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Examining the Role of Omnichannel Strategies in Shaping Shopping Intention and Customer Experience: Evidence from Indian Apparel Retail.

Ridhika Chatterjee[1], Dr. Manoj Mehrotra [2], Dr. Shubhendra Singh Parihar[3]
[1]Research Scholar, Faculty of Management, Dr. A.P.J. Abdul Kalam Technical University, Lucknow
[2]Professor, School of Management Sciences, Lucknow
[3]Professor, Jaipuria Institute of Management, Lucknow

ABSTRACT

As contemporary retail environments continue to evolve beyond the constraints of single channel operations, businesses are increasingly adopting omnichannel strategies that seamlessly integrate digital platforms such as social media and online marketplaces with traditional brick-and-mortar stores. This integrated approach aims to create a cohesive and consistent customer journey, enabling consumers to interact with brands across multiple touchpoints with minimal friction. However, despite the growing prevalence of omnichannel retailing, the underlying mechanisms through which such integration shapes customer behavior, influences purchase intentions, and enhances overall satisfaction remain insufficiently explored.

Addressing this gap, the present study investigates the behavioral and experiential outcomes associated with omnichannel retail integration. Specifically, it seeks to identify the key determinants that drive consumers to adopt multi-channel shopping practices and to examine how such adoption translates into enriched customer experiences. Grounded in an integrated theoretical framework combining the Stimulus-Organism-Response (S-O-R) model with the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), the study employs Partial Least Squares Structural Equation Modelling (PLS-SEM) to empirically test a conceptual model using data collected from 506 validated respondents. Data was gathered through a combination of online and offline survey methods, with systematic sampling ensuring that all participants qualified as omnichannel shoppers' individuals actively engaging with multiple channels throughout their purchase journey.

The empirical findings reveal four critical drivers influencing omnichannel adoption: perceived value, social influence, perceived risk, and Artificial intelligence enabled service quality. Each of these factors exerts a distinct and significant impact on consumers' willingness to engage across multiple retail channels. Perceived value enhances adoption by emphasizing convenience, personalization, and efficiency, while social influence underscores the role of peer recommendations and digital communities in shaping consumer decisions. AI-enabled service quality operationalized through chatbot responsiveness, personalization accuracy, and 24/7 availability emerges as a significant contemporary driver. Conversely, perceived risk introduces hesitation, particularly in contexts involving data security, product authenticity, and transaction reliability.

Furthermore, the study finds that omnichannel integration plays a significant mediating role between these antecedents and consumers' usage intentions. This highlights the importance of seamless channel coordination including human-AI service handoffs in translating consumer perceptions into actionable behavior. However, the relationship between omnichannel strategies and overall customer experience is found to be only partially mediated, suggesting that additional factors such as AI interaction quality, technological infrastructure, personalization capabilities, and post-purchase support may further influence customer satisfaction outcomes. Future research may explore additional moderating and mediating variables, including customer demographics, technological readiness, AI anxiety, and cultural factors, to develop a more comprehensive understanding of omnichannel retail effectiveness in the age of conversational commerce...

Keywords: Omnichannel Strategies, Customer experience, Usage intention, social influence, Perceived value, Channel integration, Chatbots, Artificial Intelligence

INTRODUCTION:

The proliferation of digital technology over the past two decades has fundamentally transformed consumer psychology and purchasing behaviour. The widespread adoption of smartphones and associated digital innovations has significantly reconfigured how customers engage with the retail environment (Agrawal & Gupta, 2023). This transformation was further accelerated by the COVID-19 pandemic, which acted as a catalyst for the rapid digitisation of commerce on a global scale. As economies transitioned from recovery to sustained growth, the structural reforms precipitated by the pandemic have exerted enduring influence on societal and commercial systems. The acceleration of online purchasing worldwide has underscored the imperative for nations to harness the benefits of digitisation equitably (UNCTAD, 2020).

Within this context, digital disruption has profoundly restructured the retailing landscape. One of the most significant manifestations of this disruption is the emergence of omnichannel retailing, a paradigm that has redefined consumer expectations and retail strategy alike (Riaz et al., 2021). Omnichannel retailing refers to a strategic approach wherein a retailer integrates all sales channels and customer touchpoints to deliver a seamless, unified shopping experience (Beck & Rygl, 2015). The term was first introduced by Rigby and Kirby (2011), who sought to transcend earlier frameworks such as multi-channel and cross-channel retailing. Under this paradigm, all available channels are leveraged collectively to shape consumer decision-making and facilitate an integrated retail experience across every point of interaction (Shen et al., 2018).

The Rise of Artificial intelligence enabled Touchpoints in Omnichannel Retailing

Since 2023, the retail landscape has witnessed an unprecedented acceleration in the deployment of artificial intelligence technologies across customer-facing channels. AI-powered chatbots, virtual shopping assistants, and generative AI recommendation engines have become integral components of the omnichannel ecosystem (Huang & Rust, 2024). These technologies enable retailers to provide 24/7 customer support, personalized product recommendations, and seamless handoffs between digital and physical channels. Research indicates that retailers implementing conversational AI have observed significant improvements in customer engagement, with chatbot interactions increasing conversion rates by 10–30% in fashion retail contexts (Luo et al., 2024). The integration of large language models (LLMs) into retail chatbots has transformed the quality of automated customer interactions. Contemporary AI assistants can understand nuanced queries, provide contextually relevant styling advice, track orders across channels, and facilitate returns functions that were previously confined to human agents (Grewal et al., 2024). Major Indian apparel retailers such as Myntra, Ajio, and Reliance Trends have deployed AI-powered virtual stylists and chatbots that assist customers in product discovery, size recommendations, and outfit coordination, thereby blurring the boundaries between online browsing and in-store consultation (Kumar et al., 2024). This technological evolution necessitates an updated theoretical understanding of how AI-enabled touchpoints influence omnichannel adoption and customer experience.

The emergence of generative AI has further disrupted traditional retail paradigms. Tools powered by models such as GPT-4, Gemini, and Claude enable retailers to create personalized marketing content, generate product descriptions at scale, and provide conversational shopping experiences that mimic human interaction (Davenport et al., 2024). In the Indian context, where linguistic diversity presents unique challenges, multilingual AI chatbots have enabled retailers to serve customers in Hindi, Tamil, Bengali, and other regional languages, thereby expanding the reach of omnichannel strategies to tier-2 and tier-3 cities (Shankar & Rishi, 2024).

Empirical evidence underscores the commercial significance of omnichannel ecosystems. Organisations that have successfully implemented such frameworks report a 250% increase in purchase frequency, a 13% rise in average order value, a 90% improvement in customer retention, and a 13.5% enhancement in engagement rates relative to single-channel approaches (Collins, 2019; McKinsey, 2024). Contemporary consumers routinely engage with multiple channels, including physical stores, e-commerce platforms, catalogues, social media, AI chatbots, voice assistants, call centres, kiosks, and networked devices, even within the course of a single transaction (Barwitz & Maas, 2018; Hossain et al., 2019; Flavián et al., 2024).

This study operates at three levels. The first level identifies the factors that drive consumers to purchase apparel on omnichannel platforms and the determinants responsible for omnichannel shopping intentions, with particular attention to AI-enabled service quality as an emerging antecedent. The second level explores the shopping journey that customers experience while using omnichannel platforms, including interactions with AI-powered touchpoints. The third level examines how omnichannel strategies mediate the relationship between shopping intention and customer experience. A conceptual model grounded in an integrated theoretical framework combining the Stimulus-Organism-Response (S-O-R) paradigm with the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is developed and tested using PLS-SEM.

Literature Review

Evolution of Retail Channels

The evolution of retail channels has been shaped by the progressive adoption of digital platforms and, more recently, by the exigencies of the global pandemic. Multi-channel retailing, an antecedent to omnichannel strategies, refers to a systematic approach in which retailers deploy and coordinate multiple channels to interact with target customers, with the overarching objective of enhancing customer value through relationship development and maintenance (Neslin et al., 2006). In practice, this involves making products available across a range of platforms and touchpoints, each operating with a degree of independence (Cao & Li, 2015).

Omnichannel retailing represents a more advanced and holistic evolution of the multi-channel model. It is defined as a retail strategy that integrates all available consumer-facing channels into a cohesive framework, thereby eliminating physical and operational barriers within the shopping journey and delivering a consistent, seamless experience (Beck & Rygl, 2015). Unlike multi-channel approaches, the omnichannel model ensures continuity of communication and experience across physical stores, e-commerce websites, mobile applications, and social media platforms and AI- powered conversational interfaces

Recent scholarship has expanded the conceptualization of omnichannel retailing to encompass what researchers' term "phygital" experiences the seamless blending of physical and digital touchpoints augmented by intelligent technologies (Pizzi et al., 2024). This evolution reflects the growing recognition that contemporary consumers do not distinguish between channels but rather expect unified experiences regardless of how they choose to interact with a brand (Verhoef et al., 2024)

Omnichannel Consumer Behaviour

A longitudinal research study by Sopadjieva et al. (2017) on 46,000 shoppers over a 14-month period revealed that omnichannel shoppers are more valuable across multiple dimensions. They spend an average of 4% more per in-store shopping occasion and 10% more online compared to single-channel customers. These consumers actively use digital applications to compare prices, retrieve coupons, and engage with in-store digital tools such as interactive catalogues, price checkers, and kiosks. The Buy Online, Pick Up in Store (BOPIS) model further illustrates how consumers blend physical and digital touchpoints within a single transaction.

Contemporary omnichannel consumers demonstrate a behaviour termed research shopping (Verhoef et al., 2007), wherein product research occurs on one channel while the final transaction takes place on another. Retailers leverage this behaviour to offer a seamless purchase journey regardless of whether the customer browses a web application, visits a physical store, or places an order via a social media platform. Extensive research by Briedis et al. (2021) explored channel equity and personalisation factors that drive consumers to search, evaluate, and purchase across channels in the apparel sector. More recently, research shopping has evolved to include AI-assisted product discovery, wherein consumers use chatbots and virtual assistants to gather information, compare options, and receive personalized recommendations before completing purchases through their preferred channel (Luo et al., 2024).

Recent studies have documented the emergence of "AI-first" shopping behaviours, particularly among Gen Z and millennial consumers, who demonstrate a preference for interacting with AI chatbots over traditional search interfaces or human customer service representatives (Ameen et al., 2024). This shift has profound implications for omnichannel strategy design, as retailers must now ensure that AI touchpoints are fully integrated into the broader channel ecosystem.

Artificial Intelligence and Chatbots in Omnichannel Retailing

The deployment of artificial intelligence in retail has progressed through several evolutionary stages. Early implementations focused on rule-based chatbots capable of handling simple queries and directing customers to appropriate resources. The advent of natural language processing (NLP) and machine learning enabled more sophisticated conversational agents that could understand context, learn from interactions, and provide increasingly relevant responses (Huang & Rust, 2021).

The release of advanced large language models (LLMs) beginning in 2022 marked a paradigm shift in conversational commerce. Contemporary AI assistants powered by models such as GPT-4, Claude, and Gemini can engage in nuanced, context-aware conversations that closely approximate human interaction quality (Davenport et al., 2024). In the retail context, these capabilities translate into virtual shopping assistants that can:

Understand complex, multi-part queries about product features, availability, and styling

Provide personalized recommendations based on stated preferences and inferred intent

Handle objections and provide persuasive responses similar to skilled human salespeople

Seamlessly hand off conversations to human agents when necessary

Maintain conversation context across multiple interactions and channels

Research by Luo et al. (2024) demonstrated that customers who interacted with AI chatbots during their shopping journey exhibited 15% higher conversion rates and 23% higher average order values compared to those who relied solely on self-service browsing. Importantly, these effects were most pronounced when the AI interaction was perceived as helpful and personalized rather than intrusive or generic.

The integration of generative AI into omnichannel retail has enabled new forms of customer engagement. Virtual try-on experiences powered by computer vision and AI allow customers to visualize how apparel items will look on their body type without visiting a physical store (Tan et al., 2024). AI-powered size recommendation engines analyze customer measurements, past purchase history, and return patterns to suggest optimal sizing, thereby reducing return rates and improving satisfaction (Kumar et al., 2024).

In the Indian apparel market, AI chatbots have proven particularly valuable in addressing the challenges of linguistic diversity and varying levels of digital literacy. Multilingual chatbots deployed by retailers such as Myntra and Flipkart Fashion can conduct conversations in multiple Indian languages, making omnichannel shopping accessible to consumers who may not be comfortable with English-language interfaces (Shankar & Rishi, 2024). This democratization of access has significant implications for expanding the omnichannel customer base beyond metropolitan centres.

Customer Experience in Omnichannel Retailing

According to Holbrook and Hirschman (1982), in-depth research on customer experience is essential to understand its full scope. Verhoef et al. (2009) define customer experience as encompassing the consumer's cognitive, sensory, relational, emotive, and behavioural responses to the retailer or brand. Companies have increasingly centred their competitive strategies on delivering superior customer experience (Bascur & Rusu, 2020). Customer experience in a retailing environment represents the co-creation between a customer (subject) and an experience provider (object), and forms the backbone of any omnichannel retailing model.

With advances in digital technology such as virtual reality, augmented reality, the metaverse, and AI-powered chatbots, many retailers are now embedding customer experience as a core component of their service offerings (Sachdeva & Goel, 2015). Managing customer experience in an omnichannel setting is challenging, as organisations must synchronise offline and online channels to deliver consistent service quality across every touchpoint.

Transition from Multi-Channel to Omnichannel

The transition from multi-channel to omnichannel retailing occurs incrementally across four stages identified by Cao and Li (2015) as Silo, Limited Integration, Moderate Integration, and Complete Integration. In the Silo stage, channels operate independently with no unified customer information. In the Limited Integration stage, brand consistency is maintained but customer data remains siloed. Moderate Integration introduces omnichannel strategies such as BOPIS, while Complete Integration delivers a fully seamless, customer-centric ecosystem with cross-channel data sharing and personalisation.

It is not straightforward for brick-and-mortar retailers to transition to omnichannel models, as it requires substantial investment in infrastructure, technology, human capital, and process redesign. Retailers may straddle multiple levels simultaneously, with different product categories, return policies, and shipment models operating at different levels of integration.

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Theoretical Framework

Stimulus-Organism-Response (S-O-R) Framework

The S-O-R framework, originally proposed by Mehrabian and Russell (1974), posits that environmental stimuli influence individuals' internal states (organism), which in turn drive behavioural responses. In the retail context, this framework has been widely applied to understand how store atmospherics, website design, and other external factors influence customer cognition, emotion, and ultimately, purchase behaviour (Eroglu et al., 2001).

In the present study, the S-O-R framework is adapted to the omnichannel context by positioning perceived value, perceived risk, social influence, and AI-enabled service quality as environmental stimuli. These factors represent the external conditions that customers encounter when engaging with omnichannel retail environments. Omnichannel shopping intention functions as the organism the internal psychological state that mediates between stimuli and response. Customer experience and continued usage behaviour represent the response outcomes.

Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)

While the S-O-R framework provides a general model for understanding environmental influences on behaviour, it offers limited guidance on the specific mechanisms through which technology-enabled touchpoints influence consumer adoption. To address this limitation, the present study integrates elements of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) proposed by Venkatesh et al. (2012).

UTAUT2 extends the original UTAUT model to consumer contexts by incorporating additional constructs relevant to voluntary technology adoption: hedonic motivation (the pleasure derived from using technology), price value (the cognitive trade-off between perceived benefits and monetary cost), and habit (the degree to which behaviour is performed automatically). The model also retains core UTAUT constructs including performance expectancy, effort expectancy, social influence, and facilitating conditions.

The integration of UTAUT2 into the present study's framework is particularly appropriate given the central role of technology specifically AI-enabled touchpoints in contemporary omnichannel retailing. UTAUT2 provides theoretical grounding for understanding how consumers evaluate and adopt AI-powered chatbots, virtual assistants, and other intelligent retail technologies. Key constructs from UTAUT2 inform the operationalization of AI-enabled service quality in the present study.

Technology Acceptance Model (TAM) and AI Acceptance

The Technology Acceptance Model (TAM), originally proposed by Davis (1989), remains one of the most influential frameworks for understanding technology adoption. TAM posits that perceived usefulness and perceived ease of use are the primary determinants of behavioural intention to use a technology. Subsequent extensions of TAM have incorporated additional factors such as trust, perceived enjoyment, and subjective norm.

Recent scholarship has adapted TAM to the specific context of AI acceptance, recognizing that consumer responses to intelligent systems may differ from responses to traditional technologies (Gursoy et al., 2019; Chi et al., 2024). AI acceptance research has identified several unique factors that influence willingness to engage with AI-powered services:

Perceived humanness: The degree to which the AI system is perceived as exhibiting human-like qualities

Perceived autonomy threat: Concerns about AI systems making decisions without adequate human oversight

Algorithm aversion/appreciation: Individual differences in willingness to rely on algorithmic recommendations

Hesitance to use Artificial Intelligence: Apprehension about interacting with AI systems because of security.

The present study incorporates insights from AI acceptance research by including AI-enabled service quality as a distinct antecedent of omnichannel shopping intention. This construct captures customers' perceptions of the quality, usefulness, and trustworthiness of AI-powered touchpoints within the omnichannel ecosystem.

Integrated Conceptual Framework

The present study proposes an integrated framework that combines the S-O-R paradigm with UTAUT2 and AI acceptance perspectives. This integration is warranted by the recognition that contemporary omnichannel retailing operates at the intersection of environmental design (captured by S-O-R), technology adoption (captured by UTAUT2), and AI-mediated service delivery (captured by AI acceptance research).

The integrated framework positions:

Stimuli: Perceived value, perceived risk, social influence, and AI-enabled service quality

Organism: Omnichannel shopping intention (cognitive and affective states)

Response: Customer experience

Omnichannel strategies (including BOPIS, BORIS, ship-from-store, and AI-enabled services) are introduced as a mediating mechanism between the organism (shopping intention) and response (customer experience). This positioning reflects the recognition that consumer intentions must be actualized through retailer-provided infrastructure and services.

Hypothesis Development

Perceived Value and Omnichannel Shopping Intention

Perceived value is a multidimensional concept representing a customer's overall assessment of the net worth of a service, based on what is received (benefits) relative to what is sacrificed (costs) (Parasuraman, 1997). Monroe (1990, p. 46) defines perceived value as a trade-off between the quality or benefits perceived relative to the price paid. In an omnichannel context, perceived value can be increased by expanding channel options and creating a seamless shopping experience. The extant literature confirms that higher perceived value is positively associated with increased usage of multiple retail channels (Gan & Wang, 2017).

H1**:** Perceived value has a significant positive influence on omnichannel shopping intention.

Perceived Risk and Omnichannel Shopping Intention

Perceived risk refers to the overall assessment of uncertainty and potentially adverse consequences during the shopping process. Prior studies confirm that perceived risk affects customers' channel preferences (Herhausen et al., 2015). In the context of omnichannel retailing, consumers face performance risk, financial risk, and privacy risk when interacting across multiple platforms (Piotrowicz & Cuthbertson, 2014). A qualitative study by Kazancoglu and Aydin (2018) revealed that customers perceive omnichannel shopping as risky due to its novelty. Channel transparency and uniformity can mitigate perceived risk, thereby improving channel selection intention.

The integration of AI-enabled touchpoints introduces additional dimensions of perceived risk. Consumers may experience concerns about algorithmic bias, data privacy in AI systems, the accuracy of AI recommendations, and the potential for AI systems to manipulate their behaviour (Grewal et al., 2024; Chi et al., 2024). Research has documented "AI anxiety"a specific form of apprehension related to interacting with AI systems that can inhibit adoption of AI-enabled services (Li & Huang, 2024).

H2: Perceived risk has a significant negative influence on omnichannel shopping intention.

Social Influence and Omnichannel Shopping Intention

Social influence refers to the extent to which consumers perceive that people important to them believe it is advisable to engage with multiple shopping channels (Venkatesh et al., 2003). Social influence encompasses both explicit and implicit cues regarding how peers and reference groups view technology adoption. In the omnichannel context, social influence has emerged as a significant predictor of purchase intention and platform adoption, particularly among digital natives (Venkatesh et al., 2012; Jeong & Jo, 2024).

H3: Social influence has a significant positive influence on omnichannel shopping intention.

AI-Enabled Service Quality and Omnichannel Shopping Intention

AI-enabled service quality refers to consumers' perceptions of the quality, usefulness, and trustworthiness of AI-powered touchpoints within the omnichannel ecosystem. This construct encompasses multiple dimensions including chatbot responsiveness, personalization accuracy, conversational naturalness, problem-solving capability, and the seamlessness of AI-human handoffs (Huang & Rust, 2024; Luo et al., 2024).

Recent research has demonstrated that AI-enabled service quality is a distinct and increasingly important driver of customer engagement in digitally-enabled retail environments. Customers who perceive AI touchpoints as helpful, accurate, and easy to use exhibit higher levels of engagement across channels and greater willingness to rely on AI-assisted shopping experiences (Grewal et al., 2024). Conversely, poor AI interactions characterized by irrelevant recommendations, unnatural conversation flow, or inability to resolve queries can undermine overall perceptions of the omnichannel ecosystem and reduce shopping intention.

In the Indian apparel context, AI-enabled service quality may be particularly salient given the importance of personalized styling advice, accurate size recommendations, and multilingual support. Retailers who deliver high-quality AI experiences can differentiate themselves and capture greater share of omnichannel shopping activity.

H4: AI-enabled service quality has a significant positive influence on omnichannel shopping intention.

Omnichannel Shopping Intention and Customer Experience

A satisfying and unique experience delivered through any touchpoint is a defining feature of the omnichannel approach (Silva et al., 2018). An efficient omnichannel retail approach offers agility, consistency, empowerment, relevance, and convenience, all of which sustain elevated customer experience levels (Chib & Gangwar, 2024). As consumers actively choose and navigate across multiple channels, their shopping intention is expected to translate into a richer, more integrated experience.

H5: Omnichannel shopping intention is significantly related to customer experience.

Omnichannel Shopping Intention and Omnichannel Strategies

Millennials and digital natives, born between 1984 and 1999, prefer personalised, seamless experiences across offline and online channels (Bento et al., 2018). Their primary motivations for using omnichannel platforms include convenience, curation, personalisation, and seamless cross-channel transitions (Hopkins, 2022). As shopping journeys become non-linear, with need recognition, evaluation, and purchase occurring across different channels, the alignment between consumer intention and retailer strategy becomes critical (Saghiri & Mirzabeiki, 2021).

H6: Omnichannel shopping intention is significantly related to omnichannel strategies.

Omnichannel Strategies and Customer Experience

Omnichannel platforms represent a unified approach that allows retailers to manage their channels as intermingled touchpoints, encompassing in-store experiences, websites, and mobile devices (Yang et al., 2024). The consistency in messaging and service quality across these touchpoints supports trust and reliability, which are foundational to customer experience. Research confirms that omnichannel consumers who encounter innovative, seamlessly integrated platforms develop stronger experiential engagement (Konus et al., 2008; Piotrowicz & Cuthbertson, 2014).

H7: Omnichannel strategies are significantly related to customer experience.

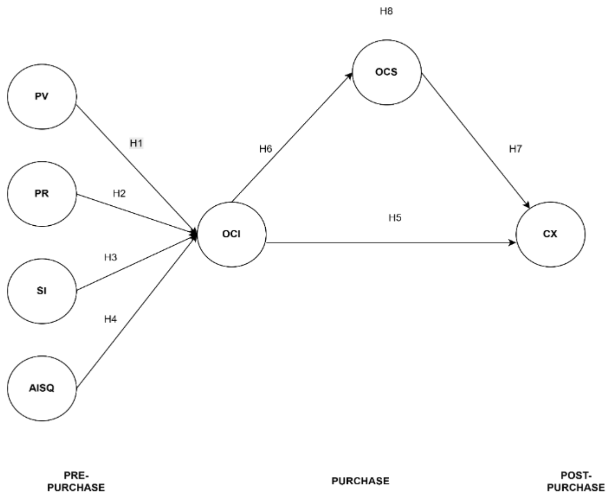
The Mediating Role of Omnichannel Strategies between Omni Channel Intention and Customer Experience

The synergetic management of multiple channels and customer touchpoints in a way that optimises customer experience across channels constitutes omnichannel retailing (Verhoef et al., 2015). Emerging technologies including virtual reality, augmented reality, chatbots, and the metaverse function as critical components of an omnichannel ecosystem (Cai & Lo, 2020). This study examines whether omnichannel strategies partially or fully mediate the relationship between omnichannel shopping intention and customer experience.

H8: Omnichannel strategies partially mediate the relationship between omnichannel shopping intention and customer experience.

Research Model

The proposed conceptual model, grounded in the Stimulus-Organism-Response (S-O-R) framework (Mehrabian & Russell, 1974), positions perceived value, perceived risk, and social influence as exogenous stimuli. Omnichannel shopping intention functions as the organism (mediating variable), while customer experience serves as the endogenous response variable. Omnichannel strategies are introduced as a further mediating mechanism between shopping intention and customer experience. Figure 1 illustrates the proposed model.



Research Methodology

Research Design

This study adopts a quantitative, cross-sectional research design. An omnichannel retailing context is operationalised as a blend of sales and marketing approaches that provides customers with a fully integrated shopping experience, uniting user experiences across multiple channels and touchpoints including brick-and-mortar stores, websites, and mobile applications (Beck & Rygl, 2015). The study employs PLS-SEM, which was selected for its suitability in testing complex models with latent variables and its effectiveness in composite-based structural modelling (Dash & Paul, 2021).

Sample and Data Collection

Data were collected through both online and offline modes. A screening question was placed at the beginning of the questionnaire to confirm that respondents were active omnichannel shoppers, defined as individuals using more than one channel (brick-and-mortar stores, social media platforms, or mobile applications) during their purchase journey. A total of 525 responses were received, of which 506 were retained after removing incomplete and duplicate entries. This sample size meets the threshold recommended by Faul et al. (2009) for adequate statistical power in PLS-SEM analyses.

Systematic probability sampling was employed, with every second eligible respondent selected. Offline data collection involved surveying shoppers in physical apparel retail stores using tablets, while online data were collected by distributing survey links via email. Table 1 presents the demographic profile of respondents.

Table 1: Demographic Profile of Respondents

Demographic Profile	Number (N = 506)	Percentage (%)
Gender		
Female	272	53.7%
Male	234	46.3%
Total	506	100%
Omni-channel Usage Status		
Both Offline and Online Channels	366	72.3%
Offline Channel (Physical Retail Stores)	75	14.8%
Online Channel (Website, social media, Mobile App)	65	12.9%
Most Convenient Channel for Apparel Category		
Both Channels (Offline and Online)	195	38.7%
Online Channels	169	33.3%
Offline Channels	142	28.0%
AI Touchpoint Interaction		
AI-Powered Recommendations	412	81.4%
Virtual Try-On	98	19.4%

Measurement and Questionnaire Design

All constructs and measurement items were adapted from validated scales in the extant literature and modified to suit the apparel omnichannel context. Perceived Value items were adapted from Parasuraman (1997) and Gan and Wang (2017). Perceived Risk items were adapted from Truong et al. (2022). Social Influence items were adapted from Jeong and Jo (2024). Omnichannel Strategy, Omnichannel Shopping Intention, and Customer Experience items were adapted from Gao et al. (2021) and Shankar and Kushwaha (2021). All items were measured on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The complete set of items is presented in Table 2.

Table 2: Measurement Items and Sources

Construct	Code	Item / Statement	Source
Perceived Value	PV1	Using multiple channels during shopping allows me to save time.	Gan et al. (2017)

	PV2	Using multiple channels is convenient for me.	
	PV3	I enjoy shopping for apparel from multiple channels.	
	PV4	Using multiple channels throughout my shopping journey offers me tangible benefits.	
Perceived Risk	PR1	I feel safe while making payments using credit cards online.	Truong et al. (2022)
	PR2	Making payments on different online platforms gives me a sense of security.	
	PR3	I feel comfortable providing my personal data to online merchants.	
	PR4	I experience anxiety when making payments online.	
Social Influence	SI1	People whose opinions I value motivate me to use different shopping channels.	Jeong & Jo (2024)
	SI2	People important to me think I should use different shopping channels, selecting whichever is most convenient.	
	SI3	People who influence my behaviour encourage me to use the most convenient shopping channel available.	
	SI4	People whose opinions I value prefer that I use different channels based on convenience.	
AI-Enabled Service Quality	AISQ1	The AI chatbot/virtual assistant provides helpful and relevant responses to my queries.	Huang & Rust (2024); Luo et al. (2024)
	AISQ2	The AI-Powered Product recommendations match my preferences and style	
	AISQ3	I find it easy to interact with the AI chatbot/virtual assistant.	
	AISQ4	The AI assistant is available whenever I need help, regardless of time.	
	AISQ5	The transition from AI assistance to human support (when needed) is seamless.	
Omni-Channel Usage Intention (OCI)	OCI1	I would continue purchasing apparel from different omnichannel platforms.	Shankar & Kushwaha (2021)
	OCI2	I would recommend omnichannel platforms to my friends, colleagues, and relatives.	

	OCI3	I intend to repeat my purchases from omnichannel platforms.	
	OCI4	Using omnichannel platforms for apparel shopping is appealing to me.	
Omni-Channel Strategy (OCS)	OCS1	I find using online platforms (websites, mobile apps) easy to navigate.	Gao et al. (2021)
	OCS2	I feel comfortable switching from one platform to another during shopping.	
	OCS3	Navigation and downloading from sites are effortless for me.	
	OCS4	I am aware of all available service channels offered by retailers.	
	OCS5	I do not perceive any barriers when switching between channels of this retailer.	
Cognitive Customer Experience (CCE)	CCE1	Using omnichannel services provides information that helps me make better purchase decisions.	Gao et al. (2021)
	CCE2	Omnichannel services help me find the right product or service I am looking for.	
	CCE3	This retailer's omnichannel service helps me locate what I need when I plan a purchase.	
	CCE4	Using this retailer's omnichannel service gives me comprehensive product, price, and promotional information.	
Affective Customer Experience (ACE)	ACE1	Shopping for apparel via omnichannel platforms is entertaining.	Gao et al. (2021)
	ACE2	Shopping for apparel via omnichannel service is pleasurable.	
	ACE3	The retailer's omnichannel service evokes positive feelings and emotions.	
	ACE4	My shopping journey feels satisfying after using different channels.	

Results

Measurement Model Analysis

Following the recommendations of Hair et al. (2016), the reliability and validity of constructs were assessed using Cronbach's alpha, composite reliability (CR), convergent validity (AVE), and discriminant validity (Fornell & Larcker, 1981). As shown in Table 3, Cronbach's alpha values range from 0.783 (Perceived Risk) to 0.957 (Customer Experience), all exceeding the threshold of 0.70. Composite reliability values for all constructs exceed 0.80, confirming internal consistency. The AVE for all constructs exceeds 0.50, confirming convergent validity. Individual item loadings range from 0.542 (PR4) to 0.949 (ACE3), with the majority exceeding 0.70. Discriminant validity was confirmed using the Fornell-Larcker criterion (Fornell & Larcker, 1981).

Note: The loading of PR4 (0.542) is marginally below the recommended threshold of 0.60. While the construct-level reliability metrics remain acceptable, future studies are encouraged to refine or replace this item.

Table 3: Measurement Model Results

Construct	Item	Loading	AVE	CR	Cronbach's α	Decision
Perceived Value	PV1 PV2 PV3 PV4	0.832 0.896 0.908 0.857	0.763	0.928	0.896	Supported
Perceived Risk	PR1 PR2 PR3 PR4	0.851 0.886 0.820 0.542	0.619	0.863	0.783	Supported
Social Influence	SI1 SI2 SI3 SI4	0.858 0.866 0.919 0.880	0.776	0.933	0.904	Supported
AI- Enabled Service Quality	AISQ1 AISQ2 AISQ3 AISQ4 AISQ5	0.798 0.799 0.895 0.894 0.912	0.738	0.934	0.912	Supported
Omni-channel Intention	OCI1 OCI2 OCI3	0.907 0.915 0.921	0.836	0.939	0.902	Supported
Omni-channel Strategy	OCS1 OCS2 OCS3 OCS4 OCS5	0.831 0.787 0.846 0.902 0.888	0.725	0.929	0.905	Supported
Customer Experience	CCE1 CCE2 CCE3 CCE4 ACE1 ACE2 ACE3 ACE4	0.894 0.927 0.948 0.892 0.831 0.687 0.949 0.880	0.774	0.964	0.957	Supported

Table 4: Correlation Matrix

	OCI	OCS	PR	PV	SI	AISQ	CX
OCI							
OCS	0.843						
PR	0.649	0.668					
PV	0.803	0.814	0.544				
SI	0.834	0.726	0.626	0.679			
AISQ	0.756	0.789	0.512	0.698	0.654		
CX	0.828	0.760	0.604	0.688	0.677	0.721	

Note: OCI = Omni-Channel Intention; OCS = Omni-Channel Strategy; PR = Perceived Risk;

PV = Perceived Value; SI = Social Influence; AISQ = Artificial Intelligence enabled Service Quality; CX = Customer Experience.

Structural Model Analysis

The measurement model was evaluated using indicator loadings, Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's alpha (α) to establish convergent validity and construct reliability.

Perceived Value (PV) was measured using four items (PV1–PV4) with factor loadings ranging from 0.832 to 0.908, exceeding the recommended threshold of 0.70 (Hair et al., 2019). The AVE was 0.763, well above the 0.50 benchmark, indicating that the construct explains the majority of variance in its indicators. CR (0.928) and Cronbach's α (0.896) both surpassed the acceptable threshold of 0.70, confirming strong internal consistency.

Perceived Risk (PR) was assessed with four items (PR1–PR4) with loadings ranging from 0.542 to 0.886. While PR4 (0.542) falls slightly below the conventional threshold, it was retained as the AVE (0.619) and CR (0.863) remained acceptable, and its removal did not substantially improve reliability. Cronbach's α was 0.783, confirming adequate reliability.

Social Influence (SI) demonstrated excellent psychometric properties with four items (SI1–SI4) loading between 0.858 and 0.919. AVE was 0.776, CR was 0.933, and Cronbach's α was 0.904, all comfortably exceeding thresholds and indicating strong convergent validity.

AI-Enabled Service Quality (AISQ) was the most comprehensive exogenous construct, measured by five items (AISQ1–AISQ5) with loadings from 0.798 to 0.912. AVE (0.738), CR (0.934), and Cronbach's α (0.912) all confirmed high reliability and convergent validity.

Omnichannel Integration (OCI), the central mediating construct, was measured with three items (OCI1–OCI3) exhibiting very high loadings of 0.907, 0.915, and 0.921, respectively. With AVE = 0.836, CR = 0.939, and α = 0.902, OCI demonstrated exceptional construct reliability.

Omnichannel Satisfaction (OCS) was measured using five items (OCS1–OCS5) with loadings ranging from 0.787 to 0.902. AVE (0.725), CR (0.929), and Cronbach's α (0.905) all confirmed robust reliability and validity.

Customer Experience (CX), the ultimate endogenous outcome, was assessed using eight items comprising both cognitive customer experience (CCE1–CCE4, loadings: 0.894–0.948) and affective customer experience (ACE1–ACE4, loadings: 0.687–0.949). The overall AVE was 0.774, CR was 0.964, and Cronbach's α was 0.957 the highest among all constructs reflecting a highly reliable and internally consistent measurement of the multidimensional customer experience construct. Taken together, all constructs met or exceeded the standard thresholds for AVE (> 0.50), CR (> 0.70), and Cronbach's α (> 0.70), establishing adequate convergent validity and reliability across the measurement model.

Following confirmation of measurement model validity, the structural model was evaluated by examining the path coefficients (β), t-statistics, and p-values for each hypothesized relationship. All eight hypotheses were supported at the $p < 0.001$ significance level.

H1: Perceived Value → OCI (β = 0.384, t = 8.734, $p < 0.001$) Perceived Value exerted a significant and positive effect on Omnichannel Integration, supporting H1. This finding suggests that consumers who perceive greater value in omnichannel offerings are more likely to integrate across channels, consistent with value-based adoption theories.

H2: Perceived Risk → OCI ($\beta = 0.144$, $t = 4.380$, $p < 0.001$) Perceived Risk had a statistically significant but relatively modest positive effect on OCI (H2 supported). This positive relationship, rather than a negative one, may suggest that in the omnichannel context, a degree of perceived risk motivates consumers to seek integration across channels as a risk mitigation strategy.

H3: Social Influence → OCI ($\beta = 0.445$, $t = 9.383$, $p < 0.001$) Social Influence was the strongest predictor of Omnichannel Integration, with the highest β-value among all exogenous constructs. This confirms H3 and underscores the pivotal role of social norms, peer influence, and community expectations in driving omnichannel adoption behavior.

H4: AI-Enabled Service Quality → OCI ($\beta = 0.247$, $t = 5.823$, $p < 0.001$) AI-Enabled Service Quality significantly predicted OCI, supporting H4.

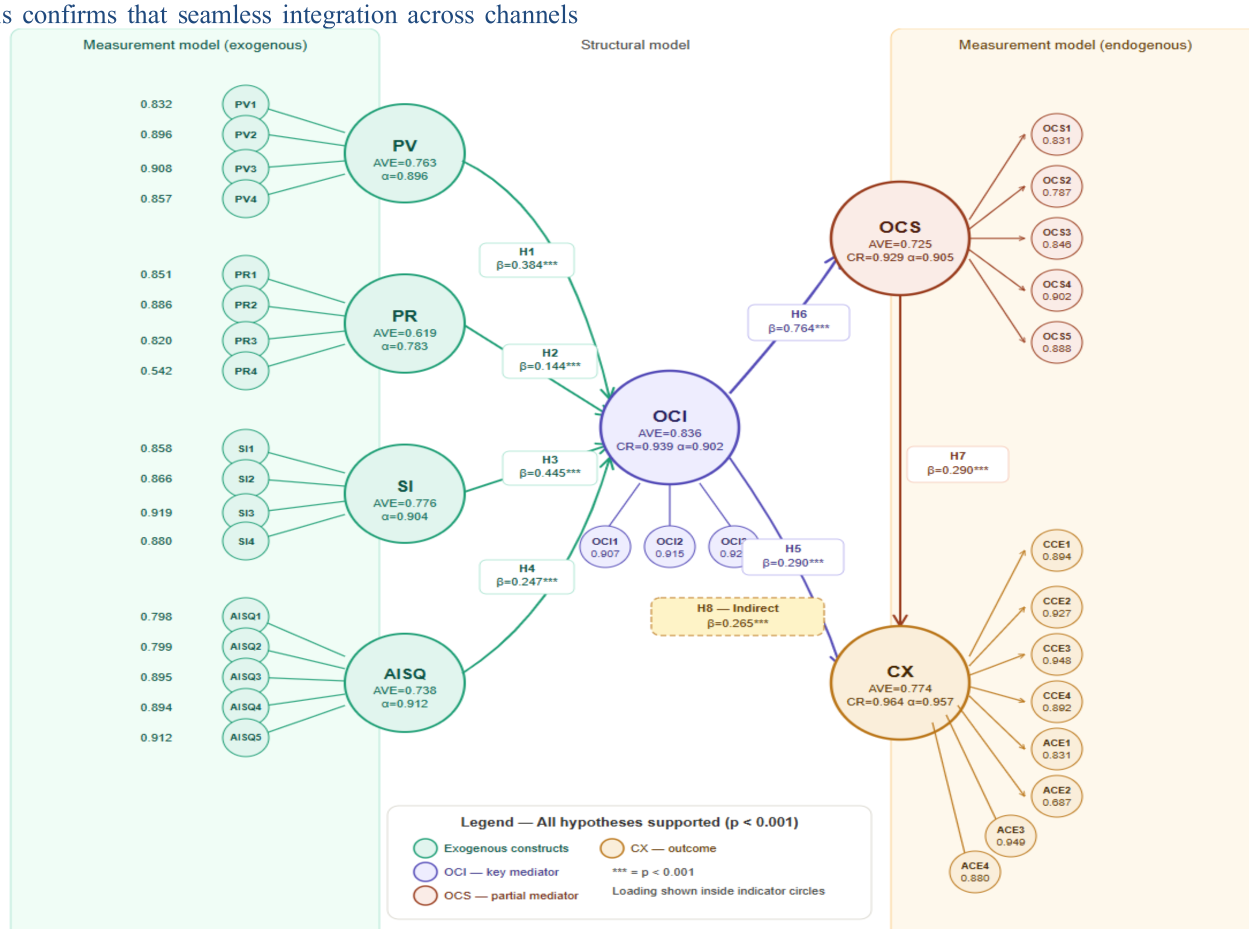
This result highlights that the quality of AI-driven service touchpoints — such as personalization, responsiveness, and intelligent recommendations meaningfully enhances consumers' integration across omnichannel platforms.

H5: OCI → Customer Experience ($\beta = 0.290$, $t = 11.209$, $p < 0.001$) Omnichannel Integration had a significant direct effect on Customer Experience, supporting H5. This confirms that seamless integration across channels directly enhances the overall customer experience, independent of satisfaction.

H6: OCI → OCS ($\beta = 0.764$, $t = 31.724$, $p < 0.001$) The path from OCI to OCS was the strongest in the entire model, with a β of 0.764 and a t-statistic of 31.724 among the most robust findings. This strongly supports H6, indicating that omnichannel integration is the primary and dominant driver of omnichannel satisfaction. The magnitude of this coefficient suggests that nearly all variation in OCS is attributable to the quality of omnichannel integration experienced by consumers.

H7: OCS → Customer Experience ($\beta = 0.290$, $t = 4.707$, $p < 0.001$) OCS exerted a significant positive effect on CX, supporting H7. This finding is consistent with satisfaction theories suggesting that a satisfying omnichannel experience naturally translates into superior overall customer experience.

H8: OCI → OCS → CX (Indirect/Mediation Path) ($\beta = 0.265$, $t = 5.923$, $p < 0.001$) The indirect effect of OCI on CX through OCS was statistically significant ($\beta = 0.265$), confirming H8 and establishing OCS as a significant mediator in the OCI–CX relationship. The coexistence of a significant direct path (H5) and a significant indirect path (H8) indicate partial mediation, whereby OCS transmits a substantial portion of OCI's influence on customer experience while OCI also retains a direct effect.



Note: PV = Perceived Value; PR = Perceived Risk; SI = Social Influence; AISQ= Artificial Intelligence Enabled Service Quality, OCI = Omni-Channel Intention; OCS = Omni-Channel Strategy; CX = Customer Experience.

Discussion

Modern retail operations increasingly require omnichannel strategies to create smooth and integrated customer experiences across diverse touchpoints. This study demonstrates that perceived value, perceived risk, and social influence are significant antecedents of omnichannel shopping intention, consistent with the Unified Theory of Acceptance and Use of Technology (UTAUT) framework (Venkatesh et al., 2003) and previous omnichannel research (Kazancoglu & Aydin, 2018; Van Nguyen et al., 2024).

Social influence emerged as the strongest driver of omnichannel shopping intention ($\beta = 0.445$), underscoring the primacy of peer effects and word-of-mouth in shaping channel adoption decisions. This finding is consistent with Jeong and Jo (2024), who found that online-offline social influence significantly shapes omnichannel behavioural intentions. Retail marketers should therefore prioritise strategies that harness positive social proof, including customer testimonials, influencer marketing, and referral programmes.

The strong relationship between omnichannel shopping intention and omnichannel strategies ($\beta = 0.764$) indicates that consumers who intend to shop across channels are highly responsive to BOPIS, BORIS, and BOSH fulfilment strategies. However, the partial mediation finding suggests that existing omnichannel strategies do not fully translate consumer intention into superior customer experience, which may reflect gaps in technical usability, service consistency, or platform personalisation. This is consistent with Mishra et al. (2024), who highlighted that the distance to market and technical literacy moderate the efficacy of omnichannel strategies.

Perceived risk, while statistically significant, exerts a relatively modest effect ($\beta = 0.144$) compared to perceived value and social influence. This may reflect the maturation of digital commerce norms in the Indian retail context, where consumer confidence in online transactions has grown substantially in the post-pandemic period. Nonetheless, retailers should continue to invest in transparent data policies, secure payment gateways, and clear return mechanisms to minimise residual risk perceptions. The strong relationship between omnichannel shopping intention and omnichannel strategies ($\beta = 0.764$) indicates that consumers who intend to shop across channels are highly responsive to BOPIS, BORIS, BOSH fulfilment strategies, and AI-enabled services. This finding suggests that retailers who invest in comprehensive omnichannel infrastructure including AI touchpoints are well-positioned to capture and convert the intentions of omnichannel-oriented consumers.

However, the partial mediation finding suggests that existing omnichannel strategies do not fully translate consumer intention into superior customer experience, which may reflect gaps in technical usability, service consistency, platform personalisation, or AI interaction quality. This is consistent with Mishra et al. (2024), who highlighted that the distance to market and technical literacy moderate the efficacy of omnichannel strategies.

The integration of UTAUT2 with the S-O-R framework provides a richer theoretical foundation for understanding omnichannel adoption than either framework alone. The S-O-R framework captures the general process through which environmental stimuli influence consumer behaviour, while UTAUT2 provides specific guidance on the mechanisms through which technology adoption occurs. The addition of AI-enabled service quality as a distinct construct extends both frameworks to account for the contemporary reality of AI-mediated retail experiences.

Implications

Managerial Implications

This study provides actionable insights for retail practitioners. First, given that social influence is the dominant driver of omnichannel intention, retailers should invest in community-building strategies, user-generated content, and peer review mechanisms to amplify social proof. Second, the partial mediation of omnichannel strategies highlights the need for retailers to move beyond standard fulfilment models (BOPIS, BORIS) toward more personalised, data-driven channel experiences that address individual consumer journeys. Third, retailers should audit their digital platforms for usability and accessibility, as technical friction remains a likely inhibitor of the omnichannel experience.

Fourth, the finding that perceived value ($\beta = 0.384$) significantly drives omnichannel intention suggests that retailers should actively communicate the value proposition of using multiple channels, such as price transparency, exclusive online-offline promotions, and personalised recommendations. Finally, reducing perceived risk through enhanced data security communications and simplified return processes is essential to building consumer confidence in omnichannel environments.

Academic Implications

This study contributes to the growing body of literature on omnichannel retailing by empirically testing a model that integrates antecedents of shopping intention with omnichannel strategy outcomes and customer experience in the Indian apparel sector. The application of PLS-SEM to a conceptual model grounded in the S-O-R framework advances the theoretical understanding of how omnichannel ecosystems operate in emerging market contexts. Future researchers are encouraged to examine the role of hedonic versus utilitarian motivations, the moderating effect of digital literacy, and the longitudinal evolution of omnichannel experience.

Limitations and Future Directions

This study is subject to several limitations. First, data collection occurred during the post-COVID-19 recovery period, which may have elevated digital channel usage beyond typical levels; longitudinal studies based on panel data are recommended to assess the durability of these behavioural patterns. Second, the study is restricted to the B2C apparel sector in Lucknow, India; future research should replicate and extend the model to other product categories, geographic regions, and B2B contexts. Third, the cross-sectional design precludes causal inference; experimental or quasi-experimental designs could strengthen causal claims. Finally, the low loading of PR4

(0.542) warrants refinement of the perceived risk scale in future work

Conclusion

This study makes a twofold contribution: first, by identifying perceived value, social influence, and perceived risk as significant determinants of omnichannel shopping intention; and second, by empirically establishing the partial mediating role of omnichannel strategies in the relationship between shopping intention and customer experience. The findings confirm that omnichannel strategies are indispensable in channelling consumer drivers toward positive experiential outcomes, yet they do not fully substitute for the direct influence of intention on experience. Retailers must therefore adopt a dual approach, strengthening both their omnichannel infrastructure and the broader experiential ecosystem to achieve enduring competitive advantage. The model presented provides a forward-looking strategic framework for retailers seeking to anticipate future demand and cultivate lasting customer loyalty in an increasingly omnichannel world.

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