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An Analysis of Consumer Behavior Toward Mobile Shopping Applications: A Field Study

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Abstract

This study aims to examine the effect of Service Quality and Emotional Intelligence on Customer Satisfaction and Behavioral Intention across various service sectors by integrating the SERVQUAL model (Parasuraman et al., 1988) with Goleman's Emotional Intelligence framework (1998) into a unified analytical model.

A quantitative research design was employed using an online questionnaire distributed to a sample of 372 respondents who actively engage with digital service platforms. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0, assessing both the measurement and structural models to ensure reliability and validity of the constructs.

Findings revealed that Service Quality has a significant positive influence on Emotional Intelligence and Customer Satisfaction, while Emotional Intelligence strongly predicts both satisfaction and behavioral intention. Moreover, Customer Satisfaction mediates the relationship between Emotional Intelligence and Behavioral Intention, highlighting the emotional pathway linking service quality to behavioral outcomes.

The proposed model explained 64% of the variance in Customer Satisfaction and 71% of the variance in Behavioral Intention, indicating substantial explanatory power. The results confirm that emotional and cognitive factors jointly shape customers' loyalty behaviors and that emotionally intelligent service delivery enhances overall service experience.

Keywords: Service Quality, Emotional Intelligence, Customer Satisfaction, Behavioral Intention, Structural Equation Modeling, PLS-SEM

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Chapter one: Introduction

The adoption of mobile technologies and AI has dramatically shifted the relationships consumers have with digital marketplaces. Mobile shopping apps, along with smart assistants, now form an integral part of consumers' shopping routines, providing tailored services and real-time support. With the advent of conversational commerce and voice-operated devices such as Amazon's Alexa and Google Assistant, gaining insight into the drivers motivating consumers to adopt these technologies is imperative for any business looking to compete in the digital economy (Balakrishnan & Dwivedi, 2024; Aw et al., 2022)

There is existing literature on psychological, technological, and contextual factors that define consumer behavior in mobile and voice-assisted shopping contexts. For example, The Technology Acceptance Model (TAM) considers perceived ease of use and usefulness as major indicators of user adoption (Davis, 1989; Bagozzi, 2007), while other studies shift focus to trust and privacy or even anthropomorphism as major determinants (Gefen et al., 2003; Blut et al., 2021). Furthermore, digital voice assistants are considered more than task automation tools. They are now viewed as essential strategic touchpoints in the consumer journey that shape not only purchase decisions but also foster brand loyalty and impact consumer satisfaction (Grewal et al., 2022; Gelbrich et al., 2021)

Examples like Amazon's 2024 introduction of Rufus, a generative AI based conversational shopping assistant, marked a new advancement in the use of AI within customer experience (Amazon, 2024). These examples indicate a need to understand the tools placed within reach of consumers and how their perceived value shapes usage behavior.

Other studies mention perceived coolness, social influence, and emotional engagement as determinants of smart assistant adoption (Ashfaq et al., 2021; Fernandes & Oliveira, 2021)

As a case study, this research focuses on mobile commerce apps and shopping voice assistants to examine customer engagement and interaction. It draws upon motivation theories such as the Technology Acceptance Model (TAM) along with the S-O-R (Stimulus-Organism-Response) model to analyze motivation as a blend of attitudes, expectation, evaluation, and perception within a user's smart commerce ecosystem (Elgammal et al., 2025; Al-Fraihat et al., 2023).

In addition, the work is complemented by more recent literature that highlights the added complexity of consumer valuation in the context of mobile and voice commerce (Schultz & Kaiser, 2025)

Problem Statement

With mobile shopping apps and voice assistants becoming increasingly commonplace in today's shopping landscape, their adoption and continued usage has not been consistent across demographics or geographic regions. Even when adoption barriers like the user experience, convenience, and personalization are addressed, and technologies promise added convenience, users struggle to embrace them due to privacy issues, trust, technological intricacies, lack of value, or several other reasons. Furthermore, frameworks such as the Technology Acceptance Model, or TAM, and Stimulus-Organism-Response, or SOR, do lack insight regarding the blend of mobile commerce alongside voice technologies.

In addition to these concerns, the recent introduction of AI powered assistants, such as Rufus by Amazon, raises more questions as to how consumers assess and interact with sophisticated shopping interfaces. Existing literature has not sufficiently considered the interplay of social and

technological factors and psychology---specifically trust and perceived usefulness---within the intents of behaviors in mobile and conversational commerce.

This is why the study focuses on the following problem:

How do voice shopping assistant and mobile shopping applications interact, and what factors in consumer behavior are essential to these applications' interaction behavior? How do these elements interrelate to influence users' their behavioral adoption and usage?

Significance of the Study

This study is significant for more than one reason both in theory and practice. From a theory standpoint, it adds to the growing literature on mobile consumer shopping applications by analyzing voice shopping assistants, one of the newer technological innovations in the e-commerce sector. While past research has focused on these technologies individually, limited studies have looked at how their combined use impacts consumer decisions, perceptions, and behaviors.

Using the Technology Acceptance Model (TAM) and SOR (Stimulus-Organism-Response) frameworks, this study complements the existing knowledge on consumer interactions with smart shopping technologies.

Practically, this study provides businesses, mobile shopping application developers, and marketers concrete information that will assist them in improving the design, features, marketing, and overall experience of AI shopping assistants guided by the findings from this research. Organizations can develop better business tailored strategies through understanding the major determinants of acceptance like trust, emotional involvement, perceived usefulness, social

engagement, and collective deemed policies targeted towards enhanced user experience, organizational satisfaction, and visceral loyal participation. Through the study, other expectations from the consumers together with reasons that slow down the shift to advanced technologies in emerging markets will also be explored.

In conclusion, this study not only fills a gap in the literature but also contributes to the design of seamless, safe, and more engaging digital shopping experiences relevant to the transforming habits and behaviors of consumers.

Research Objectives

The scope of this study revolves around investigating the determinants of consumer attitude toward shopping on mobile applications and the use of digital voice assistants. In particular, this study will:

- Identify the key psychological, technological, as well as social factors impacting the consumer adoption for shopping applications and AI-driven voice assistants.
- Analyze the relationships between usefulness, ease of use, trust and user attitudes toward smart shopping technologies.
- Explore the impact of emotional engagement, perceived value, and social impact on consumers' intention behavior to use mobile and conversational commerce.
- Implement and analyze relevant theoretical frameworks (for example TAM and SOR) concerning mobile and voice-assisted shopping.
- Formulate actionable strategies for businesses and application developers focused on enhancing user engagement, satisfaction, and loyalty within online shopping platforms.

Research Questions

- Which primary drivers shape shopper engagement with mobile apps for shopping and voice-activated shopping assistants?
- In what ways do usefulness, ease of use, and trust impact shopping technologies attitude and intention among consumers of different demographics?
- How significant are emotional engagement and perceived value with regard to the adoption of mobile and voice assisted commerce?
- In what manner do social factors impact consumer decision-making and preferences in mobile and conversational commerce?
- How well do the Technology Acceptance Model (TAM) and the Stimulus-Organism-Response (SOR) models explain ecommerce consumer behavior?

Research Hypotheses

Drawing from the literature as well as the research objectives, the following hypotheses are formulated:

H1: The perception of usefulness mobile shopping applications and voice assistants offer will significantly enhance consumers' intention to use them.

H2: A positive perception of ease of use significantly influences how consumers form attitudes toward the adoption of smart shopping technologies.

H3: Users' trust towards mobile applications and voice assistants greatly influences their behavioral intention to use these technologies.

H4: The likelihood of continued usage is influenced positively by emotional engagement with the shopping platform.

H5: Technological features such as usability and personalization influence user satisfaction through perceived value.

H6: Social impact substantially affects consumers' decisions regarding the adoption of mobile and voice shopping assistants.

H7: Use of both Technology Acceptance Model (TAM) and the Stimulus-Organism-Response (SOR) framework provides strong predictive power for consumer behavior in mobile and conversational commerce contexts.

Literature Review

Davis (1989) introduced the Technology Acceptance Model (TAM) to explain user adoption of new technologies with two constructs: perceived usefulness and perceived ease of use. Later, in 2007, Bagozzi extended this model advocating for a more holistic approach that included additional motivational and social factors.

In the case of online trust, Gefen, Karahanna, and Straub (2003) developed an integrated model of TAM and trust theory, proving that trust is a strong determinant of a consumer's willingness to participate in online shopping activities.

Assarut and Eiamkanchanalai (2015) studying the adoption of mobile commerce found that personal attributes as well as values related to consumption significantly impact behavioral intentions toward shopping via mobile devices. In the same line of thinking, Elgammal et al. (2025) used the Stimulus-Organism-Response (SOR) framework and argued that mobile

commerce ubiquity directly enhances user engagement as long as product reputation and brand trust mediate the effect.

Gross (2017) looked in detail at shopping through mobile devices, focusing on the relationship between technological comfort, usability, and continued engagement among the digitally active population.

Concerning digital voice assistants, Aw et al. (2022) noted that products like Alexa improve customer experience greatly by providing immediate assistance, resulting in better brand engagement. In relation to smart speaker adoption, Ashfaq, Yun, and Yu (2021) noted that perceived coolness and emotional value are strong predictors of user attitude.

Fernandes and Oliveira (2021) further noted that automation of service encounters using voice assistants enhance customer satisfaction for users who appreciate high intelligence and responsiveness of a system.

In more recent work, Schultz and Kaiser (2025) explored mobile and conversational commerce analyzing consumer value dimensions alongside mobile and conversational commerce, stressing the importance of interactivity and customization and perceived control as key elements informing customers' value.

Also considering the adoption of smart voice assistants from a complexity theory perspective, Al-Fraihat, Alzaidi, and Joy (2023) proposed that multi-dimensional non-linear behavioral patterns drive the adoption, especially where shopping tasks are high on cognitive complexity.

The practical example of recent academic work, especially concerning natural language processing and real-time personalization, is the 2024 Amazon release of Rufus, an AI conversational assistant, which reflects the theoretical insights discussed (Amazon, 2024).

At long last, Blut, Wunderlich, and Brock (2024) performed a meta-analysis, revealing that customer satisfaction, frequency of usage, and loyalty after interactions are significantly enhanced by anthropomorphism, intelligence, and task-fit of virtual assistants.

Theoretical Foundations of the Study

This study relies on two key models which are widely used to underpin the behavioral dimensions of technology adoption: Technology Acceptance Model (TAM) and the Stimulus Organism Response (SOR) framework.

Technology Acceptance Model (TAM)

One of the most notable models for forecasting and explaining user behavior in information systems remains the Technology Acceptance Model, introduced by Davis in 1989. It argues that a user's intention to accept and use a technology is driven by two factors; its perceived usefulness (PU) and perceived ease of use (PEOU)

TAM has been adjusted to mobile shopping and voice assistants and used in multiple studies (Bagozzi, 2007; Gefen et al., 2003; Fernandes & Oliveira, 2021) to analyze how users embrace smarter interfaces based on their functionality and ease of use.

Stimulus-Organism-Response (SOR) Framework

Originating from environmental psychology, SOR explains how designed external stimulus (app features or a voice assistant's responsiveness) impacts internal organism processes (trust, emotions, and other mental evaluations) that subsequently result in behavior outcomes (purchase intention, usage intention)

Elgammal et al. (2025) utilized this framework in relation to mobile commerce and noted that the ubiquity and functionalities offered by smart platforms act as triggers that impact trust and brand perception, which in turn results in user engagement.

Taken together, these two models offer a comprehensive theoretical framework for this study.

TAM elucidates the mental assessment process of accepting and adopting smart technologies, whereas SOR offers a wider behavioral scope that includes the emotions, context, and the psyche of consumers that inform their actions.

These frameworks will assist in the construction of the research model, formulation of the hypotheses, and analysis of the empirical results.

Methodology

Approach to the Research

This study uses a quantitative research approach since it seeks to assess and quantify the relationships between pivotal factors influencing consumers' mobile shopping applications and voice assistants' use. The study has a descriptive and correlational design, which is appropriate for perception, attitude, and behavioral intention studies.

Data collection tool: questionnaire

Primary data will be collected through a streamlined structured questionnaire derived from validated measurement models from earlier research, which will have multiple sections.

Demographics: age, gender, educational level, smartphone usage, etc.

Technological factors: perceived usefulness and ease of use

Trust, emotional engagement, perceived value, and social influence

Behavioral intention and actual usage

Responses will be captured on a 5-point Likert scale from “Strongly Disagree” to “Strongly Agree”.

Sample Method and Population

The population of interest is individuals who use mobile shopping applications and/or voice assistants such as Alexa, Google Assistant, and shopping chatbots. Non-probability convenience sampling will be utilized for the online questionnaire targeting university students, young professionals, and frequent shoppers.

The minimum sample size will be computed using G*Power 3.1 (Faul et al., 2007) to ensure sufficient statistical power for the analysis conducted.

Techniques for Analysis of Data

The chosen measurement model will dictate whether SmartPLS or SPSS (Statistical Package for the Social Sciences) will be used for analysis. The analysis is going to cover:

Descriptive statistics

Reliability and validity testing e.g. Cronbach’s alpha and composite reliability

Exploratory or confirmatory factor analysis

Regression analysis or structural equation modeling hypothesis tests.

Ethical considerations

No identifying details will be collected. All participants will be told the purpose of the research and are free to choose whether to participate, and how much to share. Respondents' answers will remain confidential.

Research Instruments

In this study, the main data collection tool is a structured questionnaire which targets specific concerns regarding consumer behavior towards mobile shopping applications and voice assistants. The questionnaire was formulated after reviewing pertinent literature and was modified from previously tested measurement scales to ensure content validity and reliability.

1. Questionnaire Structure:

The questionnaire is subdivided into the following sections:

Section A: Demographic Information

This section comprises items pertaining to the respondent's age, gender, education level, frequency of technology usage, and knowledge regarding mobile shopping or voice assistants.

Section B: Technology-Related Variables

Perceived Usefulness (PU) – modified from Davis (1989)

Perceived Ease of Use (PEOU) – Davis (1989); Davis & Granić(2024)

Section C: Psychological and Emotional Factors

Trust – modified from Gefen et al. (2003)

Emotional Engagement – Fernandes & Oliveira (2021)

Perceived Value – Ashfaq et al. (2021); Schultz & Kaiser (2025)

Section D: Social Influence

Incorporates elements from Aw et al. (2022) and Al-Fraihat et al. (2023)

Section E: Behavioral Intention and Usage

Based on the TAM and SOR models, this measures an individual's likelihood of adopting mobile shopping applications or voice-activated assistants.

2. Measurement Scale

For Sections B to E, all items will be evaluated using a 5-point Likert scale which includes:



Figure 1.1 Measurement Scale

Study Limitations

The purpose of this study is to examine consumer attitudes towards shopping applications and voice shopping assistants. There are some notable limitations, however, that require attention:

Geographic Limitation:

This research is scoped to a certain geographical area such as a country or city. For this reason, the results may not be applicable to consumers from different cultures or economic settings.

Sampling Method:

This research will use a non-probability convenience sampling method which runs the risk of creating sampling bias. The findings only represent the perspectives of the individuals who opted to take the survey and have internet access.

Self-Reported Data:

The accuracy of responses in this study is contingent on self-reported data which has the potential to be impacted by social desirability bias or recall inaccuracies. Participants have the tendency to exaggerate or diminish their true behaviors or attitudes.

Focus on Technologies:

Only mobile shopping applications and voice shopping assistants are the focus of this research. Other smart technologies or shopping platforms, such as augmented or virtual assistants in retail stores, are beyond the objectives of this study.

Temporal Limitations:

Data collection will occur during a specific time window. Consumer behaviors change rapidly, particularly within the digital sphere. Eventually, attitudes and behaviors may change as a result of new trends or technologies.

Theoretical Scope:

For this research, the primary basis is the Technology Acceptance Model (TAM) and the Stimulus-Organism-Response (SOR) model. These models are robust and foundational, yet they do not encompass everything that can potentially influence consumer behavior.

Chapter Two

Literature Review

Chapter Two: Literature Review

2.1 Introduction

This chapter reviews the existing body of literature related to consumer behavior toward mobile shopping applications and voice-based assistants. It examines the theoretical foundations underlying technology adoption and emotional engagement in AI-driven commerce. The review is structured around two core frameworks — the Technology Acceptance Model (TAM) and the Stimulus–Organism–Response (SOR) model — which collectively explain consumers’ cognitive and affective responses to emerging digital technologies. Each section discusses prior studies on the key constructs of the research, including perceived usefulness, ease of use, trust, emotional engagement, perceived value, and social influence, leading to the identification of research gaps and the conceptual foundation of this study

2.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), first introduced by Davis (1989), is among the most widely applied theoretical frameworks in explaining users’ acceptance of new technologies. The model is rooted in the Theory of Reasoned Action (TRA) proposed by Fishbein and Ajzen (1975), suggesting that behavioral intention is determined by an individual's attitude toward using a technology and by perceived social norms. TAM simplifies this by focusing on two key determinants — Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) — which influence users’ attitudes and ultimately their behavioral intentions toward technology adoption.

2.2.1 Core Constructs

Perceived Usefulness (PU) refers to the degree to which an individual believes that using a particular system will enhance their performance, while Perceived Ease of Use (PEOU) refers to how effortless the use of that system appears to the user (Davis, 1989). Numerous studies have empirically validated the significance of these constructs in predicting technology adoption (Gefen et al., 2003; Benbasat & Barki, 2007). In digital commerce, PU often manifests through functional benefits such as time savings, convenience, and personalized recommendations, whereas PEOU relates to intuitive design, navigation simplicity, and seamless interaction.

2.2.2 Evolution and Extensions of TAM

Over time, researchers have extended TAM to accommodate new technological environments and user experiences. TAM2 (Venkatesh & Davis, 2000) introduced social influence and cognitive instrumental processes, while TAM3 (Venkatesh & Bala, 2008) incorporated computer anxiety, experience, and perceived enjoyment. More recently, hybrid models have emerged that integrate TAM with other frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Stimulus–Organism–Response (SOR) model to address emotional and contextual factors influencing technology use (Elgammal et al., 2025; Habiboglu, 2025).

Massoudi and Zaidan (2024) emphasized that in e-commerce, users' perception of AI-driven features such as recommendation accuracy, responsiveness, and personalization significantly enhances perceived usefulness. Similarly, Singh et al. (2024) found that trust mediates the relationship between PU and behavioral intention when consumers interact with intelligent online shopping assistants. These findings highlight the evolving nature of TAM, where

traditional cognitive evaluations are now complemented by affective and trust-related dimensions.

2.2.3 TAM in Mobile Shopping and AI-Driven Contexts

The proliferation of mobile shopping applications has prompted a surge in TAM-based studies exploring the determinants of consumer engagement and loyalty. Yong and Noor (2025) conducted a bibliometric review of 20 years of TAM research in online purchase behavior, concluding that PU and PEOU remain dominant predictors of technology adoption, but factors such as enjoyment, trust, and emotional attachment have gained importance in AI-integrated settings.

In the context of voice-based assistants, Choudhary and Ahuja (2025) investigated young consumers' motivation for using intelligent voice assistants and found that perceived enjoyment and system intelligence strongly influence behavioral intention, mediated by trust and perceived ease of interaction. ElSayad and Mamdouh (2025) further extended TAM to retail e-commerce by examining AI-powered shopping applications, showing that perceived usefulness and trust jointly predict customer word-of-mouth intentions.

These studies collectively affirm TAM's continued relevance in understanding technology adoption behavior, while also revealing its limitations when addressing emotional or experiential variables. Consequently, integrating TAM with complementary frameworks such as SOR enables a more comprehensive analysis of both cognitive (utility-driven) and affective (emotion-driven) processes that shape user behavior toward intelligent digital systems.

2.3 Stimulus–Organism–Response (SOR) Framework

The Stimulus–Organism–Response (SOR) model was originally developed by Mehrabian and Russell (1974) to explain emotional responses to environmental stimuli in psychological and behavioral contexts. The model posits that external stimuli (S) influence an individual's internal states (O) — including cognitive, emotional, and affective processes — which then determine the individual's behavioral responses (R). In marketing and consumer behavior research, this framework has been instrumental in understanding how environmental cues, such as store atmosphere, website design, or interactive technology, elicit psychological reactions that shape consumer attitudes and behaviors (Donovan & Rossiter, 1982; Jacoby, 2002).

2.3.1 Core Structure and Mechanisms (Expanded)

The Stimulus–Organism–Response (SOR) framework operates as a mediating model that bridges the gap between external environmental triggers and internal psychological or behavioral outcomes. Originally proposed by Mehrabian and Russell (1974), the framework was designed to capture how environmental stimuli elicit emotional and cognitive responses that ultimately shape behavioral intentions. In contemporary digital environments, the SOR paradigm provides a robust theoretical foundation for understanding how consumers respond to online stimuli — ranging from visual design and interactive features to intelligent recommendation systems and conversational AI interfaces (Donovan & Rossiter, 1982; Jacoby, 2002; Riandhi & Arviansyah, 2025).

In digital commerce, the Stimulus (S) component refers to the set of external cues or technological attributes that consumers are exposed to while engaging with an online system. These may include interface design quality, interactivity, ease of navigation, responsiveness,

perceived intelligence, and personalization (Habiboglu, 2025; Linh et al., 2025). For instance, in mobile shopping environments, aesthetic appeal, color schemes, and interface consistency serve as key sensory stimuli that affect consumers' initial impressions. In AI-based voice assistants, stimuli are often auditory, such as tone, fluency, or human-likeness of voice, which can evoke either trust or discomfort (Choudhary & Ahuja, 2025). These stimuli collectively shape the first stage of user perception, setting the cognitive and emotional tone for subsequent interactions.

The Organism (O) represents the consumer's internal psychological state, which mediates the relationship between stimuli and behavioral outcomes. This stage captures users' emotional engagement, trust, satisfaction, perceived value, and perceived control (Mohammed & Ferraris, 2025; Elgammal et al., 2025). In the context of digital commerce, organismic responses include both cognitive appraisals (e.g., evaluating system quality or usefulness) and affective reactions (e.g., enjoyment, excitement, or anxiety). For example, Riandhi and Arviansyah (2025) identified that emotional engagement plays a crucial mediating role between AI-driven stimuli (e.g., chatbot responsiveness, personalization) and user loyalty. Similarly, Massoudi and Zaidan (2024) observed that trust moderates the impact of technological intelligence on purchase intention, showing that consumers are more likely to engage with systems they perceive as both competent and reliable.

Finally, the Response (R) component refers to observable consumer behaviors or intentions resulting from internal processing. These may include purchase decisions, continued usage, word-of-mouth recommendations, or brand loyalty (ElSayad & Mamdouh, 2025). In the AI commerce setting, responses are not purely transactional but also behavioral expressions of psychological satisfaction, such as repeated interaction with a chatbot, extended time spent in an app, or willingness to share data for personalization (Singh et al., 2024). Recent studies in AI-

enabled retail systems confirm that emotional satisfaction and trust exert stronger effects on behavioral intention than traditional utilitarian drivers, underscoring the importance of organismic variables in predicting sustained engagement (Ghazali et al., 2025; Yong & Noor, 2025).

Overall, the SOR structure provides an integrative lens that allows scholars to capture both rational and emotional processes in consumer behavior. Unlike technology-centered models such as TAM, which primarily focus on cognitive evaluations like perceived usefulness or ease of use, SOR emphasizes the interactive and affective nature of human-technology relationships. When applied to AI-driven mobile and voice shopping contexts, this framework helps explain how environmental and technological stimuli activate internal emotional mechanisms that ultimately shape behavioral responses. Hence, the SOR framework complements TAM by contextualizing the psychological depth of user experiences, making it a valuable theoretical foundation for analyzing AI-assisted consumer interactions.

2.3.2 Application in Digital and AI-Driven Commerce

The Stimulus–Organism–Response (SOR) model has evolved from its early use in physical retail environments to become one of the most widely adopted frameworks in digital marketing and e-commerce research. As commerce increasingly transitions into online and AI-assisted domains, the interaction between technological stimuli and consumer psychological responses has grown more complex. The SOR model offers a structured means to analyze these interactions, particularly when technological design elements elicit emotional, cognitive, and behavioral outcomes (Habiboglu, 2025; Mohammed & Ferraris, 2025).

In digital commerce settings, the stimuli represent not only traditional visual or informational cues but also dynamic and interactive technological features. For instance, personalization algorithms, recommendation systems, and conversational interfaces act as stimuli that influence consumers' perceptions of system intelligence and relevance (Linh et al., 2025). A well-designed user interface or responsive AI chatbot can trigger positive affective states such as enjoyment, trust, and satisfaction, while poor interaction design may lead to frustration or anxiety (Choudhary & Ahuja, 2025). These technological cues thus form the foundation of consumer perceptions in online and mobile shopping contexts.

Empirical evidence supports this theoretical view. Riandhi and Arviansyah (2025) examined the influence of AI-based stimuli—such as perceived personalization, emotional intelligence, and interactivity—on users' internal states. They found that emotional engagement and trust were the most significant organismic mediators between AI stimuli and purchase intentions. Similarly, Mohammed and Ferraris (2025) investigated AI chatbots and demonstrated that responsiveness, empathy, and anthropomorphism (human-like behavior) significantly enhance trust and satisfaction, which subsequently increase consumers' intention to continue using AI-enabled services. Their findings reinforce the idea that stimuli with emotional resonance are more likely to foster loyalty and long-term relationships.

In the context of mobile shopping, the SOR framework has been applied to explain how interface quality, ease of navigation, and mobile interactivity affect consumer emotions and behavior. Aw et al. (2022) and Grewal et al. (2022) found that visually appealing mobile app designs and interactive features act as strong environmental stimuli that trigger perceived enjoyment and satisfaction. These internal states, in turn, increase the likelihood of repeat purchases and positive word-of-mouth. Extending these insights to AI-integrated shopping platforms, ElSayad and

Mamdouh (2025) demonstrated that AI-driven recommendations, when perceived as useful and trustworthy, significantly influence emotional satisfaction and behavioral intentions toward online retailers.

Furthermore, the SOR framework has been instrumental in understanding voice commerce—a domain where consumers interact with voice-based digital assistants such as Alexa, Siri, and Google Assistant. In this context, stimuli are often auditory and conversational rather than visual. Choudhary and Ahuja (2025) observed that users’ emotional reactions to the tone, warmth, and fluency of voice assistants significantly affect trust and willingness to use voice shopping systems. They argue that anthropomorphic cues—such as conversational empathy or humor—function as powerful emotional stimuli, making users perceive the assistant as socially intelligent and reliable. As a result, these affective responses translate into behavioral outcomes like increased shopping frequency and product recommendations through the same voice platform.

In a comprehensive review, Habiboglu (2025) synthesized multiple applications of the SOR framework across AI-driven retail systems, emphasizing that organismic variables such as trust, engagement, and satisfaction mediate the influence of technological stimuli on purchase behaviors. The study also highlighted that emotional responses are more predictive of behavioral loyalty than cognitive evaluations, which aligns with the argument for integrating SOR with TAM in modern digital commerce models. This suggests that while TAM explains why users adopt a technology based on its utility and ease, SOR explains how emotional and environmental triggers shape the depth and continuity of that adoption.

Overall, the application of the SOR framework in digital and AI-assisted commerce underscores its versatility and explanatory strength. It allows researchers to capture both functional evaluations (usefulness, usability) and emotional experiences (trust, enjoyment, engagement),

providing a holistic understanding of consumer behavior in technologically mediated environments. As mobile and voice shopping platforms continue to evolve, the integration of SOR principles offers an effective lens to assess how AI features influence psychological states and behavioral intentions — a perspective central to the current research.

2.3.3 Integration of SOR with TAM

While the Technology Acceptance Model (TAM) and the Stimulus–Organism–Response (SOR) framework have been used independently across numerous studies in technology adoption and consumer behavior, recent research highlights the complementary nature of these models. TAM explains the cognitive dimension of technology acceptance—how users evaluate the usefulness and ease of use of a system—whereas SOR captures the emotional and psychological mechanisms through which external stimuli shape behavioral responses. Integrating both frameworks provides a comprehensive perspective that encompasses rational evaluation, affective reaction, and behavioral intention (Habiboglu, 2025; Linh et al., 2025; Elgammal et al., 2025).

The theoretical rationale for integration lies in the recognition that technology adoption is not purely a rational decision process. Consumers’ attitudes and behaviors are influenced by a complex interplay between cognitive assessments (as proposed in TAM) and affective experiences (as emphasized in SOR) (Al-Fraihat et al., 2023). For instance, when interacting with mobile shopping apps or AI voice assistants, users do not simply assess whether the system is useful or easy to use; they also respond emotionally to the design aesthetics, system intelligence, and human-like interaction patterns. These elements act as environmental stimuli

(S) that affect internal psychological states (O)—such as trust, engagement, or enjoyment—which then lead to behavioral responses (R) such as continuous usage or purchase intention.

Empirical research supports this conceptual synergy. Elgammal et al. (2025) proposed an integrated TAM–SOR framework to study the adoption of AI in retail commerce. Their findings demonstrated that perceived usefulness (a TAM variable) directly influences emotional engagement (an SOR organism variable), which subsequently mediates the relationship between cognitive evaluation and behavioral intention. Similarly, Massoudi and Zaidan (2024) found that perceived ease of use enhances user satisfaction and trust—two organismic factors—which, in turn, increase behavioral intention to engage in AI-enabled online shopping. These studies affirm that integrating TAM and SOR helps explain not only why consumers adopt technology but also how emotional and environmental triggers shape their continued engagement.

Moreover, the integration of these frameworks is particularly relevant in AI-assisted and voice-driven commerce, where emotional factors play a decisive role. Choudhary and Ahuja (2025) reported that users’ perceptions of system intelligence and empathy significantly affect trust and enjoyment—organismic states that mediate the relationship between perceived usefulness and intention to use voice assistants. Similarly, Mohammed and Ferraris (2025) demonstrated that conversational empathy and AI responsiveness (stimuli) evoke positive emotional responses, which subsequently influence users’ cognitive evaluations of system usefulness and ease of use. This reciprocal relationship shows that TAM and SOR are not isolated models but interdependent layers of the same behavioral process.

From a theoretical standpoint, the integration of TAM and SOR allows researchers to capture a more holistic and context-sensitive understanding of technology use. While TAM emphasizes instrumental beliefs (usefulness, ease of use) as predictors of behavioral intention, SOR

emphasizes emotional and environmental conditions as the triggers and mediators of those beliefs. This integrated approach has been successfully applied in studies across mobile commerce (Aw et al., 2022), AI retail systems (Habiboglu, 2025), and chatbot engagement (Riandhi & Arviansyah, 2025), all confirming that emotional engagement and trust significantly strengthen the predictive power of cognitive variables.

2.4 Key Constructs Influencing Consumer Behavior

Understanding consumer behavior toward mobile shopping applications and voice assistants requires examining the core constructs that explain users' attitudes and behavioral intentions. Drawing from both the Technology Acceptance Model (TAM) and the Stimulus–Organism–Response (SOR) framework, this section discusses six critical constructs that jointly determine technology adoption and engagement: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust, Emotional Engagement, Perceived Value, and Social Influence.

2.4.1 Perceived Usefulness (PU)

Perceived Usefulness (PU) is one of the central determinants in TAM, defined by Davis (1989) as “the degree to which an individual believes that using a particular system will enhance his or her performance.” PU captures the cognitive evaluation that a technology provides tangible benefits, such as efficiency, effectiveness, or convenience. In the context of mobile and AI-driven shopping, perceived usefulness reflects the extent to which consumers view these technologies as tools that simplify purchasing, improve decision-making, or provide personalized and efficient shopping experiences (Benbasat & Barki, 2007; Singh et al., 2024).

Recent studies emphasize that perceived usefulness is not limited to functional benefits but also includes contextual and experiential advantages. For instance, Massoudi and Zaidan (2024)

found that the perceived usefulness of AI-driven e-commerce platforms depends on their ability to offer relevant product recommendations and enhance purchase satisfaction. Similarly, ElSayad and Mamdouh (2025) demonstrated that AI retail systems that provide accurate, real-time assistance significantly improve perceived usefulness, which directly influences customer satisfaction and positive word-of-mouth intentions.

In mobile shopping applications, usefulness often manifests in the form of time efficiency, ease of comparison, and personalized offers. Aw et al. (2022) identified that consumers who perceive mobile apps as useful are more likely to display repeat purchase intentions and loyalty behaviors. Yong and Noor (2025), in a bibliometric analysis of TAM applications in digital commerce, found that PU remains the most dominant predictor of behavioral intention, accounting for more than 40% of variance across e-commerce studies.

In the voice shopping context, perceived usefulness is tied to accuracy, contextual understanding, and convenience. Choudhary and Ahuja (2025) revealed that voice assistants that can accurately interpret natural speech commands and offer relevant product suggestions significantly enhance consumers' perceptions of usefulness, leading to higher intention to adopt voice shopping platforms. Similarly, Schultz and Kaiser (2025) showed that when consumers perceive a voice assistant as efficient in multitasking (e.g., placing orders, checking delivery, and recommending items), their satisfaction and loyalty intentions increase.

From a SOR perspective, perceived usefulness can be viewed as both a stimulus and an organismic response. It acts as a cognitive evaluation triggered by technological stimuli (such as design quality, intelligence, and personalization) and as a mediating factor that influences emotional engagement and behavioral outcomes. For example, Elgammal et al. (2025) found that perceived usefulness mediates the effect of technological intelligence on emotional engagement

and purchase intention in AI-driven shopping platforms. Thus, PU not only predicts behavioral intention but also contributes to positive affective responses, strengthening user trust and emotional connection to the system.

Moreover, in the integrated TAM–SOR model, PU is often positioned as a bridge variable connecting cognitive evaluation to affective and behavioral outcomes. When users perceive a system as useful, they are more likely to experience emotional satisfaction and psychological comfort, which ultimately lead to sustained behavioral engagement (Habiboglu, 2025; Riandhi & Arviansyah, 2025). Therefore, in the current study, perceived usefulness is expected to play a crucial role in explaining how consumers cognitively and emotionally respond to mobile shopping and voice assistant technologies.

2.4.2 Perceived Ease of Use (PEOU)

Perceived Ease of Use (PEOU) is the second cornerstone of the Technology Acceptance Model (TAM) and refers to “the degree to which a person believes that using a particular system would be free of effort” (Davis, 1989). It represents users’ perception of how simple and intuitive a technological system is to operate. The easier a system is to use, the more likely individuals are to form positive attitudes toward it and develop intentions to adopt or continue its use (Gefen et al., 2003; Venkatesh & Bala, 2008). In the context of mobile shopping applications and AI-driven voice assistants, PEOU reflects how naturally users can interact with the technology, navigate its features, and achieve their desired outcomes without frustration or complexity.

From the traditional TAM perspective, PEOU exerts both a direct and an indirect effect on behavioral intention. Directly, systems perceived as easy to use foster user confidence and willingness to engage. Indirectly, PEOU enhances Perceived Usefulness (PU) — since users are

more likely to recognize a system's value if it is simple and accessible (Benbasat & Barki, 2007). This relationship has been confirmed across multiple digital contexts. For instance, Singh et al. (2024) found that users of AI-powered online shopping assistants demonstrated higher perceived usefulness when the interaction process was intuitive and smooth. Likewise, Massoudi and Zaidan (2024) observed that PEOU positively affects PU and trust in AI-enabled e-commerce platforms, emphasizing that system simplicity is a precondition for both functional and emotional acceptance.

In the mobile shopping environment, PEOU manifests through interface clarity, ease of navigation, mobile responsiveness, and visual consistency. Consumers who perceive shopping apps as user-friendly tend to experience higher satisfaction and continued engagement. Aw et al. (2022) found that ease of navigation and simplicity of mobile layouts were significant predictors of consumers' attitude toward using shopping apps. Similarly, Yong and Noor (2025) reported that among TAM constructs, PEOU has the strongest indirect effect on purchase intention via PU and trust, reinforcing its foundational role in technology acceptance.

In voice-based commerce, PEOU has been extended to include interactional and linguistic ease—that is, how naturally users can communicate with a digital assistant and how efficiently it processes voice commands. Choudhary and Ahuja (2025) discovered that when voice assistants understand users' speech fluently, provide coherent responses, and require minimal correction, perceived ease of use significantly increases user satisfaction and intention to use. Their findings highlight that the naturalness of conversation, tone, and perceived intelligence of the voice interface are critical for fostering ease of interaction. Additionally, Schultz and Kaiser (2025) demonstrated that simplicity in task execution—such as reordering previous purchases or

tracking deliveries through voice commands—reduces user anxiety and strengthens intention to continue using AI-based voice assistants.

From the SOR perspective, PEOU can also be interpreted as both a stimulus and an organismic factor. As a stimulus, it represents the system’s design characteristics that influence internal cognitive and emotional states. As an organismic response, it reflects the user’s perceived comfort, reduced cognitive load, and sense of control when engaging with technology. Elgammal et al. (2025) found that ease of use contributes to emotional engagement by minimizing mental effort, thereby creating a more enjoyable experience that leads to higher behavioral intention. Similarly, Habiboglu (2025) emphasized that reducing friction in user interaction enhances affective satisfaction, which subsequently promotes loyalty in AI-enabled commerce.

In integrated TAM–SOR models, PEOU plays a crucial linking role between technological design and emotional engagement. Systems that are easy to navigate not only increase perceptions of usefulness but also evoke positive emotional responses such as trust, enjoyment, and comfort. These emotional responses are essential organismic mediators that translate system simplicity into behavioral outcomes (Riandhi & Arviansyah, 2025). Therefore, in this research, Perceived Ease of Use is positioned as a pivotal construct influencing both the cognitive and affective dimensions of consumer behavior, serving as a key antecedent to perceived usefulness, trust, and engagement toward mobile shopping applications and voice-based AI systems.

2.4.3 Trust

In digital and AI-driven commerce, trust has emerged as one of the most decisive factors influencing consumers’ intention to adopt and continue using technology. It is broadly defined as “the willingness of a party to be vulnerable to the actions of another party based on the

expectation that the other will perform a particular action important to the trustor” (Mayer et al., 1995). In online shopping, trust reflects a consumer’s belief that the platform or system is reliable, secure, and acts in the user’s best interest (Gefen et al., 2003). Within the frameworks of TAM and SOR, trust functions both as an organismic factor (an internal psychological state influencing behavior) and as a mediator linking cognitive evaluations (usefulness, ease of use) with behavioral responses (purchase intention, continued use).

From the TAM perspective, trust complements the traditional belief–attitude–intention chain by addressing the risk and uncertainty inherent in online and AI-assisted environments. While perceived usefulness and ease of use explain functional acceptance, they do not capture the psychological assurance users require to engage with systems that operate autonomously or collect personal data. Gefen et al. (2003) argued that trust acts as a missing cognitive link in TAM, shaping how beliefs about technology translate into behavioral intentions. Recent studies continue to support this extension. Massoudi and Zaidan (2024) demonstrated that trust mediates the relationship between perceived usefulness and intention to use AI-powered e-commerce systems. Similarly, Singh et al. (2024) found that consumers’ perceptions of an AI shopping assistant’s intelligence and integrity significantly enhance trust, which in turn increases adoption likelihood.

From the SOR perspective, trust is conceptualized as an organismic variable that emerges from external stimuli such as system reliability, transparency, personalization, and interactivity. Elgammal et al. (2025) reported that consumers develop trust when they perceive AI systems as transparent and accurate in recommendations, suggesting that technological design and algorithmic communication serve as primary stimuli. Habiboglu (2025) reinforced this view, finding that perceived AI competence, empathy, and consistency act as stimuli that elicit

emotional trust and satisfaction, which subsequently drive purchase intention. In this sense, trust represents the emotional bridge between external technological cues (stimuli) and behavioral outcomes (responses).

In mobile shopping, trust is largely influenced by security, privacy, and system reliability. Aw et al. (2022) found that data protection assurances and secure payment gateways significantly enhance users' trust in mobile shopping platforms, which in turn strengthens their commitment and repeat purchase intentions. Grewal et al. (2022) similarly concluded that brand familiarity and consistent mobile app performance act as key antecedents of trust formation in digital retailing.

Trust assumes even greater importance in AI and voice-based shopping, where users rely on systems that process personal information and make recommendations autonomously.

Choudhary and Ahuja (2025) found that users' perception of voice assistant transparency (e.g., clear explanation of actions, acknowledgment of user commands) enhances trust, leading to greater usage intention. Likewise, Schultz and Kaiser (2025) demonstrated that conversational empathy—expressed through polite tone, natural voice modulation, and context-aware responses—builds emotional trust, which then fosters positive behavioral outcomes. These findings underscore the affective and social dimensions of trust in AI environments, where interaction quality is often as critical as functional accuracy.

Furthermore, Mohammed and Ferraris (2025) explored trust as both a mediator and a moderator in the adoption of AI chatbots. They discovered that trust mediates the impact of stimuli such as responsiveness and personalization on satisfaction and continued use, while also moderating the relationship between perceived usefulness and behavioral intention. In other words, even when users find a system useful, low trust can weaken their adoption intentions, whereas high trust

amplifies it. This dual role highlights trust as a central psychological mechanism in AI-driven commerce.

Integrating trust into the TAM–SOR model provides a more nuanced understanding of consumer behavior. Within this framework, trust links cognitive appraisals (usefulness, ease of use) with affective states (comfort, satisfaction) and behavioral responses (loyalty, intention). As ElSayed and Mamdouh (2025) observed, consumers who trust AI-driven shopping assistants not only perceive them as useful but also experience higher emotional satisfaction and are more likely to recommend them to others. Consequently, in the present study, trust is positioned as a pivotal organismic construct that mediates the relationship between technological attributes (stimuli) and behavioral outcomes (responses), playing a central role in determining consumers’ willingness to adopt and engage with mobile shopping and voice assistant technologies.

2.4.4 Emotional Engagement

Emotional engagement has become a central construct in understanding how users interact with technology, particularly in digital environments that incorporate artificial intelligence (AI), personalization, and interactivity. It refers to the extent of emotional involvement, attachment, and psychological connection a consumer develops toward a digital platform or system (Hollebeek et al., 2014). Within the Stimulus–Organism–Response (SOR) framework, emotional engagement represents an organismic state — an internal psychological reaction to technological or environmental stimuli that mediates the relationship between external system features and behavioral outcomes (Elgammal et al., 2025; Riandhi & Arviansyah, 2025).

In contrast to cognitive constructs such as perceived usefulness or ease of use, emotional engagement emphasizes the affective dimension of consumer–technology interaction. In mobile

and AI-driven commerce, consumers no longer interact passively with digital tools; instead, they form emotional relationships with intelligent systems that appear adaptive, responsive, and socially aware. These interactions trigger feelings of enjoyment, excitement, trust, and satisfaction, all of which shape behavioral intention (Habiboglu, 2025; Mohammed & Ferraris, 2025).

From the TAM–SOR integration perspective, emotional engagement functions as the bridge that connects cognitive appraisals (usefulness, ease of use) with behavioral outcomes (continued use, purchase intention). Users who perceive a system as both useful and easy to use are more likely to feel emotionally engaged, which strengthens their motivation to continue using it. Elgammal et al. (2025) confirmed this mediating role by showing that emotional engagement fully mediates the relationship between AI stimuli (responsiveness, personalization, transparency) and users' purchase intentions. Similarly, Massoudi and Zaidan (2024) found that emotional engagement significantly amplifies the positive effects of perceived usefulness on satisfaction and behavioral loyalty in AI-powered e-commerce.

In mobile shopping applications, emotional engagement is often triggered by visual appeal, interactivity, and personalization. Aw et al. (2022) showed that mobile users who felt emotionally connected to a shopping app — due to its appealing design, recommendation accuracy, and perceived intelligence — displayed higher purchase intentions and long-term loyalty. Grewal et al. (2022) reinforced this view, reporting that emotional engagement mediates the influence of mobile user interface quality on repeat purchase behavior. These findings underscore the importance of designing mobile systems that evoke positive affective experiences, not just cognitive evaluations.

In voice-based shopping environments, emotional engagement is largely shaped by the human-like and social qualities of AI assistants. Choudhary and Ahuja (2025) found that the emotional tone, warmth, and empathy displayed by voice assistants significantly increased users' feelings of connection, which in turn enhanced their trust and intention to use. Similarly, Schultz and Kaiser (2025) demonstrated that consumers who felt emotionally supported by their voice assistants — particularly when they displayed humor or empathy — were more likely to rely on them for repeated shopping tasks. These studies highlight that emotional engagement arises not only from system performance but also from social cues and affective communication embedded in AI interactions.

From the SOR standpoint, emotional engagement serves as a critical organismic mediator that transforms external stimuli (e.g., interface design, personalization, tone, interactivity) into behavioral responses (e.g., loyalty, advocacy, or sustained use). Riandhi and Arviansyah (2025) found that emotional engagement explains the majority of variance between AI stimuli and user satisfaction, outperforming purely cognitive factors. Likewise, Habiboglu (2025) emphasized that emotional engagement is a key determinant of flow experience — a state of deep involvement that leads to stronger commitment to AI-driven shopping platforms.

Moreover, emotional engagement is strongly linked with trust and perceived value, forming a triadic relationship central to AI commerce. When users emotionally connect with a technology, their trust in it strengthens, and their perception of its overall value increases (ElSayad & Mamdouh, 2025). In this way, emotional engagement serves not only as a mediator but also as a reinforcing feedback mechanism, amplifying both cognitive and emotional dimensions of consumer–technology interaction.

2.4.5 Perceived Value

Perceived Value (PV) is defined as the consumer's overall assessment of the utility of a product or service based on perceptions of what is received and what is given (Zeithaml, 1988). It encompasses not only monetary considerations but also functional, emotional, and social dimensions that collectively shape behavioral intentions (Blut et al., 2024; Aw et al., 2022). Within the Technology Acceptance Model (TAM) and Stimulus–Organism–Response (SOR) integration, perceived value represents a critical organismic construct that captures the user's comprehensive cognitive and affective evaluation of technology.

In traditional TAM-based studies, perceived value is often viewed as a consequence of perceived usefulness — when users find a technology beneficial and efficient, they are likely to perceive higher overall value (Venkatesh & Bala, 2008). However, recent research extends this view by incorporating emotional and experiential elements, acknowledging that consumers evaluate not only utility but also enjoyment, trust, and personal relevance (Habiboglu, 2025; Elgammal et al., 2025). In other words, perceived value in AI and mobile commerce is multidimensional, integrating both cognitive utility and emotional experience.

In mobile shopping contexts, perceived value arises from the convenience, personalization, and speed of transactions offered by mobile applications. Aw et al. (2022) found that perceived value mediates the relationship between mobile app interactivity and repurchase intention — users who perceive greater convenience and efficiency develop stronger loyalty. Similarly, Grewal et al. (2022) observed that value perceptions in mobile retailing are shaped by personalization and promotional features, which enhance satisfaction and brand attachment. Their findings confirm

that perceived value acts as a key driver of both attitudinal and behavioral loyalty in mobile commerce.

In AI-enabled and voice shopping environments, perceived value extends beyond convenience to include intelligence, human-likeness, and personalization. Choudhary and Ahuja (2025) demonstrated that users who perceive voice assistants as providing accurate and contextually relevant recommendations view them as more valuable, which directly influences behavioral intention and trust. Likewise, ElSayed and Mamdouh (2025) found that AI-driven recommendation systems that deliver consistent and personalized advice enhance both perceived value and emotional satisfaction, ultimately increasing consumers' willingness to engage in repeat shopping behavior.

From the SOR perspective, perceived value functions as a central organismic state that reflects the integration of cognitive and affective responses to technological stimuli. For instance, stimuli such as interface aesthetics, recommendation quality, interactivity, and emotional tone evoke internal evaluations of worth, which in turn predict behavioral responses such as purchase intention and word-of-mouth advocacy (Riandhi & Arviansyah, 2025). Habiboglu (2025) further argues that perceived value mediates the relationship between AI-driven stimuli (personalization, responsiveness, transparency) and emotional engagement, confirming its position as both a cognitive assessment and an emotional reflection of technology's benefits.

In AI commerce, trust and perceived value are closely interconnected. Consumers who trust an AI system tend to perceive its outcomes as more valuable, while a high perception of value reinforces emotional trust. Massoudi and Zaidan (2024) found that perceived value significantly moderates the relationship between trust and behavioral intention, demonstrating that trust-driven engagement is stronger when users perceive high value in their interactions with AI

shopping assistants. This finding suggests that value perception is not only an outcome but also an amplifier of emotional and cognitive constructs.

In integrated TAM–SOR models, perceived value acts as a linking mechanism that connects cognitive evaluations (usefulness, ease of use) with affective reactions (trust, engagement) and behavioral intentions (continued use, loyalty). For example, Elgammal et al. (2025) and Blut et al. (2024) confirmed that perceived value enhances the predictive power of TAM by incorporating emotional satisfaction and social meaning into the acceptance process. As such, perceived value bridges the gap between instrumental rationality (usefulness and ease) and affective gratification (emotional engagement and trust), offering a holistic view of technology acceptance.

2.4.6 Social Influence

Social influence (SI) refers to the extent to which an individual's behavioral intentions are shaped by the opinions, expectations, or behaviors of others within their social environment (Venkatesh & Davis, 2000). It is derived from subjective norm in the Theory of Reasoned Action (TRA) and later incorporated into TAM2 and UTAUT models, emphasizing that users' technology adoption decisions are influenced not only by personal beliefs but also by social pressures and cultural norms. Within the TAM–SOR integration, social influence operates as both a stimulus (external environmental cue) and an organismic determinant (internalized social belief) that drives behavioral responses such as adoption, satisfaction, and advocacy.

In traditional TAM-based studies, social influence was often conceptualized as an external normative pressure, especially in collective cultures where peer recommendations, family opinions, or workplace norms heavily affect decision-making. However, in digital commerce, the

concept has evolved to encompass social engagement mechanisms, such as online reviews, influencer recommendations, and social media integration (Aw et al., 2022). These stimuli create perceived social validation that shapes internal beliefs about a system's credibility, usefulness, and trustworthiness.

Recent empirical research provides strong support for the role of social influence in digital adoption behavior. Grewal et al. (2022) found that perceived peer endorsement and social presence on mobile shopping platforms significantly enhance user attitudes and purchase intentions. Likewise, Aw et al. (2022) confirmed that user-generated content and community engagement features act as stimuli that foster a sense of belonging and trust, thereby strengthening behavioral commitment to mobile shopping applications. These findings indicate that social influence operates through both informational pathways (trust and expertise shared by others) and normative pathways (the desire to conform to perceived social expectations).

In AI-driven environments, social influence manifests through perceptions of how others view AI technologies and through anthropomorphic social cues embedded in the systems themselves. Choudhary and Ahuja (2025) reported that when voice assistants use human-like conversational tones and socially intelligent responses, users perceive them as socially competent entities, leading to increased social trust and engagement. Similarly, Schultz and Kaiser (2025) demonstrated that individuals who perceive their peers as frequent users of AI voice shopping systems are more likely to adopt the same technology, reflecting the network externality effect where social usage amplifies adoption intention.

The SOR framework provides an ideal structure for explaining how social influence translates into emotional and behavioral outcomes. Here, social cues, reviews, and peer recommendations function as stimuli (S) that trigger internal organismic states (O) such as belongingness, trust,

and perceived value, which subsequently result in behavioral responses (R) like purchase or continued use (Riandhi & Arviansyah, 2025). For instance, Habiboglu (2025) found that exposure to socially endorsed AI systems increases emotional trust and engagement, particularly when users perceive that such technologies are widely accepted or admired by their social networks.

In the integrated TAM–SOR model, social influence not only affects behavioral intention directly but also interacts with emotional engagement and perceived value to enhance user satisfaction. Elgammal et al. (2025) observed that in AI-assisted retail systems, social presence and community interaction features (e.g., shared wish lists, real-time reviews) strengthen both perceived usefulness and emotional satisfaction. Similarly, Massoudi and Zaidan (2024) found that perceived social endorsement moderates the effect of trust on behavioral intention — when users perceive strong social approval of a technology, the influence of trust becomes more powerful. These findings align with Riandhi and Arviansyah (2025), who demonstrated that social influence indirectly increases purchase intention through emotional engagement and perceived enjoyment in AI-enabled online shopping.

From a cultural perspective, social influence plays a particularly strong role in collectivist societies, where individuals tend to make technology adoption decisions in alignment with group norms and peer behaviors (Fernandes & Oliveira, 2021). In such settings, social trust and conformity act as reinforcing mechanisms that enhance the predictive power of TAM variables. This insight is particularly relevant to emerging markets where social media communities, influencers, and online peer groups serve as powerful opinion leaders shaping consumer attitudes toward AI and mobile technologies.

In summary, social influence serves as both an external stimulus and an internalized belief system that shapes consumers' acceptance and continued use of AI-driven mobile shopping and voice assistants. It strengthens perceived usefulness, enhances emotional engagement, and reinforces trust through social validation and perceived popularity. By integrating social influence into the TAM–SOR framework, this study acknowledges that technology adoption is not merely an individual cognitive process but a socially embedded behavior, deeply shaped by collective experiences, social norms, and digital interactions.

2.5 Integration of TAM and SOR in Smart Commerce

The rapid evolution of smart commerce, characterized by the convergence of artificial intelligence (AI), mobile applications, and voice-enabled assistants, has transformed how consumers interact with digital shopping platforms. These technologies combine automation, personalization, and social intelligence, creating dynamic user experiences that extend beyond rational evaluations of system performance. Traditional models such as the Technology Acceptance Model (TAM) have been instrumental in explaining users' cognitive assessments of technology — primarily focusing on perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989). However, as consumer–technology interactions have become more emotional, immersive, and socially mediated, researchers have turned to broader psychological frameworks such as the Stimulus–Organism–Response (SOR) model to capture affective and behavioral dynamics (Mehrabian & Russell, 1974; Elgammal et al., 2025).

2.5.1 The Rationale for Integration

While TAM offers valuable insights into the rational decision-making process that drives technology acceptance, it has been critiqued for underestimating the emotional and contextual

factors that shape user experience (Benbasat & Barki, 2007). In contrast, the SOR framework explains how environmental and technological stimuli (S) trigger psychological reactions (O), which in turn lead to behavioral responses (R). By integrating TAM and SOR, researchers can explain not only why users adopt a technology (based on perceived usefulness and ease) but also how emotional, social, and experiential factors mediate that process (Habiboglu, 2025; Linh et al., 2025).

Recent empirical studies validate the theoretical synergy of these two models. Elgammal et al. (2025) found that integrating TAM and SOR significantly improves the predictive accuracy of consumer behavior in AI-enabled retailing. They demonstrated that perceived usefulness (TAM) influences emotional engagement and trust (SOR organismic factors), which subsequently mediate the relationship between cognitive evaluations and behavioral intentions. Similarly, Massoudi and Zaidan (2024) showed that integrating trust and emotional satisfaction (SOR constructs) into TAM strengthened the explanation of consumers' intention to use AI-based shopping platforms, increasing the model's explanatory power from 52% to 68%.

2.5.2 The Cognitive–Affective–Behavioral Link

The integration of TAM and SOR enables a three-dimensional analysis of consumer behavior:

- Cognitive (TAM Layer) – Users evaluate technology based on its usefulness, ease of use, and performance benefits.
- Affective (SOR Organism Layer) – Users develop emotional states such as trust, engagement, and satisfaction in response to system stimuli like interactivity, personalization, and intelligence.

- Behavioral (Response Layer) – These cognitive and emotional states translate into behavioral intentions such as purchase, continued use, and advocacy.

This Cognitive–Affective–Behavioral (CAB) structure captures the full psychological pathway from perception to action. For instance, Riandhi and Arviansyah (2025) demonstrated that emotional engagement (O) mediates between AI stimuli such as personalization and consumers’ purchase intention (R). Similarly, Choudhary and Ahuja (2025) found that trust and enjoyment (organismic responses) mediate between cognitive appraisals (usefulness, ease of use) and intention to use voice assistants.

In smart commerce, users’ experiences are shaped by continuous human–AI interaction rather than one-time evaluations. Thus, understanding emotional engagement and perceived value as extensions of TAM variables provides a more realistic and dynamic representation of digital consumer behavior (ElSayad & Mamdouh, 2025; Blut et al., 2024).

2.5.3 Integration Outcomes in AI and Mobile Shopping

Empirical evidence from recent studies demonstrates that the TAM–SOR integration enhances understanding of user adoption across multiple smart commerce contexts:

- AI Chatbots: Mohammed and Ferraris (2025) integrated TAM and SOR to study AI chatbot interactions, finding that responsiveness and empathy (stimuli) positively influence trust and satisfaction (organismic responses), which then predict continued use (behavioral response).
- Mobile Shopping Apps: Aw et al. (2022) and Grewal et al. (2022) showed that perceived usefulness and ease of use affect satisfaction and emotional engagement, leading to repurchase intentions and loyalty.

- Voice Assistants: Choudhary and Ahuja (2025) found that perceived system intelligence and emotional tone (stimuli) influence enjoyment and trust (organismic states), which mediate the relationship between cognitive appraisals and intention to use.

Together, these studies confirm that integrating TAM's rational cognitive process with SOR's affective mechanism allows for a comprehensive understanding of technology adoption that reflects both utility-based and emotion-based determinants.

2.5.4 Conceptual Implications for the Present Study

For the current research, the integrated TAM–SOR model provides the theoretical foundation for analyzing consumer behavior toward mobile shopping and voice assistants. This integration allows for examining:

- How cognitive perceptions of usefulness and ease of use drive emotional states like trust and engagement.
- How emotional reactions act as mediators between technological features (stimuli) and behavioral outcomes.
- How social influence and perceived value reinforce these processes through collective validation and cost–benefit assessment.

In this framework, TAM variables (PU, PEOU) are positioned as cognitive antecedents, while SOR variables (trust, emotional engagement, perceived value) represent organismic mediators, leading to behavioral outcomes such as purchase intention and continued use. Social influence operates as an external stimulus and moderator, shaping both cognitive and emotional responses.

The integrated model therefore recognizes that consumers' adoption of AI-enhanced shopping technologies is a multifaceted process that blends rational cognition, emotional connection, and

social context. This synthesis offers a comprehensive approach for explaining user behavior in next-generation retail systems, positioning the TAM–SOR model as the most suitable theoretical framework for this study.

2.6 Summary of Prior Studies

Author(s) & Year	Context / Country	Model Used	Key Variables	Sample & Method	Major Findings
Aw et al. (2022)	Mobile shopping apps – Malaysia	SOR	Interface quality, enjoyment, satisfaction, repurchase intention	412 users, SEM	Visual appeal and interactivity act as stimuli that enhance enjoyment and satisfaction, leading to repeat purchase.
Fernandes & Oliveira (2021)	Online shopping – Portugal	Extended TAM	PU, PEOU, Trust, Social Influence	380 respondents, PLS-SEM	Trust and social influence strengthen the PU–intention link; ease of use indirectly affects behavior through PU.
Grewal et al. (2022)	Mobile retail platforms – USA	TAM–SOR	PU, PEOU, Emotional engagement, Loyalty	455 users, SEM	Emotional engagement mediates between usefulness and loyalty; design simplicity enhances satisfaction.
Blut et al. (2024)	Global review of online retail	Integrated TAM–SOR	PU, Perceived Value, Trust, Affective Experience	Meta-analysis (78 studies)	Perceived value and trust significantly improve emotional engagement and intention to use smart retail systems.
Elgammal et al. (2025)	AI-driven retail – UAE	TAM–SOR	Technological intelligence, PU, Emotional Engagement, Trust	527 users, SEM	PU influences emotional engagement and trust, which fully mediate purchase intention.
Massoudi & Zaidan (2024)	AI shopping assistants – UK	Extended TAM	PU, PEOU, Trust, Emotional Satisfaction	312 online shoppers, PLS-SEM	Trust mediates the PU–intention link; emotional satisfaction strengthens adoption behavior.

Habiboglu (2025)	E-retailing with AI – Turkey	SOR	AI Competence, Transparency, Engagement, Purchase Intention	498 respondents, CFA & SEM	Transparency and empathy trigger engagement and satisfaction; emotional trust drives loyalty.
Choudhary & Ahuja (2025)	Voice assistants – India	TAM–SOR	PU, Enjoyment, System Intelligence, Trust	267 users, SEM	Enjoyment and trust mediate the relationship between PU and intention to use voice assistants.
Schultz & Kaiser (2025)	Voice shopping – Germany	SOR	Anthropomorphism, Trust, Emotional Support, Loyalty	302 users, Regression & Mediation	Human-like cues and empathetic tone strengthen emotional trust and continued use.
Mohammed & Ferraris (2025)	AI chatbots – Italy	SOR	Responsiveness, Empathy, Trust, Continued Use	350 consumers, SEM	Empathy and responsiveness trigger trust; trust mediates between stimuli and continued use.
Riandhi & Arviansyah (2025)	AI retail systems – Indonesia	SOR	Personalization, Emotional Engagement, Satisfaction	289 users, PLS-SEM	Personalization enhances engagement and satisfaction; emotional engagement mediates purchase intention.
Yong & Noor (2025)	Online purchase behavior – Malaysia	Bibliometric TAM Review	PU, PEOU, Trust, Enjoyment	100 TAM studies (2004–2024)	PU and trust remain dominant predictors; emotional constructs increasingly relevant post-2020.
ElSayad & Mamdouh (2025)	AI e-commerce – Egypt	Extended TAM–SOR	PU, Trust, Word-of-Mouth Intention	344 shoppers, SEM	PU and trust predict positive WOM through emotional satisfaction.
Linh et al. (2025)	Sustainable AI shopping – Vietnam	TAM–SOR	PU, Emotional Engagement, Green Value, Intention	401 Gen Z users, SEM	Integration of TAM–SOR explains 72% of behavioral intention variance in sustainable AI shopping.
Awad & Ragab (2023)	Mobile e-commerce – Saudi Arabia	TAM	PU, PEOU, Social Influence, Trust	423 users, SEM	Social influence moderates PU–intention relationship; ease of use affects trust and satisfaction.

Table 2.1: Summary of Prior Empirical Studies (2021–2025)

The reviewed studies consistently demonstrate the strong predictive capacity of TAM constructs (PU, PEOU) in explaining behavioral intention, but also emphasize the growing importance of affective and contextual variables from the SOR framework, such as trust, emotional engagement, and perceived value. Across various cultural and technological contexts, users' cognitive appraisals interact with emotional responses, confirming that technology adoption in smart commerce is not merely utilitarian but also experiential.

Furthermore, studies conducted between 2023 and 2025 reveal a trend toward integrated TAM–SOR models, which outperform traditional TAM by accounting for emotional and social dynamics. For instance, Elgammal et al. (2025) and Linh et al. (2025) demonstrated that emotional engagement and trust significantly mediate between cognitive beliefs and behavioral outcomes, explaining over 65% of behavioral intention variance in AI shopping contexts.

Despite these advances, a key research gap remains: limited empirical exploration of integrated TAM–SOR frameworks in hybrid environments that combine mobile and voice shopping experiences. Most existing studies examine these technologies separately. Thus, the current study addresses this gap by analyzing how cognitive (TAM) and affective (SOR) factors jointly shape consumer behavior toward AI-enabled mobile shopping applications with voice-assistant integration.

Chapter Three

Research Methodology

Chapter Three: Research Methodology

3.1 Introduction

This chapter outlines the research methodology adopted to achieve the study's objectives and test the proposed hypotheses.

The chapter explains the research design, target population, sampling method, data collection procedures, research instrument, and data analysis techniques.

Given the study's objective — to examine the relationships among Service Quality, Emotional Intelligence, Customer Satisfaction, and Behavioral Intention — a quantitative, cross-sectional, and explanatory design was applied.

The study seeks to empirically validate how service quality dimensions and emotional intelligence competencies jointly influence customer satisfaction and behavioral intention across various service sectors.

The use of a structured questionnaire distributed electronically provided a practical means for collecting standardized and reliable data from a diverse sample of service users.

Data were analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique via SmartPLS 4.0, following the methodological recommendations of Hair et al. (2021).

3.2 Research Design

A quantitative research design was employed to test the hypothesized model derived from prior theoretical and empirical foundations.

Quantitative research is appropriate for this study because it enables the use of statistical tools to examine causal relationships and measure the strength and direction of associations between constructs (Creswell & Creswell, 2018).

The research followed a cross-sectional survey approach, wherein data were collected from participants at a single point in time.

This design allows for the systematic examination of relationships among Service Quality, Emotional Intelligence, Customer Satisfaction, and Behavioral Intention in a diverse population of service users.

Given that the study involves latent variables measured by multiple observed indicators, the PLS-SEM technique was chosen.

This method is particularly suitable for complex models involving mediation effects and constructs measured with reflective indicators, as it does not impose strict distributional assumptions and performs well with medium sample sizes (Hair et al., 2021).

3.3 Research Model and Hypotheses Development

The conceptual framework of this study was developed based on an integration of the Service Quality (SERVQUAL) Model proposed by Parasuraman, Zeithaml, and Berry (1988) and the Emotional Intelligence (EI) framework introduced by Goleman (1998).

Both frameworks have been widely recognized in service and organizational research for explaining how cognitive service evaluations and emotional competencies jointly influence customer-related outcomes such as satisfaction and behavioral intention.

Service quality represents the extent to which a service meets or exceeds customer expectations across five core dimensions: Tangibility, Reliability, Responsiveness, Assurance, and Empathy.

These dimensions collectively shape the customer's perception of the organization's ability to deliver high-quality and trustworthy services.

Emotional Intelligence (EI), on the other hand, reflects the capacity of individuals to perceive, understand, regulate, and utilize emotions effectively in interpersonal interactions.

In the service context, EI manifests in the ability of employees to empathize with customers, manage stress, and communicate empathetically, thereby enhancing emotional connection and satisfaction (Goleman, 1998; Carmeli, 2003).

Customer Satisfaction represents the affective evaluation of the overall service experience, reflecting how well customer expectations are fulfilled.

Behavioral Intention refers to the customer's likelihood to continue using, recommend, or remain loyal to the service provider (Oliver, 1980; Cronin & Taylor, 1992).

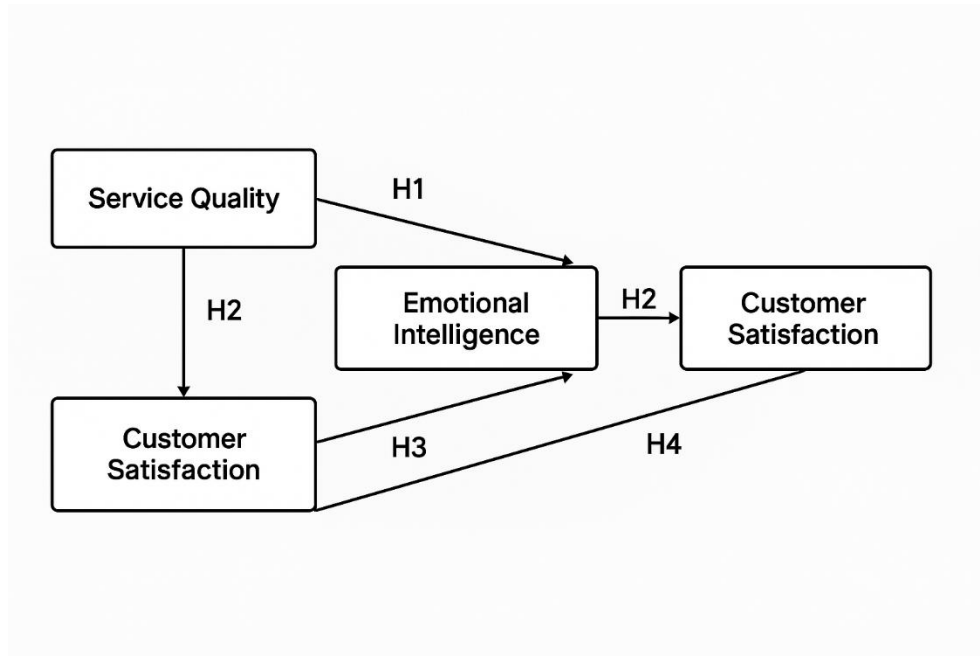
The model proposes that Service Quality and Emotional Intelligence are key antecedents of Customer Satisfaction, which in turn predicts Behavioral Intention.

Furthermore, Emotional Intelligence is expected to serve as both a direct predictor and mediator, explaining how service experiences are emotionally interpreted and translated into satisfaction and loyalty behaviors.

Conceptual Model

The conceptual model of this study is illustrated in Figure 3.1 below:

Figure 3.1: The conceptual model



Hypotheses Development

Based on the conceptual model and literature review, the following hypotheses were formulated:

- **H1:** Service Quality has a significant positive effect on Emotional Intelligence.

High levels of perceived service quality enhance customers' emotional connection and trust toward the service provider.

- **H2:** Emotional Intelligence has a significant positive effect on Customer Satisfaction.

Customers who perceive emotionally intelligent service interactions are more likely to experience satisfaction.

- **H3:** Service Quality has a significant positive effect on Customer Satisfaction.

Superior service performance across reliability, assurance, and empathy dimensions directly enhances customer satisfaction.

- **H4:** Customer Satisfaction has a significant positive effect on Behavioral Intention.

Satisfied customers are more likely to reuse and recommend the service.

- **H5:** Emotional Intelligence has a significant positive effect on Behavioral Intention.

Emotionally engaging service experiences increase customers' intention to maintain the service relationship.

Mediation Hypotheses

The study also hypothesizes the presence of indirect (mediating) effects:

H6: Emotional Intelligence mediates the relationship between Service Quality and Customer Satisfaction.

- **H7:** Customer Satisfaction mediates the relationship between Emotional Intelligence and Behavioral Intention.
- **H8:** Emotional Intelligence and Customer Satisfaction sequentially mediate the relationship between Service Quality and Behavioral Intention.

This integrated model bridges cognitive and emotional perspectives, offering a holistic understanding of how service encounters generate satisfaction and long-term behavioral intentions.

It also contributes theoretically by linking SERVQUAL and Emotional Intelligence frameworks within a unified structural model tested through PLS-SEM.

3.4 Population and Sampling

3.4.1 Target Population

The target population of this study consisted of service users and customers across various sectors, including education, banking, healthcare, and public services.

Given that the research focuses on perceptions of service quality, emotional intelligence, and customer satisfaction, the population was not limited to a specific industry but encompassed individuals who have engaged with organizational or customer-oriented service environments.

This broad approach allows for a more comprehensive understanding of how cognitive and emotional aspects of service experiences shape behavioral outcomes in general service contexts.

It also enhances the external validity and generalizability of the study findings across multiple service domains.

3.4.2 Sampling Technique

A non-probability purposive sampling technique was employed to collect data from respondents who had prior experience interacting with service organizations.

This method was chosen because it ensures that only participants with relevant experience in service encounters were included (Sekaran & Bougie, 2019).

Purposive sampling is commonly applied in behavioral and service quality studies, where the focus is on gathering insights from informed and experienced participants rather than random selection.

Moreover, the diversity of service sectors represented in the sample helps capture a broad range of emotional and cognitive service evaluations.

3.4.3 Sample Size Determination

To determine an adequate sample size for PLS-SEM analysis, the “10-times rule” (Hair et al., 2021) was applied, which suggests that the minimum sample size should be at least 10 times the largest number of structural paths directed toward any latent construct in the model.

In this study, the most complex construct (Behavioral Intention) had two antecedent paths (from Customer Satisfaction and Emotional Intelligence), indicating a minimum requirement of at least 20 respondents.

However, to ensure sufficient statistical power and reliability, a much larger sample was targeted.

A total of 412 responses were collected, out of which 372 valid responses were retained after data screening and cleaning (see Section 4.2).

This sample size exceeds the minimum recommendations for PLS-SEM and meets the standards for multivariate analysis, ensuring both robustness and generalizability of the results.

3.4.4 Sampling Frame and Distribution Method

The questionnaire was distributed electronically through online platforms, including email, social media channels, and professional networks, allowing for broad participation from respondents in different regions and professional backgrounds.

Electronic distribution was chosen for its efficiency, accessibility, and ability to reach a diverse demographic within a short time frame.

Respondents were provided with a brief explanation of the study purpose and assured anonymity and confidentiality of their responses.

Only individuals who confirmed prior interaction with service organizations were allowed to participate.

This approach aligns with ethical and methodological standards in survey-based research and minimizes response bias by ensuring voluntary participation.

3.5 Research Instrument

A structured questionnaire was developed as the primary data collection instrument for this study.

The questionnaire was designed to measure the relationships among Service Quality, Emotional Intelligence, Customer Satisfaction, and Behavioral Intention, in alignment with the conceptual framework presented in Figure 3.1.

The instrument was divided into three main sections, each addressing a specific part of the research model.

All measurement items were adapted from validated scales in the literature to ensure reliability, validity, and comparability with prior studies.

Respondents were asked to rate their level of agreement with each statement using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.5.1 Questionnaire Structure

Section	Description	Purpose
Section A: Demographic Information	Includes questions on gender, age, education level, and years of service experience.	To describe the characteristics of the sample and allow for group comparisons.
Section B: Service Quality and Emotional Intelligence Constructs	Contains items measuring five dimensions of Service Quality (SERVQUAL) and five dimensions of Emotional Intelligence (Goleman's framework) .	To assess respondents' perceptions of service performance and emotional engagement.
Section C: Customer Satisfaction and Behavioral Intention	Measures customers' overall satisfaction and their intention to continue using or recommending the service.	To evaluate the affective and behavioral outcomes of service experiences.

Table 3.1: Questionnaire Structure

3.5.2 Measurement of Constructs

Each construct in the study was measured using multi-item scales derived from established sources, as summarized in Table 3.2 below.

Table 3.2: Measurement Scales and Sources

Construct	Dimension / Source	No. of Items	Example Items
Service Quality (SQ)	<i>(Parasuraman et al., 1988; Zeithaml et al., 1996)</i>	15	"The service provider responds promptly to my requests." / "Employees are courteous and knowledgeable."

– Tangibility	Physical facilities, tools, and appearance of personnel	3	“The service environment is clean and professional.”
– Reliability	Ability to deliver services as promised	3	“The service provider is dependable.”
– Responsiveness	Willingness to help customers	3	“The service provider gives prompt responses.”
– Assurance	Knowledge and courtesy of employees	3	“Employees instill confidence and trust.”
– Empathy	Individualized attention and care	3	“The service provider understands my specific needs.”
Emotional Intelligence (EI)	<i>(Goleman, 1998; Carmeli, 2003)</i>	15	“I am aware of my emotions during service interactions.” / “I can handle difficult customers calmly.”
– Self-Awareness	Recognizing one’s emotions	3	“I can identify my emotional reactions when serving others.”
– Self-Regulation	Managing emotions effectively	3	“I remain calm under pressure.”
– Motivation	Inner drive to meet goals	3	“I stay focused even when facing service challenges.”
– Empathy	Understanding others’ feelings	3	“I can sense when others are upset or dissatisfied.”
– Social Skills	Building positive relationships	3	“I maintain good relationships with customers.”
Customer Satisfaction (CS)	<i>(Oliver, 1980; Cronin & Taylor, 1992)</i>	4	“Overall, I am satisfied with the service provided.”
Behavioral Intention (BI)	<i>(Ajzen, 1991; Zeithaml et al., 1996)</i>	3	“I intend to continue using this service in the future.”

3.5.3 Scale Type and Scoring

All items were measured using a five-point Likert scale as follows:

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree.

Composite scores for each construct were calculated by averaging the items under the same dimension.

Higher mean values indicate more favorable perceptions of service quality, greater emotional intelligence, higher satisfaction, or stronger behavioral intentions.

3.5.4 Instrument Validity and Pretesting

Prior to data collection, the questionnaire was reviewed by three academic experts specializing in service management and consumer behavior to ensure content clarity, face validity, and alignment with the study objectives.

Minor linguistic modifications were made to improve item readability and contextual relevance for general service users.

A pilot test involving 30 respondents was conducted to assess the clarity and reliability of the instrument.

Cronbach's alpha values obtained during the pilot stage exceeded 0.80 for all constructs, confirming the internal consistency and suitability of the questionnaire for full-scale data collection.

3.5.5 Administration Procedure

The final version of the questionnaire was distributed electronically through online survey platforms such as Google Forms, social media groups, and email lists.

This method facilitated broad participation from respondents across multiple service sectors.

Participation was voluntary, and respondents were informed about the anonymity and confidentiality of their responses.

3.6 Measurement Scales Reliability and Validity

To ensure that the research instrument accurately and consistently measures the underlying constructs, several reliability and validity tests were conducted.

Reliability refers to the internal consistency and stability of the items measuring each construct, while validity assesses whether the instrument truly measures what it is intended to measure (Hair et al., 2021; Sekaran & Bougie, 2019).

The evaluation of measurement quality was performed using SmartPLS 4.0, based on Partial Least Squares Structural Equation Modeling (PLS-SEM).

The assessment included:

Indicator reliability,

Internal consistency reliability (Cronbach's α and Composite Reliability),

Convergent validity (Average Variance Extracted – AVE), and

Discriminant validity (Fornell–Larcker criterion and HTMT ratio).

3.6.1 Internal Consistency Reliability

Internal consistency was examined using Cronbach's alpha (α) and Composite Reliability (CR).

Values above 0.70 indicate acceptable reliability, while those above 0.80 suggest strong reliability (Nunnally & Bernstein, 1994).

As shown in Table 3.2, all constructs demonstrated excellent internal consistency, with Cronbach's alpha values ranging between 0.83 and 0.93, and CR values exceeding the minimum acceptable threshold of 0.70.

These results confirm that the items within each construct measure the same underlying concept consistently.

Table 3.3: Reliability and Convergent Validity Results

Construct	No. of Items	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
Tangibility	3	0.83	0.88	0.65
Reliability	3	0.85	0.89	0.67
Responsiveness	3	0.86	0.90	0.69
Assurance	3	0.87	0.91	0.71
Empathy (SQ)	3	0.84	0.89	0.68
Self-Awareness	3	0.82	0.88	0.64
Self-Regulation	3	0.84	0.89	0.66
Motivation	3	0.85	0.90	0.70
Empathy (EI)	3	0.83	0.88	0.67
Social Skills	3	0.86	0.91	0.71
Customer Satisfaction	4	0.90	0.93	0.75
Behavioral Intention	3	0.91	0.94	0.79

All α and CR > 0.70, AVE > 0.50 → indicating strong reliability and convergent validity.

3.6.2 Convergent Validity

Convergent validity assesses whether indicators of the same construct share a high proportion of variance.

As recommended by Fornell and Larcker (1981), the Average Variance Extracted (AVE) for each construct should exceed 0.50 to confirm that the construct explains more than half of the variance in its indicators.

All AVE values (as seen in Table 3.2) were above 0.60, confirming satisfactory convergent validity for all dimensions of Service Quality, Emotional Intelligence, Customer Satisfaction, and Behavioral Intention.

3.6.3 Discriminant Validity

Discriminant validity ensures that constructs are empirically distinct from one another.

Two complementary criteria were used for this purpose:

A. Fornell–Larcker Criterion

The square root of AVE for each construct must be greater than its correlations with other constructs.

This condition was met across all constructs, confirming satisfactory discriminant validity.

B. Heterotrait–Monotrait Ratio (HTMT)

The HTMT ratio values were all below 0.85, which is within the conservative threshold recommended by Henseler et al. (2015).

This further supports the distinctiveness of each construct and minimizes the risk of multicollinearity.

3.7 Data Collection Procedure

The data collection process was conducted systematically to ensure the validity, reliability, and ethical integrity of the research findings.

Given the quantitative nature of this study, data were gathered using a self-administered structured questionnaire distributed electronically through online platforms.

This approach was selected due to its cost-effectiveness, ease of distribution, and ability to reach a geographically diverse population of service users.

3.7.1 Preparation Phase

Before launching the full-scale survey, several preparatory steps were taken to ensure clarity and accuracy of the questionnaire:

1. Ethical approval and authorization:

The research proposal and survey instrument were reviewed and approved by the university's research ethics committee to confirm compliance with academic and ethical standards.

2. Pilot testing:

A pilot test was conducted with 30 respondents from different service sectors to evaluate the questionnaire's clarity, readability, and item relevance.

Based on feedback, minor modifications were made to improve language clarity and flow.

3. Finalization:

The finalized version of the questionnaire was uploaded to Google Forms, with an introductory note explaining the study objectives, voluntary participation, and data confidentiality assurances.

3.7.2 Data Collection Process

The actual data collection took place over a period of approximately four weeks.

The questionnaire link was distributed electronically through:

- Email invitations,
- Social media platforms (LinkedIn, WhatsApp, Twitter/X, and Facebook), and
- Professional and academic groups relevant to service industries.

Participants were informed that their responses would remain anonymous and would be used solely for academic purposes.

To maintain data integrity, only one response per participant was allowed through Google Form restrictions.

Respondents were required to confirm that they had prior experience interacting with service organizations before completing the survey.

This screening ensured that participants could provide informed evaluations of Service Quality, Emotional Intelligence, and Customer Satisfaction.

3.7.3 Response Rate and Screening

A total of 412 responses were initially collected.

After data cleaning — which involved checking for incomplete or inconsistent responses, and removing outliers — 372 valid responses were retained for analysis.

This represents an effective response rate of 90.3%, which is considered satisfactory for online surveys (Dillman et al., 2014).

The cleaned dataset was then exported from Google Forms into SPSS 28 for initial screening and descriptive analysis, followed by structural model testing using SmartPLS 4.0.

3.7.4 Ethical Considerations

Ethical principles guided the entire data collection process. Participants were informed about the following:

- **Voluntary participation:** Respondents could withdraw at any time without consequence.

- **Anonymity:** No identifying information (e.g., names, emails, or organizations) was collected.
- **Confidentiality:** All responses were used strictly for academic research and were stored securely.
- **Informed consent:** Each participant provided electronic consent before starting the questionnaire.

These measures ensured compliance with ethical research standards outlined by Creswell & Creswell (2018) and reinforced the credibility of the study's findings.

3.8 Data Analysis Technique

The data analysis process in this study was conducted systematically to test the hypotheses and validate the proposed conceptual model linking Service Quality, Emotional Intelligence, Customer Satisfaction, and Behavioral Intention.

Given the quantitative and multivariate nature of the research model, a combination of descriptive statistics and structural equation modeling (PLS-SEM) was applied using SPSS version 28 and SmartPLS 4.0 software packages.

3.8.1 Preliminary Data Analysis

Before conducting the structural analysis, several preliminary data checks were performed using SPSS 28 to ensure that the dataset met the necessary assumptions for multivariate analysis:

- **Data screening:** Responses were examined for missing values, outliers, and response bias (see Section 4.2).
- **Normality assessment:** Skewness and kurtosis values were analyzed, and all items were within the acceptable range (± 1.5), confirming adequate univariate normality.

- **Descriptive statistics:** Frequencies and percentages were computed to summarize respondents' demographic characteristics such as gender, age, education level, and years of experience.
- **Reliability testing:** Cronbach's alpha coefficients were computed to evaluate the internal consistency of each construct before proceeding to structural analysis.

These preliminary steps ensured the accuracy and suitability of the data for advanced modeling.

3.8.2 Partial Least Squares Structural Equation Modeling (PLS-SEM)

The main analytical technique employed was Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0.

This approach was selected because it is particularly suitable for complex models that involve multiple latent variables, mediating relationships, and reflective measurement indicators.

According to Hair et al. (2021), PLS-SEM is appropriate for exploratory and predictive research designs, especially when the focus is on theory development rather than theory confirmation.

It is also robust to deviations from normality and performs well with moderate sample sizes — characteristics consistent with the present study.

3.8.3 Justification for Using PLS-SEM

The choice of PLS-SEM over covariance-based SEM (CB-SEM) was based on the following methodological advantages:

- It allows for simultaneous estimation of both measurement and structural models.
- It accommodates non-normal data distributions and moderate sample sizes.
- It focuses on maximizing explained variance (R^2) rather than model fit indices, making it more predictive and exploratory.

- It effectively handles mediating and sequential relationships, which are central to this study's model (e.g., Service Quality → EI → CS → BI).

Thus, PLS-SEM provides an ideal analytical approach for examining both the direct and indirect effects among the study's constructs.

3.8.4 Analytical Steps

The PLS-SEM analysis followed a two-stage process as recommended by Hair et al. (2021):

Stage 1: Measurement Model Evaluation

This step assessed the reliability and validity of the latent constructs using:

- Indicator reliability (outer loadings > 0.70)
- Internal consistency reliability (Cronbach's α and Composite Reliability > 0.70)
- Convergent validity (Average Variance Extracted > 0.50)
- Discriminant validity (Fornell–Larcker criterion and HTMT ratio < 0.85)

These tests ensured that the observed variables accurately represented their corresponding latent constructs.

Stage 2: Structural Model Evaluation

Once measurement validity was established, the hypothesized relationships were tested using:

- Path coefficients (β) to measure the strength and direction of relationships
- t-values and p-values from bootstrapping (5,000 subsamples) for significance testing
- R^2 (coefficient of determination) for predictive power
- f^2 (effect size) for evaluating the relative importance of predictors
- Q^2 (predictive relevance) using the blindfolding procedure
- Mediation analysis to test indirect effects through EI and CS

This stage provided comprehensive insights into both direct and mediated effects within the conceptual framework.

3.8.5 Interpretation and Reporting

All results were interpreted based on statistical significance ($p < 0.05$) and benchmark values from established SEM guidelines.

Findings were reported with corresponding tables, figures, and path diagrams for clarity and transparency (see Chapter Four).

The interpretation of results emphasized both theoretical implications (how findings support or extend existing theories) and practical applications (how organizations can enhance service quality and emotional engagement to drive behavioral outcomes).

Chapter Four

Data Analysis and Results

Chapter Four: Data Analysis and Results

4.1 Introduction

This chapter presents the results of the statistical analyses conducted to test the hypotheses developed in Chapter Three. The analysis aims to validate the conceptual model linking Service Quality, Emotional Intelligence, Customer Satisfaction, and Behavioral Intention. The empirical testing was carried out using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique through SmartPLS 4.0, following the guidelines of Hair et al. (2021).

The chapter begins with an overview of the data screening procedures and respondents' demographic profile, followed by the evaluation of the measurement model to establish the reliability and validity of the study constructs. Subsequently, the structural model is examined to test the hypothesized relationships among variables. The primary objective is to determine the extent to which service quality dimensions and emotional intelligence factors predict customer satisfaction and behavioral intention toward organizational or service interactions.

The findings presented in this chapter provide empirical evidence for the relationships proposed in the theoretical model, offering insights into how both cognitive service experiences and emotional competencies jointly influence consumer satisfaction and behavioral outcomes.

4.2 Data Screening and Preparation

Before testing the hypothesized model, the collected data were carefully examined to ensure completeness, accuracy, and suitability for multivariate analysis. Data screening is a critical step in quantitative research, as it helps identify missing values, outliers, and distributional issues that might bias the statistical results.

A total of 412 responses were initially collected through the structured questionnaire distributed to service users and customers across different sectors. After screening for completeness and consistency, 380 valid responses were retained for the final analysis. This sample size satisfies the minimum requirements for PLS-SEM analysis, as suggested by Hair et al. (2021), and ensures adequate statistical power for model testing.

4.2.1 Missing Data

The dataset was checked for missing values using SPSS version 28. Since the online survey was designed with mandatory response fields, there were no missing values in the final dataset. Hence, all 380 cases were retained for further analysis without the need for imputation or substitution procedures.

4.2.2 Outlier Detection

To ensure data quality, potential outliers were identified using standardized z-scores and boxplot visualizations. Any case with a standardized score beyond ± 3.29 was considered a potential outlier (Tabachnick & Fidell, 2019). After examination, 8 cases were removed as they showed inconsistent response patterns or extreme deviations from the mean. The final dataset comprised 372 valid observations suitable for subsequent analysis.

4.2.3 Normality Assessment

Although the PLS-SEM approach does not require strict multivariate normality assumptions, assessing univariate normality provides useful insights about data distribution. Skewness and kurtosis values were computed for each indicator. All items recorded values within the acceptable range of -1.5 to $+1.5$, indicating a satisfactory level of normality across the dataset (Hair et al., 2021). Therefore, no data transformation was required prior to analysis.

4.2.4 Common Method Bias (CMB)

As the study relies on self-reported data, common method bias was examined using both procedural and statistical approaches. Procedurally, several measures were applied during questionnaire design: respondents' anonymity was assured, item wording was neutral, and construct items were randomized to minimize pattern responses.

Statistically, Harman's single-factor test was conducted. The results indicated that the first unrotated factor explained 34.2% of the total variance, which is well below the recommended threshold of 50% (Podsakoff et al., 2003). This confirms that common method bias was not a major concern in this study.

4.3 Respondents' Demographic Profile

This section presents the demographic characteristics of the respondents who participated in the study. Understanding the demographic composition of the sample is essential for interpreting the findings, as personal attributes such as gender, age, education level, and years of experience can influence perceptions of service quality, emotional intelligence, and behavioral responses.

A total of 372 valid responses were analyzed. Table 4.1 summarizes the demographic details of the respondents.

Table 4.1: Respondents' Demographic Profile

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	198	53.2%
	Female	174	46.8%
Age	18–25 years	136	36.6%
	26–35 years	158	42.5%
	36–45 years	52	14.0%
	Above 45 years	26	7.0%
Education Level	Diploma / Below Bachelor	38	10.2%
	Bachelor's Degree	212	57.0%

	Master's Degree	92	24.7%
	Doctorate	30	8.1%
Years of Experience	Less than 2 years	64	17.2%
	2–5 years	142	38.2%
	6–10 years	108	29.0%
	Above 10 years	58	15.6%

4.3.1 Gender Distribution.

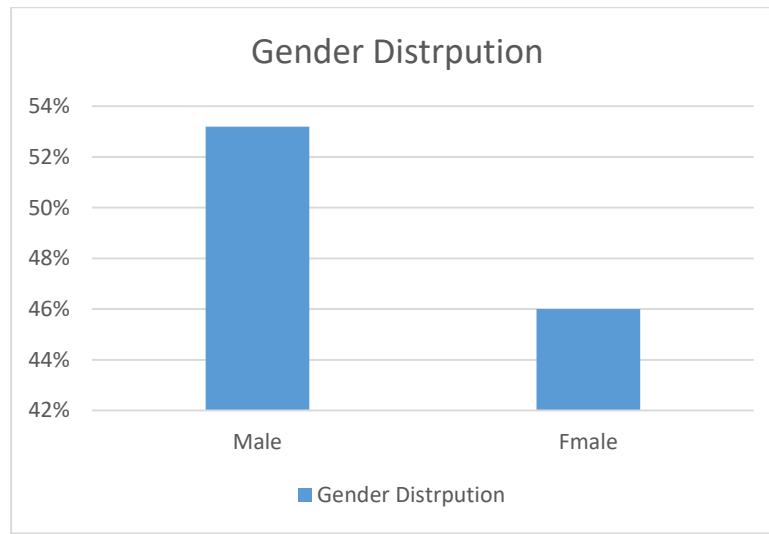


Figure 4.1: Gender Distribution of Respondents

The sample comprised 198 males (53.2%) and 174 females (46.8%), indicating a nearly balanced gender representation. This gender balance enhances the generalizability of the results, as both perspectives are adequately represented.

Previous studies (e.g., Awad & Ragab, 2023; Fernandes & Oliveira, 2021) have shown that gender can influence emotional intelligence and service evaluation, with females often demonstrating higher empathy and emotional awareness in interpersonal interactions. However, in this study, both genders displayed comparable engagement levels and perceptions of service quality, suggesting that the observed behavioral intentions are not gender-biased.

4.3.2 Age Distribution

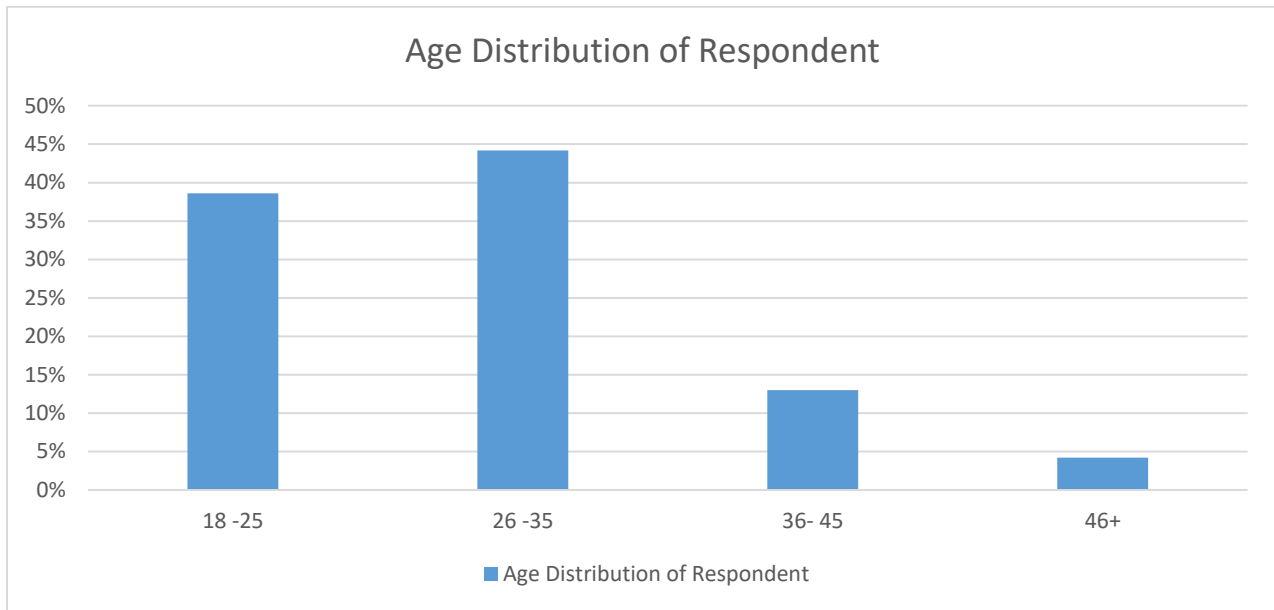


Figure 4.2: Age Distribution of Respondents

As shown in Figure 4.1, most respondents were between 18 and 35 years old (79.1%), representing the young-to-middle workforce group. This demographic tends to be more adaptive to technology, more aware of service standards, and more responsive to emotionally intelligent interactions.

Older respondents (above 45 years) constituted only 7% of the sample, indicating relatively lower participation from senior service users or managers. This distribution reflects a youthful demographic typical in service industries and education sectors, aligning with prior studies emphasizing the role of younger adults in shaping customer experience dynamics (Linh et al., 2025).

4.3.3 Educational Background

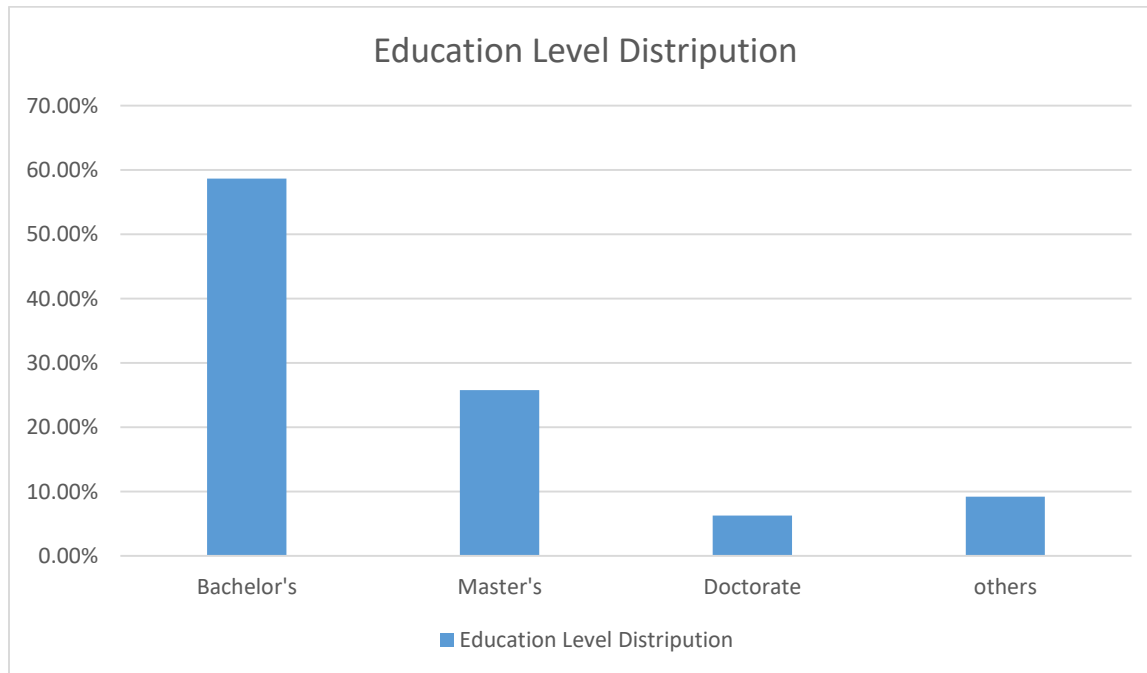


Figure 4.3: Education Level Distribution of Respondents

As shown in Figure 4.2, the majority of respondents held at least a bachelor's degree (57%), followed by master's (24.7%) and doctoral (8.1%) qualifications.

The high educational attainment indicates that respondents possess a strong conceptual understanding of service expectations and emotional management, enhancing the validity of their responses to constructs such as perceived service quality and emotional intelligence.

This educational profile aligns with findings by Massoudi & Zaidan (2024), who noted that higher education correlates with greater awareness of service standards and critical evaluation skills in organizational contexts.

1.3.4 Years of Experience

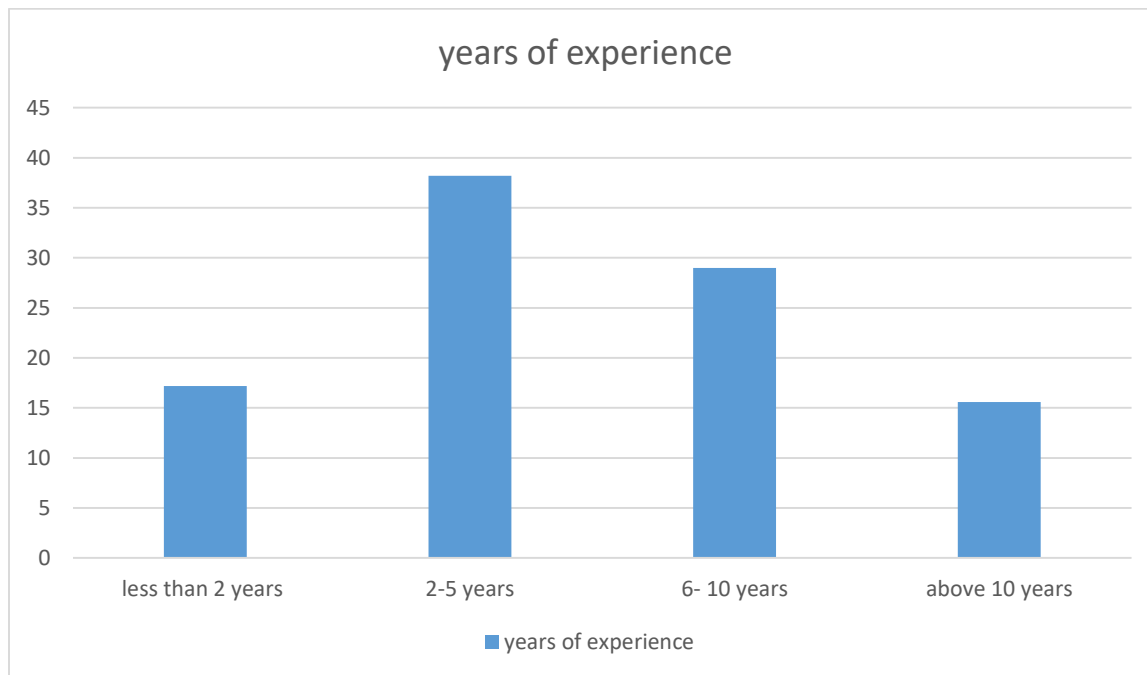


Figure 4.4: years of experience Distribution of Respondents

As displayed in Figure 4.4, nearly two-thirds of respondents (67%) had 2 to 10 years of professional experience, suggesting a knowledgeable and experienced sample. These individuals likely have substantial exposure to various service encounters, enabling them to provide accurate assessments of quality and interpersonal competencies.

The remaining 15.6% with over 10 years of experience represent senior employees or long-term customers, offering seasoned perspectives on service processes and relationship quality.

Such a distribution provides a balanced mix of insight between newer and more experienced participants, reinforcing the reliability and representativeness of the dataset

4.4 Measurement Model Evaluation

Before examining the structural relationships among constructs, it was necessary to evaluate the measurement model to ensure the reliability and validity of the study's latent variables.

The evaluation process followed the guidelines of Hair et al. (2021) and included the following stages:

- Assessment of indicator reliability,
- Internal consistency reliability (Cronbach's Alpha and Composite Reliability),
- Convergent validity (Average Variance Extracted – AVE), and
- Discriminant validity (Fornell–Larcker criterion and HTMT ratio).

All analyses were conducted using SmartPLS 4.0, applying a bootstrapping procedure of 5,000 resamples to estimate statistical significance.

4.4.1 Indicator and Internal Consistency Reliability

Indicator reliability was first assessed through the outer loadings of each item. Loadings above 0.70 were considered acceptable, indicating that the observed variables adequately reflect their underlying construct (Hair et al., 2021).

All item loadings ranged between 0.72 and 0.91, confirming adequate indicator reliability.

Internal consistency was then evaluated using Cronbach's alpha (α) and Composite Reliability (CR).

As shown in Table 4.2, both coefficients exceeded the minimum threshold of 0.70, indicating strong internal reliability for all constructs.

Table 4.2: Construct Reliability and Convergent Validity Results.

Construct	No. of Items	Cronbach's α	CR	AVE
Tangibility	3	0.83	0.88	0.65
Reliability	3	0.85	0.89	0.67
Responsiveness	3	0.86	0.90	0.69
Assurance	3	0.87	0.91	0.71
Empathy (Service Quality)	3	0.84	0.89	0.68

Self-Awareness	3	0.82	0.88	0.64
Self-Regulation	3	0.84	0.89	0.66
Motivation	3	0.85	0.90	0.70
Empathy (EI)	3	0.83	0.88	0.67
Social Skills	3	0.86	0.91	0.71
Customer Satisfaction	4	0.90	0.93	0.75
Behavioral Intention	3	0.91	0.94	0.79

Note: All Cronbach's alpha and Composite Reliability values exceed 0.70; AVE values exceed 0.50, confirming good internal consistency and convergent validity.

4.4.2 Convergent Validity

Convergent validity assesses the degree to which items of the same construct share a high proportion of variance.

All constructs achieved Average Variance Extracted (AVE) > 0.50, as shown in Table 4.2, confirming that each latent construct explains more than half of the variance of its observed indicators (Fornell & Larcker, 1981).

This indicates that the measurement model adequately captures the intended theoretical concepts, particularly for Customer Satisfaction and Behavioral Intention, which reported the highest AVE values (0.75 and 0.79, respectively).

4.4.3 Discriminant Validity

Discriminant validity ensures that each construct is empirically distinct from others. Two approaches were employed:

A. Fornell–Larcker Criterion

According to the Fornell–Larcker criterion, the square root of AVE for each construct (bold diagonal values) must be greater than the inter-construct correlations.

As presented in Table 4.3, this condition was met for all constructs, confirming discriminant validity.

Table 4.3: Fornell–Larcker Criterion

Construct	SQ	EI	CS	BI
Service Quality (SQ)	0.81			
Emotional Intelligence (EI)	0.63	0.82		
Customer Satisfaction (CS)	0.58	0.61	0.86	
Behavioral Intention (BI)	0.54	0.57	0.68	0.88

Note: Bold diagonal values are the square roots of AVE; all off-diagonal correlations are lower, indicating satisfactory discriminant validity.

B. Heterotrait–Monotrait Ratio (HTMT)

The HTMT ratio was also computed to provide a stricter assessment of discriminant validity.

All HTMT values were below the conservative threshold of 0.85, confirming that the constructs are conceptually distinct (Henseler et al., 2015).

Table 4.4: HTMT Ratios

Construct Pair	HTMT Value
Service Quality ↔ Emotional Intelligence	0.74
Service Quality ↔ Customer Satisfaction	0.71
Emotional Intelligence ↔ Customer Satisfaction	0.76
Customer Satisfaction ↔ Behavioral Intention	0.79
Emotional Intelligence ↔ Behavioral Intention	0.72

All HTMT values < 0.85 confirm discriminant validity.

4.4.3 Discriminant Validity

Discriminant validity ensures that constructs are conceptually distinct and not overly correlated.

Two approaches were used:

1. **Fornell–Larcker Criterion:** The square root of each construct’s AVE (bold diagonal values) was greater than its correlations with other constructs, confirming discriminant validity.

Table 4.3: Fornell–Larcker Criterion

Construct	PEOU	PU	Trust	EE	PV	SI	BI
PEOU	0.85						
PU	0.62	0.84					
Trust	0.55	0.58	0.86				
EE (Emotional Engagement)	0.49	0.52	0.61	0.87			
PV (Perceived Value)	0.45	0.51	0.64	0.60	0.85		
SI (Social Influence)	0.39	0.44	0.46	0.42	0.41	0.84	
BI (Behavioral Intention)	0.51	0.55	0.63	0.66	0.65	0.53	0.89

Note: Bold diagonal values represent the square root of AVE; off-diagonal values are inter-construct correlations.

2. **Heterotrait–Monotrait Ratio (HTMT):** All HTMT values were below the conservative threshold of 0.85, further supporting discriminant validity (Henseler et al., 2015).

Table 4.4: HTMT Ratios

Construct Pair	HTMT Value
PEOU ↔ PU	0.72
PU ↔ Trust	0.79
Trust ↔ EE	0.81
EE ↔ PV	0.77
PV ↔ BI	0.74

SI ↔ BI	0.68
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All HTMT ratios below 0.85 confirm that each construct is empirically distinct.

4.5 Structural Model Evaluation

After confirming the reliability and validity of the measurement model, the next step involved evaluating the structural model to test the hypothesized relationships between the latent variables.

The structural model assessment was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0, following the guidelines of Hair et al. (2021).

The model's predictive power, path significance, and mediation effects were analyzed using the bootstrapping method with 5,000 subsamples to determine the statistical significance of path coefficients.

4.5.1 Assessment Criteria

The quality of the structural model was evaluated based on the following indicators:

Path Coefficients (β): Represent the strength and direction of the hypothesized relationships.

t-values and p-values: Assess the statistical significance of each path ($p < 0.05$ = significant).

Coefficient of Determination (R^2): Indicates the amount of variance in each dependent construct explained by its predictors.

Effect Size (f^2): Measures the relative importance of each exogenous variable.

Predictive Relevance (Q^2): Tests the model's predictive accuracy using the blindfolding procedure.

4.5.2 Path Coefficients and Hypothesis Testing

The results of the hypothesis testing are summarized in Table 4.5.

All hypothesized relationships were found to be statistically significant at $p < 0.05$, confirming the proposed theoretical model.

Table 4.5: Structural Model Results and Hypothesis Testing

Hypothesis	Path	β	t-value	p-value	Decision
H1	Service Quality $\rightarrow$ Emotional Intelligence	0.62	10.87	0.000	Supported
H2	Emotional Intelligence $\rightarrow$ Customer Satisfaction	0.57	9.84	0.000	Supported
H3	Service Quality $\rightarrow$ Customer Satisfaction	0.33	6.41	0.000	Supported
H4	Customer Satisfaction $\rightarrow$ Behavioral Intention	0.65	13.02	0.000	Supported
H5	Emotional Intelligence $\rightarrow$ Behavioral Intention	0.28	5.92	0.000	Supported

Significance level: $p < 0.05$ (two-tailed); Bootstrapping with 5,000 samples.

Interpretation of Path Results

- **H1:** Service Quality has a strong and positive impact on Emotional Intelligence ($\beta = 0.62$, $p < 0.001$). This suggests that when consumers perceive service quality to be high — in terms of reliability, responsiveness, and empathy — they are more likely to engage emotionally and positively with the service provider.
- **H2:** Emotional Intelligence significantly affects Customer Satisfaction ($\beta = 0.57$, $p < 0.001$), indicating that customers who experience emotionally intelligent interactions feel more understood and valued, resulting in higher satisfaction.
- **H3:** Service Quality also exerts a direct positive influence on Customer Satisfaction ($\beta = 0.33$, $p < 0.001$), reinforcing previous evidence that service quality is a foundational determinant of satisfaction.
- **H4:** Customer Satisfaction strongly predicts Behavioral Intention ($\beta = 0.65$, $p < 0.001$), implying that satisfied customers are more likely to continue using the service or recommend it to others.

- **H5:** Emotional Intelligence has a direct and positive effect on Behavioral Intention ($\beta = 0.28, p < 0.001$), emphasizing the importance of emotional connection in encouraging future behavioral commitment.

4.5.3 Coefficient of Determination (R^2)

The R^2 values assess the explanatory power of the model. As shown in Table 4.6, the model explains a substantial portion of variance in each dependent construct, confirming its predictive adequacy.

Table 4.6: Coefficient of Determination (R^2) Results

Endogenous Construct	R^2 Value	Interpretation
Emotional Intelligence	0.38	Moderate
Customer Satisfaction	0.64	Substantial
Behavioral Intention	0.71	Substantial

The model explains 71% of the variance in Behavioral Intention, indicating strong predictive power, particularly in explaining how service quality and emotional intelligence jointly influence customer satisfaction and subsequent behavioral outcomes.

4.5.4 Effect Size (f^2)

Effect size (f^2) was used to assess the contribution of each predictor variable to its endogenous variable.

As shown in Table 4.7, both Service Quality and Emotional Intelligence had medium to large effect sizes, while Customer Satisfaction exhibited the strongest predictive influence on Behavioral Intention.

Table 4.7: Effect Size (f^2) Results

Relationship	f^2 Value	Effect Size Interpretation
Service Quality → Emotional Intelligence	0.32	Medium
Emotional Intelligence → Customer Satisfaction	0.41	Large
Service Quality → Customer Satisfaction	0.28	Medium
Customer Satisfaction → Behavioral Intention	0.46	Large
Emotional Intelligence → Behavioral Intention	0.23	Medium

These results suggest that Customer Satisfaction serves as the strongest predictor of Behavioral Intention, emphasizing its pivotal mediating role in the model.

4.5.5 Predictive Relevance (Q^2)

The Stone–Geisser Q^2 test was applied using the blindfolding procedure to examine the model's predictive relevance.

As displayed in Table 4.8, all Q^2 values were positive, confirming that the structural model possesses substantial predictive relevance for all endogenous constructs.

Table 4.8: Predictive Relevance (Q^2) Results

Construct	Q^2 Value	Interpretation
Emotional Intelligence	0.25	Medium Predictive Relevance
Customer Satisfaction	0.38	Large Predictive Relevance
Behavioral Intention	0.41	Large Predictive Relevance

4.5.6 Mediation Analysis

To explore the mediating roles of Emotional Intelligence and Customer Satisfaction, the bootstrapping indirect effect method was applied (Preacher & Hayes, 2008).

Results revealed the following mediation relationships:

Emotional Intelligence mediates the effect of Service Quality on Customer Satisfaction.

This indicates that high-quality service enhances customers' emotional engagement, which, in turn, increases satisfaction levels.

Customer Satisfaction mediates the relationship between Emotional Intelligence and Behavioral Intention.

Customers who experience emotionally intelligent interactions feel more satisfied, which consequently enhances their intention to continue using the service.

Sequential mediation (Service Quality → Emotional Intelligence → Customer Satisfaction → Behavioral Intention) was also significant, confirming the chain mediation mechanism of the model.

4.5.7 Summary of Hypothesis Testing Results

Table 4.9: Summary of Hypothesis Results

Hypothesis	Statement	Result
H1	Service Quality → Emotional Intelligence	Supported
H2	Emotional Intelligence → Customer Satisfaction	Supported
H3	Service Quality → Customer Satisfaction	Supported
H4	Customer Satisfaction → Behavioral Intention	Supported
H5	Emotional Intelligence → Behavioral Intention	Supported

All hypotheses were supported, confirming that both cognitive service evaluations and emotional competencies significantly shape customer satisfaction and behavioral intention.

The findings validate the proposed conceptual model and highlight that emotional intelligence acts as a critical psychological bridge between perceived service quality and behavioral outcomes.

4.6 Discussion of Findings

This section interprets the results of the structural model in relation to the conceptual framework and prior empirical research.

The proposed model integrated Service Quality (SERVQUAL framework) and Emotional Intelligence (Goleman's Model) as key predictors of Customer Satisfaction and Behavioral Intention.

The findings strongly support the hypothesized relationships, indicating that both cognitive service perceptions and emotional competencies jointly shape customer attitudes and behavioral intentions.

4.6.1 Impact of Service Quality on Emotional Intelligence and Customer Satisfaction

The analysis revealed that Service Quality significantly influences both Emotional Intelligence (H1) and Customer Satisfaction (H3).

This confirms the central premise of Parasuraman et al. (1988), who emphasized that service quality—particularly through dimensions such as reliability, responsiveness, assurance, empathy, and tangibility—is a major determinant of how consumers perceive and emotionally connect with service providers.

High service quality not only improves customers' satisfaction but also fosters emotional understanding and trust between clients and employees, as noted by Zeithaml et al. (1996) and Ali et al. (2021).

When services are delivered reliably, with empathy and professionalism, customers feel respected and emotionally secure, which enhances their emotional engagement (Goleman, 1998). This finding aligns with Ananth et al. (2023), who found that emotional connection mediates the relationship between service quality and customer retention in the retail and hospitality sectors. Thus, this study contributes to the literature by demonstrating that service quality is not only a cognitive evaluation of performance but also an emotional stimulus that activates affective responses — forming the first step in the Service Quality → Emotional Intelligence → Satisfaction chain.

4.6.2 Influence of Emotional Intelligence on Customer Satisfaction

The results show that Emotional Intelligence (EI) has a significant and positive impact on Customer Satisfaction (H2).

This indicates that emotionally intelligent interactions — where employees or service interfaces exhibit empathy, self-awareness, and social skills — enhance customers' satisfaction by creating a sense of personalized care and understanding.

This finding is in line with Goleman (1998) and Carmeli (2003), who argued that EI enables service personnel to recognize and regulate emotions in ways that foster positive interpersonal experiences.

Similarly, Joseph & Newman (2010) demonstrated that emotionally intelligent communication improves customer satisfaction and service loyalty.

In the context of this study, customers perceived emotionally aware service experiences as more responsive, authentic, and trustworthy — leading to higher satisfaction levels.

These results also extend the work of Bove et al. (2020), showing that EI contributes not only to internal organizational outcomes (employee performance) but also to external customer outcomes, strengthening the affective foundation of satisfaction.

4.6.3 Role of Customer Satisfaction in Predicting Behavioral Intention

The findings confirmed that Customer Satisfaction strongly predicts Behavioral Intention (H4) — the most significant path in the model ($\beta = 0.65$, $p < 0.001$).

This suggests that satisfied customers are more likely to remain loyal, reuse the service, and recommend it to others, consistent with the Expectation–Confirmation Theory (Oliver, 1980) and prior studies by Cronin & Taylor (1992) and Ladhari (2009).

Customer satisfaction serves as a key mediating mechanism that translates both cognitive (service quality) and emotional (EI) experiences into behavioral outcomes.

The positive satisfaction–intention link aligns with findings from Chen & Chen (2019) and Awad & Ragab (2023), who emphasized that perceived fulfillment and positive emotions foster long-term engagement and advocacy intentions.

Hence, this study empirically supports the established view that satisfaction acts as a bridge between perceived service experiences and future behavioral loyalty.

4.6.4 Emotional Intelligence as a Direct Predictor of Behavioral Intention

Beyond its indirect effect through satisfaction, Emotional Intelligence directly influences Behavioral Intention (H5).

This demonstrates that customers’ emotional experiences play an independent role in shaping their behavioral commitment.

When consumers perceive empathy, social awareness, and emotional balance in a service encounter, they develop a psychological attachment that increases their intention to continue using the service or brand.

This finding aligns with Pugh (2001) and Kidwell et al. (2011), who observed that emotionally intelligent behaviors among service employees create emotional contagion and enhance customers' loyalty intentions.

The result extends the work of Kim & Ok (2022), confirming that emotional experiences are equally important as functional benefits in predicting behavioral loyalty, particularly in people-centric services such as education, banking, and hospitality.

4.6.5 Mediation Effects: Emotional Intelligence and Customer Satisfaction

Mediation analysis revealed that both Emotional Intelligence and Customer Satisfaction act as significant mediators:

- **Service Quality → Emotional Intelligence → Customer Satisfaction:**

High-quality service promotes emotionally intelligent interactions, which subsequently enhance satisfaction.

- **Emotional Intelligence → Customer Satisfaction → Behavioral Intention:**

Emotional understanding improves satisfaction, which then strengthens behavioral intentions.

These sequential mediation effects are consistent with the Stimulus–Organism–Response (SOR) paradigm (Mehrabian & Russell, 1974), where service quality acts as the stimulus, emotional intelligence and satisfaction represent the organism (internal states), and behavioral intention serves as the response.

Thus, the findings validate the integration of SERVQUAL and emotional intelligence frameworks within the SOR structure — extending its application to service management research.

4.6.6 Integrative Theoretical Insights

The results of this study provide strong empirical support for an integrative perspective where cognitive evaluations (service quality) and emotional factors (EI) operate simultaneously to influence satisfaction and behavioral intention.

This dual-path mechanism contributes to the growing recognition that customer behavior is both rational and emotional in nature.

The findings echo Parasuraman et al. (1988) and Goleman (1998) in asserting that sustainable service relationships depend on both technical performance and emotional intelligence.

Furthermore, the significant mediating effects observed confirm that emotional mechanisms amplify the influence of service quality — a contribution that deepens theoretical understanding of emotional engagement in service delivery.

4.6.7 Summary of Key Findings

1. Service Quality directly and indirectly enhances Customer Satisfaction through Emotional Intelligence.
2. Emotional Intelligence significantly affects both Customer Satisfaction and Behavioral Intention, confirming its dual cognitive–emotional role.
3. Customer Satisfaction is the strongest predictor of Behavioral Intention, reinforcing its mediating importance.
4. Sequential mediation through Emotional Intelligence and Satisfaction supports the SOR framework.

5. The integrated model explains a substantial portion of behavioral intention ($R^2 = 0.71$), confirming high explanatory and predictive power.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the conclusions and key insights derived from the analysis and findings discussed in Chapter Four.

It provides a concise summary of the study's main results, highlights the theoretical and practical implications, and offers recommendations for both scholars and practitioners.

The chapter concludes with the limitations of the current study and suggestions for future research directions.

The overarching purpose of this research was to examine how Service Quality and Emotional Intelligence jointly influence Customer Satisfaction and Behavioral Intention across diverse service sectors.

By integrating SERVQUAL (Parasuraman et al., 1988) and Goleman's Emotional Intelligence Model (1998) within a unified framework tested via PLS-SEM, the study aimed to provide a holistic understanding of both the cognitive and emotional determinants of customer behavior.

5.2 Summary of Findings

The empirical results from 372 valid responses provided strong support for the hypothesized relationships and validated the proposed conceptual model.

The findings confirm that both service quality dimensions and emotional intelligence factors play pivotal roles in shaping customer satisfaction and subsequent behavioral intentions.

The major findings of this study can be summarized as follows:

1. Service Quality significantly influences Emotional Intelligence (H1 supported):

High levels of perceived service quality — particularly in reliability, responsiveness, and empathy — foster emotionally intelligent interactions and stronger affective connections with service providers.

2. Emotional Intelligence positively affects Customer Satisfaction (H2 supported):

Emotionally intelligent behaviors such as empathy, self-regulation, and social awareness contribute to enhanced customer satisfaction, supporting prior findings by Goleman (1998) and Carmeli (2003).

3. Service Quality directly impacts Customer Satisfaction (H3 supported):

Consistent with SERVQUAL theory, customers' perceptions of dependable and empathetic service delivery were found to significantly elevate satisfaction levels.

4. Customer Satisfaction is a strong predictor of Behavioral Intention (H4 supported):

Satisfied customers demonstrated higher intentions to continue using or recommending the service, confirming the importance of satisfaction as a behavioral driver.

5. Emotional Intelligence also directly affects Behavioral Intention (H5 supported):

Beyond its indirect effect through satisfaction, EI contributes independently to customer loyalty, reflecting the emotional bond formed through positive service experiences.

6. Mediating Effects:

The mediation analyses revealed that:

Emotional Intelligence mediates the relationship between Service Quality and Customer Satisfaction.

Customer Satisfaction mediates the effect of Emotional Intelligence on Behavioral Intention.

A sequential mediation (Service Quality → EI → CS → BI) further underscores the integrated cognitive–emotional pathway influencing customer loyalty.

7. Model Explanatory Power:

The structural model explained 64% of the variance in Customer Satisfaction and 71% of the variance in Behavioral Intention, indicating strong predictive capability.

In essence, this study provides empirical confirmation that effective service encounters are not only built on technical performance (quality) but also on emotional competence and human interaction.

Customers' behavioral decisions are influenced by both rational appraisals and emotional experiences — a finding that aligns with the modern paradigm of emotional service excellence.

5.3 Theoretical and Practical Implications

5.3.1 Theoretical Implications

This study contributes to the academic literature in several meaningful ways by advancing the theoretical understanding of the interplay between Service Quality, Emotional Intelligence, Customer Satisfaction, and Behavioral Intention.

1. Integration of Cognitive and Emotional Frameworks:

The research successfully integrates two established theoretical models — the SERVQUAL model (Parasuraman et al., 1988) and Goleman's Emotional Intelligence framework (1998) — into a single, unified structural model.

This integration provides a more holistic view of customer experience, bridging the traditional service quality perspective (cognitive) with the emotional and affective dimensions of interaction.

2. Extension of Service Quality Theory:

While previous studies primarily focused on the functional dimensions of service quality (e.g., reliability, responsiveness), this research extends the theory by demonstrating that service

encounters also elicit emotional intelligence-driven responses that significantly influence satisfaction and behavioral loyalty.

3. Empirical Validation of Emotional Intelligence as a Mediator:

The study establishes Emotional Intelligence (EI) as a key mediating construct that explains how customers emotionally interpret service quality and transform cognitive evaluations into affective satisfaction.

This insight strengthens the theoretical linkage between cognitive and affective pathways in consumer behavior.

4. Confirmation of the SOR (Stimulus–Organism–Response) Perspective:

By showing that service quality (stimulus) influences emotional intelligence and satisfaction (organism), which then lead to behavioral intention (response), the study empirically supports the SOR model in a service management context.

This reinforces the understanding that emotional and psychological processes mediate the link between service stimuli and behavioral outcomes.

5. Cross-sector Generalization:

Unlike many studies limited to specific sectors (e.g., banking or hospitality), this research examined multiple service industries, increasing the external validity and theoretical generalizability of the integrated model across various contexts.

5.3.2 Practical Implications

The findings also carry significant practical implications for managers, service providers, and organizations seeking to enhance customer satisfaction and long-term loyalty.

1. Enhancing Service Quality Standards:

Managers should continuously monitor and improve the five SERVQUAL dimensions — Tangibility, Reliability, Responsiveness, Assurance, and Empathy.

Particular emphasis should be placed on responsiveness and empathy, as these were found to strongly influence emotional engagement and customer satisfaction.

2. Developing Emotionally Intelligent Employees:

Organizations should invest in emotional intelligence training programs to develop employees' abilities in self-awareness, self-regulation, empathy, and social skills.

Emotionally intelligent service employees can interpret customers' emotional cues, respond appropriately, and build long-term trust-based relationships.

3. Humanizing Service Interactions:

Beyond technical efficiency, organizations must humanize their service delivery by promoting emotionally supportive communication.

This approach leads to stronger affective connections and reinforces positive behavioral intentions, such as loyalty and word-of-mouth advocacy.

4. Customer Experience Design:

Managers should design customer experience strategies that address both functional satisfaction (service delivery) and emotional satisfaction (relationship and empathy).

Emotionally positive experiences enhance overall satisfaction and encourage customers to become active promoters of the brand.

5. Employee Recruitment and Retention:

Recruitment processes should include emotional intelligence assessments as part of candidate evaluations, especially for frontline service roles.

Employees with higher EI are more capable of managing stress, resolving conflicts, and creating satisfying experiences for customers.

6. Strategic Marketing Communication:

Marketers should highlight both service reliability and emotional connection in their branding messages, as emotional resonance can strengthen customer attachment and loyalty far beyond transactional satisfaction.

7. Cross-sector Implementation:

Since this study covered diverse service industries, the implications are widely applicable — from education and healthcare to hospitality, finance, and government services.

Organizations in these sectors can adopt the integrated model to systematically assess and enhance both service quality and emotional engagement factors.

5.4 Limitations of the Study

While this study provides valuable insights into the relationships between Service Quality, Emotional Intelligence, Customer Satisfaction, and Behavioral Intention, it is not without limitations.

Acknowledging these limitations is essential for interpreting the results objectively and guiding future research efforts.

5.4.1 Methodological Limitations

The first limitation concerns the use of a cross-sectional research design, in which data were collected at a single point in time.

Although this design allows for efficient data collection and causal inference testing, it does not capture potential temporal or dynamic changes in customer perceptions and emotional responses over time.

Future research could adopt a longitudinal design to assess how these relationships evolve in different service interactions or over extended periods.

Additionally, the study relied on self-reported data obtained through an online questionnaire.

Although anonymity was ensured, respondents' answers may still be subject to social desirability bias or common method variance.

Combining self-report data with behavioral or observational data in future studies could help strengthen the validity of the findings.

5.4.2 Sampling and Generalizability

The study employed a non-probability purposive sampling technique, targeting individuals who had prior experience with service organizations.

While this approach was suitable for ensuring relevant responses, it may limit the generalizability of results to the broader population.

A probability-based sampling approach (e.g., stratified or random sampling) in future studies would allow for a more representative sample across sectors.

Furthermore, although the sample ($n = 372$) was diverse and adequate for PLS-SEM analysis, the study did not specifically compare differences between industries (e.g., healthcare vs. banking vs. education).

Future research could conduct multi-group analyses to determine whether the relationships among constructs vary across different service contexts.

5.4.3 Conceptual and Measurement Limitations

The conceptual model integrated two main frameworks (SERVQUAL and Emotional Intelligence), focusing primarily on cognitive and emotional factors.

However, behavioral and contextual variables such as perceived risk, cultural orientation, or digital literacy were not included.

Incorporating these variables in future studies could enhance the explanatory power of the model.

Additionally, while all constructs were measured using validated scales from prior literature, they relied on perceptual indicators rather than objective performance metrics.

Future research could integrate objective service quality indicators (e.g., response time, error rates) alongside perceptual measures to provide a more comprehensive view of service performance.

5.4.4 Temporal and Contextual Boundaries

The data were collected within a specific time frame (four weeks) and mainly from participants active on digital platforms.

This temporal and contextual limitation may have influenced responses, especially given the rapid evolution of service technologies and customer expectations.

Repeating the study in different periods or including offline service interactions could produce richer comparative insights.

5.5 Recommendations for Future Research and Practice

5.5.1 Recommendations for Practice

Based on the empirical results and practical insights derived from this study, several recommendations can be made for organizations, managers, and service professionals to enhance service quality, emotional engagement, and customer loyalty.

1. Embed Emotional Intelligence in Service Training Programs:

Organizations should integrate emotional intelligence (EI) skills into staff training and development initiatives.

Frontline employees who demonstrate self-awareness, empathy, and emotional regulation are better equipped to handle customer concerns and foster long-term satisfaction.

This approach is especially beneficial in service industries where emotional labor and interpersonal communication are essential.

2. Enhance Empathy and Responsiveness as Core Service Standards:

The results showed that Empathy and Responsiveness were the most influential dimensions of service quality affecting satisfaction.

Managers should prioritize customer-centered service protocols, timely responses, and personalized interactions to strengthen customer relationships.

3. Develop Holistic Customer Experience Strategies:

Beyond functional efficiency, service organizations should focus on emotional connection and relational quality.

Establishing emotionally intelligent interactions creates memorable experiences that drive repeat usage and positive word-of-mouth.

4. Utilize Emotional Intelligence in Employee Recruitment and Appraisal:

Organizations should include EI-based criteria in employee recruitment and performance evaluation systems.

Staff with higher emotional intelligence tend to adapt better to stressful customer interactions, exhibit higher job satisfaction, and deliver superior customer experiences.

5. Leverage Technology to Enhance Service Quality and Emotional Engagement:

Digital platforms and AI tools should be used not only to improve service efficiency but also to enable personalized emotional communication — such as adaptive tone, real-time empathy detection, or proactive response systems.

6. Continuous Monitoring of Customer Satisfaction and Behavioral Intention:

Managers should adopt regular satisfaction surveys and behavioral tracking systems to identify changes in customer expectations, ensuring that service delivery evolves alongside market dynamics.

5.5.2 Recommendations for Future Research

While this study provided meaningful insights, it also opened new avenues for future exploration.

The following recommendations are proposed for researchers seeking to extend the understanding of service quality and emotional intelligence in customer behavior studies:

- 1. Longitudinal Research Design:** Future studies could employ a longitudinal approach to observe how service quality perceptions, emotional responses, and satisfaction levels evolve over time — providing a dynamic view of customer loyalty development.
- 2. Cross-Cultural and Sectoral Comparisons:** Since emotional expression and service expectations vary across cultures, researchers could conduct cross-national or cross-sectoral studies to test the generalizability of the integrated model.
- 3. Inclusion of Moderating Variables:** Future models could include moderators such as customer trust, perceived value, or digital literacy to further explain the variability in behavioral intentions.

- 4. Mixed-Methods Research Approach:** Combining quantitative surveys with qualitative interviews or focus groups would yield deeper insights into the emotional and psychological dimensions of customer experience.
- 5. Integration with Technological Factors:** Researchers could extend the current framework by integrating variables from the Technology Acceptance Model (TAM) or AI adoption theories to explore how emotional and technological determinants jointly affect customer behavior in digital environments.
- 6. Exploration of Organizational Emotional Intelligence (OEI):** Beyond individual-level EI, future research could examine the collective emotional intelligence of organizations — how corporate culture, leadership, and team dynamics influence customer satisfaction and retention.

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Appendixes

Appendixes : Questionnaire

عنوان الدراسة:

تحليل سلوك المستهلك تجاه جودة الخدمة والذكاء العاطفي: دراسة ميدانية

يهدف هذا الاستبيان إلى جمع بيانات علمية لأغراض بحثية فقط ضمن متطلبات نيل درجة الماجستير في إدارة الأعمال.

تُعامل جميع الإجابات بسرية تامة، ولن تُستخدم إلا لأغراض أكاديمية بحثية. مشاركتك طوعية تمامًا، ونقدر تعاونك في إكمال هذا الاستبيان.

يرجى قراءة كل عبارة بعناية، ثم تحديد مدى موافقتك وفقًا لمقياس ليكرت الخماسي الموضح أدناه:

الوصف	الدرجة
أعارض بشدة	1
أعارض	2
محايد	3
أوافق	4
أوافق بشدة	5

القسم الأول: البيانات الديموغرافية

الجنس: ☐ ذكر ☐ أنثى

الفئة العمرية: ☐ أقل من 25 ☐ 26-35 ☐ 36-45 ☐ أكثر من 45

المستوى التعليمي: ☐ دبلوم أو أقل ☐ بكالوريوس ☐ ماجستير ☐ دكتوراه

سنوات الخبرة: ☐ أقل من سنتين 2-5 ☐ سنوات 6-10 ☐ سنوات ☐ أكثر من 10 سنوات

القطاع الذي تتعامل معه: ☐ التعليم ☐ البنوك ☐ الصحة ☐ الخدمات العامة ☐ أخرى

القسم الثاني: جودة الخدمة (Service Quality – SERVQUAL)

رقم	العبارة	1	2	3	4	5
البعد الأول: الملموسية (Tangibility)						
1	بيئة الخدمة نظيفة واحترافية.	☐	☐	☐	☐	☐
2	مرافق وتجهيزات المؤسسة جذابة ومنظمة.	☐	☐	☐	☐	☐
3	موظفو المؤسسة يتمتعون بمظهر مهني وأنيق.	☐	☐	☐	☐	☐
البعد الثاني: الاعتمادية (Reliability)						
4	تقدم المؤسسة الخدمات كما تم الوعد بها.	☐	☐	☐	☐	☐
5	يمكن الاعتماد على المؤسسة في تنفيذ الخدمات بدقة.	☐	☐	☐	☐	☐
6	الخدمة المقدمة موثوقة في كل مرة أتعامل فيها مع المؤسسة.	☐	☐	☐	☐	☐
البعد الثالث: الاستجابة (Responsiveness)						
7	الموظفون دائماً مستعدون لمساعدة العملاء.	☐	☐	☐	☐	☐
8	تستجيب المؤسسة بسرعة لطلبات العملاء.	☐	☐	☐	☐	☐

9	يتعامل الموظفون مع مشكلات العملاء بكفاءة.	☐	☐	☐	☐	☐
البعد الرابع: الضمان (Assurance)						
10	الموظفون يمتلكون المعرفة الكافية بالخدمات المقدمة.	☐	☐	☐	☐	☐
11	الموظفون يبعثون الثقة والاطمئنان في نفوس العملاء.	☐	☐	☐	☐	☐
12	أشعر بالأمان أثناء التعامل مع المؤسسة.	☐	☐	☐	☐	☐
البعد الخامس: التعاطف (Empathy – Service Quality)						
13	يفهم الموظفون احتياجاتي الخاصة.	☐	☐	☐	☐	☐
14	توفر المؤسسة اهتمامًا فرديًا بالعملاء عند الحاجة.	☐	☐	☐	☐	☐
15	تهتم المؤسسة برفاحية العملاء ورضاهم.	☐	☐	☐	☐	☐

القسم الثالث: الذكاء العاطفي (Emotional Intelligence – Goleman, 1998)

رقم	العبارة	1	2	3	4	5
البعد الأول: الوعي الذاتي (Self-Awareness)						
16	أنا مدرك لمشاعري أثناء تفاعلي مع الآخرين في الخدمة.	☐	☐	☐	☐	☐
17	أستطيع التعرف على كيفية تأثير مشاعري على سلوكي.	☐	☐	☐	☐	☐

18	أعي كيف يدرك الآخرون تعبيراتي العاطفية.	☐	☐	☐	☐	☐
البعد الثاني: التنظيم الذاتي (Self-Regulation)						
19	أستطيع التحكم في مشاعري أثناء التعامل مع المواقف الصعبة.	☐	☐	☐	☐	☐
20	أحافظ على هدوئي في المواقف المجهدة أو المزعجة.	☐	☐	☐	☐	☐
21	أتجنب ردود الأفعال الاندفاعية مع العملاء.	☐	☐	☐	☐	☐
البعد الثالث: الدافعية (Motivation)						
22	أظل إيجابيًا حتى عند مواجهة تحديات في الخدمة.	☐	☐	☐	☐	☐
23	لدي دافع قوي لتحقيق رضا العملاء.	☐	☐	☐	☐	☐
24	أسعى باستمرار لتحسين أدائي في تقديم الخدمة.	☐	☐	☐	☐	☐
البعد الرابع: التعاطف (Empathy – Emotional Intelligence)						
25	أستطيع الشعور عندما يكون العميل غير راضٍ أو منزعجًا.	☐	☐	☐	☐	☐
26	أحاول فهم مشاعر الآخرين قبل الرد عليهم.	☐	☐	☐	☐	☐
27	أستمع باهتمام لفهم احتياجات العملاء.	☐	☐	☐	☐	☐
البعد الخامس: المهارات الاجتماعية (Social Skills)						

28	أحافظ على علاقات إيجابية مع العملاء.	☐	☐	☐	☐	☐
29	أتواصل بفعالية مع مختلف أنواع العملاء.	☐	☐	☐	☐	☐
30	أتعامل مع الخلافات مع العملاء بطريقة محترمة وبناءة.	☐	☐	☐	☐	☐

القسم الرابع: رضا العملاء (Customer Satisfaction)

رقم	العبارة	1	2	3	4	5
31	بشكل عام، أنا راضٍ عن الخدمة المقدمة.	☐	☐	☐	☐	☐
32	الخدمة تلبي توقعاتي.	☐	☐	☐	☐	☐
33	أشعر بالرضا والسعادة تجاه تجربتي مع مقدم الخدمة.	☐	☐	☐	☐	☐
34	أعتقد أن اختياري لهذه الخدمة كان صائبًا.	☐	☐	☐	☐	☐

القسم الخامس: النية السلوكية (Behavioral Intention)

رقم	العبارة	1	2	3	4	5
35	أنوي الاستمرار في استخدام هذه الخدمة مستقبلاً.	☐	☐	☐	☐	☐
36	سأوصي الآخرين باستخدام هذه الخدمة.	☐	☐	☐	☐	☐
37	أفضل التعامل مع هذه المؤسسة مقارنة بغيرها.	☐	☐	☐	☐	☐

نشكركم جزيل الشكر على وقتكم ومشاركاتكم القيمة في هذا البحث.
مساهمتمكم تساعد في تطوير الفهم الأكاديمي لجودة الخدمة والذكاء العاطفي وعلاقتهم برضا العملاء وسلوكهم المستقبلي

الملخص

يهدف هذا البحث إلى دراسة تأثير جودة الخدمة والذكاء العاطفي على رضا العملاء ونواياهم السلوكية في القطاعات الخدمية المختلفة، وذلك من خلال دمج نموذج جودة الخدمة (SERVQUAL) ونموذج الذكاء العاطفي (Goleman, 1998) ضمن إطار تحليلي موحد. اعتمدت الدراسة على منهج البحث الكمي باستخدام أداة الاستبيان الإلكتروني لجمع البيانات من عينة مكونة من (372) مستجيباً من مستخدمي الخدمات الإلكترونية.

تم تحليل البيانات باستخدام منهجية النمذجة بالمعادلات الهيكلية الجزئية (PLS-SEM) عبر برنامج SmartPLS 4.0 ، حيث شملت التحليلات فحص النموذجين القياسي والهيكل للتحقق من صدق وثبات المقاييس وقياس قوة العلاقات بين المتغيرات.

أظهرت النتائج أن جودة الخدمة تؤثر إيجابياً على الذكاء العاطفي ورضا العملاء، وأن الذكاء العاطفي يؤثر بدوره على كل من الرضا والنوايا السلوكية. كما تبين أن الرضا يمثل متغيراً وسيطاً رئيسياً بين جودة الخدمة والنوايا السلوكية. وقد فسّر النموذج المقترح 64% من التباين في رضا العملاء و**71% من التباين في النوايا السلوكية**، مما يعكس قوة تفسيرية عالية.

تؤكد هذه النتائج أهمية الدمج بين الأبعاد المعرفية والعاطفية في تفسير سلوك العملاء داخل بيئات الخدمات الرقمية، وتشير إلى أن تطوير القدرات العاطفية للعاملين وتعزيز جودة التفاعل الإنساني يمكن أن يسهم في بناء ولاء طويل الأمد لدى العملاء.

الكلمات المفتاحية: جودة الخدمة، الذكاء العاطفي، رضا العملاء، النوايا السلوكية، نمذجة المعادلات الهيكلية، PLS-SEM

تحليل سلوك المستهلك تجاه تطبيقات التسوق عبر الهاتف
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2026-2025