Digital Banking Support Platforms and Customer Switching Behavior: Implications for Customer Education and Retention

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ABSTRACT:

Digital banking support platforms have become an integral component of customer relationship management, enabling banks to deliver timely assistance, resolve service issues, and enhance customer experiences through technology-enabled channels. Understanding the factors that influence customers decisions to remain with or switch from these platforms is essential for improving customer retention in an increasingly competitive banking environment. Drawing on the Stimulus–Organism–Response (SOR) framework, this study examines how self-efficacy, perceived relative advantage, and perceived complexity influence customers switching intentions, and how these intentions subsequently affect actual switching behavior. Data were collected through structured questionnaires using purposive sampling from bank customers in Karnataka, resulting in 387 valid responses. Structural Equation Modeling (SEM) was employed to examine the relationships among the study constructs. The findings reveal that perceived complexity in using existing bank support platforms and the perceived relative advantage of competing platforms significantly influence customers switching intentions, which subsequently drive actual switching behavior. However, self-efficacy did not exhibit a significant direct influence on switching intentions. The results demonstrate that customers perceptions of digital support platforms play a pivotal role in shaping switching decisions within the banking sector. From a managerial perspective, the findings suggest that banks should complement technological improvements with structured customer education initiatives that simplify digital interactions, reduce perceived complexity, improve awareness of available support services, and strengthen long-term customer retention. The study contributes to the literature by extending the application of the Stimulus–Organism–Response framework to digital

banking support platforms and by highlighting the importance of customer education as a strategic implication for enhancing digital service experiences and reducing customer switching.

Keywords: Customer Education; Online banking; Customer Retention; Complaint Management System; Switching Intention.

1. Introduction

Customer relationship management (CRM) in India is moving from the traditional human relationships to a technology driven, feature rich relationship management with minimal personal contacts (Bagla & Singh, 2016). A strong complaint management system in the banking sector is important for resolving customer grievances efficiently, thereby enhancing service quality and developing trust and satisfaction. Customer complaints arise when a service falls short of expectations at any stage before, during or after the experience, leading to customer dissatisfaction. Customers may be deterred from complaining due to a lack of connection between the support channel and the incidence of a service problem. With the introduction of the technology the level of perceived complaint barrier may decrease (Meik et al., 2014). With the introduction of AI in banking operations there is reduction in processing delays, lower operational errors, enhanced credit assessment, and improved financial inclusion indicators (Dash et al., 2026).

As banks increasingly rely on digital platforms to deliver customer support services, the effectiveness of these platforms depends not only on technological capabilities but also on customers ability to understand and utilize them effectively. Digital support platforms offer multiple self-service features, yet many customers remain unaware of their functionalities or encounter difficulties while navigating them. Consequently, customer education has emerged as an important managerial approach for improving digital service experiences by enhancing customers understanding of available support channels and promoting effective platform usage.

"A channel is a customer point of contact or a medium through which a company and customers interact" (Neslin et al., 2006). A virtual channel is a way of communicating with a consumer that uses "advanced telecommunications, information and multimedia technologies", whereas a physical channel refers to a communication method that relies on physical infrastructure to interact with customers. In virtual mode customer service experiences are shared in an automated way whereas in physical mode it is shared with human involvement through virtual or physical channels (Sousa & Voss, 2006). Customers might experience frustration and emotional distress if they are compelled to migrate channels or if they lose the freedom to choose their preferred channels, potentially resulting in discontinuity with the service provider. Hence offering a reward could be an alternative solution for channel migration (Reis et al., 2019).

Providing an effective support is very important for enhancing customer satisfaction and loyalty, preventing negative word-of-mouth and switching and strengthening customer relationships (Frasquet et al., 2019). Complaint systems need to be strengthened and promoted since they will improve the number of customers who genuinely voice their unhappiness, providing business entities an opportunity to rectify their mistakes and retain their customers (Andreassen & Streukens, 2013). Today, allot of customers are using social media as a tool to share their dissatisfaction and expecting the companies to respond them quickly (Melancon & Dalakas, 2018). Hence, firms are striving to offer a quick and concerned reaction to moderate negative comments that can affect a large audience and potentially harm their reputation (Istanbullioglu et al., 2017).

Customer education extends beyond promoting digital banking adoption; it involves equipping customers with the knowledge and confidence

required to effectively access support services, resolve service-related issues, and utilize platform functionalities independently. Educational initiatives such as onboarding tutorials, interactive guidance, digital awareness campaigns, and AI-enabled assistance can reduce customers perceived complexity while increasing confidence in using digital support platforms. Such initiatives are expected to improve customer experiences and reduce unnecessary switching resulting from limited platform familiarity rather than actual service deficiencies.

To gain a better insight of online complaint behaviors, deeper investigation is required in the subject area, as this will help in mitigating or minimizing the impact of negative online feedback. Within scholarly literature, there is an increasing focus on exploring the importance of social media as a support tool for customers during their post-purchase phase (Baron et al., 2014). The literature on customer complaint behavior lacks sufficient studies on the factors influencing complaint channel selection (Frasquet et al., 2019). Existing research on digital banking support platforms has primarily focused on service quality, complaint management, customer satisfaction, and technology adoption. Comparatively limited attention has been devoted to understanding how customers perceptions of platform usability influence switching behavior and how these insights can guide customer education strategies aimed at improving digital engagement and customer retention. Addressing this gap is important because reducing customer switching requires not only technological innovation but also effective customer education that minimizes perceived complexity and enhances user confidence in digital support services.

Therefore, this study applies the Stimulus–Organism–Response (SOR) framework to examine the influence of self-efficacy, perceived complexity, and perceived relative advantage on customers switching intentions and subsequent switching behavior in the context of digital banking support platforms. Furthermore, the study discusses how these findings provide practical implications for customer education initiatives designed to improve digital platform utilization and strengthen customer retention.

1.1 Objectives

- To examine the most preferred complaint platforms of the banks
- To examine the relationship between self-efficacy, complexity, relative advantage, switching intention and switching behavior
- To evaluate switching intentions and switching behavior of the customers with respect to support platforms of the bank
- To recommend customer education and digital support strategies that reduce perceived complexity, improve platform utilization, and strengthen customer retention.

Theoretical Framework

Customer switching behavior encompasses the inclination of customers to change brands, products or services. This behavior is influenced by various factors, including dissatisfaction with current services, the availability of competitive alternatives, evolving customer preferences or attractive incentives offered elsewhere. To adapt their strategies, enhance customer retention efforts and stay competitive in dynamic markets, businesses must understand and analyze their customers switching behaviors.

Switching behaviors can manifest as either complete or partial switches (Ye & Potter, 2011). A complete switch involves discontinuing the use of a service altogether. A partial switch occurs when customers use a new service while still retaining the old one, either occasionally or simultaneously.

The S-O-R model has been extensively used in studies related to marketing, especially in analyzing consumer behavior in retail contexts (Arora, 1982; Donovan & Rossiter, 1994). It was first created by Mehrabian and Russell in 1974 and then revised by Jacoby in 2002. This model was initially created for wider environmental psychology applications, but many researchers have since modified and validated it for use in retail settings.

The three main components of this model stimulus, organism and response to external stimuli explain how people respond to different stimuli. Environmental elements serve as triggers, affecting people's emotional and cognitive states and ultimately eliciting particular behavioral reactions (Donovan & Rossiter, 1994). Thus, the organism serves as a mediator in the interaction between environmental cues and consumer behavioral responses (Hsin & Su, 2008). Based on their cognitive and emotional states, consumers form viewpoints, make findings and assess stimuli (S-O-R model). Consumer behaviors, such as brand loyalty, purchase habits and overall satisfaction, are representations of these assessments and opinions (Sautter et al., 2004). Further, numerous e-commerce scenarios have made extensive use of this idea.

The identified research gap in previous studies underscores the necessity for a comprehensive exploration of consumer behaviors within the banking and financial sector, particularly concerning the complicated decision-making process associated with switching between different banking transactions and service providers. This gap aligns with the Stimulus-Organism-Response (S-O-R) model, which suggests that external stimuli (such as self-efficacy, relative advantage and complexity) influence the organism (customer intentions to switch), leading to specific behavioral responses (such as actual switching behaviors). Therefore, a deeper investigation into consumer behaviors in the banking and financial sector can provide valuable insights into the stimuli that prompt customers to consider switching services or providers, how customers process these stimuli and the resulting behavioral responses.

Additionally, applying the S-O-R model, which focuses on understanding the dynamics associated with switching service providers, can serve as a strong foundation for delving into and examining each aspect of the switching procedure. By expanding the framework of the study in this field using the S-O-R model, researchers can contribute to a deeper perspective of customer behavior in the financial industry and assist businesses and regulatory authorities in making more informed decisions.

2.1 Platforms

Customer Complaining Behavior is "a set of multiple (behavioral and non-behavioral) responses, some or all of which are triggered by perceived dissatisfaction with a purchase episode" (Singh, 1988). Discontinuing the business relationship, conveying unhappiness are examples of behavioral complaints (Hirschman, 1970). In terms of voice, public complaint is requesting remedy from the seller or filing a lawsuit, whereas private complaint entails word-of-mouth (Singh, 1988). The customer complaining behavior (CCB) taxonomy has been expanded to include a new level, channel choice, which builds on the previous classifications. When a customer decides to go public with their complaint and seeks justice from the seller, there are a number of complaint channels to choose from, each with varying degrees of involvement with the company: As interactive channels, face-to-face and telephone and as remote channels, letter and email (Mattila & Wirtz, 2004). The importance of CCB has grown as a result of digital technologies, which have expanded the number of complaint channels available (Istanbullioglu et al., 2017). Currently by using the machine learning techniques we are able to develop novel models that uses content and profile features to predict and identify types of online complaints, offering a flexible approach to enhance complaint management (Dobrucalı et al., 2023). By leveraging modern technology, firms can effectively resolve customer complaints by understanding the relationship between these features and complaint types. If a consumer does not receive adequate attention in the first attempt, they may switch from offline to online channels or vice versa in their second attempt (Frasquet et al., 2021). Complaint channel selections are shaped by a range of purposes, which define distinct categories of customers who use channels in different ways.

2.2 Self-Efficacy and Switching Intentions

Self-efficacy refers to an individual's confidence in their ability to perform a specific task or activity (Bandura et al., 1987). When applied to the paradigm, it refers to consumer's ability and confidence in using multiple channels to complete a transaction, from information search to purchase (Chiu et al., 2011). The search process can be affected by differences in customer's channel self-efficacy (Brown et al., 2001). If consumers are having low self-efficacy, they may be hesitant to search through multiple channels for their information search. As a result, consumers experience higher search costs and perceive increased channel switching costs, which lowers their willingness to switch channels (Gensler et al., 2017; Ray et al., 2012). Higher self-efficacy significantly shaped the relationship between information search scope and cross-channel switching, especially for customers who moved entirely to the online channels while purchasing across both online and offline platforms (Haridasan et al., 2021). While analyzing the show-rooming behaviors of the customers, it is inferred that show rooming behavior is more likely to occur if the customer feels more comfortable using many channels simultaneously (Arora et al., 2017. Hence, we can hypothesize that

H1: self-efficacy significantly impacts switching intentions

2.3 Complexity and Switching Intentions

The concept of complexity pertains to the challenges associated with utilizing new information technologies (Kim & Ammeter, 2014). When examining the adoption of Internet Protocol version 6 (IPv6) by Australian and Chinese companies, complexity emerged as a crucial factor influencing IPv6 adoption. Governments advocating for IPv6 implementation should recognize that complexity invariably affects IPv6 acceptance (Wang & Zander, 2018a). In the case of public bicycle sharing systems, the relative advantage directly influenced switching intentions, while complexity influenced switching intentions indirectly through perceived risk (Wang et al., 2021). Conversely, in the transition from wristwatches to innovative products like smart watches, the relative advantage significantly influenced switching intentions, whereas complexity had a minimal direct impact (Bölen, 2020). Notably, in the banking sector's shift towards proximity mobile payments from traditional methods, the substantial influence of ease of use on switching intentions underscores the importance of service providers continually enhancing platform usability and enhancing user's perceptions of ease of use (Mu & Lee, 2022). Thus, based on the insights obtained from prior research, we emphasize the significant impact of complexity on switching intentions within the banking domain.

H2: Complexity significantly impacts switching intentions

2.4 Relative Advantage and Switching Intentions

Innovation is the introduction of a new concept, practice or object as perceived by an individual or adopting entity (Rogers, 1995). Within the Indian banking scenario, attributes of innovations such as relative advantage and complexity significantly influence customer's behavioral intentions (Kapoor et al., 2015). Relative advantage measures the perceived superiority of an innovation over its predecessor, directly influencing consumer's switching intentions (Liao & Lu, 2008). Studies on understanding customer switching behavior related to Information Technology (IT) substitutes have consistently shown a positive interrelationship between relative advantage and switching intentions (Ye et al., 2008). Particularly in the field of technology products, relative advantage is an important driver that positively influences switching intentions (Lin & Huang, 2014). Thus, it is reasonable to presume that

H3: Relative advantage significantly influences switching intentions

2.5 Switching Intention & Switching Behavior

Switching intentions serve as a strong predictor of switching behavior, influencing it positively

(Wu et al., 2018). It is widely acknowledged that behavioral intention, the final cognitive phase before behavior, plays a crucial role in determining actual behavior (Bonfield, 1974; Oliver, 1980). From the Davis Technology Acceptance Model (TPB) (1989) and the Expectation-Confirmation Model by Bhattacherjee (2001), past research has indicated the significant influence of behavioral intention on customers' real-world actions. The integration of the TPB and migration theory, as employed by previous scholars (Bansal, 2005; Taylor, 1999), reveals a close relationship between switching intention and the actual decision to switch (Saeed & Azmi, 2019).

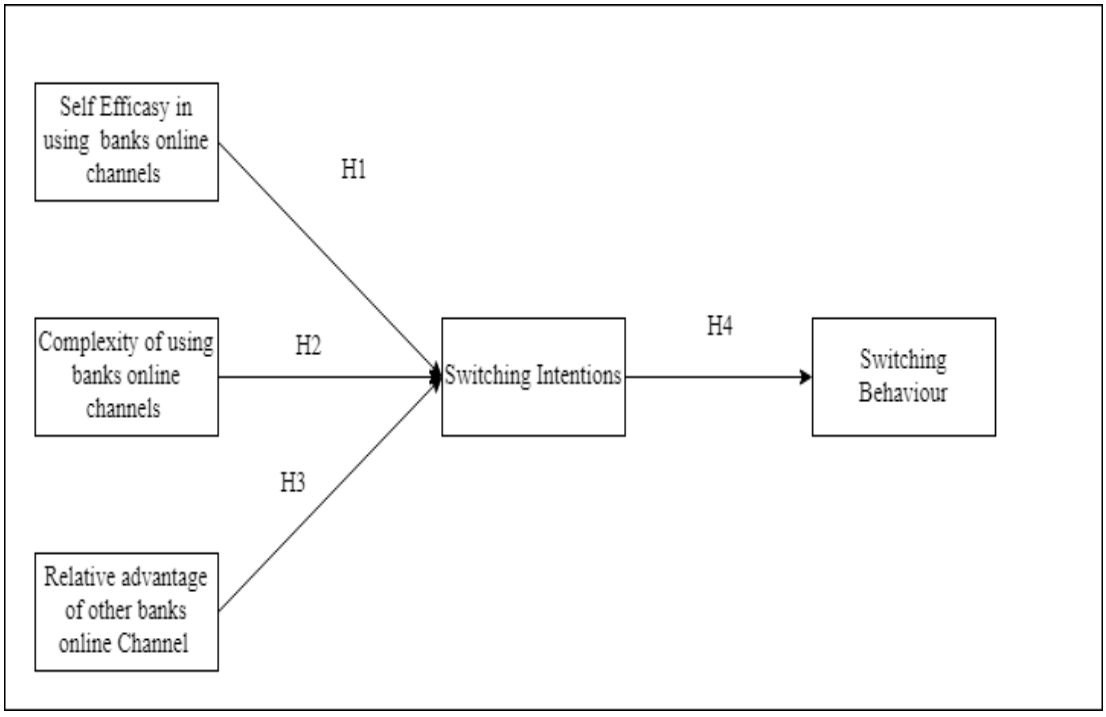
Analyzing switching behavior in online services requires a unique approach due to its significant divergence from switching behavior in traditional tangible services (Liu et al., 2016). Therefore, for the present study, we presume that..

H4: Switching intentions significantly influences switching behaviors

Based on the theoretical and conceptual framework, study presents the research model as illustrated in Figure 1.

Conceptual Model

Figure 1. Conceptual Model



Source: Author's conceptualization

3. Methodology

3.1 Study Sample and Data collection Method

The study targeted customers from both Public and Private sector banks in India. Rigorous criteria were employed during data screening to ensure the validity of participants:

1. Only respondents who are using their banks online support platforms to complain about the services offered by the banks were considered.

2. For respondents with multiple banks, preferences were given to the bank in which they predominantly used online support services.

Strictly adhering to these criteria was essential to ensure the active participation of respondents. The survey was structured into three sections: gathering demographic data, screening banking details and exploring aspects such as self-efficacy, complexity, relative advantage, switching intentions and switching behavior.

Before gathering the complete dataset, a pilot test was carried out with a subset of 90 bank customers to validate the data collection tools reliability. The chosen instruments were found suitable for the primary study.

The study employed purposive sampling, with questionnaires distributed after acquiring contact details from acquaintances. Utilizing different social media platforms like Facebook, LinkedIn WhatsApp, approximately 500 questionnaires were disseminated online. Of the 435 responses received, 48 were excluded for not meeting the established criteria, resulting in 387 valid responses. This resulted in a 70% response rate, which is considered adequate to meet the study's objectives (Baruch & Holtom, 2008).

3.2 Measurement

The questionnaire employs a five-point Likert scale to measure respondents level of agreement with various statements, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). This standardized scale is used to evaluate both dependent and independent variables.

Specifically, the self-efficacy scale comprises 4 items, the relative advantage scale consists of 4 items and the complexity scale encompasses 4 items as well. The switching intentions scale includes 5 items, while the switching behavior scale comprises 3 items.

The study included a sample of 208 males and 179 females. Regarding educational qualifications, 197 participants were graduates, 153 were postgraduates, 25 had education below the graduate level, and 12 had qualifications beyond post-graduation. Age-wise, 286 were between 18 to 30 years, 68 were in the age bracket of 31 to 40 years, 21 people are of 41 to 50 years, 11 people belongs to the age group of 51 to 60 years and one person was above 60 years. Detailed description of demographic data is mentioned in the table 1 below.

Table1. Demographic Information

Characteristics	Description	Frequency	Percentage
Age	18 to 30 years	286	73.90
	31 to 40 years	68	17.57
	41 to 50 years	21	5.43
	51 to 60 years	11	2.84
	Above 60 years	1	0.26
Gender	Male	208	53.75
	Female	179	46.25
Educational Qualification	Below Graduation	25	6.46
	Graduation	197	50.91
	Post-Graduation	153	39.53
	Above Post Graduation	12	3.10
Employment Status	Student	73	18.86
	Home Maker	12	3.10

	Business	39	10.08
	Public Sector Company	38	9.82
	Private Sector Company	225	58.14
Annual Income	Less Than 2 Lakhs	154	39.79
	200001-400000	131	33.85
	400001-600000	51	13.18
	600001-800000	15	3.88
	800001-1000000	11	2.84
	Above 10 Lakhs	25	6.46

3.3 Measurement model

The study employed SMARTPLS for data analysis using the Partial Least Squares (PLS) - Structural Equation Modeling (SEM) technique (Ringle & Becker, 2015). Following Anderson and Gerbing's recommendations, a two-step analytical approach was applied, consisting of a measurement model and a structural model (Anderson & Gerbing, 1988). The measurement model assessed validity and reliability, while the structural model was used to test the hypotheses (Hair et al., 2014).

To ensure reliability and convergent validity, composite reliability, factor loadings and average variance extracted (AVE) were examined. Most items indicated factor loadings above 0.70 (Hair et al., 2006), except for one item each in self-efficacy, complexity, relative advantage and switching intentions. After removing these items, the pooled measurement model was considered suitable for further investigation.

As shown in Table 2, all constructs had AVE values exceeding the recommended 0.50 threshold (Hulland, 1999), CR values above 0.70 and AVE values lower than CR, ensuring model fit. Convergent validity was confirmed as both factor loadings and AVE met the required thresholds. Additionally, communality and redundancy yielded positive results. Internal consistency, measured by Cronbach's alpha, was above the recommended 0.70 benchmark (Nunnally, 1978), further supporting the model's reliability.

Table 2. Factor loadings

Latent Variable	**Indicator**	**Loadings ≥0.70**	**Internal consistency ≥0.70**	**CR ≥0.70**	**AVE ≥0.50**
Self-efficacy	MSE1	0.802	0.830	0.825	0.633
	MSE2	0.878			
	MSE3	0.839			
Complexity	C2	0.832	0.772	0.781	0.596
	C3	0.797			
	C4	0.776			
Relative Advantage	RLA1	0.793	0.797	0.785	0.585

	RLA2	0.870			
	RLA3	0.813			
Switching Intentions	SWIN1	0.828	0.903	0.905	0.721
	SWIN 2	0.857			
	SWIN 4	0.884			
	SWIN 5	0.829			
Switching Behavior	SWB1	0.920	0.858	0.865	0.780
	SWB2	0.894			
	SWB3	0.832			

Note: M- self-efficacy, C-Complexity, RA- Relative Advantage, SI-Switching Intention, SB-Switching behavior, CR-Composite Reliability, AVE-Average variance extracted

Discriminant validity was assessed using the Fornell-Larcker criterion to determine whether the square roots of the average variance extracted (AVE) for all constructs were greater than the inter-construct correlations, as presented in Table 3. This analysis confirmed the strong validity and reliability of the research model (Hair et al., 2014). Additionally, Tables 3 and 4 summarize the reliability and validity results derived from the analysis of the reflective measurement models.

Table 3. Discriminant Validity Assessment

Predicators	**C**	**OSE**	**RA**	**SB**	**SI**
C	0.772				
MSE	-0.039	0.796			
RLA	0.195	0.445	0.765		
SWB	0.353	-0.122	0.023	0.883	
SWIN	0.442	-0.059	0.177	0.745	0.849

Note: *Square roots of AVE mentioned in diagonal

3.4 Structural Model

The evaluation of the model primarily relied on the significance and magnitude of path coefficients, along with R^2 measurements (Lohmoller, 1989). Given that the PLS-SEM approach is prediction-oriented, it aims to explain the variance in endogenous latent variables, making a high R^2 value important for key constructs (Lohmoller, 1989). While an R^2 value of 0.20 is considered strong in areas such as consumer behavior, the acceptable level depends on the specific research context (Hair et al., 2011). In this study, the R^2 value for switching intention was 0.207, while for switching behavior, it was 0.566, both meeting the recommended thresholds.

To mitigate common method bias, both ex-ante and ex-post approaches were employed. Initially, an expert review was conducted to minimize ambiguity in questionnaire items, ensuring content reliability (Shetty & Basri, 2019; Podsakoff et al., 2003). Additionally, to address potential multicollinearity concerns, variable inflation factor (VIF) values were examined (Kline, 1988). Since none of the VIF values exceeded the critical threshold of 5.0, multicollinearity among independent variables was not a concern (Grewal et al., 2004).

Table 4. Evaluation

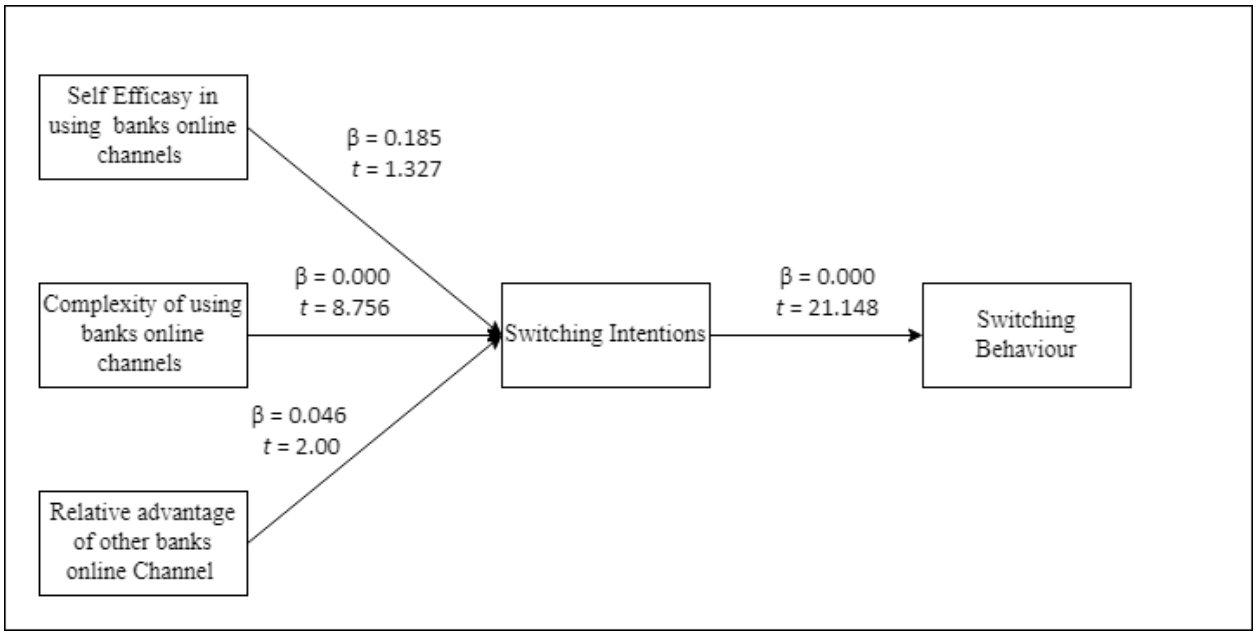
Relationship	T -Test statistics	Significance Level (P)	Result
C ->SWIN	8.756	0.000	Supported
MSE-> SWIN	1.327	0.185	Not supported
RLA -> SWIN	2.000	0.046	Supported
SWIN-> SWB	21.148	0.000	Supported

4. Discussion

Using SmartPLS, which offers detailed insights such as t-statistics for data inference, the relationships were examined using the partial least squares (PLS) approach (Chin, 2001). Table 4 presents the t-statistics and corresponding significance levels for each relationship within the model.

The hypothesized relationships between the paths were significantly supported, except for the link between self-efficacy and switching intention. Complexity ($\beta = 0.000$; $t = 8.756$; $p < 0.05$) and relative advantage ($\beta = 0.046$; $t = 2.00$; $p < 0.05$) had a significant impact on switching intentions. Additionally, switching intention ($\beta = 0.000$; $t = 21.148$; $p < 0.05$) significantly influenced switching behavior. However, self-efficacy ($\beta = 0.185$; $t = 1.327$; $p < 0.05$) did not show a significant effect on switching intentions, as illustrated in Figure 2.

Figure 2. Structural model



Source: Author's conceptualization based on Data analysis

This study aimed to explore the important factors driving customers switching intentions and actual switching behavior with respect to the complaint platforms of the banks. The study's findings indicate that consumer switching intention is significantly influenced by complexity and relative advantage, while switching behavior is strongly driven by switching intention. These factors play an important role in determining the credibility and effectiveness of the bank's online complaint channels.

The study's findings reveal that complexity plays an important role in driving customer's intentions to switch banks, particularly in the context of online support platforms. When these platforms are perceived as difficult to use, customers experience frustration and inconvenience, making them more likely to search for alternative banking options. The results of the study go in accordance with the prior research on IPv6 adoption (Wang & Zander, 2018), wherein it is evident that technology acceptance occurs primarily when the system is less complex. Similarly, in a study on the adoption of public bicycle systems, complexity indirectly influenced switching intention through perceived risk (Wang et al., 2021). From a broader perspective, existing research highlights how complexity affects switching intention across various domains. In technology adoption, system quality and information overload have been key determinants in contexts such as ILAs and ERP systems (Li & Wang, 2024; Jo & Park, 2023). Within consumer behavior, choice task complexity and information confusion have been shown to impact switching decisions in social commerce and discrete choice experiments (Oehlmann et al., 2014; Boxall et al., 2009; Wang et al., 2023). Moreover, in decision-making, task complexity and cognitive control play a crucial role in multifactor decision-making scenarios (Matsui et al., 2021; Swait & Adamowicz, 2001). But, in the context of online complaint platforms, respondents were firsthand users of these systems, leading to a stronger direct relationship between complexity and switching intention. Unlike other domains where complexity may have an indirect impact, this study finds that the perceived difficulty of using these platforms directly heightens customer's likelihood of switching banks.

The relative advantage of online platforms offered by other banks has been found to significantly influence switching intentions. This finding aligns with previous research by Kapoor et al. (2015) on inter-bank mobile payment services and Hsie (2021) on customers decisions to switch from cash payments to medical mobile payments. Additionally, studies across various industries, including smart phones, social networking sites and banking, consistently highlight that consumers are more likely to switch when they perceive a higher relative advantage in an alternative product or service (Lin & Huang, 2014; Fei & Bo, 2014; Shrestha et al., 2024). For instance, in the Smartphone industry, the perceived benefits of enhanced features and functionalities in new devices significantly impact switching decisions (Lin & Huang, 2014; Mu et al., 2014). Hence in this study customers perceive that alternative banks online complaint platforms may be more user-friendly compared to their own bank's online complaint system. Therefore, it is very important to note that relative advantage plays a crucial role in shaping consumers switching intentions across various industries; including banking and banks need to pay an attention for the same.

Previous research has consistently signified that switching intentions positively influence switching behavior, establishing them as a strong predictor of actual switching decisions (Wu et al., 2018). In line with prior studies (Bhattacherjee et al., 2012; Liu et al., 2016; Saeed & Azmi, 2019), the current study also confirms a significant positive relationship between switching intention and switching behavior. Bhattacherjee and Premkumar (2004) highlighted how shifts in customer's beliefs and attitudes toward information technology significantly impact their actual usage behaviors, reinforcing the crucial role of user intentions in technology adoption and switching. Similarly, Kim and Kankanhalli (2009) emphasized that the perceived value of a new system influences users intentions to switch, which in turn affects their actual switching behavior. Overall, these findings collectively reinforce the idea that switching intention serves as an important determinant of switching behavior across various industries, further validating the results of the present study.

Self-efficacy of the customers advances them to use multiple support platforms of the banks for complaining. The study result goes in accordance with few of the previous studies, wherein no relationship was found between bank-switching

intention and the sources that promote self-efficacy and perceived behavioral control (Bortne et al., 2024). Similarly, research by Farah (2017) applied the Theory of Planned Behavior to customer switching intentions among banks during mergers and acquisitions. The findings indicated that self-efficacy, conceptualized as perceived behavioral control, did not have a significant direct effect on switching intentions. Since most of the complaint platforms of the banks are seems similar in operation, customers perceive that these platforms doesn't motivate them to retain or switch the bank.

The influence of complexity and relative advantage on switching intention is very much significant and highlights the significance of user-friendly interfaces in maintaining customers. The study's conclusion that complexity and switching intention have a significant direct positive link adds depth to the body of literature already in existence, particularly when considering the online support platforms. Apart from that, the relationship between perception of relative advantage of other banks support platforms and intention to switch also goes in accordance with the earlier researches. Further, the study reaffirms the established relationship between switching intention and switching behavior, which is consistent with similar research in many fields. This realization highlights how switching intentions are predictive and how important they are as a lead-up to actual switching behavior.

5. Theoretical Implications

The research examines the interrelationship between complexity, self-efficacy, relative advantage, switching intention and thereby switching behavior within the banking sector. It reveals that while complexity in using the support platforms of current bank and the perception of relative advantage of other banks support platforms may lead to switching, while self-efficacy having no impact on customers intentions to switch banks. This detailed understanding of customer behavior strengthens the S-O-R framework by providing insights into how internal factors (organism) mediate the relationship between external stimuli and responses. It provides an in depth understanding of digital stimuli that influences customer behavior through internal processes, providing valuable insights for both researchers and professionals in the digital banking sector. By presenting the empirical evidence from the banking industry, the study adds to the limited body of knowledge on complaint platforms. It shows that customers prefer using bank websites, call centers and email for lodging complaints. This empirical contribution validates the application of the S-O-R theory in a new context and offers a foundation for future research on digital banking and customer behavior.

6. Managerial Implications

As the competitions are intensifying the banks are pressurized to provide the best of the services to their customers through multiple support channels. Complexity in the use of support platforms may lead to lesser adaption and the customers might be inclined to switch for a simpler platform. These results are relevant with the previous studies in the context of new product development wherein the customers were hesitant to purchase the new product due to the perceived risk which is implied by complexity (Holak & Lehmann, 1990). When consumers found any product to be easy to use and having less complexity with relative advantage, they were ready to adapt to the new system and switch from the existing system (Chang & Pan, 2011). For banking Industries, it is evident that when the customers perceive the existing platforms to be more complicated than the alternate platform, the intentions of switching's are more. Hence the banks should focus on developing the platforms which are of minimal complexity (Mu & Lee, 2022). Customers perception about relative advantage, intend them to switch to alternative product which is very much evident in the previous studies of inter-bank mobile payment service (Kapoor et al., 2015) and in customers intentions to switch from cash mode payment to medical mobile mode payment. The customers pursue that the other banks online complaint platforms

might be easy to use and have more advantages compared to their own banks online complaint platforms (Hsie, 2021). The study advances prior research by proposing and testing a research framework for examining the interrelationship between switching-intention and switching behavior, contending that switching intention drives customer's switching behavior.

Although switching intentions has previously been examined in a number of circumstances, it has rarely been used in the online support platforms of the banks. This study adds to the body of knowledge and extends the literature on migration and switching in the context of complaining platforms. Major respondents in the study preferred banks websites as a channel to complain their service issues followed by call centers and email. In light of the increased competition, banks should concentrate on creating platforms that are simple for customers to use. For achieving financial inclusion, a powerful strategy has to be created for Fin-tech innovation and revolution. Financial institutions may form partnerships with telecom firms to serve as their channel partners (Siddiqui & Siddiqui, 2020). Additionally, the AI technologies like ChatGPT-4 can measure the severity of service failures based on customer complaints and can provide better responses within seconds and with little effort (Koc et al., 2023). Apart from that, by applying ISO 9001 and ISO 20000 concepts, such as incident, problem, change, service level, availability, capacity, information technology service continuity and financial management, can help managers of traditional and digital banks enhance their complaint management performance (Pio et al., 2024).

The findings further suggest that customer education should be recognized as a strategic component of digital banking service management rather than merely a supplementary activity. Banks should invest in structured educational initiatives such as interactive onboarding sessions, instructional videos, AI-powered virtual assistants, frequently asked question repositories, and periodic awareness campaigns to familiarize customers with digital support services. Improving customers understanding of available platform functionalities can reduce perceived complexity, enhance confidence in digital interactions, and minimize switching decisions driven by insufficient platform awareness. Such educational efforts can complement technological enhancements and contribute significantly to long-term customer retention.

7.Limitations and Directions for Future Research

Despite the fact that this study offered pertinent and interesting insights into the attributes of switching in the context of banks online support platforms in Indian context, it is important to note this study's limitations. First, since the sample was chosen using a specific set of criteria in the purposive sampling method, results may alter when it is applied to a larger audience. Therefore, sample size and representation should be more carefully considered in future study. Second, since the survey was restricted to a group of individuals who met the aforementioned criteria, other people's perceptions of online complaint management channels may differ. Finally, since the study was conducted in the context of India, it will be unable to extrapolate the findings to other nations because their cultures, habits and economic situations are different. This study has considered only self-efficacy; complexity and relative advantage, future research in this area can use other dimensions as well to understand the switching behavior in the context of online complaining platforms.

Conclusion

This study employed the Stimulus–Organism–Response (SOR) framework to examine the influence of self-efficacy, perceived complexity, and perceived relative advantage on customers switching intentions and switching behavior in digital banking support platforms. The findings reveal that perceived complexity and relative advantage significantly influence customers switching intentions, which subsequently lead to actual switching behavior, while self-efficacy does not have a significant direct effect. These

results extend the application of the SOR framework by providing a deeper understanding of customer switching behavior in digital banking support environments.

From a managerial perspective, the study suggests that customer retention depends not only on technological improvements but also on customers ability to effectively use digital support platforms. Banks should therefore focus on reducing platform complexity and implementing customer education initiatives such as digital onboarding, user guidance, and awareness programs to improve platform utilization and strengthen customer retention. By combining user-friendly digital support systems with effective customer education, banks can enhance customer experiences and foster long-term customer relationships.

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Conflict of Interest

Both authors further declare that there is no conflict of interest among the authors regarding the publication of this paper.

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