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Article

Customer Perception of Social Media Marketing: A Reliability Analysis in Banking Services

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Abstract: The study examines the effect of "Social Media Factors (SMF), Electronic Word-of-Mouth (EWM), and Informational Content (INF)" on customer perception and examines the effect of customer perception on behavioral intention and customer satisfaction (CS) in the digital banking sector. The objective of this study is to examine the effect of digital engagement factors on customers' cognitive appraisals and long-term behavioral intentions. The study adopts a quantitative research methodology. The data is collected using a structured questionnaire with pre-designed scales. The study adopts statistical analysis, such as reliability analysis and structural equation modeling (SEM), to examine the hypotheses and to examine the mediating role of customer perception. The findings of this study indicate that SMF, EWM, and INF significantly affect customer perception, which has a positive effect on behavioral intention and CS. Customer perception is found to be a significant mediating variable that reinforces the effect of digital engagement factors on satisfaction outcomes. The implications of this study indicate that banks should focus on digital communication, online reviews, and social media engagement to enhance digital perception of usefulness and trust. Digital perception management is identified as a key driver of sustainable CS and long-term competitive advantage in the banking sector.
Keywords: Behavioral Intention, Customer Perception, Digital Banking, Electronic Word-of-Mouth, Social Media Factors

1. Introduction

The Global "Banking industry is undergoing a swift digital transformation, driven by a combination of factors such as the fast-paced development of information and communication technologies, heightened competition, and shifting customer expectations (Diener & Špaček, 2021). Digital transformation refers to the integration of digital technologies" not only in the backend banking operations but also in the customer service areas, like Internet and mobile banking, self-service, and technology-assisted communication. Therefore, the traditional branch-based service delivery models should be restructured (Kitsios et al., 2021; Diener & Špaček, 2021).

Largely, banks are switching from the old-fashioned one-way advertising technique to the new interactive models through social platforms (Rehman et al., 2025). Customers engage not only by seeing the advertisements but also through their actions of liking, sharing, commenting, and recommending. Social media interactions between banks and customers in the sector have a positive impact on the customers' attitudes and actions by increasing brand equity and promoting loyalty (Ferm & Thaichon, 2021).

The role of banking emphasizes the necessity of social media marketing for the purpose of trust and emotional attachment to a brand. Unstructured social media marketing activities produce more brand trust. Thus, the overall impression of banking services by customers is improved (Hafez, 2021). In banking situations with limited direct human interaction, perceived reliability, how much customers see digital services as consistent, accurate, and trustworthy, becomes the main factor for customer trust and satisfaction (Kaur et al., 2021). Customers' perceptions of corporate reliability are heavily influenced by the significance and continuity of information disseminated on digital and social media (Waluyo et al., 2025).

Table 1: Social Media Marketing Trends in Banking

Trend / Metric	Key Findings
AI-Driven Personalization	Banks use AI to deliver personalized content, improving customer engagement and satisfaction while reducing operational costs through AI-powered chatbots.
Video & Short-Form Content	Short-form videos generate significantly higher engagement than text posts, enabling banks to communicate brand stories and explain products effectively.
Consumer Behavioral Impact	Social media strongly influences banking customer behavior, with interactivity, reliability, and personalization shaping perceptions and engagement.

(Source: https://cacpro.com/insights/social-media-marketing-for-financial-institutions-7-key-trends/?.com)

Banks use social media platforms for customer communication and service promotion, yet customer trust and social media engagement with banking content show unpredictable patterns. Customers usually consider banking posts to be untrustworthy because they provide delayed answers and deliver confusing details that differ between different channels. Trust-sensitive banking practices suffer from customer perception because they create situations that make customers doubt banking security. Banks need to establish social media marketing practices because they currently lack an understanding of customer trust, which these practices establish. The current study investigates how customers view social media marketing within banking services while focusing on its trustworthiness aspect.

The study examines customer social media evaluations of banking services because customers lack trust in banks and banks fail to maintain a consistent social media presence. “The study investigates how Perceived Usefulness (PU) and Perceived Ease Of Use (PEOU)” affect Customer Behavior to interact with banks through their social media marketing channels while examining the connection between these two customer perceptions. The study tests how social media banking services establish customer satisfaction (CS) through their impact on customer behavioral patterns. The study evaluates how behavioral intention functions as a mediator between PU, PEOU, and CS. The study results will help banks create social media marketing strategies that they can use to build trustworthy platforms that provide easy access to their services.

Apart from the introduction, “the rest of the paper is structured as follows: section 2 describes reviews of different authors from past studies related to PEOU, PU Behavioural Intention, CS, section 3 summarizes conceptual framework and research methods for the study, section 4 discusses the results and findings, section 5 explains the discussion, and Section 6 shows the conclusions, implications, limitations, and recommendations for Further Studies. Finally, references are presented.”

2. Literature Review

2.1 Theoretical framework

i) **Technology Acceptance Model (TAM): “**TAM was proposed by Davis in 1989, which elucidates the technology acceptance of users through the perception of usefulness (PU) and the perceived ease of use (PEOU), which in turn are predictive of behavioral intention (BI).” Over the years, TAM has been used in different technological contexts. PU and PEOU influence the adoption of ICT in service-oriented environments (Sorce & Issa, 2021). The study refers to TAM as the reason for consumers' intention to utilize banking services through social media marketing, particularly concerning the ease and effectiveness of the technology and the corresponding behavioral response.

ii) **Expectation–Confirmation Theory (ECT): "**Expectation–Confirmation Theory (ECT), which was developed by Oliver (1980), was later adapted by Bhattacherjee (2001) as he used ECT to explain CS because of both adoption and continuous usage intention, along with the anticipation being met." The study points out that when users perceive a system as not meeting their requirements, then positive behavioral intention does not help satisfaction grow (AlSokkar et al., 2024). In this context, ECT is applied together with the TAM to account for the influence of customers' BI on the analysis of system characteristics PU, PEOU and CS in social media–driven banking services, thereby inferring the adoption results to the discontent levels.

2.2 Technology Acceptance Factors in Banking Social Media Marketing

The study on how consumers accept technology in banking social media marketing points out several main factors that drive adoption. The internet banking usage was pushed by the COVID-19 pandemic as it made social media more important for sharing information and lessened the risk of visiting a bank physically. The change is explained by social practice and technology affordance theories (Naeem & Ozuem, 2021). The "TAM and Unified Theory of Acceptance and Use of Technology (UTAUT)" frameworks are most frequently used. The study reveals that users' attitudes and behavioral intentions toward digital banking and social media marketing are mainly influenced by PU, trust, social influence, and facilitating conditions (Ly & Ly, 2022; Tariq et al., 2024; Puriwat & Tripopsakul, 2021). Motivation, self-efficacy, and demographic factors such as age and income significantly determine the usage level of e-wallets, especially among young users like Gen Z who are the trendsetters in using social media and e-wallets for banking (Rosli et al., 2023; Ferm & Thaichon, 2021; Puriwat & Tripopsakul, 2021). FinTech platform adoption is highly influenced by perceived risk and perceived value, which act as mediators between performance expectancy and actual usage (Xie et al., 2021; Tariq et al., 2024). Banking institutions, therefore, can benefit from a thorough understanding of these acceptance factors to not only focus their marketing strategies but also transform their digital channels most effectively for customer engagement and loyalty through social media (Kitsios et al., 2021; Ferm & Thaichon, 2021).

2.3 Behavioural Intention as a Driver of Customer Satisfaction in Social Media–Based Banking Services

Behavioral intention is at the focal point of satisfied customers becoming loyal users of social media-driven banking. It detects what digital banking customers' desires and expectations are who are already pleased with the service; thus, it acts as the link to real usage. Studies employing frameworks such as UTAUT have shown that factors like performance advantages, trust, and facilitating conditions play a role in forming these intentions, and afterwards, intentions completely account for the connection to taking up digital banking (Tariq et al., 2024). Social media marketing in banking results in increased customer interaction and customer base, which in turn creates more relationship equity and loyalty; that is, the intention to operate coincides with the attitudinal loyalty in the case of mobile banking on social media (Ferm & Thaichon, 2021; Rehman et al, 2025). Communication about corporate social responsibility (CSR) of the companies through social media channels has a significant influence on customers' behavioral results, such as the inclination to buy and post about the product as well as the brand attitudes and the emotional responses of the customers, like happiness and admiration, being the mediators of such relationships (Cheng et al., 2021; Ahmad et al., 2021; Liu et al., 2023). Moreover, the commitment, which is grounded on involvement and trust in social media activities, is viewed as one of the major factors that lead to customer loyalty, thus reflecting the intention to behave as the main indicator of satisfaction and loyalty (Vinerean & Opreana, 2021). Generally, behavioral intention plays a crucial role as a connecting point between social media interactions, trust, CSR communication, and CS in banking services delivered through

2.4 Mediating Role of Behavioural Intention in Technology Acceptance–Satisfaction Relationships

In TAM, the behavioral intention to use technology plays a vital mediating role in connecting various factors such as PU, PEOU, trust, and satisfaction to the actual adoption or continued use of technology. The study based on the UTAUT and its variations has shown that behavioral intention acts as a significant mediator between user perceptual variables (e.g., performance expectancy, effort expectancy, trust) and their satisfaction or technology use behavior (Tariq et al., 2024; Mishra et al., 2023; Yang et al., 2024). To illustrate, behavior intention is a perfect mediator of the relationship between cognitive factors and actual use in the cases of digital banking and AI, powered CRM systems (Chatterjee et al., 2021; Tariq et al., 2024), thus pointing to the central role of behavioral intention in adoption processes. Similarly, the level of user satisfaction appears to be an important factor mediating the effect of technology quality on intent, influencing in a similar manner e-tax systems and robot service restaurant cases (Seo & Lee, 2021; Saptono et al., 2023). The emotional and hedonic factor of enjoyment helps to increase satisfaction and behavioral intention, which, in turn, are associated with technology acceptance and continuous use (Mishra et al., 2023; Shi et al., 2025). In every case, behavioral intention is recognized to be the key psychological factor that transforms the users' evaluations of the technology into real acceptance and satisfaction that occur in a wide range of technology cases (Orden-Mejía et al., 2025; Andrés-Sánchez & Gené-Albesa, 2023).

2.5 Hypothesis Development

The "hypotheses developed in this research were based on a robust foundation derived from related research." Numerous studies have been done on social media marketing, technology acceptance, and digital banking use with the help of the TAM framework. The study is based on PU, ease of use, trustworthiness, and customer engagement leading to loyalty. However, the majority of the studies have solely concentrated on adoption intent or the outcomes of usage after adoption. They ignore the behavioral intention aspect in linking users' perceptions of technology to their satisfaction in the context of banking via social media. Besides that, previous studies mostly focus on awareness, engagement, and brand equity outcomes, whereas studies of an empirical nature, which are based on customer perception of reliability, are still limited. Furthermore, few studies have been carried out in social media marketing of banks to validate such relationships simultaneously with the help of SEM, based studies. This paper aims to bridge these gaps by empirically testing an integrated model of PU and PEOU, mediated by behavioural intention, to explain CS with a reliability-centered analytical approach. To address these gaps, the following hypotheses are proposed:

H1: "Perceived usefulness (PU) has a positive and significant influence on customers' behavioural intention (BI) to use banks' social media marketing platforms."

H2: "Perceived ease of use (PEOU) has a positive and significant influence on customers' behavioural intention (BI) in the context of banking social media marketing."

H3: "Perceived ease of use (PEOU) has a positive and significant influence on perceived usefulness (PU) of social media marketing platforms in banking services."

H4: "Behavioural intention (BI) has a positive and significant impact on customer satisfaction (CS) with banking services delivered through social media platforms."

H5: "Behavioural intention (BI) mediates the relationship between perceived usefulness (PU) and customer satisfaction (CS) in banking social media marketing."

H6: "Behavioural intention (BI) mediates the relationship between perceived ease of use (PEOU) and customer satisfaction (CS) in banking social media marketing."

3. Research Methodology

3.1 Conceptual Framework

The "conceptual framework investigates how customers from the banking industry comprehend social media marketing through its core components of social media marketing. The study defines factor bank marketing through four variables, which it labels as Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention

(BI), and Customer Satisfaction (CS). The study proposes that BI functions as a mediator between PU and PEOU effects on CS while BI connects to CS through its relationship with PU and PEOU." Hence, the model is very useful in measuring the impact of social media marketing on increasing the level of customer engagement and satisfaction with banks' digital service offerings.

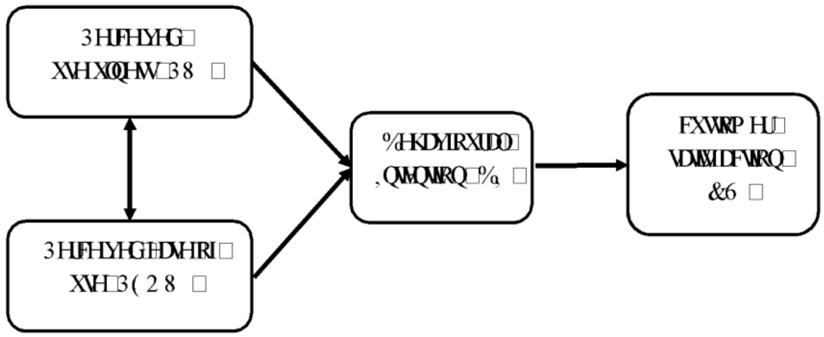

Figure 1: Conceptual Framework

(Source: Self-Prepared by Author)

3.2 Research Design

The study "uses an exploratory research design because there is currently insufficient understanding of how customers respond to social media marketing in banking. The Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention (BI), and Customer Satisfaction (CS) relationship will show new patterns through this research." The research design permits researchers to gather information through multiple data collection methods while conducting their study to find hidden relationships between different variables. The process helps researchers develop a better understanding of the study topic because it enables them to establish better research questions about how social media changes the banking industry.

3.3 Targeted Population

The targeted population consists of Bank customers who are actively engaged in digital banking services and who communicate through the bank's social media marketing platforms.

3.4 Sample size & Sampling Technique

The calculation of the sample size is made according to Cochran's (1977) formula, which sets a minimum of 385 respondents, but for a better understanding of the study, the study sends a questionnaire to 450 respondents, out of which 407 respondents responded. A stratified random sampling method is used to present equal representation among the major demographic groups. Thus, the trustworthiness and the applicability of the findings of the study are increased.

3.5 Measurement of Constructs

The study is using a structured questionnaire, which is one of the means of collecting primary data. To measure CS and behavioural intention, scales adapted from Roberts, Lombard & Jaiyeoba (2025) are used, which provide excellent indicators of consumer behaviour and behavioural intention in the service sector. PEOU and PU are measured using scales adopted from Elareshi et al., (2023), which are most commonly used in banking social media marketing studies. The use of previously validated scales contributes to the reliability and construct validity of the tool. Nevertheless, the measurement items may be changed and modified to fit the present study's context and validity requirements.

3.6 Tools and Techniques

The study utilized “both descriptive and inferential statistical methods to analyze the data. Mean and standard deviation were the techniques used to describe the respondents' demographic profiles and key constructs. Correlation and regression analysis were used to reveal the interrelationships among the variables under study. Structural Equation Modeling (SEM) was employed to test the hypothesized relationships” and the mediating role of behavioural intention. Smart PLS software was chosen for SEM analysis. In contrast, SPSS and MS Excel were used for data coding, preliminary analysis, and result presentation.

3.7 Validity and Reliability Test

The study carried out a pilot study to estimate the reliability and validity of the data. A Cronbach's Alpha value of 0.70 or more is generally recognized as a mark of measurement that is reliable and internally consistent.

3.8 Ethical Considerations

The study follows the ethical norms of conducting human subject research in order to protect the rights and privacy of the respondents. The respondents are free to decide to participate or not, and all willing respondents sign a consent form before any data is collected. Respondents' names and other personal details are not disclosed and are only used in the context of this article. The study handled the data carefully when collecting, storing, and analyzing. The study also makes sure that by conducting this research, people's privacy and confidentiality are respected and that the research does not lead to any harm or misrepresentation.

4. Results

This section provides the results obtained and discussions with respect to data analysis. The results have been arranged according to the respondents' demographic characteristics, the study objectives, and the research hypotheses. Statistical research support is given for each hypothesis, and the correspondence between the text and the tables is ensured. The addition of tables improves understanding, whereas the text explanation focuses on the importance of the findings for the research.

Table 2: Reliability and Validity Statistics

Variables	Cronbach's Alpha	N of Items	KMO and Bartlett’s Value	Sig. value
Customer's Behavioral Intention	.961	7	.939	.000
Customer Satisfaction	.946	7	.939	.000
Perceived Ease of Use	.951	5	.883	.000
Perceived Usefulness	.882	6	.896	.000

Table 2 shows the reliability and sampling adequacy figures for the study variables. The internal consistency of all constructs shows excellent results because the Cronbach alpha values range from 0.882 to 0.961, which establishes high reliability for the measurement scales (Taber, 2017). “The Kaiser–Meyer–Olkin (KMO) values for the constructs range from 0.883 to 0.939, which shows both good and excellent sampling adequacy, while the data becomes suitable for factor analysis according to Kaiser 1974.” The outcome of Bartlett's Test of Sphericity reveals that the significance level for all variables is 0. 000, that is, the correlations between the variables reach a sufficient level. The findings of the study confirm excellent reliability with sufficient sampling capacity, thereby enabling the performance of both exploratory and confirmatory factor analysis with the acquired data.

Table 3 The Respondents' Demographic Profile

Sr. no.	Demographic characteristics	Category	N	%

1.	Gender	Male	76	50.7
		Female	74	49.3
	Age	Less than 25 years	45	30.0
		25-35 years	35	23.3
		35 - 45 Years	40	26.7
		More than 45 years	30	20.0
3.	Educational Qualification	Bachelor's Degree	32	21.3
		Master’s Degree	52	34.7
		Doctorate	23	15.3
		Professional Certification	43	28.7
4.	Occupation	Student	27	18.0
		Private Job	33	22.0
		Government Job	32	21.3
		Self-Employed / Business Owner	28	18.7
		Other (Please Specify)	30	20.0
5.	Experience with Digital Banking Services	Less than 1 year	34	22.7
		1 - 3 Years	26	17.3

		3 - 5 Years	43	28.7
		More than 5 Years	47	31.3

"Table 3 shows the demographic profile of the respondents who participated in the study." Males constituted 50.7% of the sample, whereas females accounted for 49.3%. So, women and men were equally represented in the sample. Most of the cases, however, came from the younger and middle-aged groups, with 30% of respondents being under the age of 25, 26. 7% between 35 and 45 years, 23. 3% in the 25-35 years age bracket and 20% over 45 years. Regarding educational qualifications, the majority of respondents have advanced education, 34. 7% are master's degree holders, 28. 7% have professional certificates, 21. 3% hold a bachelor's degree, and 15. 3% have a Doctorate. The occupational structure shows that there is a well-balanced and diverse group of respondents. About 22.0% of the respondents are working in the private sector, followed closely by those working in the government sector, which is about 21.3%. Self-employed and business owners make up 18.7% of the respondents, followed by students at 18.0%. The remaining 20.0% of the respondents are working in other occupations, which shows the overall diversity of the respondents in terms of occupation. In terms of the experience of digital banking services, most of the respondents have long-term experience. About 31.3% of the respondents have been using digital banking services for more than 5 years, followed by 28.7% who have experience of 3-5 years, while 22.7% have less than 1 year of experience and 17.3% have experience of 1-3 years. The demographic structure shows that the sample represents a diverse group of respondents with sufficient experience, which suggests that the respondents were suitable for the study of perceptions and behavioral intentions towards digital banking services.

4.1 Results Based on Hypothesis

- **Dropped Items**

In this paper, one item (PEOU3) of the PEOU construct was omitted from the analysis after its extraction value during factor analysis was found inappropriate, suggesting its redundancy. The removal of this item, therefore, contributed to having a more balanced measurement framework and extended the strength and validity of the measurement model.

- **Factor Analysis**

Table 4 Rotated Component Matrix and Communalities

Rotated Component Matrix					Communalities	
Component						
	1	2	3	4	Initial	Extraction
PU1			0.765		1.000	0.698
PU2			0.624		1.000	0.596
PU3			0.798		1.000	0.708
PU4			0.672		1.000	0.613
PU5			0.680		1.000	0.607
PU6			0.678		1.000	0.616
PEOU1				0.698	1.000	0.805

PEOU2				0.766	1.000	0.806
PEOU4				0.800	1.000	0.874
PEOU5				0.718	1.000	0.853
PEOU6				0.740	1.000	0.841
CBI1		0.759			1.000	0.838
CBI2		0.749			1.000	0.824
CBI3		0.696			1.000	0.763
CBI4		0.779			1.000	0.808
CBI5		0.729			1.000	0.819
CBI6		0.699			1.000	0.820
CBI7		0.805			1.000	0.824
CS1	0.751				1.000	0.792
CS2	0.769				1.000	0.757
CS3	0.787				1.000	0.798
CS4	0.739				1.000	0.779
CS5	0.741				1.000	0.693
CS6	0.747				1.000	0.771
CS7	0.779				1.000	0.776
"Extraction Method: Principal Component Analysis." "Rotation Method: Varimax with Kaiser Normalization."						
"a. Rotation converged in 6 iterations."						

The "rotated component matrix in Table 4 above shows the outcome of the Principal Component Analysis with Varimax rotation, which clearly shows a four-factor solution for the constructs in the study. All the items that are retained in the component matrix have loadings well above the cut-off point of 0.50 (Laher, 2010)," thus showing a high level of convergent validity. The items for PU have high loadings on Component 3 (0.624 to 0.798), items for PEOU on Component 4 (0.698 to 0.800), items for Customer's Behavioral Intention (CBI) on Component 2 (0.696 to 0.805), and items for CS on Component 1 (0.739 to 0.787), thus clearly showing a distinct separation among the constructs. The communalities range from 0.596 to 0.874, which are all above the minimum acceptable level of 0.50, thus showing a satisfactory explanation of variance. The rotation converged in six iterations, thus clearly showing that the solution is stable and reliable.

- **Construct Validity**

Table 5 Convergent Validity of the Constructs

SR No.	Construct	Items	Standardized Loadings	Collinearity (VIF)	Composite Reliability (CR)	Average Variance Extracted (AVE)

1.	**Perceived Usefulness**	**PU1**	0.825	2.259	0.884	0.63
		PU2	0.783	1.886		
		PU3	0.788	2.037		
		PU4	0.794	1.916		
		PU5	0.782	1.901		
		PU6	0.787	1.912		
2.	**Perceived Ease Of Use**	**PEOU 1**	0.903	3.878	0.952	0.835
		PEOU 2	0.89	3.731		
		PEOU 4	0.928	4.931		
		PEOU 5	0.93	4.898		
		PEOU 6	0.919	4.244		
3.	**Customer's Behavioral Intention**	**CBI1**	0.911	4.654	0.962	0.809
		CBI2	0.909	4.327		
		CBI3	0.879	3.803		
		CBI4	0.893	3.888		
		CBI5	0.909	4.597		
		CBI6	0.904	4.541		
		CBI7	0.887	3.824		
4.	**Customer Satisfaction**	**CS1**	0.895	3.752	0.947	0.755
		CS2	0.858	3.105		
		CS3	0.890	3.563		
		CS4	0.873	3.407		
		CS5	0.808	2.335		
		CS6	0.879	3.325		

		CS7	0.879	3.419		

Table 5 reports the outcomes of the "confirmatory factor analysis (CFA) for PU, PEOU, Customer Behavioral Intention, and CS, presenting standardized factor loadings, collinearity statistics (VIF), Composite Reliability (CR), and Average Variance Extracted (AVE). All standardized factor loadings indicate a range from 0. 782 to 0. 930, thereby surpassing the normative limit of 0. 70. Consequently, this authenticates a good indicator reliability for each of the constructs (Hair et al., 2022). The collinearity diagnostics figure that the Variance Inflation Factor (VIF)" values are in the interval of 1. 886 and 4. 931, none of which is above the allowed limit of 5, thus showing that there are no multicollinearity issues among the variables (OBrien, 2007). This indicates that the constructs do not contain redundant items and are appropriate for structural analysis. The "Composite Reliability (CR) values of all constructs are well above the recommended minimum of 0. 70, ranging from 0.884 to 0.962, thus exhibiting a high degree of internal consistency and trustworthiness of the construct (Hair et al., 2022). Similarly, the Average Variance Extracted (AVE) values range from 0.630 to 0.835, surpassing the benchmark of 0.50 and confirming satisfactory convergent validity across all constructs. In particular, the two constructs PEOU (CR = 0. 952, AVE = 0. 835) and Customers' Behavioral Intention (CR = 0. 962, AVE = 0. 809) have been shown to have very strong convergent validity through their reliability (the factor loadings for each item are all quite high). CS (CR = 0. 947, AVE = 0. 755) also reveals highly satisfactory features of the concerned construct, whereas PU (CR = 0. 884, AVE = 0. 630)" attests to fair and acceptable tests of the constructs. Generally, the results substantiate that all constructs show strong indicator reliability, high internal consistency, adequate convergent validity, and no multicollinearity problems. Therefore, the measurement model is well, grounded and appropriate for continuation of structural equation modeling and hypothesis testing.

Table 6 Discriminants Validity Table

	CBI	**CS**	**PEOU**	**PU**
CBI	0.899			
CS	0.717	0.869		
PEOU	0.783	0.676	0.914	
PU	0.657	0.647	0.651	0.793

Table 6 shows the evaluation of discriminant validity by means of the Fornell-Larcker criterion for "Customer's Behavioral Intention (CBI), CS, PEOU, and PU. The square roots of the Average Variance Extracted (AVE), which are on the diagonal, are greater than the corresponding inter, construct correlations, thus meeting the Fornell-Larcker criterion (Cheung et al., 2024). Specifically, CBI (√AVE = 0.899)" exceeds its correlations with CS (0.717), PEOU (0.783), and PU (0.657). CS also demonstrates adequate discriminant validity, with √AVE = 0.869 exceeding its correlations with CBI (0.717), PEOU (0.676), and PU (0.647). Similarly, PEOU shows an √AVE value of 0.914, which is higher than its correlations with CBI (0.783), CS (0.676), and PU (0.651). PU is another variable that meets the criterion, as indicated by the √AVE of 0.793, which is higher than "its correlations with the other constructs. In general, the results show that each construct is different from the others. Thus, it provides good discriminant validity, which also supports the strength of the measurement model for further structural model analysis."

Table 7 Model Fit Table

	Saturated Model	Estimated Model
SRMR	0.043	0.046
d_ULS	0.763	0.851
d_G	0.423	0.429
Chi-square	733.627	742.403
NFI	0.872	0.87

Table 7 shows the model fit indices of the saturated and estimated models, the measurement model can be considered very adequate. “The SRMR values for the saturated (0. 043) and estimated models (0. 046) are both significantly lower than the recommended level of 0. 10, thus the models fit very well (Hu & Bentler, 1999). The d_ULS values (0.763 and 0.851) and d_G values (0.423 and 0.429) are relatively low, suggesting minimal discrepancies between the observed and model-implied correlation matrices.” Although the Chi-square values (733.627 and 742.403) are relatively high, this is expected in large samples and complex models and does not necessarily indicate poor fit. The NFI values of 0.872 and 0.870, while slightly below the ideal cutoff of 0.90, exceed the acceptable threshold of 0.70 for complex models (Hooper et al., 2008). Overall, the fit indices point to a good and steady fit of the model, which supports the measurement model's robustness and its appropriateness for the next steps of structural analysis and hypothesis testing.

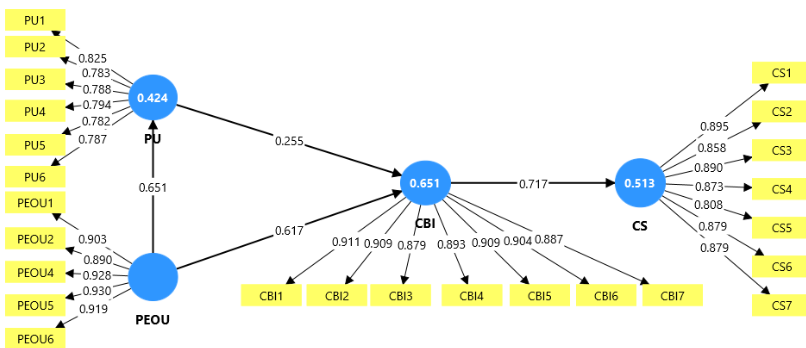

Figure 2 SEM Model

Figure 2 shows a structural model of the hypothetical relationships between PEOU, PU, CBI, and CS. Each factor from the measurement model has a loading of over 0. 70 on its corresponding standardized factor. This confirms good indicator reliability and convergent validity. The path coefficients show that PEOU strongly and positively impacts PU (β = 0. 651), indicating that the higher the level of ease of use, the more significantly PU increases. Besides that, PU (β = 0. 255) and PEOU (β = 0. 617) are both positively and significantly impacting CBI, thus revealing the joint influence of the two factors, usability and usefulness, in increasing consumer brand identification. Besides, CBI significantly affects CS (β = 0. 717), highlighting its extremely important role in CS. The data from the research are in agreement with the theory and validate the dependence relations as well as the performance of the explanatory structural model. The study has also revealed through the results that consumer behavioral intention is majorly influenced by PEOU and PU and in turn, the impact on CS is driven most by behavioral intention. The whole set of relationships between usability,

Table 8 Hypothesis Testing Table

Hypothesis	Predicted Relationship	Original sample	Sample mean	Standard deviation	T statistics	P values	Decision
H1	PU -> CBI	0.255	0.260	0.066	3.863	0.000	Supported

H2	PEOU -> CBI	0.617	0.614	0.067	9.213	0.000	Supported
H3	PEOU -> PU	0.651	0.654	0.044	14.755	0.000	Supported
H4	CBI -> CS	0.717	0.718	0.042	17.118	0.000	Supported
H5	PU -> CBI -> CS	0.183	0.187	0.051	3.600	0.000	Supported
H6	PEOU -> CBI -> CS	0.442	0.440	0.052	8.464	0.000	Supported

Table 8 presents the outcomes of the structural and mediation analyses carried out to assess the interplay between PU, PEOU, CBI, and CS. The analysis revealed that all the hypothesized relationships are positive and statistically significant, providing evidence for the model proposed. PU has a significant "positive effect on CBI (β = 0.255, t = 3.863, $p < 0.001$), while PEOU exerts a strong influence on CBI (β = 0.617, t = 9.213, $p < 0.001$). PEOU also significantly enhances PU (β = 0.651, t = 14.755, $p < 0.001$), indicating that ease of use strengthens PU. In addition, CBI has a strong positive effect on CS (β = 0.717, t = 17.118, $p < 0.001$). The mediation analysis confirms that CBI significantly mediates the relationships between PU and CS (β = 0.183, t = 3.600, $p < 0.001$) and between PEOU and CS (β = 0.442, t = 8.464, $p < 0.001$)." Overall, the findings highlight the pivotal mediating role of Consumer Behavioral Intention and validate the proposed structural relationships. All in all, the study results corroborate that the extent to which customers perceive the use of digital banking services as being easy The source of PU significantly influence the Consumer Behavioral Intention which positively affects the Consumer Brand Identification Directly to them, the results also reveal that Consumer Behavioral Intention is a crucial mediating mechanism that helps explain how "ease of use and usefulness" indirectly lead to CS. It means that the factors related to ease of use and functionality mainly contribute to satisfaction through the identification of a stronger brand. Overall, the study results are consistent with the hypothesized structural and mediating model, and they also provide the theoretical basis of the study by means of empirical evidence.

5. Discussion

The findings of this study provided strong empirical evidence on the importance of SMF, EWM, and INF in shaping customer perception in the digital banking environment. The structural model indicated that these factors had a significant influence on customer perception and behavioral outcomes, which supported the argument that digital interactions were the driving forces behind users' perceptions of banking services. In support of the extended TAM, constructs associated with perception were found to be significant determinants of satisfaction and intention (Ngubelanga & Duffett, 2021). The strong path coefficients indicated that digital communication channels were more than just marketing tools; they were strategic tools that enhanced PU and trust, resulting in improved behavioral intentions. This was supported by research in mobile banking, which found that factors associated with perception had a significant influence on shaping sustainable usage intentions (Naruetharadhol et al., 2021).

From a theoretical perspective, this research work further develops the Social Media Marketing (SMM) theory by proving the impact of different social media factors on cognitive and behavioral aspects in the banking sector. By incorporating the perception variable, this research work fills the theoretical gap between online engagement and customer satisfaction. This research work not only incorporates the perception variables into the TAM model but also enhances the perception theory by proving the impact of information stimuli triggered by social media as external variables on PU and BI. The results further validate the TAM and UTAUT models by proving the impact of online communication variables on cognitive evaluations, which ultimately lead to different behavioral outcomes (Tariq et al., 2024).

When compared with the results of previous studies, the results of the current study are in close synchronization with the international literature on social media marketing (SMM) and customer perception. The previous studies have also emphasized the significance of digital engagement and online information in the improvement of PU and adoption intentions in banking and fintech services (Kumar et al., 2020; Tariq et al., 2024). The current study also supports the positive effect of EWM on purchase and usage intention, as emphasized by the Information Adoption Model (IAM), which emphasizes that the credibility and quality of online information play a crucial role in the effect of user intention (Rahaman et al., 2022). However, the current study extends beyond the previous studies in the sense that it provides a more precise understanding of the interaction of these variables with each other in the specific context of banking. The differences in context, such as the relatively more significant role of social proof and peer influence in emerging markets due to collectivist cultural values, provide a new perspective that is often neglected in the literature, which is more focused on the developed markets. This makes the results of the current study particularly relevant to the understanding of banking services in different socio-cultural contexts, particularly in emerging markets where the effect of social media engagement on customer behavior is relatively more significant.

Finally, the implications of this study are vast for the marketing and digital strategy teams of banks. The implications of this study are that banks need to manage social media factors, EWM, and information content in a strategic manner to create positive perceptions among customers. Banks need to focus on effective communication, genuine testimonials, and social interactions to create trust and improve customer satisfaction. Moreover, for the digital transformation teams of banks, the implications of this study are that it is essential to incorporate perception analysis into digital transformation strategies. By analyzing online reviews, sentiment, and user-generated content, banks can mitigate concerns related to PU and remove customer uncertainty. The implications of this study are that banks need to promote active customer participation on social media platforms, which will improve the positive impact of EWM and help banks create sustainable usage intentions (Naruetharadhol et al., 2021).

6. Conclusion

The study discovered that SMF, EWM and INF, together with their respective SMF and EWM elements and INF elements, showed significant effects on customer perception, which further affected digital banking CS and behavioral intention. The results demonstrated that customer perception functioned as an essential mediating factor that enhanced the connection between digital engagement elements and CS results. Customers who found online banking platforms to be useful, credible and transparent showed higher levels of satisfaction and greater intention to use the service.

From an industry perspective, the results showed that digital perception management had important value for the banking sector. The banks needed to spend money on creating content and managing their social media platforms. The company needed to monitor both online reviews and user-generated content. The company used perception analytics to improve its digital transformation efforts, which enhanced its competitive edge and customer relationship management. The marketing strategies which emphasized transparency and trust built stronger customer relationships through increased customer loyalty.

Despite the contributions, there are some limitations to the study. The study was carried out in a specific geographical context. The study used a cross-sectional approach. This made it difficult to establish the long-term causal link. Moreover, the use of self-reporting may have resulted in response bias. Future studies may use a longitudinal approach to explore the development of perception and satisfaction. The study may be carried out in a wider geographical context to enhance generalizability. Another area of research may be the application of digital technology, such as AI personalization and fintech.

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