR
CCB	0.844						
CEG	0.780	0.774					
CEH	0.254	0.174	0.912				
PCA	0.426	0.477	-0.219	0.825			
PCB	0.513	0.539	-0.053	0.657	0.848		
PCC	0.197	0.165	0.725	-0.099	0.007	0.894	
PCR	0.062	0.086	0.654	-0.194	-0.090	0.793	0.894

Table 5. Cross-loadings

	CCB	CEG	CEH	PCA	PCB	PCC	PCR
CCB1	0.870	0.692	0.199	0.375	0.377	0.143	0.035
CCB2	0.832	0.646	0.200	0.375	0.479	0.143	0.073
CCB3	0.831	0.636	0.247	0.329	0.447	0.215	0.048
CEG1	0.558	0.816	0.055	0.470	0.434	-0.007	-0.013
CEG2	0.680	0.822	0.103	0.390	0.414	0.152	0.044
CEG3	0.589	0.710	0.191	0.343	0.466	0.158	0.114
CEG4	0.577	0.742	0.198	0.263	0.349	0.214	0.129
CEH1	0.252	0.178	0.914	-0.149	0.007	0.667	0.597
CEH4	0.211	0.139	0.909	-0.252	-0.105	0.654	0.595
PCA1	0.306	0.383	-0.212	0.791	0.595	-0.118	-0.181
PCA2	0.367	0.382	-0.238	0.888	0.522	-0.172	-0.197
PCA3	0.412	0.438	-0.180	0.843	0.526	-0.064	-0.164
PCA4	0.311	0.364	-0.088	0.772	0.526	0.030	-0.092
PCB1	0.423	0.474	-0.100	0.517	0.840	-0.036	-0.105
PCB2	0.427	0.387	0.008	0.622	0.837	-0.007	-0.119
PCB3	0.454	0.497	-0.034	0.548	0.868	0.057	-0.017
PCC1	0.178	0.146	0.579	0.022	0.078	0.872	0.676
PCC2	0.221	0.183	0.721	-0.157	-0.004	0.919	0.741
PCC3	0.125	0.111	0.631	-0.112	-0.048	0.892	0.708
PCR1	0.022	0.090	0.446	-0.073	-0.021	0.580	0.848
PCR2	0.078	0.070	0.684	-0.241	-0.121	0.804	0.938

Table 6. Hypothesis Testing Results

Hypotheses and Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Remarks
CEG -> CCB	0.758	0.765	0.058	13.043	0.000	Supported
CEH -> CCB	0.122	0.121	0.047	2.582	0.010	Supported
PCA -> CEG	0.216	0.216	0.096	2.253	0.024	Supported
PCB -> CEG	0.397	0.405	0.092	4.306	0.000	Supported
PCC -> CEH	0.556	0.549	0.097	5.700	0.000	Supported
PCR -> CEH	0.213	0.222	0.106	2.002	0.045	Supported

citizenship behavior were examined to assess the model's in-sample fit, as shown in Table 6. Third, the significance of the main and mediating effects was tested.

To assess significance, we used SmartPLS with 10.000 bootstrap samples and bias-corrected and accelerated (BCa) bootstrapping. Partial Least Squares (PLS) path modeling was chosen because it typically reduces parameter bias compared to covariance-based structural equation modeling (CB-SEM) (J. F. Hair & Sarstedt, 2019). PLS is non-parametric, making it suitable for non-normal data and heteroskedasticity (J. F. Hair, Black, et al., 2019). As a result, we did not test for homogeneity or analyze the normality of dependent variables. A summary of the results is presented in Table 6.

The structural model evaluation supported all hypotheses. Hypothesis 1, predicting that customer exhaustion mediates the relationship between perceived complexity and customer citizenship behavior, was supported ($p < 0.05$). Hypothesis 2, predicting that customer exhaustion mediates the relationship between perceived risk and customer citizenship behavior, was also supported ($p < 0.05$). Similarly, Hypotheses 3, 4, 5, and 6 were all supported, indicating that both customer engagement and exhaustion significantly influence customer citizenship behaviors concerning perceived advantages, compatibility, complexity, and risk (all $p < 0.05$).

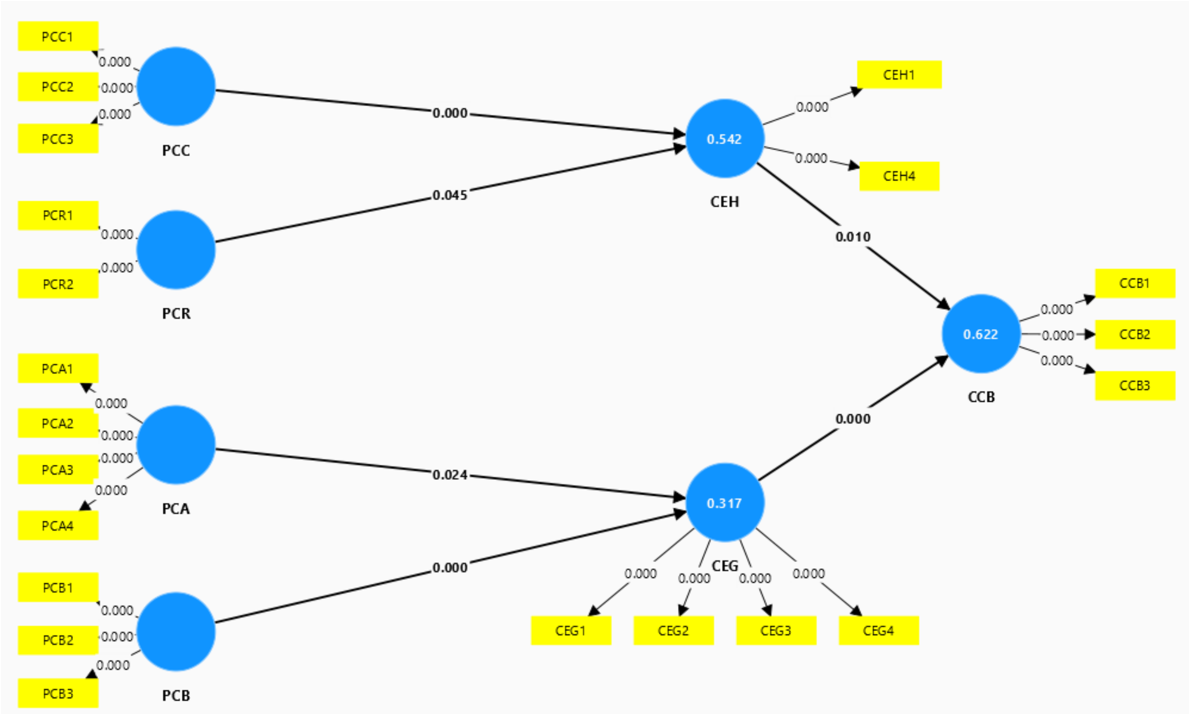

Figure 2. Structural model testing

4.2. Discussion

The results of this research provide compelling evidence for the proposed hypotheses, underscoring the critical role of in-store retail technology in shaping consumer behavior, particularly regarding customer engagement, fatigue, and their subsequent impact on customer citizenship behavior. The findings indicate that perceived complexity (PCC) significantly increases customer exhaustion (CEH), supporting previous research (Mortimer et al., 2021), which suggests that the cognitive demands of complex technologies can deplete customers' mental resources, leading to fatigue. Similarly, perceived risk (PCR) exacerbates customer exhaustion, in line with Stuhldreier (2024), who argued that perceived technology failures and uncertainties heighten stress and drain consumer energy. Both studies highlight how technological barriers can reduce customer participation, with customer fatigue limiting their inclination to engage in civic behaviors, as confirmed by Hypothesis 5 (Petrou et al., 2017).

Furthermore, the research identifies a significant positive impact of perceived advantage (PCA) and perceived compatibility (PCB) on customer engagement (CEG). This aligns with Demerouti et al. (2012), who emphasized that customers are more likely to engage with technologies that offer tangible benefits, such as increased convenience, and that align with their values and lifestyles. Such engagement fosters behaviors like advocacy and support, as evidenced by strong support for Hypothesis 6, which links customer engagement with customer citizenship behavior (Roy, Balaji, Quazi, et al., 2018).

Thus, while greater involvement with retail technology can enhance customer loyalty and brand advocacy, fatigue can have a detrimental effect on both, highlighting the dual impact of technology on consumer behavior. Retailers must carefully balance the introduction of innovative technologies with considerations for ease of use to avoid creating barriers for consumers. By prioritizing user-friendly technologies, companies can foster deeper, sustained customer engagement, enhance satisfaction, and promote long-term loyalty (Grewal, Roggeveen, Runyan et al., 2017). These findings emphasize the need for ongoing improvements in retail technology to encourage customer civic behaviors, ultimately enhancing a retailer's competitive advantage.

5. Conclusion and Implications

5.1. Conclusion

The research by Gong et al. (2022) has highlighted the relationship between in-store retail technology elements and consumer citizenship behavior (CCB). Several technological components can enhance the current retail environment by fostering increased consumer interaction and voluntary contributions. Studies have demonstrated that key attributes, such as customization, ease of use, and interactivity, positively influence CCB (H. Lee et al., 2009; Meuter et al., 2000). Interactive technology, which allows customers to actively engage with products and services, fosters a sense of participation and ownership. When customers perceive clear advantages, their satisfaction and loyalty increase, motivating them to exceed basic expectations. The ease of use and intuitive design of the technology further encourage positive interactions with fewer frustrations. Moreover, perceived compatibility enhances the perceived advantage and trust, acting as a moderator in the relationship between technological features and CCB (Wang et al., 2013). Customers who view technology as beneficial and trustworthy are more likely to engage in civic behaviors, such as providing feedback, assisting other customers, and endorsing the company. Our study specifically focuses on the influence of retail technology on consumer behavior while also linking the results to the Sustainable Development Goals (SDGs). The findings demonstrate that retail technology may help promote sustainable consumption by increasing consumer involvement and fostering pro-sustainable brand support. This advances our knowledge of the role of technology in fostering green transformation in current retail systems.

5.2. Implications

5.2.1. Theoretical implications

This research aimed to identify the variables influencing consumer acceptance and the future trends in adopting in-store retail technology. It also examines the relationship between these variables and consumer citizenship behavior, particularly the impact of in-store retail technology features on customer citizenship behavior. The analyses provide strong support for the proposed conceptual model. Using Rogers' (2003) PCI framework, this study identified that perceived complexity, perceived risk, perceived advantage, and perceived compatibility are key characteristics of in-store retail technology.

Adapted from Bakker & Demerouti's (2007) JD-R theory, this research applies the framework to the context of in-store retail technology. Perceived complexity and perceived risk are classified as customer demand factors, as they are associated with heightened customer pressure, psychological needs, and uncertainty about the role of technology in the retail environment. Conversely, perceived advantage and perceived compatibility are categorized as customer resource factors, as these elements enable customers to achieve their shopping goals and fulfill basic needs. The study further reveals that customer demand factors, such as complexity and risk, lead to customer exhaustion, which in turn reduces customer citizenship behavior. In contrast, customer resource factors, such as perceived advantage and compatibility, foster customer engagement, thereby enhancing customer citizenship behavior. This research contributes to the existing literature by highlighting the contrasting roles of customer needs and resources in predicting customer citizenship behavior, with exhaustion and engagement serving as key mediators of these effects.

5.2.2. Managerial implications

Managers aim to reduce customer demand factors, such as perceived complexity and perceived risk, to alleviate customer exhaustion and increase engagement in corporate behaviors. Specifically, they seek to make in-store retail technology more intuitive, simpler, and user-friendly (Chouk & Mani, 2019; Mani & Chouk, 2018; Wang et al., 2012). They focus on familiarizing customers with the technology by providing clear instructions and guidance (Kleijnen et al., 2007; Reynolds & Ruiz de Maya, 2013). Managers also aim to reduce cognitive load and mitigate perceived risks by offering immersive, interactive training simulations (Adapa et al., 2020). To address confusion from mistakes, managers must monitor customer interactions, proactively resolving issues to reduce anxiety from technological errors (Renko & Druzijanic, 2014).

Furthermore, managers strive to enhance the perceived advantages and compatibility of in-store technology to boost adoption. They work to demonstrate that the technology aligns with customers' lifestyles, making it more likely for customers to embrace it (Chouk & Mani, 2019). This alignment allows customers to express their social identities and enjoy a more engaging shopping experience. Managers also emphasize the unique benefits, such as greater control, time savings, and improved payment privacy (Renko & Druzijanic, 2014). Practically, this study gives useful information for retailers on how to optimize in-store technology to increase consumer engagement and encourage customer citizenship behavior. Retailers should use these insights to alter their technology strategy, ensuring that technology not only enhances service efficiency but also provides consumers with a simple, pleasant, and long-lasting purchasing experience.

In addition to improving the technology, managers can reduce customer exhaustion by implementing stress-reduction interventions. While employee stress management programs are common, customer-focused initiatives are less developed. Managers should consider strategies to reduce customer exhaustion, such as fostering strong engagement through social media and creating a dynamic, interactive experience (So et al., 2016).

5.2.3. Limitations and Future Research

Although our study sample is predominantly made up of students who have used self-checkout technology, the acquired data is directly relevant to the research issue. However, this sample may not completely represent the behavior of other consumer groups in the actual retail scenario. To improve the generalizability of the findings, future studies should widen the sample size to encompass a more varied range of age groups, income levels, and consumer profiles, allowing researchers to investigate the influence of retail technology on other customer segments.

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