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The Impact of Artifical Intelligence on Consumer Purchase Behaviour in Omnichannel Retailing: An Integration of UTAUT 2 And S-O-R Model

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***Abstract*—Accelerated application of Artificial Intelligence (AI) in retailing has transformed customer interaction, especially in omnichannel settings where digital and physical touch points overlap. AI-powered technologies such as chatbots, recommendation engines, and voice assistants drive personalization, convenience, and decision-making, and have an impact on purchasing intentions. Though the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) has been extensively utilized to account for technology adoption via constructs like performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation, it does not extend to explain the affective and experiential aspects of consumer behavior in AI contexts. To fill this void, this research combines the Stimulus-Organism-Response (S-O-R) model with UTAUT2 and offers a twin theoretical perspective with which to explore how technological, cognitive, and affective dimensions together influence consumer buying intention. Trust in AI and satisfaction are specifically herein posited as mediators between stimuli on the basis of UTAUT2 and responses to behavior, furnishing further explanation of consumer trust in AI recommendations. By empirically validating this integrated model, the study makes both theoretical and practical contributions by informing marketers and retailers on how to maximize AI-facilitated omnichannel strategies to generate trust, improve satisfaction, and build consumer loyalty.**

***Index Terms*—Artificial Intelligence, Omnichannel Retailing, UTAUT2, S-O-R Framework, Trust in AI, Satisfaction, Purchase Intention, Consumer Behavior.**

I. INTRODUCTION

The integration of Artificial Intelligence (AI) in retailing has significantly transformed the consumer shopping experience, particularly in omnichannel environments where digital and physical touchpoints converge. Omnichannel retailing enables seamless consumer interaction across various platforms—such as websites, mobile apps, and physical stores—through AI-driven tools like chatbots, recommendation engines, and voice assistants (Huang & Rust, 2021). These technologies enhance convenience, personalization, and decision-making, thereby shaping consumer purchase behavior in profound ways (Grewal et al., 2021).

As consumers increasingly interact with AI technologies during their shopping journey, it becomes crucial to understand the psychological mechanisms that influence their purchase intentions. Traditional models such as the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) have been widely used to explain technology adoption behavior in consumer contexts. UTAUT2 includes constructs such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Hedonic Motivation (HM), which are critical in understanding how consumers perceive and engage with AI-based retail services (Venkatesh et al., 2012).

However, while UTAUT2 explains technology adoption, it does not fully account for the emotional and experiential dimensions of consumer behavior in AI contexts. Therefore, this study integrates the Stimulus-Organism-Response (S-O-R) framework, originally proposed by Mehrabian and Russell (1974), to complement UTAUT2. The S-O-R model posits that environmental stimuli (e.g., AI functionalities) affect internal organismic states (e.g., trust in AI, satisfaction), which in turn influence behavioral responses (e.g., purchase intention). This integration allows for a more comprehensive understanding of how technological, cognitive, and affective factors jointly shape consumer decisions in AI-enabled omnichannel retailing (Pantano & Pizzi, 2020).

Existing research highlights the importance of trust in AI as a mediating factor between technological features and consumer outcomes. Trust reduces perceived risk and increases reliance on AI recommendations, which can drive satisfaction and eventual purchase intentions (Choi & Kandampully, 2020; Moriuchi, 2021). Similarly, satisfaction with AI interactions—resulting from effective performance, ease of use, and enjoyment—has been shown to influence repurchase intentions and customer loyalty in retail environments (Prentice et al., 2020).

Despite growing interest in AI in marketing, there remains a gap in understanding how UTAUT2-based stimuli interact with S-O-R-based organismic states to influence consumer behavior in omnichannel retail contexts. This study aims to address this gap by proposing and empirically testing a conceptual model that integrates UTAUT2 and S-O-R, focusing on the roles of trust in AI and satisfaction as mediators between AI-related stimuli and purchase intention. The findings will offer valuable insights for marketers and retailers seeking to optimize AI deployment across omnichannel strategies.

Conceptual Background

The rapid integration of Artificial Intelligence (AI) into retail environments has transformed the way consumers engage across omnichannel platforms. Researchers have increasingly applied behavioral theories to understand the cognitive and emotional underpinnings of AI-driven consumer decision-making. Among these, the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Stimulus-Organism-Response (S-O-R) model offer a comprehensive lens to evaluate consumer responses to AI-enabled services in omnichannel retailing.

UTAUT2 and AI Adoption in Retail

UTAUT2, proposed by Venkatesh et al. (2012), extends the original UTAUT model by incorporating consumer-centric constructs such as hedonic motivation (HM), price value, and habit. The core constructs of performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and HM are highly relevant in AI retail applications. For instance, PE reflects the perceived effectiveness of AI tools like virtual assistants or chatbots in enhancing purchase decisions (Gursoy et al., 2019).

EE relates to how easily customers can use these technologies, while SI captures peer influence on AI adoption. FC evaluates whether consumers feel supported in using AI tools across devices and channels. HM underscores the enjoyment derived from AI interaction, such as personalization or gamification elements (Pantano & Timmermans, 2014).

Stimulus-Organism-Response (S-O-R) Framework in Retail Context

Mehrabian and Russell's (1974) S-O-R model posits that external stimuli affect internal emotional states (organism), which then drive behavioral responses. In the retail context, stimuli (e.g., AI-driven recommendations, virtual try-ons) elicit cognitive and affective responses like trust in AI and customer satisfaction, which influence the purchase intention (response) (Jacobs et al., 2016). Integrating UTAUT2 with S-O-R, as visualized in the conceptual model, allows mapping the technological stimuli (PE, EE, SI, FC, HM) to internal psychological states (trust and satisfaction), leading to behavioral outcomes (purchase intention).

Trust in AI as a Mediating Construct

Trust in AI is central to consumer engagement with AI technologies. Studies show that trust mediates the relationship between technology attributes and behavioral outcomes (Moriuchi, 2021). Consumers are more likely to rely on AI systems if they perceive them as competent, reliable, and secure (Choi et al., 2020). In omnichannel settings, trust in AI enhances customer experience by reducing uncertainty and perceived risk, especially when AI operates across touchpoints (Lemon & Verhoef, 2016).

Customer Satisfaction and Purchase Intention

Customer satisfaction, defined as the post-usage emotional evaluation of service experiences, is a strong predictor of behavioral intention (Oliver, 1999). In AI-enabled omnichannel retailing, satisfaction can stem from convenience, personalization, and accuracy provided by AI systems (Poushneh, 2018). The combination of trust and satisfaction significantly enhances purchase intention, consistent with prior research on AI in marketing (Prentice et al., 2020).

Omnichannel Retail and AI Synergy

Omnichannel retailing entails seamless integration of physical and digital platforms to provide a unified shopping experience. AI contributes to this integration by offering intelligent personalization, predictive analytics, and automated customer support (Huang & Rust, 2021). The synergy between AI and omnichannel strategy leads to improved customer journeys, higher engagement, and loyalty (Verhoef et al., 2015).

H1: UTAUT 2 (performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation) influence on trust in AI
H2: UTAUT 2 (performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation) influence on satisfaction
H3: trust influence on satisfaction of consumer
H4: trust and satisfaction influence on purchase intention
H5: UTAUT 2 (performance expectancy, effort expectancy, social influence, facilitating condition, hedonic motivation) influence on purchase intention
Introduce the background of the study, define the problem, highlight its significance in the field of Commerce, Management, or Economics, and state the objectives of the research.

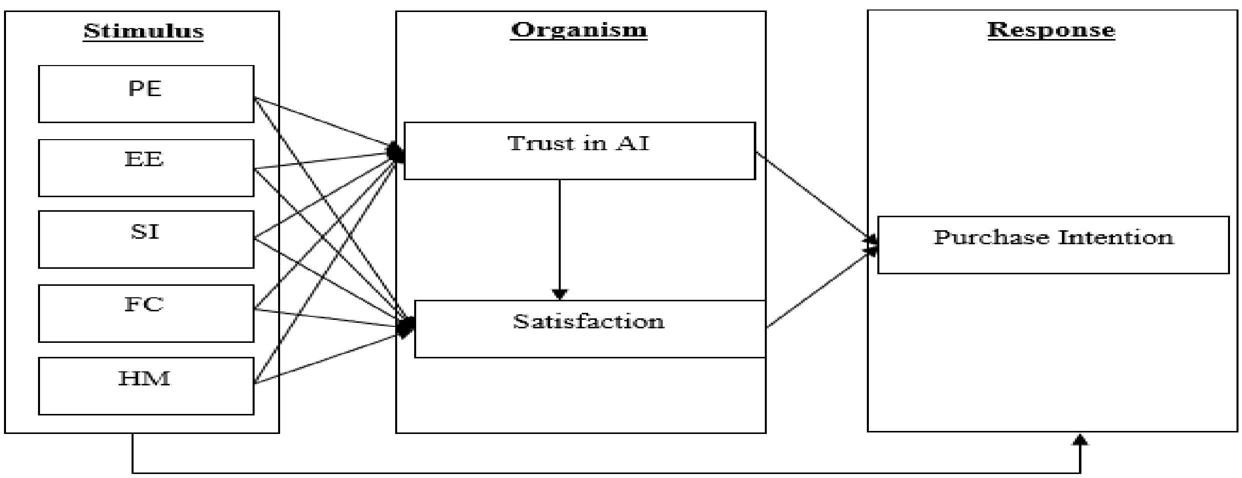

Figure:1Conceptual Model
Source: Venkatesh (2013); Mehrabian and Russell (1974)

Note: PE-performance expectancy, EE-effort expectancy, SI-social influence, FC-facilitating condition, HM-Hedonic motivation, TAI-Trust in AI, SAT-Satisfaction, and PI-Purchase Intention

While previous studies have examined consumer adoption of AI technologies using cognitive models such as UTAUT2, they have largely overlooked the emotional and experiential dimensions—particularly trust in AI and satisfaction—that drive consumer behavior in omnichannel retail settings. Moreover, there is a lack of research that integrates UTAUT2 with the S-O-R model to comprehensively explain both rational and emotional pathways leading to purchase intention in AI-mediated retail environments.

II. METHODS AND MEASURES

This study employs a quantitative, descriptive, and causal research design to explore how AI-enabled features in omnichannel retailing influence consumer purchase behaviour through the integration of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Stimulus-Organism-Response (S-O-R) model. The deductive approach is applied, wherein the hypotheses are formulated based on established theories (Venkatesh et al., 2012; Mehrabian & Russell, 1974), and empirical data are collected to validate the proposed conceptual framework.

The target population for this research comprises consumers who have used AI-powered technologies—such as virtual assistants, chatbots, personalized recommendations, or voice assistants—within an omnichannel retail context, including both online and physical channels. Purposive sampling is adopted to ensure that only Coimbatore city consumers with prior experience in interacting with AI technologies in retail environments are included in the study. To ensure adequate statistical power and generalizability of findings, a sample size of 238 respondents is targeted, following the recommendation by Hair et al. (2010) for Structural Equation Modeling (SEM).

Data are collected using a structured questionnaire composed of items adapted from prior validated scales. Constructs from UTAUT2—namely Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Hedonic Motivation (HM)—serve as stimulus variables. Trust in AI and Satisfaction are considered organismic states, while Purchase Intention represents the consumer's response. The items are measured using a five-point Likert scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5). The questionnaire is distributed via online platforms such as Google Forms and Qualtrics to ensure broad geographic reach and accessibility.

Data analysis is performed using SPSS for preliminary checks including descriptive statistics and reliability testing (with Cronbach's Alpha threshold set at >0.70), and AMOS is used to conduct Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). Validity tests include convergent validity (Average Variance Extracted > 0.50) and discriminant validity (Fornell-Larcker criterion). Model fit is assessed through indices such as CFI (Comparative Fit Index), RMSEA (Root Mean Square Error of Approximation), and SRMR (Standardized Root Mean Residual). Hypotheses are tested by examining the path coefficients and their statistical significance (p-values).

The study adheres to strict ethical guidelines, ensuring informed consent, voluntary participation, and confidentiality of respondent data. Participants are informed that the data will be used solely for academic research purposes. However, the research acknowledges limitations such as the use of self-reported data, which may be subject to response bias, and the cross-sectional nature of the study, which limits the ability to infer causality. Additionally, as the sample is restricted to users with experience in AI-driven retail, the findings may not be generalizable to all consumer segments.

III. RESULTS

This section presents the results of the data analysis using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to assess the measurement model and examine the hypothesized relationships among variables within the integrated UTAUT2–S-O-R framework.

Table 1 this table represents CFA model fit indices

Fit indices	Value	Accepted value	Result
Cmin/df	2.073	Less than 3	Supported
GFI	.981	Value greater than .90	Supported
CFI	.980	Value greater than .90	Supported
IFI	.981	Value greater than .90	Supported
RMSEA	.062	Value less than .08	Supported

Source: Kline, 2010

Table 1 represents the model fit indices obtained from the Confirmatory Factor Analysis (CFA) to assess the validity and overall fit of the measurement model. The results indicate a good fit between the proposed model and the observed data, as all fit indices meet the recommended thresholds suggested by Kline (2010).

Firstly, the Chi-square divided by degrees of freedom (Cmin/df) is 2.073, which falls well within the acceptable range of less than 3, indicating a reasonably good fit of the model (Kline, 2010). This suggests that the discrepancy between the observed and estimated covariance matrices is minimal. The Goodness-of-Fit Index (GFI) is reported at 0.981, exceeding the recommended minimum value of 0.90, thus demonstrating strong model adequacy. Similarly, both the Comparative Fit Index (CFI) and the Incremental Fit Index (IFI) are above 0.980, further supporting the model's fit. These values reflect that the hypothesized model provides a significantly better fit than a null or baseline model (Hu & Bentler, 1999).

Lastly, the Root Mean Square Error of Approximation (RMSEA) value is 0.062, which is below the threshold of 0.08, indicating an acceptable level of approximation error in the population (Browne & Cudeck, 1993). Lower RMSEA values generally suggest better model fit and parsimony. Taken together, these indices provide robust evidence that the measurement model demonstrates a good overall fit, supporting the validity of the constructs used in the study.

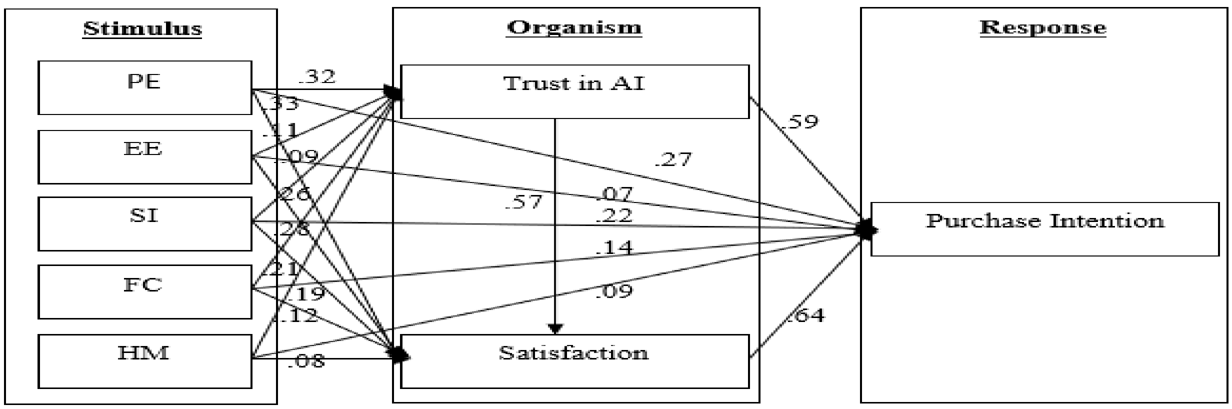

Figure:2 Hypothesis Model

Source: Primary Source

Table 2 this table represents SEM model fit indices

Fit indices	Value	Accepted value	Result
Cmin/df	2.432	Less than 3	Supported
GFI	.967	Value greater than .90	Supported
CFI	.968	Value greater than .90	Supported
IFI	.968	Value greater than .90	Supported
RMSEA	.069	Value less than .08	Supported

Source: Kline, 2010

Table 2 presents the Structural Equation Modeling (SEM) fit indices, which assess how well the hypothesized structural model aligns with the empirical data. All indices reported indicate a good fit, thereby validating the overall structure of the conceptual model used in the study.

The Chi-square divided by degrees of freedom (Cmin/df) is 2.432, which is well below the accepted threshold of 3.0. This suggests that the model exhibits a good level of parsimony and adequately represents the observed data with minimal error (Kline, 2010). A lower Cmin/df value typically indicates a better fitting model, especially in large sample sizes. The Goodness-of-Fit Index (GFI) is 0.967, exceeding the minimum criterion of 0.90, which signifies that a high proportion of variance is explained by the estimated model (Hu & Bentler, 1999). Similarly, both the Comparative Fit Index (CFI) and the Incremental Fit Index (IFI) are reported at 0.968, surpassing the conventional cutoff value of 0.90. These values demonstrate that the proposed structural model is substantially better than the null model in explaining the relationships among the variables (Bentler, 1990).

Additionally, the Root Mean Square Error of Approximation (RMSEA) is 0.069, which falls within the acceptable range of less than 0.08. This indicates a reasonable level of error approximation in the model and suggests good model fit (Browne & Cudeck, 1993). Overall, the SEM model demonstrates a satisfactory fit, thereby supporting the structural validity of the hypothesized relationships among constructs, including UTAUT2 factors, trust in AI, satisfaction, and purchase intention.

Table 3 This table represents hypothesis and relationships between variables

Path	Hypothesis	Estimate	P value	Sign	Result
PE→ TAI	H_1	.331	*** (P<0.001)	+	Supported
EE→ TAI		.109	* (P<0.05)	+	Supported
SI→ TAI		.263	*** (P<0.001)	+	Supported
FC→ TAI		.211	*** (P<0.001)	+	Supported
HM → TAI		.117	*** (P<0.001)	+	Supported
PE→ SAT	H_2	.334	*** (P<0.001)	+	Supported
EE→ SAT		.088	(P>0.05)	+	Unsupported
SI→ SAT		.279	*** (P<0.001)	+	Supported
FC→ SAT		.192	*** (P<0.001)	+	Supported
HM → SAT		.081	(P>0.05)	+	Unsupported
TAI → ATT	H_3	.574	*** (P<0.001)	+	Supported
TAI → PI	H_4	.591	*** (P<0.001)	+	Supported
SAT→ PI		.639	*** (P<0.001)	+	Supported
PE→ PI	H_5	.268	*** (P<0.001)	+	Supported
EE → PI		.067	(P>0.05)	+	Unsupported
SI → PI		.222	*** (P<0.001)	+	Supported
FC → PI		.139	*** (P<0.001)	+	Supported
HM → PI		.089	(P>0.05)	+	Unsupported

Source: Primary Source

Table 3 provides the results of the hypothesis testing derived from the Structural Equation Modeling (SEM), examining the direct relationships among constructs within the integrated UTAUT2–S-O-R framework. The findings indicate strong support for most hypothesized paths, highlighting the significant role of technological stimuli in influencing consumer trust in AI (TAI), satisfaction (SAT), attitude (ATT), and purchase intention (PI) in an AI-driven omnichannel retail context. Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Hedonic Motivation (HM) were all found to have a significant positive influence on Trust in AI, thereby supporting H1 and its sub-paths. Among these, PE ($\beta = .331$, $p < 0.001$) and SI ($\beta = .263$, $p < 0.001$) emerged as strong predictors, suggesting that when AI tools are perceived as useful and endorsed by others, consumers are more likely to develop trust (Venkatesh et al., 2012; Choi & Kandampully, 2020). PE ($\beta = .334$, $p < 0.001$), SI ($\beta = .279$, $p < 0.001$), and FC ($\beta = .192$, $p < 0.001$) significantly influenced consumer satisfaction, confirming their relevance in enhancing post-adoption emotional evaluations. However, EE ($\beta = .088$, $p > 0.05$) and HM ($\beta = .081$, $p > 0.05$) did not show significant impact, indicating that ease of use and enjoyment may not directly drive satisfaction in the presence of more functional and social drivers. These findings partially support the S-O-R model, where environmental stimuli affect internal emotional responses (Mehrabian & Russell, 1974). Trust in AI significantly predicts both consumer attitude ($\beta = .574$, $p < 0.001$) and purchase intention ($\beta = .591$, $p < 0.001$), providing strong support for H3 and H4. This reinforces the idea that trust serves as a central mediating variable in AI adoption and conversion behavior (Moriuchi, 2021). Consumers who perceive AI as reliable and competent are more likely to develop favorable attitudes and are more inclined to complete purchases. Satisfaction was found to be a strong predictor of purchase intention ($\beta = .639$, $p < 0.001$), confirming prior studies that emphasize the importance of positive post-use evaluations in shaping future behavior (Oliver, 1999; Prentice et al., 2020).

Several UTAUT2 constructs also exhibited significant direct effects on purchase intention. PE ($\beta = .268$, $p < 0.001$), SI ($\beta = .222$, $p < 0.001$), and FC ($\beta = .139$, $p < 0.001$) were all positively associated with purchase behavior, indicating that consumers' decisions are shaped not only by emotional and trust-based evaluations but also by direct perceptions of usefulness, social context, and support. In contrast, EE ($\beta = .067$, $p > 0.05$) and HM ($\beta = .089$, $p > 0.05$) did not show significant influence on purchase intention, suggesting that these factors may be more relevant in early adoption stages than in actual purchase behavior. Overall, the model highlights the multidimensional influence of UTAUT2 factors on trust, satisfaction, and purchase intention, validating the integration of UTAUT2 with the S-O-R model. Trust in AI and satisfaction emerges as critical mediators, reinforcing their importance in AI-based consumer behavior research. These findings have significant implications for AI designers and retailers aiming to enhance consumer engagement and conversions in omnichannel retailing.

Implication

This study offers several theoretical and practical implications for researchers, marketers, and technology designers operating within the domain of AI-enabled omnichannel retailing.

Theoretical Implications

The integration of UTAUT2 and the S-O-R model provides a more holistic framework for understanding consumer behavior in AI-driven retail contexts. While UTAUT2 primarily addresses cognitive and utilitarian aspects such as performance expectancy and facilitating conditions (Venkatesh et al., 2012), the addition of the S-O-R framework enables the incorporation of emotional and psychological constructs like trust and satisfaction, which are critical in influencing purchase intention (Mehrabian & Russell, 1974; Pantano & Pizzi, 2020). This integrative approach advances the theoretical discourse on AI acceptance by demonstrating how both rational and affective factors jointly shape consumer responses in omnichannel environments.

Moreover, the study confirms trust in AI as a central mediating construct between technological factors and behavioral outcomes, aligning with prior research that positions trust as fundamental in AI-human interactions (Moriuchi, 2021; Choi & Kandampully, 2020). By highlighting the differential influence of each UTAUT2 construct on trust, satisfaction, and purchase intention, this study provides a fine-grained understanding of the mechanisms driving AI adoption in retail.

Practical Implications

From a managerial perspective, the findings underscore the importance of enhancing performance expectancy, social influence, and facilitating conditions in order to build consumer trust in AI systems. Retailers should invest in developing AI tools that are not only functionally effective but also socially validated—through endorsements, reviews, and peer influence—so that consumers feel confident and supported while interacting with these technologies (Grewal et al., 2021).

Furthermore, the significant role of satisfaction in driving purchase intention suggests that retailers must continuously monitor and optimize the post-interaction experience. AI interfaces should prioritize user-centric design, personalization, and reliability to foster emotional engagement and customer loyalty (Prentice et al., 2020). Retailers operating across omnichannel platforms must ensure consistency in AI interactions—whether online, in-store, or via mobile—since a fragmented experience could erode trust and satisfaction.

Interestingly, the non-significant impact of effort expectancy and hedonic motivation on satisfaction and purchase intention implies that ease of use and enjoyment may no longer be differentiating factors in mature markets where consumers are already accustomed to AI. This shifts the managerial focus toward functionality, reliability, and social validation as key levers for increasing adoption and driving sales.

Policy and Ethical Implications

Given the increasing role of AI in influencing consumer decisions, ethical considerations such as data privacy, transparency, and algorithmic fairness must be prioritized. Building trust also involves providing users with clear information on how their data is used and ensuring that AI recommendations are not manipulative but supportive of informed decision-making (Huang & Rust, 2021).

IV. CONCLUSION

This study examined the impact of Artificial Intelligence (AI) on consumer purchase behaviour within omnichannel retailing, by integrating the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and the Stimulus-Organism-Response (S-O-R) model. The results of the Structural Equation Modeling (SEM) provided empirical support for most of the hypothesized relationships, validating the integrated theoretical model.

The findings confirmed that constructs such as Performance Expectancy, Social Influence, and Facilitating Conditions significantly influence Trust in AI and Satisfaction, which in turn strongly predict Attitude and Purchase Intention. These outcomes highlight the dual importance of technological performance and social validation in shaping how consumers engage with AI in retail environments (Venkatesh et al., 2012; Choi & Kandampully, 2020). Furthermore, the central mediating role of Trust in AI underscores the importance of building credible and transparent AI systems that can foster consumer confidence and long-term engagement (Moriuchi, 2021). The study also revealed that while Hedonic Motivation and Effort Expectancy contribute to trust, their impact on Satisfaction and Purchase Intention is limited. This suggests that in mature AI retail ecosystems, functional value and perceived usefulness take precedence over mere ease or enjoyment of use (Huang & Rust, 2021). Additionally, Satisfaction emerged as the strongest predictor of Purchase Intention, reinforcing the relevance of emotional experiences in post-adoption behavior (Prentice et al., 2020).

By integrating UTAUT2's utilitarian dimensions with the emotional and psychological perspective of S-O-R, this study provides a comprehensive framework for understanding consumer responses to AI in omnichannel retailing. It offers both theoretical advancement and practical direction for marketers, system developers, and retail managers seeking to enhance AI deployment in ways that are functionally effective, emotionally engaging, and trust-enhancing.

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