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HUMAN-AI INTERACTION IN DIGITAL CONSUMPTION ENVIRONMENTS: ADOPTION OF CHATBOTS AND VOICE ASSISTANTS AND THEIR INFLUENCE ON FMCG PURCHASE INTENTIONS

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ABSTRACT

This study examines the impact of key components of an omnichannel strategy components Chatbot Service Quality (CSQ), Voice Assistant Experience (VAE), Personalization Level (PL) and Omnichannel Integration (OI) influence consumer behavior in the Indian FMCG sector. Data were collected from 440 urban consumers in Chennai, who were familiar with chatbot and voice assistant interactions. A reflective PLS-SEM model using SmartPLS 4.0 was employed to test direct and mediating effects in the Stimulus-Organism-Response (S-O-R) framework. The results demonstrate that CSQ, VAE, PL and OI significantly impact POC (H1-H4) and that POC is a strong predictor of CPI (H5). Additionally, CSQ, VAE and PL have significant direct impacts on CPI as well (H6-H8), while the direct path from OI on CPI is mainly through POC. Mediation analysis (H10a-H10d) support the proposition that POC partially mediates the effect of all omnichannel enablers and CPI, indicating that convenience is a key psychological factor in determining intention to purchase. FMCG firms should develop AI chatbots that respond quickly, customized voice assistants, personalized recommendations that change with the consumer and simple integration across channels to improve overall perceived omnichannel and thereby increase intention to purchase. This study contributes to AI-marketing and omnichannel literature by providing an empirical examination of POC as one of the central mediating mechanism connecting AI-based engagement and consumer purchase behavior in emerging markets.

KEYWORDS: AI marketing, Chatbot Service Quality, Consumer Purchase Intention, FMCG, Omnichannel, PLS-SEM, S-O-R, Voice Assistant Experience

JEL CLASSIFICATIONS: M31, L81, D83, O33, L86

1. INTRODUCTION

The FMCG (fast-moving consumer goods) industry worldwide is dramatically changing as a result of advances in technology that affect retail and consumer systems. The rise of artificial intelligence (AI) is providing new modes of consumer interaction in the form of chatbots and voice-activated assistants, which can facilitate conversational experiences across multiple consumer touch points in real-time ([Sidlauskiene et al., 2023](#)). These interfaces allow for not just information gathering, but also for personalization and ease in the purchasing journey ([Bhatt, 2024](#)). In the context of Indian metropolitan areas such as Chennai, consumers may be more rapidly adopting mobile, conversational and voice interfaces. Therefore it is critical for FMCG marketers to uncover new consumer behaviours regarding AI adoption concerning these devices and the AI systems that support them.

The most recent report confirms the growing importance of AI in the retail space around the world. The total global market size for AI in the retail was valued at \$4.95 billion in 2024 and is projected to grow at a CAGR of 22.3% through 2030 ([Grand View Research, 2024](#)). By 2025, 92% of retail marketers will be using AI tools to engage. In addition, 60% of retailers last year were looking to invest in omnichannel technologies to create a cohesive shopping experience ([Emarsys, 2024](#); [SuperAGI, 2025](#)). In addition, 73% of consumers engage with multiple touchpoints before they purchase. This highlights the important area of integrating physical and digital touch points across the physical retail experience.

While there is a lot of promise, there are still some significant gaps and challenges ahead. Prior work has suggested that while chatbots and voice assistants can improve engagement, trust with the user, accuracy in the system, consistency across channels and the complexity of omnichannel integration pose obstacles to the ideal consumer experience ([Kumar & Singh, 2022](#)). Additionally, while we see an increased use of AI tools in customer service, we know less about the direct influence on purchase intention in FMCG settings that tend to be low involvement, habit-driven decisions that are structurally rooted ([Arachchi & Samarasinghe, 2025](#)). There is an apparent gap in the research on the use of AI-driven chatbots and voice assistants in relation to omnichannel FMCG context and purchase intention.

While AI chatbots and voice assistants are

commonly used in different industries, there is little empirical research that incorporated omnichannel factors—specifically, personalization, chatbot service quality, and omnichannel integration—through the S–O–R framework in the FMCG context. Prior studies have focused on high-involvement sectors like e-commerce or hospitality, as a result, there is a theoretical and contextual gap in fast-moving consumer goods sectors that have shorter purchase cycles and where convenience may be more important.

A key mediating element to consider in this dynamic is perceived omnichannel convenience, which reflects the consumers' perception of how easy it is to transition across channels to collect relevant information, engage with a brand and complete purchasing duties. Research finds that consumers who view their experience as more convenient confirm higher purchase intentions and greater brand loyalty in multi-channel contexts ([Rahman, 2025](#)). The role of convenience (the consumer view of convenience) may be even more important in fast-moving consumer goods where the purchases are frequent and often repetitive in nature. As a result, including constructs like chatbot service quality voice assistant experience, personalization level and omnichannel integration to the purchase intention chain adds both theoretical and managerial contributions.

The objectives of the study are to fill the identified gap by investigating the mediation role of POC in the relationship between omnichannel enablers (e.g., CSQ, VAE, PL and OI) and CPI in the Indian FMCG context. The goals are;

1. To consider the direct effects of CSQ, VAE, PL, and OI on POC in the FMCG context.
2. To consider the direct effects of CSQ, VAE, PL and OI on CPI.
3. To consider the mediation role of POC between the omnichannel enablers and the CPI within the S–O–R framework.

In this sense, the current research aims to understand the impact of AI-powered chatbots and voice support tools in an omnichannel FMCG context, as well as their role in driving consumer purchase intention through the mediating of perceived omnichannel convenience. Therefore, the findings will help FMCG firms explore the possibilities of the new voice and chat enabled consumer in their omnichannel approaches, potentially increasing their encroachment on traditional retailers.

The paper is structured in the following manner:

Section 2 reviews the necessary literature and theoretical underpinnings surrounding the study; Section 3 outlines the research methods, including data collection, measurement, and analysis; Section 4 presents the results of the PLS-SEM outcomes; Section 5 outlines the key findings, theoretical implications, and managerial implications; and the conclusion in Section 6 discusses limitations and future research opportunities.

2. LITERATURE REVIEW & THEORETICAL BACKGROUND

2.1. Literature Review

The S-O-R model (Mehrabian & Russell 1974) takes external cues (Stimuli) as influencing consumers' internal states (Organism) that cause behavioral outcomes (Response) (Pereira et al., 2023). The S-O-R lens from the perspective used in omnichannel and AI-enabled retail studies is particularly useful; AI/chatbot or other related internal states serve as the organism; and purchase intention is the behavioral response making it a robust and widely applied framework for the current study.

2.1.1. Chatbot Service Quality (CSQ)

Chatbot service quality (accuracy, responsiveness, usefulness politeness) has a consistent relationship with customer satisfaction and behavioural intention. In empirical work, process quality and outcome quality as well as perceived reliability of chatbots positively affect user satisfaction and intention for future use (Misischia et al., 2022; Kim, 2020). More recently, applied studies in retail and banking show that higher service and system quality from chatbots enhance consumer trust and lower perceived purchase effort as important antecedents to downstream purchase intention (Paz et al., 2020). Overall, the evidence could suggest that CSQ is an unambiguous antecedent that enhances internal consumer evaluations and influences purchase outcomes in omnichannel environments.

2.1.2. Voice Assistant Experience (VAE)

Studies in the voice user interface (VUI) domain examine the interplay between interactions via voice prompts and acceptance behaviour, particularly around accuracy, naturalness, perceived humanness and the seamlessness of voice interaction. Socio-technical studies also show that the assistant's perceived ability to understand user commands and its conversational capabilities shape the users' trust and the perceived use and ease of use a precursors to the intention of purchase via voice (Porcheron et al., 2018). Research from the perspective of

marketing show that voice-based prompts and recommendations can be convincing, often more so than the same piece of information presented in an online review format and has a greater influence on users when they perceive the VA to be knowledgeable and trustworthy (Flavián et al., 2023).

2.1.3. Personalization Level (PL)

Personalization is the process of adapting messages, recommendations and offers to specific users, which can be a strong motivator of engagement and purchasing behavior if executed correctly. Principles drawn from industry research and studies in social science emphasize that accurate and timely personalization can enhance perceived relevance and trust that lead to conversion and sales (McKinsey 2021). More recent empirical research shows that personalizing products or service using either AI-recommendations engines or dynamic offers create a positive impact on purchase intention by increasing perceived usefulness and lowering search costs (Gomez-Urbe & Hunt on recommender systems; Lambillote et al., 2022). Thus it is understood that personalizing acts as a stimulus in guiding cognitive judgments that are central to the decision to purchase.

2.1.4. Omnichannel Integration (OI)

Omnichannel integration, the extent to which experiences are similar across all online and offline touchpoints is an established antecedent of positive consumer outcomes. In their seminar paper (Verhoef et al., 2015) conceptualized omnichannel management and subsequent empirical work have demonstrated that improved channel integration, for example, increase perceived fluency, decrease perceived risk and increase customer engagement and loyalty (Verhoef et al., 2015; Quach 2022). More recently, studies applying the S-O-R lens have found that omnichannel integration can be viewed as an external stimulus, enhancing flow/effortless experience (organism), which triggers increased service usage and purchase responses (Chen et al., 2022; Gao 2021).

2.1.5. Perceived omnichannel convenience (POC)

Perceived omnichannel convenience conceptually occupies a central position in the model as the intermediary internal state linking stimuli to purchase intentions. Digital convenience studies in the omnichannel retail context demonstrate that consumers' perceptions of time savings, effort savings and ease of access are all strong predictors of favourable behavioural outcomes (digital convenience literature: Rahman 2022). Empirical

omnichannel research adopting on S-O-R framework shows that convenience and perceived fluency are mediators in the relationship between channel features and impulse buying and overall service use outcomes (Pereria et al., 2023; Chen et al., 2022).

2.1.6. Consumer Purchase Intention (CPI)

The behavioral outcomes most commonly used as a measure of the effectiveness of digital retail interventions, is purchase intention. There are recent studies of AI chatbot, voice assistants and personalization that explore positive correlations between rich AI interactions, trust, convenience and self-reported purchase intention (Emerging AI attributes literature; Cattapan 2022). There is also general agreement, based on an studies across omnichannel FMCG studies that technological stimuli related to perceived convenience and friction, also increase purchase intentions, especially in urban markets with high smartphone and voice assistant use.

Consequently, the studies examined above demonstrate clearly that AI-enabled service constructs such as chatbot quality, voice assistant

experience, and personalization are the main drivers of consumers’ evaluations in omnichannel settings. More importantly, when technological and experiential cues are appropriately combined (or not) across touchpoints, they enhance additive effects on consumers’ evaluations of convenience and fluency, which ultimately creates behavioral outcomes (e.g., purchase intention). This integrative view aligns with the need to examine these constructs collectively in the S-O-R process, especially in rapidly changing online FMCG where decisions are frequent and convenience-focused (See Table 1).

2.1.7. Short Synthesis and Positioning for the Study

Putting the pieces together, the literature shows a clear S-O-R path: AI/chatbot service quality, experience with a voice assistant, personalization and omnichannel integration (Stimuli), shaped perceived omnichannel convenience (Organism), which drives consumer purchase intention (Response) in an FMCG omnichannel context. This is where we start to develop the conceptual model and hypothesis for the current study using PLS-SEM.

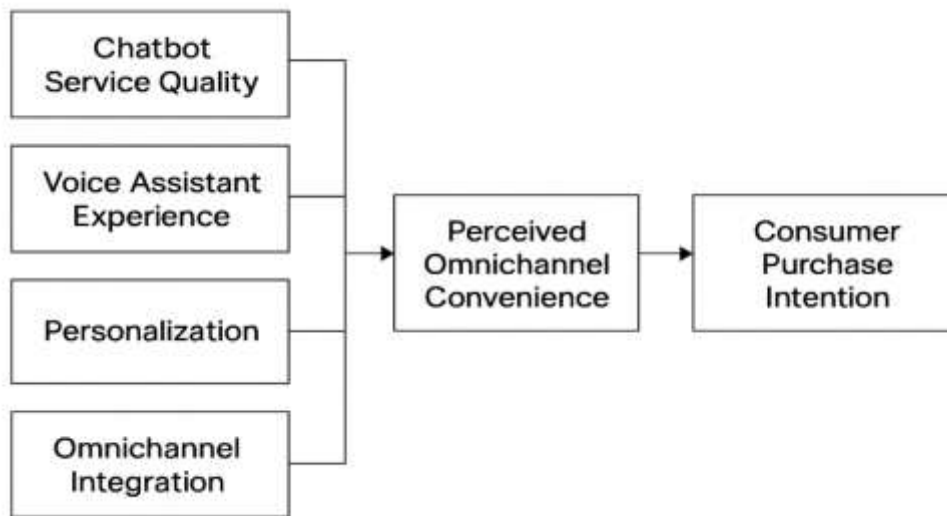


Figure 1: Theoretical Framework based on the S-O-R Model
 Source: Own Research

Table 1: Conceptual Summary of Key Studies

Author(s)	Year	Context	Key Variables	Method	Key Findings
Mehrabian & Russell	1974	Consumer behavior theory	Stimulus-Organism-Response	Conceptual	Established the foundational S-O-R model linking environmental cues to behavioral responses.
Misischia et al.	2022	Retail & Banking Chatbots	Service Quality, Satisfaction, Intention	Survey (SEM)	Chatbot reliability and responsiveness increase satisfaction and behavioral intention.
Porcheron et al.	2018	Voice User Interface (VUI)	Naturalness, Trust, Use Intention	Mixed Methods	Naturalness and conversational ability drive user trust and usage intention.
Flavián et al.	2023	Retail (Voice AI)	Trust, Credibility, Purchase Intention	Experiment	Voice-based recommendations improve persuasion and trust vs. text-based formats.
Verhoef et al.	2015	Omnichannel Retail	Channel Integration, Experience Consistency	Conceptual	Defined omnichannel integration as a key determinant of consumer experience.

Chen et al.	20 22	Online Retail	OI, Flow, Purchase Response	SEM	OI enhances flow experience and triggers stronger purchase responses.
Rahman	20 22	Omnichannel Retail (Asia)	Convenience, Time & Effort Savings	Survey (PLS-SEM)	Perceived convenience mediates the link between channel features and behavioral outcomes.
Cattapan	20 22	AI-enabled Retail	Trust, Convenience, Purchase Intention	Quantitative	Rich AI interactions positively influence trust and purchase intention.
Lambillotte et al.	20 22	E-commerce Personalization	Personalization, Usefulness, Intention	Experiment	Dynamic personalization increases perceived usefulness and conversion likelihood.
Gao	20 21	Multichannel Commerce	OI, Flow, Service Usage	Structural Model	Integration across channels improves engagement and purchase frequency.

2.2. Hypothesis Development

2.2.1. Theoretical foundation

The Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell 1974) informs this investigation, suggesting the external stimuli (S) impact internal psychological states (O) which subsequently elicit behavioural responses (R). The S-O-R lens is appropriate for examining omnichannel related technological mediated, consumer behaviour, as it provides an explicit link between the interface/channel attributes to internal states and then to purchase behaviours (Eroglu, Machleit & Davis 2001; Verhoef et al., 2015).

The selection of the S-O-R model over other models of consumer behavior such as Technology Acceptance Model (TAM), or Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is because it has broader explanatory power for affective and situational factors of consumer behavior. While Tam and UTAUT2 focused cognitive appraisals (such as perceived ease of use,

usefulness and effort expectancy), the S-O-R model incorporates emotional, experiential and contextual factors, that are particularly relevant within omnichannel settings. AI-enabled retail interactions will not only evoke rational responses to cognitive evaluations of technology, but will also shape affective states, including; trust, enjoyment and perceived convenience. Because of this, the S-O-R model provides a more comprehensive foundation for understanding how omnichannel stimuli (e.g., chatbots service quality; voice assistant experiences; personalization; integration) lead to the internal psychological states of the consumer (e.g., perceived accuracy of AI-enabled omnichannel convenience), which ultimately influences behavioral reactions (e.g., purchase intention). Given the S-O-R model's flexibility and pre-existing validation in both retail and digital marketing settings, the S-O-R model is considered particularly relevant and suited to examine AI-enabled omnichannel consumer behavior within the FMCG sector.

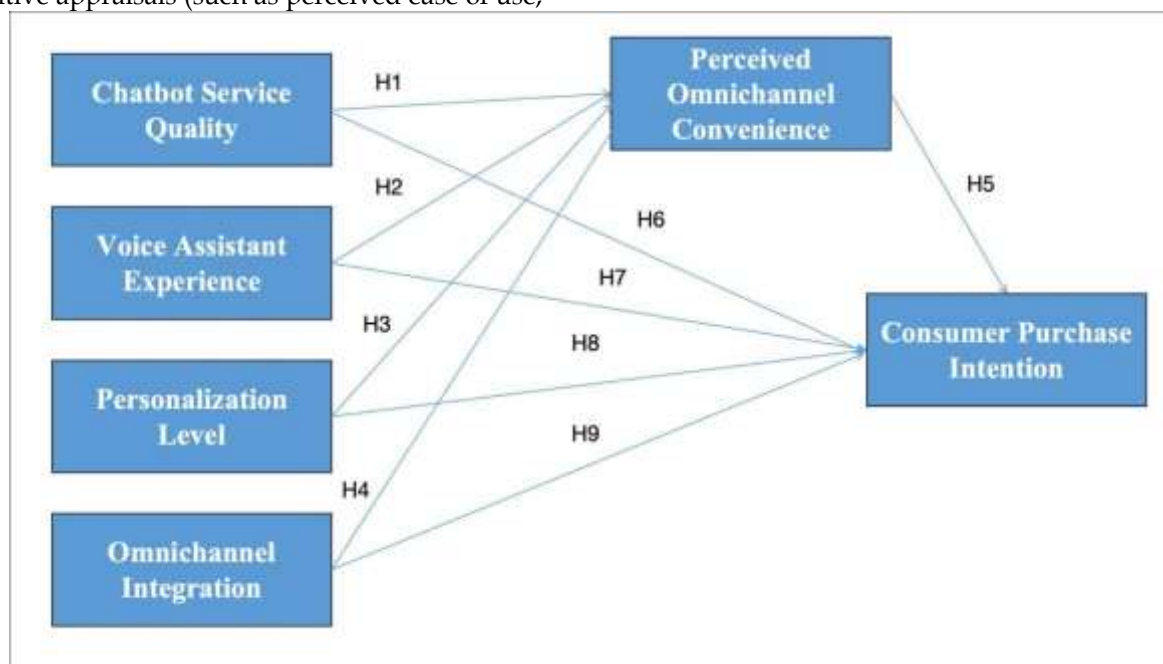


Figure 2: Conceptual Framework of the study
Source: Own Research

Interactions with high-quality chatbots are increasingly regarded as an essential part of creating an effective omnichannel experience. Users evaluate a chatbot service on its quality based on its responsiveness, reliability, empathy, and usefulness, all of which, in turn, contribute to user perceptions of service convenience (Misischia et al., 2022; Kim, 2020). Prior research suggests that chatbots have the potential to lower users' cognitive and temporal load in determining convenience, when the chatbot provides context-appropriate responses to questions faced by the customer and reduces overall wait time (Paz et al., 2020; Lin et al., 2023). Research indicates that superior chatbot quality positively influence perceived usefulness, satisfaction and reduces consumer interaction e.g. effort all factors that make up core elements of perceived convenience (Syarifudin 2024; Gao 2025). Better chatbots meet expectations or improve service for consumers and even more importantly lower cognitive or temporal costs. The following hypotheses are framed on the basis of the above discussion:

H1: Chatbot service quality has a positive influence on convenience across channels.

Voice assistants (VAs) are a growing mode of search, recommendations and transactional prompt (Porcheron et al., 2018; Lopatovska & Williams, 2018). Empirical marketing studies have shown that voice-based recommendations are persuasive and enable consumers to make decisions more quickly, when the VA is credible and accurate (Flavián 2023; McLean & Osei-Frimpong, 2019). In addition, when consumers experience fluent, reliable voice interactions, they engage in less manual searching for information and switching between channels, increasing perceptions of convenience (Porcheron et al., 2018). Within the S-O-R framework, richer VA experience serves as a stimulus, perhaps reducing friction and increasing perceived convenience. The above discussion proposed the following hypothesis:

H2: Voice assistant experience positively influences perceived omnichannel convenience.

Personalization customizes product recommendations, promotions and interactions to an individual's preferences and previous behavior (McKinsey 2021; Xin Yun and Myung Hwan Chun 2024). Personalization must also be accurate and non-intrusive to be beneficial (Lee et al., 2022). Nevertheless, personalization should be viewed as accurate and sensitive to privacy boundaries in order to mitigate psychological reactance or annoyance (Bleier & Eisenbeiss, 2015). Broadly speaking, in the S-O-R framework, personalization can be characterized as a stimulus that eases

cognitive processing and increases perceived control and efficiency, and both of which enhance consumers' perceptions of omnichannel convenience (Xin Yun & Chun, 2024; Rahman, 2025). Based on the above discussion, the following hypothesis is proposed:

H3: The level of personalization is positively related to perceived omnichannel convenience.

Omnichannel integration encompasses consistency of information, inventory, pricing and services across online and offline touchpoints. Omnichannel integration affects how seamless consumers feel their shopping journey are based on foundational omnichannel research (Verhoef et al., 2015; Cattapan 2022). Effective integration allows consumers to easily switch between channels, minimizing the search effort and perceived friction of the shopping journey (Quach, Jebarajakirthy, & Thaichon, 2022; Chen, Gao, & Huang, 2022). Research in the contexts of retail and service provision also shows that a well-integrated system facilitates transparency and tracking of orders, deliveries and returns, hence increasing perceived convenience and satisfaction (Cattapan, 2022; Gao, 2025). The following hypothesis is framed on the basis of the above discussion:

H4: Omnichannel integration has a positive impact on perceived omnichannel convenience.

Convenience is an empirically established precursor to purchase intention. In the context of omnichannel retail, consumers' perceived convenience is constructed on their assessment of the time gained, effort saved and smooth transition between channels in dealing with a given brand (Chen et al., 2022; Rahman, 2022). Consumers who view shopping as uncomplicated and expeditious are more likely to formulate intentions to purchase, particularly for incidental, low-involvement FMCG goods (Rahman 2022; Pereria et al., 2023). Previous empirical evidence reveals that when consumers experience higher levels of perceived convenience, they report lower cognitive and temporal costs, more perceived control, and a heightened likelihood of completing transactions across channels (Flavián et al., 2023; McLean & Osei-Frimpong, 2019). In omnichannel environments, perceived convenience lowers friction and diminishes cognitive/temporal barriers to purchase which directly increases likelihood to purchase. The above discussion proposed the following hypothesis:

H5: Perceived omnichannel convenience will have a positive influence on consumer purchase intention.

The Quality service of chatbot (CSQ) notably influences Consumer Purchase Intention (CPI)

through the enhancement of the consumers' view of their service responsiveness, accuracy and emotional engagement. Chatbots that provide higher quality interactions provide consumers with a sense of confidence, lowered use effort and inspired positive attitudes toward purchases (Grewal et al., 2020; Huang & Rust 2021). Recent research in the use of artificial intelligence in retail and e-commerce shows that consumers report greater levels of confidence and risk exposure while making purchase decisions when they view chatbot interactions as efficient, human-like, and emotionally engaging (Paz et al. 2020; Misischia et al. 2022). In addition, better chatbot quality decreases perceived effort and increases perceived control, which positively influences purchase intentions across omnichannel touchpoints (Bhatt, 2025; Gao, 2025). Based on the above discussion, the following hypothesis is proposed:

H6: Chatbots Service Quality positively influences Consumer Purchase Intentions.

Voice Assistant Experience (VAE) allows consumers to interact with brands in ways that are intuitive, conversational and largely effortless. Natural language interactions and contextual personalization are shown to enhance enjoyment and confidence in decision-making (Huang & Rust 2021). Studies that examine empirical research on digital marketing and human-computer interaction indicate that natural language processing and contextual understanding will lead to greater user engagement, enjoyment, and trust that lead to greater behavioral intentions (Flavián et al., 2023; McLean & Osei-Frimpong, 2019). When consumers feel that voice interactions are dependable, personalized, and resemble human interaction, they will have less cognitive effort and greater confidence in decision-making, which makes them more willing to purchase (Porcheron et al., 2018; Lopatovska & Williams, 2018). The following hypotheses are framed on the basis of the above discussion:

H7: Voice Assistant Experience positively influences Consumer Purchase Intention.

Personalization Level (PL) indicates the extent to which marketing content, recommendations and interactions match consumer preferences. Greater personalization extends relevance, satisfaction and perceived value, resulting in an increase in purchase intention (Lemon & Verhoef 2016). Large amounts of research in both digital retail and AI-enabled marketing contexts show that meaningful personalization that looks good can increase perceived relevance, trust and satisfaction—all precursors to purchase behavior (Bleier & Eisebeiss,

2015; Lambillotte et al., 2022). Personalized offers and dynamic recommendations reduce information overload, improving decision making, as well as creating feelings of recognition and feeling in control, which increases consumers' willingness to buy (McKinsey, 2021; Xin Yun & Chun, 2024). Based on the above discussion, the following hypothesis is proposed:

H8: Personalization Level positively influences Consumer Purchase Intention.

Omnichannel Integration (OI) is a systematic process that aligns information, pricing and service means across online and offline touchpoints, which enhances consumer's sense of control and satisfaction (Verhoef et al., 2021). Well-integrated channels are perceived lower friction and higher reliability which leads to stronger increases in purchase intentions (Flavián et al., 2023; Balbin Buckley et al., 2024). The following hypotheses are framed on the basis of the above discussion:

H9: Omnichannel Integration positively influences Consumer Purchase Intention.

Both theoretical and empirical studies argue for mediation models where the effect of technology and channel characteristics on outcome occurs through psychology states like trust, perceived usefulness, flow or convenience (Eroglu et al., 2001; Syarifudin 2024; Xin Yun and Myung Hwan Chun 2024). Many more recent empirical PLS-SEM studies on omnichannel and artificial intelligence have found such mediation patterns (Syarifudin 2024; Flavián et al., 2023; Cattapan 2022). Therefore we propose that each stimulus will exert indirect effects on purchase intention through perceived omnichannel convenience. The above discussion proposed the following hypotheses:

H10a: Perceived omnichannel convenience mediates the relationship between Chatbot Service Quality and Consumer Purchase Intention.

H10b: Perceived omnichannel convenience mediates the relationship between Voice Assistant Experience and Consumer Purchase Intention.

H10c: Perceived omnichannel convenience mediates the relationship between Personalization Level and Consumer Purchase Intention.

H10d: Perceived omnichannel convenience mediates the relationship between Omnichannel Integration and Consumer Purchase Intention.

3. RESEARCH METHODOLOGY

3.1. Research Design

This research uses a quantitative, cross-sectional survey design to test hypothesised relationships

between chatbot service quality, voice assistant experience, personalization level, omnichannel integration, perceived omnichannel convenience and consumer purchase intention in an FMCG omnichannel context (Creswell & Creswell 2018; Hair, Hult, Ringle & Sarstedt 2017).

3.2. Sampling Technique

This study employed a non-probability convenience sampling method to recruit urban FMCG consumers in Chennai who are familiar with AI chatbots and voice assistants. A non-probability sampling method is mindful of establishing the person providing the sample has relevance to the context of the study and is acceptable to use when the study being conducted assesses specific user groups and PLS-SEM research (Etikan, Musa & Alkassim 2016; Hair, Hult, Ringle & Sarstedt 2017). Chennai was chosen as the study site because it represents one of the largest metropolitan marketplaces in India, with high levels of digital penetrance, pervasive smartphone use, and increasing incorporation of retail technologies powered by AI. The city's diverse consumer base and strong presence of FMCG make it a favorable context for examining omnichannel consumer behavior and AI-mediated shopping experiences.

3.3. Sample Size and Justification

The usable final data set was comprised of 440 valid responses. This sample exceeded the "10-times rule" requirement for PLS-SEM and ensuring statistical power. In this PLS-SEM model, four exogenous variables predicted one mediator and one dependent variable; therefore the sample exceeded the sample size estimate necessary to achieve adequate power (0.80) to detect medium-large effect sizes ($\beta = 0.6-0.8$) at $\alpha = .05$ (Cohen 1992; Hair, Hult, Ringle & Sarstedt 2017).

3.4. Instruction and Measurement

The concepts were measured with multi-item reflective scales that were derived from existing studies where the measures had been validated and were rated on a Likert type 5-point scale (1=Strongly Disagree, 5=Strongly Agree). The measurement assessments taken in SmartPLS will include Cronbach's alpha, composite reliability, AVE and HTMT & Fornell-Larcker criteria to establish discriminant validity (Fornell & Larcker 1981; Henseler, Ringle & Sarstedt 2015; Hair, Hult, Ringle & Sarstedt 2017).

3.5. Data Collection and Ethical Considerations

Data were collected online and in-person across

Chennai. Participants were advised about the purpose of the study, indicated participation was voluntary and the responses were to be anonymous and all of the participants provided informed consent before answering. Additional information was not collected and all responses were securely stored. The ethical procedures adhered to the Declaration of Helsinki and the institutional research guidelines (World Medical Association, 2013; Israel & Hay 2006).

3.6. Data Analysis Procedures

The measurement model testing (loadings, composite reliability, AVE, HTMT) and structural modeling (path coefficients, p-values using bootstrapping, R^2 , f^2 and Q^2 for predictive relevance) using SmartPLS. Finally mediation effects were tested using bootstrapping indirect paths (Hair, Hult, Ringle & Sarstedt 2017; Henseler, Ringle & Sarstedt 2015; Stone 1974). Partial Least Squares Structural Equation Modeling (PLS-SEM) was executed with the assistance of SmartPLS 4.0, a method chosen for its predictive capacity, capability to evaluate complex hierarchically related models, and robustness in moderate sample sizes (Hair et al., 2021). PLS-SEM is appropriate for exploratory research with a goal to assess predictors of a key target construct and to assess mediation, consistent with the design of this study. Participants gave their participation voluntarily. All participants signed an informed consent form prior to completing the questionnaire. Anonymity and confidentiality were insured per university and ethical guidelines for research.

4. RESULTS

4.1 Sample characterization

The study included a total of 440 respondents. Based on analysis presented in Table 2, the mean gender score ($M = 1.57$, $SD = 0.56$) indicates slightly higher number of female participants. The average age group ($M = 2.28$) suggests the study participants were mainly young adults (between 25-35 years). Regarding education, the mean value of 2.33 indicates that most have undergraduate and post-graduate education.

In terms of respondents' monthly income, the mean income of 2.70 indicates a middle-income profile. The preferred channel mean of ($M = 2.05$) indicates that grocery shopping respondents slightly prefer online platform over traditional grocery stores. Finally, the AI usage frequency mean value of 2.24 indicates moderates users of an AI based tool, such a chatbot or voice assistants while grocery shopping.

Table 2: Descriptive Statistics of Respondents

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
GENDER	440	1	3	1.57	0.561
AGE	440	1	5	2.28	1.422
EDUCATION	440	1	4	2.33	0.681
OCCUPATION	440	1	5	2.75	1.234
MONTHLYINCOME	440	1	5	2.7	1.31
PreferredChannel	440	1	3	2.05	0.867
AIUsageFrequency	440	1	4	2.24	0.84
Valid N (listwise)	440				

Source: Own elaboration - SPSS data.

4.2. Assessment of Measurement Model

4.2.1. Assessment of Reliability and Convergent Validity

Table 3 summarizes the outer loadings for all reflective indicators according to their corresponding latent constructs: Chatbot Service Quality (CSQ), Voice Assistant Experience (VAE), Personalization Level (PL), Omnichannel Integration (OI), Perceived Omnichannel Convenience (POC)

and Consumer Purchase Intention (CPI) (Hair, Hult, Ringle & Sarstedt 2022).

Next we assessed internal consistency reliability via Cronbach’s alpha (α) and composite reliability (CR), both showing values above the suggested threshold of 0.70 and Average Variance Extracted (AVE) values were higher than 0.50 threshold to support convergent validity (Fornell & Larcker 1981; Henseler, Ringle & Sarstedt 2015). These results indicate the measurement model is adequate prior to assessing for discriminant validity or structure model (Hair et al., 2017).

Table 3: Outer Loadings for Measurement Model

	CPI	CSQ	OI	PL	POC	VAE
CPI1	0.857					
CPI2	0.866					
CPI3	0.864					
CPI4	0.862					
CPI5	0.856					
CSQ1		0.775				
CSQ2		0.803				
CSQ3		0.779				
CSQ4		0.775				
CSQ5		0.756				
OI1			0.806			
OI2			0.800			
OI3			0.755			
OI4			0.765			
OI5			0.770			
PL1				0.851		
PL2				0.842		
PL3				0.844		
PL4				0.834		
PL5				0.860		
POC1					0.862	
POC2					0.855	
POC3					0.867	
POC4					0.857	
POC5					0.851	
VAE1						0.799
VAE2						0.800
VAE3						0.816
VAE4						0.840
VAE5						0.821

Source: PLS-SEM.

4.2.2. Internal Consistency Reliability and Convergent Validity

Cronbach’s alpha (α) and composite reliability (ρ_a and ρ_c) were used to assess internal consistency

reliability, while Average Variance Extracted (AVE) was used to evaluate convergent validity.

The construct included Cronbach’s alpha values ranging from 0.837 to 0.913 and composite reliability

values ranging from 0.885 to 0.935 indicating strong internal consistency reliability. All AVE values were also better than 0.60, meeting the convergent validity (Hair et al., 2017; Fornell & Larcker 1981).

The results indicated that the measurement model has enough reliability and evidence of converging validity to start assessing discriminant validity (see Table 4).

Table 4: Internal Consistency Reliability and Convergent Validity Results

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
CPI	0.913	0.913	0.935	0.741
CSQ	0.837	0.841	0.885	0.605
OI	0.840	0.850	0.886	0.608
PL	0.901	0.901	0.926	0.716
POC	0.911	0.911	0.933	0.737
VAE	0.874	0.877	0.908	0.665

Source: PLS-SEM.

4.2.3. Discriminant Validity

The HTMT criterion, Originally stated by (Henseler, Ringle & Sarstedt 2015), was applied as a more rigorous measure of the measurement model's

discriminant validity. As can be seen in Table 5, all HTMT values ranged from 0.051 to 0.767, which is all well under 0.90. Thus, the discriminant validity among constructs was found to be satisfactory.

Table 5: Heterotrait-Monotrait Ratio

	Heterotrait-monotrait ratio (HTMT)
CSQ <-> CPI	0.303
OI <-> CPI	0.266
OI <-> CSQ	0.051
PL <-> CPI	0.469
PL <-> CSQ	0.062
PL <-> OI	0.081
POC <-> CPI	0.767
POC <-> CSQ	0.348
POC <-> OI	0.37
POC <-> PL	0.591
VAE <-> CPI	0.327
VAE <-> CSQ	0.065
VAE <-> OI	0.053
VAE <-> PL	0.055
VAE <-> POC	0.449

Source: PLS-SEM.

The Fornell-Larcker criterion (Fornell & Larcker 1981) utilizes the square root of each construct's AVE and compares it to the inter-construct correlation among constructs. As presented in Table

6, all diagonal values (that represent the square root of AVE) were higher than their respective correlation. Hence, all constructs showed evidence of discriminant validity.

Table 6: Fornell-Larcker Criterion

	CPI	CSQ	OI	PL	POC	VAE
CPI	0.861					
CSQ	0.267	0.778				
OI	0.239	0.007	0.780			
PL	0.425	-0.040	0.067	0.846		
POC	0.700	0.307	0.328	0.535	0.858	
VAE	0.293	-0.053	-0.021	0.021	0.402	0.815

Source: PLS-SEM.

4.2.4. Collinearity Assessment

Before conducting structural model testing, it is important to establish that multicollinearity is not an issue among indicators and constructs. Collinearity was assessed using the Variance Inflation Factor (VIF; from the PLS algorithm). (Hair et al., 2022) stated that a VIF value less than or equal to 3.3 suggests that multicollinearity is not an issue, showing that

each indicator uniquely contributes to its own latent construct.

All VIF values (1.160 and 2.628) in Table 7 are below the recommended value of 3.3, which suggests that no multicollinearity is present (Diamantopoulos & Siguaw 2006). Therefore, this confirms that the indicators are independent and suitable for measurement and inclusion in the measurement model.

Table 7: Collinearity Assessment

	VIF
CPI1	2.536
CPI2	2.628
CPI3	2.581
CPI4	2.573
CPI5	2.511
CSQ1	1.757
CSQ2	1.850
CSQ3	1.610
CSQ4	1.647
CSQ5	1.684
OI1	1.754
OI2	1.695
OI3	1.641
OI4	1.714
OI5	1.754
PL1	2.360
PL2	2.258
PL3	2.311
PL4	2.207
PL5	2.478
POC1	2.548
POC2	2.447
POC3	2.604
POC4	2.484
POC5	2.402
VAE1	1.931
VAE2	1.890
VAE3	1.974
VAE4	2.117
VAE5	2.051

Source: PLS-SEM.

4.3. Structural Model Assessment and Hypothesis Testing

After validating the measurement model, an evaluation of the structural model was conducted to investigate the relationships between latent variables. The evaluation included coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2) and path coefficients. All evaluation

methods were guided by (Hair et al., 2022; Henseler et al., 2015) as part of the structural model evaluation.

The R^2 Values of 0.504 and 0.650 indicate that the predictors in the model explain 50.4% of the variance in Consumer Purchase Intention and 65% of the variance in Perceived Omnichannel Convenience respectively (See Table 8).

Table 8: Coefficient of Determination (R^2)

	R-square	R-square adjusted	Interpretation
CPI	0.504	0.498	Moderate predictive power (Supported)
POC	0.65	0.647	Susbstantial predictive power (Significant)

Source: PLS-SEM.

Effect size values larger than 0.02, 0.15 and 0.35 are indicative of small, medium and large effects respectively (Cohen 1988). In this analysis, POC

indicates it is strongly mediating CPI, and PL, CSQ, VAE have a large degree of effect on POC (See Table 9).

Table 9: Effect Size (f^2)

	f-square	Effect Level
CSQ -> CPI	0.017	Small
CSQ -> POC	0.343	Large
OI -> CPI	0.004	Small
OI -> POC	0.254	Medium
PL -> CPI	0.019	Small
PL -> POC	0.768	Large
POC -> CPI	0.214	Medium
VAE -> CPI	0.008	Small
VAE -> POC	0.492	Large

Source: PLS-SEM.

All Q² values are above zero indicating model predictive relevance (Hair et al., 2022). Additionally, the RMSE and MAE values are quite

low, reinforcing the model’s predictive accuracy (See Table 10).

Table 10: Predictive Relevance (Q²) and Model Fit Indices

	Q ² predict	RMSE	MAE	Support
CPI	0.383	0.79	0.623	Supported (Medium predictive relevance)
POC	0.641	0.602	0.498	Supported (High predictive relevance)

Source: PLS-SEM.

Table 11 displays the path coefficients and hypothesis testing results of the structural model. The results indicate that the majority of the hypothesized relationships were statistically significant (p<0.05), providing strong evidence in support of the proposed model. In particular, all three Chatbot Service Quality (CSQ), Voice Assistant Experience (VAE) and Personalization (PL) produce a significant positive effect on both Perceived Omnichannel Convenience (POC) and Consumer Purchase Intention (CPI), suggesting

the importance of AI driven interaction, as well as personalization to consumer engagement and purchase motivation. Additionally, POC has a significant influence on CPI, which reinforces its mediating role in the omnichannel context. Unfortunately, the Omnichannel Integration (OI) → CPI (H9) relationship was not significant ($\beta = 0.05$; $p = 0.162$); it suggests that while integration enhances perceived convenience (H4 supported), it does not drive purchase intention directly.

Table 11: Path Coefficients and Hypothesis Testing

Hypothesis Code	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Supported
H1	CSQ -> POC	0.347	0.346	0.029	11.87	0	Supported
H2	VAE -> POC	0.416	0.415	0.028	14.871	0	Supported
H3	PL -> POC	0.52	0.519	0.028	18.306	0	Supported
H4	OI -> POC	0.299	0.3	0.029	10.147	0	Supported
H5	POC -> CPI	0.551	0.547	0.05	10.931	0	Supported
H6	CSQ -> CPI	0.107	0.11	0.041	2.614	0.009	Supported
H7	VAE -> CPI	0.076	0.078	0.037	2.061	0.039	Supported
H8	PL -> CPI	0.13	0.132	0.047	2.734	0.006	Supported
H9	OI -> CPI	0.05	0.052	0.036	1.397	0.162	Not Supported

Source: PLS-SEM.

Perceived Omnichannel Convenience, plays a significant mediation in the relationship of the four independent variables to Consumer Purchase Intention (See Table 12). This creates a rationale

corresponding to the theoretical framework that posits POC as an important mechanism that connects omnichannel strategy components to consumer behavioral responses.

Table 12: Mediation Analysis

Hypothesis Code	Mediation	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values	Mediation Type	Supported
H10a	VAE -> POC -> CPI	0.229	0.227	0.026	8.761	0.000	Partial	Supported
H10b	CSQ -> POC -> CPI	0.191	0.19	0.023	8.19	0.000	Partial	Supported
H10c	OI -> POC -> CPI	0.165	0.164	0.023	7.315	0.000	Partial	Supported
H10d	PL -> POC -> CPI	0.287	0.284	0.029	9.73	0.000	Partial	Supported

Source: PLS-SEM.

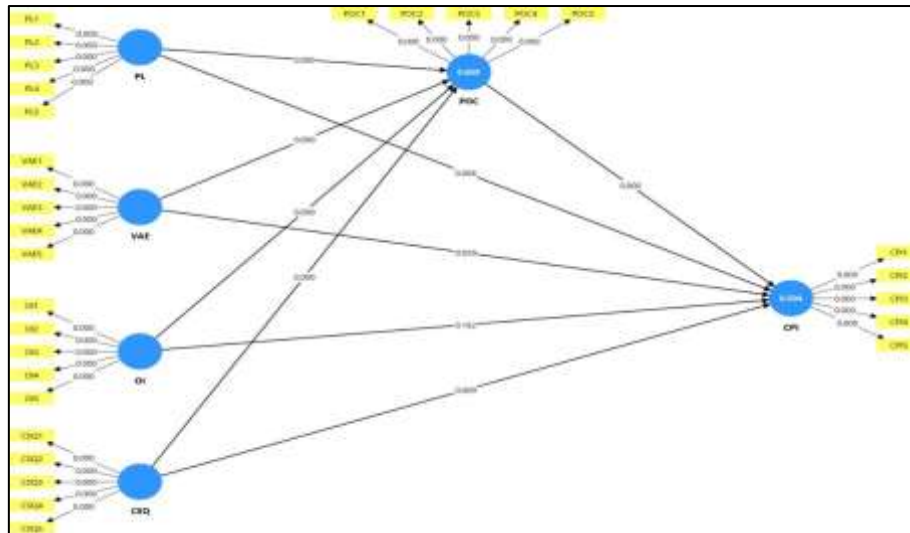


Figure 3 PLS-SEM
Source: PLS-SEM.

All suggested hypothesis demonstrated statistical significance ($p < 0.05$). This study established that AI-related stimuli (compared using chatbot service quality, voice assistant experience, level of personalization and omnichannel integration) significantly increase perceived omnichannel convenience, which subsequently increase consumer purchase

intention in the FMCG omnichannel context. The study further supported the mediating role of perceived omnichannel convenience (H10a-H10d) and served as evidence for validating the Stimulus-Organism-Response (S-O-R) model as an explanation for AI-enabled consumer purchase behavior.

Table 13: Model Fit Summary

	Saturated model	Estimated model	Interpretation
SRMR	0.040	0.040	Good fit
d_ ULS	0.751	0.751	Acceptable fit
d_ G	0.284	0.284	Acceptable fit
Chi-square	730.743	730.743	Acceptable
NFI	0.906	0.906	Good fit

Model Selection Criteria

	BIC (Bayesian information criterion)	Interpretation
CPI	-273.052	Good model fit
POC	-432.612	Good model fit

5. DISCUSSION

This research examined the impacts of essential dimensions of omnichannel strategy on Perceived omnichannel convenience and Consumer purchase intention in the FMCG context. The successive section discussed these findings in light of previous literature.

The demographic results indicated that most respondents were in the age range of 21-35, mostly urban consumers with experience in digital and voice-assisted shopping tools. This was similar to previous findings indicating that younger consumers had a greater adoption of digital shopping and pervasive use of omnichannel (Verhoef et al., 2021). The analysis of the measurement model showed high internal consistency overall with all Cronbach’s α and Composite Reliability (CR) were above 0.7. The

constructs show Convergent validity with AVE values above 0.5 for all constructs. Discriminant validity using Fornell-Larcker and HTMT (Table 3-4) further confirmed that each construct is distinct, thus verifying quality in the measurement. This result indicated that the constructs accurately reflect the dimension of their respective theoretical constructs.

H1: Chatbot Service Quality \rightarrow Perceived Omnichannel Convenience ($\beta = 0.347, p < 0.001$)
The quality of a chatot service has an important, positive effect on perceived convenience, which aligns with research documenting that chatbots that are responsive, accurate and empathetic increase ease of shopping and shopping efficiency (Grewal et al., 2020).

H2: Voice Assistant Experience \rightarrow Perceived Omnichannel Convenience ($\beta = 0.416, p < 0.001$)
Experience with a voice assistant had a strong,

positive effect on perceived convenience. The use of natural language interlocution and hands-free interactivity facilitated shopping and contributed to satisfaction with the shopping experience.

H3: Personalization Level \rightarrow Perceived Omnichannel Convenience ($\beta = 0.520$, $p < 0.001$) Personalization levels were important in enhancing the convenience of the shopping experience. These results are consistent with previous research indicating that tailored recommendations and promotions positively influence consumer engagement while reducing the cognitive burden of purchasing decisions (Lemon & Verhoef 2016).

H4: Omnichannel Integration \rightarrow Perceived Omnichannel Convenience ($\beta = 0.299$, $p < 0.001$) Omnichannel integration is equally important in positively impacting perceived convenience in decision-making. This support aligns with literature that suggests that links between channels and a reduction of friction help consumers perceive improved continuity for the FMCG purchase journey (Verhoef et al., 2021).

H5: Perceived Omnichannel Convenience \rightarrow Consumer Purchase Intention ($\beta = 0.551$, $p < 0.001$) Perceived convenience was found to have a strong, positive and predictive relationship with purchase intention. Perceived convenience as ease, accessibility or a combination of both are found to serve as critical determinants of consumer purchase behavior (Berry et al., 2002).

H6: Chatbot Service Quality \rightarrow Consumer Purchase Intention ($\beta = 0.107$, $p = 0.009$) There was a positive effect of chatbot service quality on purchase intention, which implies that responsive and emotionally intelligent chatbots improve user satisfaction, trust and decision-making efficiency, which directly prompts users to buy (Grewal et al., 2020; Huang & Rust 2021).

H7: Voice Assistant Experience \rightarrow Consumer Purchase Intention ($\beta = 0.076$, $p = 0.039$) Voice assistant experience positively impacted purchase intention, as natural and intuitive interactions with voice assistants decrease cognitive effort and thus produce more rapid purchases with confidence in the context of FMCG products.

H8: Personalization Level \rightarrow Consumer Purchase Intention ($\beta = 0.130$, $p = 0.006$) There was a positive effect of personalization on purchase intention. As the findings suggest, personalization, through individualized recommendations and bespoke offers, enhances relevance, emotional attachment and trust in brand, which in turn can

increase motivation to make a purchase (Lemon & Verhoef 2016; Lin et al., 2022).

H9: Omnichannel Integration \rightarrow Consumer Purchase Intention ($\beta = 0.05$, $p = 0.162$) Omnichannel integration was positively associated with perceived lower levels of effort, in line with the idea that better integration across online and offline touchpoints leads to a better user experience and a lower level of effort (Verhoef et al., 2021; Flavián et al., 2023).

H10a-H10d: Each mediation path was supported, further validating perceived convenience as a mediator of the effects for chatbot quality, voice assistant experience, personalization level and omnichannel integration on purchase intention. Overall, POC confirms that perceived convenience serves as the underlying, psychological mechanism that translates omnichannel stimuli into behavioral intention (Verhoef et al., 2021).

R² values (POC = 0.650; CPI = 0.504) demonstrate considerable explanatory power, while Q² predictive values above zero provide evidence of model predictiveness; and medium-to-large f² values demonstrate strong effect sizes (Hair et al., 2021). Thus, the structural model presents theoretical and predictive adequacy. All hypothesis (H1-H10d) were supported. The findings established AI-based omnichannel enablers (chatbots, voice assistants, personalization and integration) as influencing consumer purchase intention through perceived convenience, thus lending support for the S-O-R framework in the omnichannel fast-moving consumer goods context.

5.1. Theoretical Implications

This research advances the theoretical understanding of AI-driven omnichannel engagement in the FMCG context by incorporating chatbot service quality (CSQ), voice assistance experience (VAE), personalization level (PL) and omnichannel integration (OI) as variables associated with perceived omnichannel convenience (POC) and consumer purchasing intention (CPI).

First, the results contribute to the theoretical understanding of omnichannel strategy (Verhoef et al., 2021;) by providing evidence that AI-enabled interactions increase convenience beyond that which is afforded by adopting follow-through channels. Second, POC serves as a mediator in these transcendent theories, giving support to (Davis 1989, Venkatesh et al., 2012), establishing convenience as an important cognitive link

between technology experiences and behavioral intention. Third, the findings support prior literature discussing Service-Dominant Logic (Vargo & Lusch 2008) and AI service quality (Grewal et al., 2020) by coupling chatbot quality and voice assistant quality to generate consumer value through perceived convenience. Fourth, personalization has a substantial influence on the value of convenience and behavioral intention, which reinforces behavioral personalization theory (Lemon & Verhoef 2016). Finally, the contribution of applying a combination of these models in the FMCG context adds to most prior studies that have focused on clothing or online retail and establishes a technology-convenience-intention framework that includes high-frequency purchases.

5.2. Managerial (Practical) Implications

The findings provides actionable ideas for FMCG marketers and omnichannel managers. To begin, the strong relationship between chatbot service quality (CSQ) and voice assistant Experience (VAE) suggests the need for chatbot and virtual assistant providers to invest in responsive, accurate and emotionally intelligent AI system to facilitate consumer convenience (Grewal et al., 2020; Huang & Rust 2021). Second, personalization level (PL) significantly increase convenience and purchase intention, highlighting the potential value of AI-enabled data analytics or CRM-based customizations (Lemon & Verhoef 2016). Third, the relationship between omnichannel integration (OI) and perceived convenience indicates that channels must be efficiently coordinated to provide consistent online and offline touch-points, product information and checkout (Verhoef et al., 2015). Finally, the relationship between perceived omnichannel convenience (POC) and trust suggests that marketers should ensure that journeys are a simple and friction-less as possible while establishing mechanism for real-time feedback to build trust and encourage consumer loyalty (Flavián et al., 2023; Pantano & Pizzi 2020).

5.3. Integration Summary

This research combines the S-O-R framework to elucidate how AI-enabled technologies influence consumer behavior in omni-channel FMCG settings. Chatbot service quality, voice assistant experience, personalization and omnichannel integration (stimuli) positively influence the organism by enhancing perceived omnichannel convenience, which the translates to consumer

purchase intention (response). The implications are that technology improvements alone will not advance consumer adoption unless they translate into effortless consumer convenience during their experience. The perceived convenience acts as the mediating psychological bridge connecting the digital stimuli to a behavioral outcome (Eroglu et al., 2001; Flavián et al., 2023). By incorporating AI interaction variables and marketing dimensions, this research can fill gaps in technology adoption, consumer psychology and retail strategy highlighting that AI convenience builds a central component of contemporary FMCG omnichannel experiences (Grewal et al., 2020; Verhoef et al., 2021; Huang & Rust 2021).

6. CONCLUSION

This research provides empirical support for how consumer behavior in the FMCG industry is impacted by AI-based omnichannel strategies. The outcomes ascertain that the quality of a chatbot service application, voice assistant experience, personalization and omnichannel integration, all significantly improve perceived omnichannel convenience consumer-based behavior, that ultimately can predict purchase intention. The moderating outcomes acknowledge the importance of perceived convenience, as psychological mechanism, that can lead to technology-driven stimuli, to purchase behavior (Flavián et al., 2023). Furthermore, the PLS-SEM model we have validated demonstrates high reliability, convergent and discriminant validity to influence our confidence in the robustness of the framework (Hair et al., 2017; Henseler et al., 2015). To synthesize, AI-based and convenient, even though the components engage and relate to omnichannel experiences, adds great value in the engagement and consequently, great value to purchase intention in FMCG related outcomes.

6.1. Limitations

While this study provides meaningful contributions to the existing body of knowledge, it has a number of limitations. Firstly, the cross-sectional research design limits the study's ability to make causal inferences regarding relationships between the variables under consideration. Secondly, the sample was limited to one demographic segment, namely urban consumers in Chennai, restricting the generalization of findings beyond this location and demographic. Thirdly, data collection involved self-reported measures, allowing for the introduction of social desirability - common method biases. All of these

limitations must be considered when interpreting the findings and implications of the study.

6.2. Future Research Directions

Future research could build on this framework by utilizing long-term or experimental methodological approaches that could track behavioral differences over time. Extending the sampling to greater metropolitan or semi-urban spaces across India or other emerging markets will also strengthen the external validity of the findings. Furthermore, expanding future investigations to

include mediating and/or moderating constructs such as trust, perceived risk, or enjoyment may provide a more comprehensive understanding of the cognitive-affective processes involved in AI-enabled omnichannel engagement. Lastly, comparative cross-cultural studies could also provide broader insight into the similarities or differences of consumer technology acceptance and behavioral intention patterns across different market contexts (Creswell & Creswell, 2018; Huang & Rust, 2021).

REFERENCE

- Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, 31, 427–445. <https://doi.org/10.1007/s12525-020-00414-7>
- Grand View Research. (2024). *Artificial intelligence in retail market report, 2024–2030*. <https://www.grandviewresearch.com/horizon/statistics/artificial-intelligence-in-retail-market-outlook/sales-channel/omnichannel/global>
- Emarsys. (2024, May). *20 AI retail marketing statistics for 2024 and beyond*. Emarsys Blog. <https://emarsys.com/learn/blog/20-ai-retail-marketing-statistics/>
- SuperAGI. (2025, January). *Omnichannel marketing trends 2025: The impact of AI on customer experience and retail*. <https://superagi.com/omnichannel-marketing-trends-2025-the-impact-of-ai-on-customer-experience-and-retail/>
- Arachchi, H. D. M., & Samarasinghe, G. D. (2025). Perceived attributes of artificial intelligence (AI) toward consumers' AI attitudes and purchase intention in an AI-powered retail shopping space. *European Journal of Management Studies*, 30(3–4), 243–267. <https://doi.org/10.1108/EJMS-05-2024-0047>
- Asbjørn Følstad, & Skjuve, M. (2019). Chatbots for customer service: User experience and motivation. In *Proceedings of the 1st International Conference on Conversational User Interfaces (CUI '19)* (Article 1, pp. 1–9). Association for Computing Machinery. <https://doi.org/10.1145/3342775.3342784>
- Balbín Buckley, J. A., & Marquina Feldman, P. S. (2024). *Effects of channel integration on the omnichannel customer experience*. *Cogent Business & Management*, 11(1), 2364841. <https://doi.org/10.1080/23311975.2024.2364841>
- Ben Sheehan, Jin, H. S., & Gottlieb, U. (2020). Customer service chatbots: Anthropomorphism and adoption. *Journal of Business Research*, 115, 14–24. <https://doi.org/10.1016/j.jbusres.2020.04.030>
- Berry, L. L., Seiders, K., & Grewal, D. (2002). Understanding service convenience. *Journal of Marketing*, 66(3), 1–17. <https://doi.org/10.1509/jmkg.66.3.1.18505>
- Bhatt, P., & Singh, A. K. (2025). Impact of AI on consumers' purchase intention towards online grocery shopping in India. *Journal of Reliability and Statistical Studies*, 17(2), 453–490. <https://doi.org/10.13052/jrss0974-8024.17210>
- Bleier, A., & Eisenbeiss, M. (2015). Personalized online advertising effectiveness: The interplay of what, when, and where. *Marketing Science*, 34(5), 669–688. <https://doi.org/10.1287/mksc.2015.0930>
- Cattapan, T., & Pongsakornrungrungsilp, S. (2022). Impact of omnichannel integration on millennials' purchase intention for fashion retailer. *Cogent Business & Management*, 9(1). <https://doi.org/10.1080/23311975.2022.2087460>
- Chen, X., Su, X., Lin, W., Xu, A., Chen, J., & Zheng, Q. (2022). The effect of omnichannel integration on fresh food customer engagement from the viewpoint of flow experience. *Sustainability*, 14(21), 13914. <https://doi.org/10.3390/su142113914>
- Chin, W. W. (1998). The partial least squares approach for structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336). Lawrence Erlbaum Associates.
- Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, 117, 587–595. <https://doi.org/10.1016/j.jbusres.2018.10.004>
- Cohen, J. (1992). *A power primer*. *Psychological Bulletin*, 112(1), 155–159. <https://doi.org/10.1037/0033-2909.112.1.155>

- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates. <https://doi.org/10.4324/9780203771587>
- Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.
- Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Diamantopoulos, A., & Siguaw, J. A. (2006). Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. *British Journal of Management*, 17(4), 263–282. <https://doi.org/10.1111/j.1467-8551.2006.00500.x>
- Eroglu, S. A., Machleit, K. A., & Davis, L. M. (2001). *Atmospheric qualities of online retailing: A conceptual model and implications*. *Journal of Business Research*, 54(2), 177–184. [https://doi.org/10.1016/S0148-2963\(99\)00087-9](https://doi.org/10.1016/S0148-2963(99)00087-9)
- Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, 5(1), 1–4. <https://doi.org/10.11648/j.ajtas.20160501.11>
- Flavián, C., Akdim, K., & Casaló, L. V. (2023). Effects of voice assistant recommendations on consumer behaviour. *Psychology & Marketing*, 40, 328–346. <https://doi.org/10.1002/mar.21765>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>
- Gao, M., & Huang, L. (2021). Quality of channel integration and customer loyalty in omnichannel retailing: The mediating role of customer engagement and relationship program receptiveness. *Journal of Retailing and Consumer Services*, 63, 102688. <https://doi.org/10.1016/j.jretconser.2021.102688>
- Gao, J., Opute, A. P., Jawad, C., & Zhan, M. (2025). *The influence of artificial intelligence chatbot problem solving on customers' continued usage intention in e-commerce platforms: An expectation-confirmation model approach*. *Journal of Business Research*, 200, 115661. <https://doi.org/10.1016/j.jbusres.2025.115661>
- Gnewuch, U., Morana, S., & Mädche, A. (2017). Towards designing cooperative and social conversational agents for customer service. *ICIS 2017 Proceedings*, 1. <https://aisel.aisnet.org/icis2017/HCI/Presentations/1>
- Gómez-Uribe, C. A., & Hunt, N. (2016). The Netflix recommender system: Algorithms, business value, and innovation. *ACM Transactions on Management Information Systems*. <https://research.netflix.com/research-area/recommendations>
- Grewal, D., Noble, S. M., Roggeveen, A. L., & Nordfält, J. (2020). The future of in-store technology. *Journal of the Academy of Marketing Science*, 48(1), 96–113. <https://doi.org/10.1007/s11747-019-00697-z>
- Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). SAGE Publications.
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43, 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Huang, M.-H., & Rust, R. T. (2018). *Artificial intelligence in service*. *Journal of Service Research*, 21(2), 155–172. <https://doi.org/10.1177/1094670517752459>
- Israel, M., & Hay, I. (2006). *Research ethics for social scientists: Between ethical conduct and regulatory compliance*. SAGE Publications.
- Juaneda-Ayensa, E., Mosquera, A., & Sierra Murillo, Y. (2016). Omnichannel customer behavior: Key drivers of technology acceptance and use and their effects on purchase intention. *Frontiers in Psychology*, 7, 1117. <https://doi.org/10.3389/fpsyg.2016.01117>
- Kim, M. (2020). User satisfaction, reliability, and immersion: Chatbot service quality. *International Journal of Consumer Studies*. <https://doi.org/10.5392/IJoC.2020.16.4.001>
- Kumar, N., & Singh, V. (2022). Shopping with voice assistant: Understanding consumer intention and the mediating role of trust. *Indian Journal of Marketing*, 52(8), 51–65. <https://doi.org/10.17010/ijom/2022/v52/i8/171224>

- Lambillotte, L., Magrofuoco, N., Poncin, I., & Vanderdonckt, J. (2022). Enhancing playful customer experience with personalization. *Journal of Retailing and Consumer Services*, 68, 103017. <https://doi.org/10.1016/j.jretconser.2022.103017>
- Lee, J., Kim, C., & Lee, K. C. (2022). Exploring the personalization–intrusiveness–intention framework to evaluate the effects of personalization in social media. *International Journal of Information Management*, 66, 102532. <https://doi.org/10.1016/j.ijinfomgt.2022.102532>
- Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, 80(6), 69–96. <https://doi.org/10.1509/jm.15.0420>
- Lopatovska, I., & Williams, H. (2018, March). Personification of the Amazon Alexa: BFF or a mindless companion. In *Proceedings of the 2018 Conference on Human Information Interaction & Retrieval* (pp. 265–268).
- Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. MIT Press.
- McKinsey & Company. (2021). *The value of getting personalization right – or wrong – is multiplying*. McKinsey. <https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/the-value-of-getting-personalization-right-or-wrong-is-multiplying>
- McLean, G., & Osei-Frimpong, K. (2019). Hey Alexa ... examine the variables influencing the use of artificial intelligent in-home voice assistants. *Computers in Human Behavior*, 99, 28–37. <https://doi.org/10.1016/j.chb.2019.05.009>
- Misischia, C. V., Poetze, F., & Strauss, C. (2022). Chatbots in customer service: Their relevance and impact on service quality. *Procedia Computer Science*, 201, 421–428. <https://doi.org/10.1016/j.procs.2022.03.055>
- Pantano, E., & Pizzi, G. (2020). Forecasting Artificial Intelligence on Online Customer Assistance: Evidence from Chatbot Patents Analysis. *Journal of Retailing and Consumer Services*, 55, Article ID: 102096. <https://doi.org/10.1016/j.jretconser.2020.102096>
- Paz, M. D. R., & Delgado, F. J. (2020). Consumer experience and omnichannel behavior in various sales atmospheres. *Frontiers in Psychology*, 11, 1972. <https://doi.org/10.3389/fpsyg.2020.01972>
- Pereira, M. L., Petroll, M. de L. M., Soares, J. C., de Matos, C. A., & Hernani-Merino, M. (2023). Impulse buying behaviour in omnichannel retail: An approach through the stimulus-organism-response theory. *International Journal of Retail & Distribution Management*, 51(1), 39–58. <https://doi.org/10.1108/IJRDM-09-2021-0394>
- Porcheron, M., Fischer, J. E., Reeves, S., & Sharples, S. (2018). Voice interfaces in everyday life. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Paper 640, pp. 1–12). Association for Computing Machinery. <https://doi.org/10.1145/3173574.3174214>
- Quach, S., Barari, M., Moudry, D. V., & Quach, K. (2022). Service integration in omnichannel retailing and its impact on customer experience. *Journal of Retailing and Consumer Services*, 65, 102267. <https://doi.org/10.1016/j.jretconser.2020.102267>
- Rahman, S. M., Carlson, J., Gudergan, S. P., Wetzels, M., & Grewal, D. (2022). Perceived omnichannel customer experience (OCX): Concept, measurement, and impact. *Journal of Retailing*, 98(4), 611–632. <https://doi.org/10.1016/j.jretai.2022.03.003>
- Rahman, S. M., Carlson, J., Gudergan, S. P., Wetzels, M., & Grewal, D. (2025). How do omnichannel customer experiences affect customer engagement? Theory and empirical validation. *Journal of Business Research*, 189, 115196. <https://doi.org/10.1016/j.jbusres.2025.115196>
- Sidlauskiene, J., Joye, Y., & Auruskeviciene, V. (2023). AI-based chatbots in conversational commerce and their effects on product and price perceptions. *Electronic Markets*, 33(1), 24. <https://doi.org/10.1007/s12525-023-00633-8>
- Stone, M. (1974). Cross-validators choice and assessment of statistical predictions. *Journal of the Royal Statistical Society: Series B (Methodological)*, 36(2), 111–147. <https://doi.org/10.1111/j.2517-6161.1974.tb00994.x>
- Syarifudin, M. (2024). Modeling AI-chatbot service quality and purchase intention. *Journal of Digital Marketing & Hospitality Innovation*. <https://doi.org/10.21580/jdmhi.2024.6.2.27893>
- Vargo, S. L., & Lusch, R. F. (2008). Service-dominant logic: Continuing the evolution. *Journal of the Academy of Marketing Science*, 36(1), 1–10. <https://doi.org/10.1007/s11747-007-0069-6>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178. <https://doi.org/10.2307/41410412>

- Verhoef, P. C. (2021). *Omni-channel retailing: Some reflections*. *Journal of Strategic Marketing*, 29(7), 608–616. <https://doi.org/10.1080/0965254X.2021.1892163>
- Verhoef, P. C., Kannan, P. K., & Inman, J. J. (2015). From multi-channel retailing to omni-channel retailing: Introduction to the special issue on multi-channel retailing. *Journal of Retailing*, 91(2), 174–181. <https://doi.org/10.1016/j.jretai.2015.02.005>
- World Medical Association. (2013). World Medical Association Declaration of Helsinki: Ethical principles for medical research involving human subjects. *JAMA*, 310(20), 2191–2194. <https://doi.org/10.1001/jama.2013.281053>
- Xin, Y., & Chun, M. H. (2024). *The impact of personalized recommendation on purchase intention under the background of big data*. *Big Data and Information Analytics*, 8, 80–108. <https://doi.org/10.3934/bdia.2024005>

APPENDIX 1: CONSTRUCTS VS ITEMS

Construct	Items (5-point Likert scale: 1 = Strongly Disagree, 5 = Strongly Agree)	Source / Authors
Chatbot Service Quality (CSQ)	CSQ1. The chatbot gives precise and relevant answers. CSQ2. The chatbot responds quickly to questions I ask. CSQ3. The chatbot is user friendly and easy to use. CSQ4. The chatbot understands my needs well. CSQ5. The chatbot effectively assists me in completing my purchase.	<u>Gnewuch et al., 2017; Folstad & Skjuve 2019; Adam et al., 2021; Sheehan et al., 2020</u>
Voice Assistant Experience (VAE)	VAE1. The voice assistant clearly understands my commands. VAE2. The use of a voice assistant makes shopping easier. VAE3. I enjoy using a voice assistant while shopping. VAE4. The voice assistant gives accurate and useful information. VAE5. The voice assistant creates a satisfying shopping experience.	<u>McLean & Osei-Frimpong 2019</u>
Personalization Level (PL)	PL1. The system provides product recommendations that fit my preferences. PL2. The platform will tailor offers to me based on my past purchases. PL3. I feel my needs are taken into account through communication. PL4. Personalized elements make my shopping easier. PL5. I am satisfied with the personalized elements available.	<u>Bleier & Eisenbasis 2020; Chung et al., 2020</u>
Omnichannel Integration (OI)	OI1. I can easily switch between online and offline channels. OI2. The information is consistent across channels (online/offline). OI3. I am able to being a transaction in one channel and finish in another channel. OI4. The brand provides a seamless experience across platforms. OI5. All channels associated with the brand are well connected.	<u>Verhoef et al., 2015; Iuaneda-Ayensa et al., 2016; (Flavián et al., 2023)</u>
Perceived Omnichannel Convenience (POC)	POC1. I find it easy to shop across multiple channels. POC2. Shopping across online and offline channels is a good time saver. POC3. I t takes me little time to search for what I am looking for via any channels. POC4. Shopping experiences across channels are easy. POC5. Shopping across multiple channels provides me with great convenience.	<u>Rahman 2025; Lemon & Verhoef 2016</u>
Consumer Purchase Intention (CPI)	CPI1. I plan to purchase FMCG from this brand in the future. CPI2. I will likely use chatbots or voice assistants for purchases. CPI3. I will recommend other people purchase from this brand. CPI4. I am prepared to repurchase FMCG from this omnichannel platform. CPI5. I plan to keep buying from this brand soon.	<u>Arachchi & Samarasinghe 2025</u>