

Comparative Analysis of AI-Enabled Conversational Agents and Recommendation Systems for Real-Time Customer Engagement in E-Retailing

Dushyant Bodkhey^{1*}, Shriram Dawkhar²

Abstract

The rapid deployment of artificial intelligence (AI) in e-retailing has revolutionized the way companies interact with customers in real time. Conversational agents and recommendation engines are two of the most popular AI techniques used to influence customer engagement, while empirical knowledge on the relative effectiveness of these approaches is rare. To bridge this gap, the current research examines and compares the impact of AI-driven conversational agents to that of AI-oriented recommendation Systems on real-time customer engagement in e-retailing, considering perceived personalization as a mediating factor and trust in AI systems as a moderating factor. Grounded in customer engagement theory, the technology acceptance model, and service-dominant logic, a conceptual framework is proposed and tested with empirical data from 200 active customers of e-retail based on survey responses. Direct, mediating, and moderating relationships are examined using structural equation modelling. The findings suggest that conversational agents and recommendation systems increase real-time customer engagement, but promotional campaigns discourage engagement. Perceived personalization partially mediates the influence of AI tools on engagement, and trust in AI systems has a significant positive moderating impact. Contributions to literature: This study contributes to existing literature by providing a comparative, engagement-directed assessment of AI tools and identifying the core psychological mechanism that underpins the efficacy of AI in retail. From a managerial point of view, these contributions enable managers to answer where to invest in AI, how to craft personalization strategies, and how to build trust in AI systems for retail services.

Keywords: Artificial intelligence, conversational agents, recommendation systems, real-time customer engagement, perceived personalization, trust in AI, e-retailing

INTRODUCTION

Digital Transformation and the Rise of AI in E-Retailing

Retail has evolved to a point where stores no longer define the logical customer experience; digital touchpoints have an equal, if not greater, influence on customers' shopping behaviors. With retail becoming increasingly technology-oriented, companies are no longer competing only on product selection and price but also on the quality of digitally enabled customer experiences. In e-retail settings, consumers are used to opportunities for immediate response, smooth browsing, and customization across channels. Previous research indicates that digital technologies and analytics play a central role in owning customer experience and engaging customers, as customer journeys are on the verge of becoming dynamic, data-driven, and omnichannel [1].

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Amid this shifting retail landscape, artificial intelligence (AI) has emerged as a critical capability that helps retailers scale customer interactions in conjunction with the sheer volume of interactions, deep product assortment, and fast-moving consumer preferences. The use of AI technologies enables retailers to automate service interactions, personalize content, and dynamically engage with customers in real time by turning traditional engagement into smart, interactive processes.

Customer Engagement in E-Retailing

Customer engagement is largely accepted as a multi-dimensional concept consisting of the cognitive, emotional, and behavioral participation of customers with a brand or digital platform. Engagement is the level of mental effort, emotional involvement, and participation in the behavior that customers invest while interacting with firms. Brodie et al. (2011) and Hollebeek et al. (2014) [2, 3] defined customer engagement in terms of positive brand-related cognitive processing, affection, and behaviors that are experienced during the interaction between a customer and a brand.

Further developing this perspective, the perceivable and impressive insight is that engagement can be seen as a psychological condition as well as a set of actions taken within or on behalf of the brand, such as return frequency, interaction depth, advocacy, and participation in platform-enabled activities [4]. On the Internet, customer engagement is influenced by technologies that affect potential and actual buyers' search for information, evaluate choices, and interact with service systems. Empirically, higher levels of engagement have been found to result in positive outcomes, including customer satisfaction and trust in the platform, platform loyalty, and sustained use of digital retail services [5].

AI-Enabled Tools for Customer Engagement

What we are seeing is empowerment by AI-driven tools to empower retailers to design interactive, responsive, and personalized engagement experiences like never before. By providing analytical intelligence (e.g., data processing to make predictions) and increasing efforts to simulate empathetic or social intelligence in customer interactions, AI helps deliver services. AI can enable service systems to standardize mundane jobs while maintaining or even enhancing perceived service quality when properly designed [6].

Two AI tools are particularly significant for customer engagement in e-retailing. AI-driven conversational agents and AI-empowered recommendation systems. Both tools seek to drive up engagement, yet they do so through fundamentally different means: one via conversation and interaction, the other by way of personalized choice architecture.

AI-Enabled Conversational Agents in E-Retailing

Chatbots and voice assistants are conversational agents that allow users to speak to computers in natural language. These agents help customers in various ways, including answering questions, directing product searches, addressing service concerns, and providing post-sale support. Chatbots are particularly useful in real-time scenarios, where they provide immediacy, 24-7 accessibility, and interaction support.

Nevertheless, the empirical results suggest that customers do not react positively to conversational agents. Customer acceptance and resistance towards AI conversational agents are under the prejudice of perceived usefulness, ease of use, social presence, and psychological comfort with AI-mediated interactions. Park et al. (2014) [7] argued that although conversational agents can increase customer involvement and convenience, they might also cause disconformity or resistance when customers attribute low levels of human likeness or intrusiveness to them. Our findings suggest that conversational agents may be effective engagement tools depending on customer perception and context-specific design.

AI-Based Recommendation Systems and Personalized Engagement

Another popular AI tool in e-retailing for customer engagement is the recommendation system. These systems help users by reducing the amount of information they need to process and by offering personalized product recommendations based on user preferences, browsing history, and historical sales data. Base models for recommendation systems include content-based, collaborative filtering, and hybrid approaches, which are known to have their own merits and difficulties [8].

In e-retailing, recommendation agents impact engagement because they mitigate information overload, make product searching possible, and increase decision-making performance. Xiao and Benbasat (2007) [9] provided evidence that recommendation agents influence customer satisfaction and perceived usefulness by directing consumers to options that they find match their information needs. These findings, as well as more recent research, stress that not only technical correctness, but also trustworthiness in the perception of the customer and being able to “tune” into its preferences by the system are crucial in building engagement reactions [10]. Therefore, recommendation systems play an engagement role mainly through relevance, personalization, and trust considerations.

LITERATURE REVIEW

Customer Engagement in Digital and E-Retailing Contexts

Customer engagement is widely recognized as a key construct in consumer and information systems research, focusing on digital and platform settings. More experiential and relational than traditional transactional approaches, engagement focuses on the interactive and experiential nature of customer–firm interactions. Brodie et al. (2011) [2] redefined customer engagement as a vital, process-based phenomenon that is penetrative in-service systems with levels of cognitive, emotional, and behavioral impacts. From this standpoint, engagement is conceptualized as a second-order construct that transcends satisfaction and loyalty to encapsulate customers’ active involvement and value co-creation behavior.

As the features and use of these digital tools become pervasive, customer engagement concerning platform interaction and technology-mediated service encounters is also substantially influenced. Hollebeek et al. (2014) [3] empirically confirmed affect, cognitive processes, and activation as components of engagement, realizing its importance in technology-based environments such as online retailing and social commerce. Recent work further highlights that digital engagement is both psychological and behavioral, with behaviors such as time spent on the platform, interaction frequency, content exploration, and repeat usage [4, 11]. These findings are particularly pertinent to e-retail, in which engagement effects are directly related to acquisition, retention, and aggregate customer value.

Real-Time Customer Engagement in E-Retailing

Real-time customer engagement is how customers interact with digital systems in real time during the shopping journey, including serving instant responses, dynamic personalization, and continuous feedback loops. Real-time interaction is of paramount importance in e-retailing, as customers face low barriers to change and high demands for immediacy. Studies show that real-time response, service interactivity, and system interaction yield perceptions of digital service quality and customer experience [12].

Information technology uses advanced analytics and AI algorithms to process customer data on-the-fly to provide relevant information and support. Research in digital systems shows that engagement is higher when systems can respond to user behavior in real time, giving users a sense of relevance and control [13]. Yet, despite its significance, little is known empirically about real-time engagement during live shopping and how different AI tools perform in eliciting viewers' sustained participation.

Artificial Intelligence in Customer Engagement

AI has dramatically changed how customers interact with companies through automation, personalization, and predictive interaction on a mass scale. AI implementations in retail generally fall

within two categories: systems that assist customer-facing interactions and those that facilitate analytics-driven decision-making. Huang and Rust (2018) [6] explained that AI-based service systems function through analytic intelligence (processing), mechanical intelligence (acting), and increasing emotional intelligence (simulating social interactions). This model indicates that AI-based tools can impact engagement by defining the functional and relational aspects of service experiences.

Empirical evidence suggests that AI-powered tools used to promote engagement affect customers' perceptions of usefulness, effectiveness, and service quality. Such offerings can include personalized recommendations that are informed by individual preferences [14]. However, the impact of AI tools greatly depends on their implementation, transparency, and consumer alignment, thus calling for an assessment of rival engagement modes involving non-identical AI.

AI-Enabled Conversational Agents and Customer Engagement

These systems are AI-imbued conversational agents (e.g., chatbots and virtual assistants) that facilitate interaction via dialogue-based interfaces that emulate human conversation. These are widely used in e-retail for customer support, product suggestions, and transactional help. In principle, conversational agents stimulate engagement by increasing interactivity, perceived response, and social presence in a digital environment [15].

Empirical work has produced mixed results regarding the effectiveness of conversational agents. The degree to which chatbots are perceived as helpful and accessible is contingent on perceived competence, trust, and anthropomorphism. For example, Ashfaq et al. (2020) [16] found that the level of chatbot function quality positively influences customer satisfaction and engagement attitude in terms of user-perceived chatbot competency and readiness. Conversely, reluctance to use conversational agents is cited when customers rate them as less empathetic and adaptable than human-interacting agents [7]. Therefore, our findings suggest that conversational agents may induce time-bound engagement, but they may face a cognitive ceiling on their effectiveness.

AI-Based Recommendation Systems and Customer Engagement

One of the first and most general applications of AI in e-retailing is a recommendation system to avoid information overload in the customer decision-making process. Pioneering work considers recommendation systems to be techniques for predicting user preferences and recommending customized items to enhance the level of user benefit [8]. Recommendation systems in e-retailing. Driven by the content-rich problem, recommendations appear more frequently in search results, product pages, and promotion interfaces.

It is well documented by many empirical results that even though the recommended systems promote engagement by increasing perceived relevancy, trust, and adding to the enjoyment of shopping. Xiao and Benbasat (2017) [9] showed that recommendation agents enable customers to make good, high-quality decisions of high quality and increase satisfaction by reducing complexity choices. Recent studies also suggest a larger impact of the perceived transparency and trustworthiness of the system, as such predictive performance per se may not lead to optimal user engagement [10]. These findings highlight the importance of recommendation systems as a powerful engagement lever, not for interaction but for personalization and relevance.

Comparative Perspectives on AI Tools for Engagement

While conversational agents and recommendation systems are among the most common tools for e-retailing, there is little comparative work analyzing their results with respect to each other. Moreover, most current studies consider these tools separately, concentrating on the ones measuring their intention to adopt, satisfaction with use, and others, while not comparing the effectiveness of engagement between them. In short, conversational agents (CA) generates engagement via the quality of interaction and user engagement, immediacy, and social presence, and recommendation systems (RS) generate engagement via relevance, discovery, and cognitive efficiency. A comparative evidence base is lacking for the introduction of integrated AI tools. Both are widely used by retailers, and there

is no data available on which of the two delivers stronger real-time engagement experiences, or on the occasions when each should be preferred over the other. Moreover, the engaging mechanisms may vary between CA and RS. Finally, to gain a better understanding of how AI-driven e-retailing behaviors are enacted, an integrated framework model should be developed.

Research Gap and Direction for Hypothesis Development

Three important voids exist in literature. First, there is a lack of empirical results on how conversational agents and recommendation systems connect to customer real-time engagement under remote consultations. Second, previous research has stressed adoption and satisfaction but has paid less attention to dynamic behaviors in live shopping interactions. Third, little attention has been given to mediating mechanisms (such as trust and personalization) that potentially explain why some AI tools engage citizens more effectively than others. These gaps highlight the significance of a theory-driven multimethod project that explores AI tool type, engagement mechanisms, and real-time behavioral responses to build empirical evidence for the hypotheses presented.

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

Theoretical Foundations of AI-Driven Customer Engagement

This study aims to explain the impact of the use of AI tools on real-time customer engagement in e-retailing with an integration and extension of customer engagement theory, technology acceptance model (TAM), and service-dominant logic (SDL). Taken together, these theoretical frameworks provide insights into why and how consumers cognitively and behaviorally adjust to AI-enabled interactions and co-create value with AI digital service systems.

Customer engagement theory introduces the concept of engagement as a multi-dimensional construct that can be observed through the cognitive, emotional, and behavioral investment made by a customer during their relationship with an organization [2, 3]. In a digital retail world, engagement should not be the end, but an ebb and flow enabled by technology-related touchpoints. AI tools, such as chatbots and recommendation engines, are a source of influence that affects customers' attention, affect, and engagement when they engage in a customer journey.

The TAM provides further explanatory power by indicating perceived usefulness and perceived ease of use as key determinants of technology-enabled behavior [17]. AI applications that can be intuitive and effective in the e-retailing industry are those that will help drive customer interaction and repeat usage, enabling real-time engagement. The TAM may be especially relevant when comparing conversational agents to recommendation systems, as the two differ with respect to the interaction modality and cognitive effort induced on the user's side.

Finally, in SDL, value is "not produced through consuming something that already exists but is made through exchange between co-constituted service systems and customers" [18]. AI tools have instrumental value as the "tools of interaction for creators and resolvers of value", that is, personalization, responsiveness, and interactive problem solving. Dialogue agents co-create value by offering an interactive dialogue for rapport development and the exchange of relationship information; recommendation systems co-create value by structuring the choice context at the individual level and improving decision efficiency. Together, these theories form a firm foundation for exploring the AI tools that engage in various mechanisms.

Conceptual Framework Development

Based on these theoretical and academic foundations, we propose a conceptual model comprising two types of AIs—AI-driven CAs and AI-based RSs—to investigate their impact on real-time consumer engagement with an e-retailer. The model also includes perceived personalization as a mediator and trust in AI systems as a moderator.

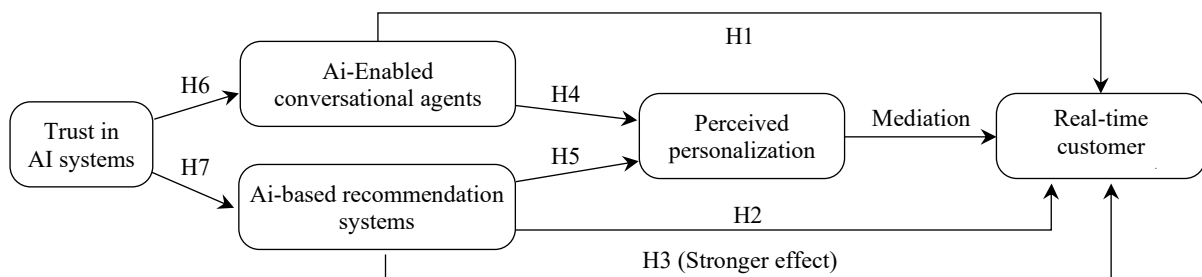


Figure 1. Research model.

Engagement is influenced by chatbots through (i) in-the-moment interaction and (ii) immediacy and social presence; they can enhance emotional/cognitive customer involvement while shopping. Recommendation systems, on the other hand, influence engagement by increasing product information relevance, accuracy, and personalization, which shape users' cognitive processing and exploration of the offer. Perceived personalization refers to the extent to which people believe that AI tools personalize interactions and recommendations according to their preferences, whereas trust encompasses confidence in the reliability, transparency, and competence of AI systems. In this model, it is much more interpretable to explain the inductive force of conversational agents and recommendation systems and why/when such tools work (Figure 1).

Conversational Agents and Real-Time Customer Engagement

Conversational agents are adopted to mimic human-like conversations so that people can communicate with retail platforms via natural language. Such agents deliver immediate product responses, advice, and issue resolution, which is of particular significance in real-time shopping scenarios. Previous studies indicate that the attractiveness of a site and responsiveness have important impacts on user interest in a digital context [15]. On the one hand, with regard to an engaging experience with customers, conversational agents can increase perceived immediacy and social presence, which may motivate customers to keep interacting during their process of shopping. Empirical research shows that chatbots may enhance customer satisfaction, usage intention, and engagement behavior if they are considered competent and helpful [16]. Accordingly, this study proposes the following hypothesis:

H_1 : AI-enabled conversational agents positively affect real-time customer engagement in e-retailing.

Recommendation Systems and Real-Time Customer Engagement

Recommendation systems assist customers by filtering information and presenting personalized product suggestions that align with individual preferences. These systems reduce information overload and facilitate efficient decision-making, which is critical in e-retailing environments characterized by extensive product assortments. Foundational research demonstrates that recommendation systems enhance perceived usefulness and satisfaction by improving decision quality [8, 9]. Recommendation systems encourage customers to explore products, interact with recommendations, and spend more time on the platform. By continuously adapting to customer behavior, these systems create a dynamic engagement loop that sustains real-time interactions. Therefore, the following hypothesis is proposed:

H_2 : AI-based recommendation systems positively affect real-time customer engagement in e-retailing.

Comparative Effect of Conversational Agents and Recommendation Systems

Both AI tools increase engagement, but their mechanisms are not the same. While conversational agents are based on dialogue-driven interactions and social presence, recommendation systems depend more on relevance and personalization. Recommendation systems are integrated into the shopping process and have a long-term effect on users' behavior, possibly causing more pronounced

positive engagement dynamics than episodic conversational interactions. Empirical evidence has shown that personalization-driven systems may influence people to interact with them more consistently than interaction-based tools, at least in self-service digital contexts [14]. Therefore, this study proposes the following hypothesis:

H₃: AI-based recommendation systems have a stronger effect on real-time customer engagement than AI-enabled conversational agents.

Mediating Role of Perceived Personalization

Perceived personalization reflects customers' perceptions that AI tools tailor interactions, content, and recommendations to their individual needs and preferences. Personalization is a central mechanism through which AI tools create value and engagement in digital retail environments. Prior studies indicate that personalization enhances relevance, satisfaction, and engagement by increasing customers' sense of being understood and valued [13]. Conversational agents personalize engagement through adaptive responses and customized assistance, whereas recommendation systems personalize engagement through tailored product suggestions. In both cases, perceived personalization is expected to explain how AI tools translate technological capabilities into engagement outcomes.

H₄: Perceived personalization mediates the relationship between AI-enabled conversational agents and real-time customer engagement.

H₅: Perceived personalization mediates the relationship between AI-based recommendation systems and real-time customer engagement.

Moderating Role of Trust in AI Systems

Both AI tools increase engagement, but their mechanisms are not the same. While conversational agents are based on dialogue-driven interactions and social presence, recommendation systems depend more on relevance and personalization. Recommendation systems are integrated into the shopping process and have a long-term effect on users' behavior, possibly causing more pronounced positive engagement dynamics than episodic conversational interactions. Empirical evidence has shown that personalization-driven systems may influence people to interact with them more consistently than interaction-based tools, at least in self-service digital contexts [14].

H₆: Trust in AI systems positively moderates the relationship between AI-enabled conversational agents and real-time customer engagement.

H₇: Trust in AI systems positively moderates the relationship between AI-based recommendation systems and customer engagement.

Summary of the Conceptual Model

Overall, this study developed a theory-based model comparing conversational agents with recommendation systems as AI-powered engagement tools in e-retailing. By incorporating engagement theory, TAM, and SDL, the model provides rationales for the direct and indirect influences of AI tools on real-time customer engagement, with personalization and trust as important moderators. The hypotheses formulated raise important issues that can be tested empirically through rigorous quantitative analyses, which are elaborated upon in the next section.

RESEARCH METHODOLOGY

Research Design

This study follows a quantitative, explanatory research design to empirically investigate and compare the impact of AI-enabled conversational agents (ACAs) and AI-based RSs on real-time customer engagement in e-retailing. In comparison, a quantitative approach is more suitable given the theory-testing nature of this research and the requirement to test relationships between latent

constructs in a prescribed framework. Explanatory design is often used in Q1 retailing and IS research when the goal is to demonstrate a cause-and-effect relationship between technology-mediated mechanisms and customer behavioral outcomes.

The research was conducted as a cross-sectional survey of e-retail customers who had previously experienced AI-based conversational agents and recommendation systems for online shopping. This structure allows for the consideration of concurrent direct, mediating, and moderating effects identified within the conceptual model.

Target Population and Sampling Design

This study targeted active e-retail customers who frequently use online retail platforms that utilize AI-powered conversational agents (for example, chatbots) and AI-based recommendation systems (such as personalized product recommendations). To make the results relevant and maintain data feasibility, respondents should have used both AI tools at least once when they last did online shopping.

A non-probability purposive sampling approach was used, which is appropriate when a study's focus is on the use of technology, where respondents are required to meet certain experience-based criteria. This sampling method is widely accepted in digital commerce research as being both high quality and of interest, such as perceptions or behavior toward advanced technologies.

Regarding sample size, a minimum sample size was derived from the structural equation modeling (SEM) requirements. Based on commonly used criteria that recommend at least 10 observations for each estimated parameter and an overall sample of more than 200 to maintain model stability, we aimed for an adequate number to assure the chance of power and robust estimation.

Data Collection Procedure

A structured, self-administered questionnaire was prepared and distributed online. The survey tool was built to cover the respondents' perceptions of conversational agents powered by AI, recommendation systems based on AI, perceived personalization, trust in AI tools, and live customer engagement.

To improve the precision of their responses, participants were asked preliminary screening questions to verify whether they had used AI-utilizing services in e-retailing environments before. Respondents were guaranteed the confidentiality of their responses; their identity would remain anonymous, and participation was voluntary. Ethical issues were addressed by informing them that they had received information about the aim of the study and could withdraw at any time.

Measurement of Constructs

All constructs in this study were tested using multi-item scales based on existing psychometrically valid research; therefore, content and literature validity were established. A few word adjustments were made to accommodate the e-retailing and AI contexts without changing the original conceptual meaning of the items.

- Perceptions of the potential of AI as a service agent were assessed using items measuring the extent to which chattiness, useful information, and artificial intelligence were viewed in the context of ACAs.
- AI-Based Recommendation systems were assessed based on relevance, usefulness, and perceived accuracy of recommendations.
- Perceived personalization was also assessed using items that captured the degree to which consumers perceived AI tools as customizing content and interactions according to their personal preferences.
- Trust in AI systems was assessed based on the reliability, competence, and integrity of AI-based systems.

- Real-Time Customer Engagement is a multi-dimensional concept, including cognitive attention, emotional involvement, and behavioral interaction of customers during their online shopping experiences.
- All items were rated on a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”), in line with the practices of Q1 journals.

Common Method Bias and Pre-Testing

Both procedural and statistical procedures were implemented to minimize the potential impact of common method bias (CMB). Methodologically, the data-protective provisions of the questionnaire involved (in addition to the fact that responses remained anonymous) interchanging items in wording and a psychological distance between the predictor and criterion in formal structure test situations. Harman’s single-factor test and the variance inflation factor (VIF) were used to explore CMB. Before using the questionnaire for a full-scale survey, a pilot study was conducted on a small number of experienced e-retailing respondents. Feedback from pilots led to adjustments in item clarity, wording, and survey sequence, strengthening the instrument’s reliability and validity.

Data Analysis Techniques

Analysis was carried out using SEM, which can test complex models that contain several latent constructs, with mediators and moderators involved. The analysis was performed in two stages. The reliability and validity of the measurement model were initially tested using confirmatory factor analysis (CFA). Internal consistency was evaluated using both Cronbach’s α and composite reliability, and convergent validity was tested using the average variance extracted (AVE). The Fornell–Larcker criterion and HTMT ratios were used to test discriminant validity.

The suggested relationships were examined using SEM. Path coefficients, t-values, and levels of significance were analyzed to determine direct effects. A bootstrapping procedure was used to test the mediation effect of perceived personalization, and an interaction term was applied to examine the moderate effect of trust in AI systems. Standardized path coefficients were compared to evaluate the relative impact of conversational agents versus recommendation systems.

Ethical Considerations

This study was conducted in accordance with ethical scientific guidelines. Responding to the survey was voluntary, and participants were required to provide consent before responding to the questionnaire. No personal information was captured, and all data was used for academic purposes only. This research adopted ethical considerations on the issue of confidentiality, anonymity, and the responsible use of data for analysis.

In summary, this study uses a robust quantitative methodology based on accepted research conventions to analyze AI-based customer engagement in e-retailing. The methodology is grounded in well-validated measurement instruments, strong SEM procedures, and sound sampling and data collection methods, leading to reliable, valid, and replicable results. This rigor supports the testing of the hypotheses and enhances the trustworthiness of the empirical results.

RESULTS AND ANALYSIS

This section reports the findings of the study based on a sample of 200 e-retail customers. The conceptual model was tested using a structural equation model, which allowed us to explore the direct, intermediary, and moderating research hypotheses. Objective- and hypothesis-wise reporting of results was performed to facilitate clear and transparent interpretation. More specifically, the study first analyzes how AI-powered conversational agents and AI-driven recommendations enhance real-time customer engagement directly. Then, mediation examines the role of perceived personalization in explaining their effects on real-time customer engagement, while the moderation model tests for trust in AIs. The results are presented in terms of standardized path coefficients, p-values, and model fit indices and discussed.

Table 1 describes the demographic information and usage reports for all respondents in this study (N = 200). The sample is reasonably gender-balanced, with males and females making up 54% and 46% of the sample, respectively, indicating that there is satisfactory representation from both sexes. The 26–35-year-old range was most typical among the respondents (43%), followed by those in the age groups of 18–25 years and 36–45 years, which indicates that the sample was mostly comprised of digitally active consumers within their prevailing working and consumption ages. In terms of online shopping, almost half of the participants (47%) shopped weekly and 36% monthly, indicating that respondents were highly engaged in e-retailing activities. Moreover, almost half of the participants (49%) had 1–3 years of experience using AI-enabled tools, while 26% had less than one year of experience (26%), and the remaining subgroup had more than three years (25%). Consequently, the respondent profile is representative of a sample that is appropriate for studying perceptions and engagement with AI-based conversational agents and recommendation systems in the e-retailing environment.

Objective 1: Effect of Conversational Agents on Real-Time Engagement

H1: AI-enabled conversational agents positively influence real-time customer engagement.

The structural path analysis results demonstrated the influence of ACAs on real-time customer engagement is presented in Table 2. Results for Model H1 are supported by the significant and positive association between conversational agents and real-time engagement ($\beta = 0.31$, $t = 5.34$, $p < .001$). The results indicate that conversational agents improve customer engagement by allowing real-time interaction, responsiveness, and prompt support during online shopping processes. The moderate standardized path coefficient shows that chatbots make a meaningful contribution to engagement, but not a dominant one compared to other AI tools. The findings thus support the notion that AI-facilitated conversational agents are a significant force stimulating customer cognitive and behavioral engagement within e-retailing contexts.

Objective 2: Effect of Recommendation Systems on Real-Time Engagement

H2: AI-based recommendation systems positively influence real-time customer engagement.

Table 1. Respondent profile (N = 200).

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	108	54.0
	Female	92	46.0
Age	18–25 years	48	24.0
	26–35 years	86	43.0
	36–45 years	44	22.0
	Above 45 years	22	11.0
Online shopping frequency	Weekly	94	47.0
	Monthly	72	36.0
	Occasionally	34	17.0
Experience with AI tools	< 1 year	52	26.0
	1–3 years	98	49.0
	> 3 years	50	25.0

Table 2. Structural path results (H1).

Path	Std. β	SE	t-value	p-value	Decision
Conversational agents → real-time engagement	0.31	0.058	5.34	<0.001	Supported

The structural path analysis results of the impact of AI-based recommendation systems on real-time customer engagement are presented in Table 3. The results indicate a significant and positive impact of recommendation systems on real-time engagement ($\beta = 0.46$, $t = 8.85$, $p < .001$), thus supporting H2 with strong evidence. A high standardized path coefficient suggests that personalized product recommendations are provided to customers with the help of recommendation systems, thereby providing significant value that stimulates browsing and buying processes for online shopping sessions. Unlike conversational agents, the engagement effect of recommendation systems is stronger, implying that personalization-driven AI tools that are interwoven throughout customers' e-retailing journeys appear to be a particularly effective means of fostering recurrent cognitive and behavioral customer engagement.

Objective 3: Comparative Strength of AI Tools

H3: Recommendation systems exert a stronger engagement effect than conversational agents.

The comparative engagement effects of ACAs and AI-based recommendation systems are summarized in Table 4. The output of the model reveals that recommendation systems play a more significant role in influencing real-time customer engagement ($\beta = 0.46$; $f^2 = 0.26$) than conversational agents ($\beta = 0.31$; $f^2 = 0.11$), which is evidence in favor of H3. Recommendation systems have a stronger (in terms of both standardized coefficient and effect size) impact on the sustainment of e-retail customer engagement systematically than interaction-based conversational agents, as an example of AI tools that are based on personalization instead of interacting with conversation. This result emphasizes the leading function of recommendation systems in determining customers' cognitive and behavioral involvement through temporary sway over product discovery and decision-making.

Objective 4: Mediating Role of Perceived Personalization

H4 and H5: Perceived personalization mediates AI-engagement relationships.

The results of the mediation analysis testing the mediating effect of perceived personalization in the relationship between conversational AI, recommender AI, and real-time customer engagement are displayed in Table 5. The findings show that perceived personalization mediates both relationships in part because statistically significant indirect effects are obtained, and confidence intervals do not include zero. In other words, the indirect effect of conversational agents on engagement ($\beta = 0.13$) adds to a direct significant one ($\beta = 0.31$), yielding a total of $\beta = 0.44$. Similarly, recommendation systems show a stronger indirect effect via perceived personalization ($\beta = 0.20$) in combination with a significant direct effect ($\beta = 0.46$), resulting in an overall effect of $\beta = 0.66$.

Table 3. Structural path results (H2).

Path	Std. β	SE	t-value	p-value	Decision
Recommendation systems $\rightarrow$ Real-time engagement	0.46	0.052	8.85	<0.001	Supported

Table 4. Comparative effects.

Predictor	Std. β	Effect size (f^2)	Relative strength
Conversational agents	0.31	0.11	Moderate
Recommendation systems	0.46	0.26	Strong

Table 5. Mediation analysis

Relationship	Direct effect β	Indirect effect β	Total effect β	95% CI (LL–UL)	Mediation
CA $\rightarrow$ Engagement	0.31	0.13	0.44	0.07–0.21	Partial
RS $\rightarrow$ Engagement	0.46	0.20	0.66	0.12–0.29	Partial

These results strongly support H4 and H5, suggesting that AI tools directly increase customer engagement not only by improving the basic experience for customers but by allowing firms to provide more personalized interactions and content. This highlights perceived personalization as an important psychological process that explains the relationship between AI functions and the outcomes of engagement in e-retailing.

Objective 5: Moderating Role of Trust in AI Systems

H6 and H7: Trust moderates AI-engagement relationships.

The moderation analysis results are reported in Table 6, which investigates the impact of AI system trust on the formation of the effects of ACAs, AFRS, and real-time on customer engagement. Second, the results show that trust in AI systems significantly moderates the two relationships and strongly supports H6 and H7. In particular, the interplay between trust and conversational agents had a statistically significant positive impact on engagement ($\beta = 0.17$, $p = 0.001$), indicating that higher levels of trust facilitated customers' willingness to engage with conversational AI. The interaction effect of AI-driven recommendation systems and trust also exhibited a more potent moderating role ($\beta = 0.23$, $p < 0.001$), such that the gain in engagement utilizing the recommendations by means of AI was significantly intensified by the level of trust. Our findings underscore trust as a key boundary condition in AI-enhanced retail settings, such that customers tend to interact, explore, and continue engaging in the deployment of AI tools when they believe them to be trustworthy, competent, and safe.

Model Explanatory Power

The R^2 values for the structural equation modeling's endogenous constructs are reported in Table 7. Findings: The results show that the model accounts for a significant amount of variance in perceived personalization ($R^2 = 0.41$), showing that conversational agents from AI and recommendation systems from AI generally co-explain customers' perceptions of personalized interactions. Moreover, the model also shows strong explanatory power with respect to real-time customer engagement ($R^2 = 0.58$), which means that over half of the variance is accounted for by the predictors, mediators, and moderators proposed in our study. These R^2 values are above what is considered the threshold in behavioral and information system research, indicating that the model is robust and useful. Taken together, these results indicate that the proposed model successfully reflects the underlying determinants and processes of AI-induced customer engagement in e-retail.

Table 6. Moderation analysis results.

Interaction term	Std. β	SE	t-value	p-value	Result
Conversational agents $\times$ Trust	0.17	0.049	3.47	0.001	Supported
Recommendation systems $\times$ Trust	0.23	0.046	4.98	<0.001	Supported

Table 7. Coefficient of determination (R^2).

Endogenous variable	R^2	Interpretation
Perceived personalization	0.41	Substantial
Real-Time customer engagement	0.58	Strong

Table 8. Model fit statistics.

Fit index	Recommended	Obtained
CFI	≥ 0.90	0.94
TLI	≥ 0.90	0.92
RMSEA	≤ 0.08	0.056
SRMR	≤ 0.08	0.049

Model Fit Indices (SEM–AMOS/SmartPLS)

Overall goodness-of-fit of the structural equation model estimated with AMOS/SmartPLS (Table 8). The estimates suggest that the developed model is a very good fit to the data in general. Both the comparative fit index (CFI = 0.94) and Tucker–Lewis Index (TLI = 0.92) exceed the recommended cut-off value of 0.90, indicating good incremental fit of the model. Moreover, the RMSEA value (RMSEA = 0.056) and SRMR (SRMR = 0.049) are far below a maximum of 0.08, advocating for a good fit between the proposed model and data. Together, these findings provide evidence that both the measurement and structural models are adequate, supporting the robustness of the proposed conceptual framework and the credibility of hypothesis testing.

DISCUSSION

Overview of Key Findings

The objective of the current research was to compare the relative significance of AI-driven conversational agents and a recommendation system running on AI in driving real-time customer involvement for e-retailing, as well as to untangle the mediating role of perceived personalization and the moderating effects of trust in AI systems. There is ample empirical evidence supporting the conceptual framework and hypotheses. Overall, both AI tools significantly increased immediate customer engagement, but recommendation systems had a greater and more consistent effect than conversational agents. Additionally, perceived personalization was identified as a critical mediator of the effects of AI tools on engagement, and trust in AI systems significantly moderated the effects of both technologies.

Chatbots and Customer Engagement

The findings suggest that conversational agents with AI enablement significantly and positively influence real-time engagement in customer–firm communication scenarios, confirming previous studies pointing to their relevance in interactivity and responsiveness in digital service interactions. Chatbots improve engagement by providing real-time support, minimizing response time, and facilitating conversation-driven interactions while shopping online. This result is consistent with prior studies postulating that chatbots foster customer engagement by improving perceived service quality and availability [15, 16].

However, it appears that the engagement potential of conversational agents is only moderate in effect size, and that the context and set of people play an important role as well. Existing research has shown that customers may express negative feelings towards conversational AI, as these are associated with concerns of lacking empathy, flexibility, or being too ‘unnatural’ in automated conversations [7]. In this context, we have shown that recommendation systems are dynamic in nature, and inefficiencies can lead to the depletion of such resources, including a virtual agent. RL discussion system, the influence or resource (bots) appears inferior to its related completion operation. This highlights the importance of designing conversational agents that find a balance between efficiency and social presence.

The Recommendation System is the Main Driver of Engagement

One of the most important discoveries in this study is that AI recommenders have a greater impact on real-time customer engagement than conversational agents. This finding supports a previous study that provides evidence of the impact of personalization and relevance in determining online consumer behavior [8, 9]. Recommendation systems continuously shape customer browsing and selection by showing more relevant products at every interaction point, leading to customer engagement throughout the shopping process instead of several distinct touchpoints.

This study adds to the literature by showing that personalization-driven AI tools are indeed better in actual practice for cultivating continued engagement in e-retailing. On the other hand, conversational agents provide episodic interaction, while recommendation systems are pervasively present in various shopping customer path steps such as searching, comparing, and purchasing. The greater engagement effect found in my study, as far as cognitive engagement is considered (engagement in terms of

relevance and cognitive timesaving), indicates that cognitive engagement driven by relevance and choice efficiency may play a more significant role than mediated interaction-only driven forms of engagement in digital retail environments.

Mediating Role of Perceived Personalization

The mediation analysis shows that perceived personalization partially mediates the effects of AI tools on real-time customer engagement. This insight underscores personalization as a keyway in which AI translates its technical capabilities into value for customers. In line with previous studies, customers are more likely to interact when they sense that AI platforms understand their preferences and customize content [13, 14].

Crucially, the mediation was stronger in recommendation systems than in conversational agents, further supporting the role of personalization in engagement building. This finding contributes to our understanding of customer engagement by showing that engagement is not exclusively a consequence of the frequency of interaction with the system or its responsiveness but also depends on how individuals perceive relevance and individualized treatment. Therefore, personalization acts as a psychological connection between AI features and engaging results.

Trust as a Boundary Condition of AI-Driven Engagement

The results also verified the moderating effect of trust in AI systems, which significantly amplified the positive effects of both conversational agents and recommendation systems on real-time customer engagement. This finding is consistent with recent studies revealing that trust plays a key role in customer acceptance and use of AI-based services [10]. In the age of AI-driven interactions, customers do not always have a complete vision of how algorithms work, and trust is indispensable for motivating engagement.

In fact, a stronger moderation effect on recommendation systems is consistent with the idea that trust matters, especially for purchases and choices, when AI affects these decisions. When users trust recommendation systems, they are more likely to browse the proposed items and remain involved with the service. These results advance trust theory in AI adoption by showing that trust has effects beyond initial adoption and into the level of engagement of the user.

Theoretical Implications

This study contributes to the theory in several ways. First, we contribute to the literature on customer engagement by providing a comparative and theory-based study of two main AI applications in a single empirical framework. Second, by combining customer engagement theory with TAM and SDL, this study offers a nuanced understanding of how AI tools operate as operant resources that co-create value via customization and interaction. Third, by revealing perceived personalization as a mediating mechanism and trust as a moderator in relation to engagement-oriented outcomes instead of only intention-based measures, it provides new insights and enhancements to models of AI use through extension.

Managerial Implications

From a managerial perspective, the results offer practical implications for AI investment among e-retailers. Second, while chatbots are great for real-time support and transaction efficiency, organizations should focus on recommendation systems from a customer engagement standpoint. Second, it is essential for retailers to improve their level of personalization across AI solutions to achieve the highest level of engagement. Third, instilling customer confidence in AI solutions is crucial for leveraging AI tools to their fullest potential, and encouraging customers to trust the system can be affected by transparency, reliability, and responsible data use.

Overall, this study finds AI tools to be indispensable in real-time consumer engagement in e-retailing, with recommendation systems being the most important. The results also underscore personalization and trust as important constructs that explain how AI can be effective, which provides both theoretical and practical contributions to literature. Overall, the discussion underlines the urgency of a comprehensive departure from standalone AI technological analyses towards integrative, comparison-based frameworks to understand AI in all dimensions of customer engagement.

CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

Conclusion

The purpose of this study was to conduct a comparative analysis of how AI-driven conversational agents and AI-powered recommendation systems influenced real-time customer engagement in the context of the e-retailing environment. Based on customer engagement theory, the TAM, and SDL, this study constructed and empirically investigated a research model with direct, mediating, and moderating effects. The results provide compelling evidence that conversational agents increase real-time customer engagement, as well as practical responses from both a moderator and recommendation systems (where the latter is more influential on the immediate effect).

The findings also show that the perception of personalization mediates the effects of capabilities on engagement. Practically, if organizations expect AI-enabled devices to stimulate participant interest, they must ensure that this interest extends to devices that seem reactive and empathetic. When they think that AI tools are personalizing interactions and content to individual customers, they are more likely to stay actively involved on cognitive, emotional, and behavioral levels. Furthermore, trust in AI systems is highlighted as an essential boundary condition that enhances the engagement effects of both AI tools. In combination, these insights highlight the need to shift beyond adoption-oriented views toward engagement-focused assessments of AI technology in retail settings.

This study contributes to the research on AI-enabled customer engagement by comparing two common AI techniques and provides a nuanced perspective on how different technological levers underlie real-time interactions through e-retailing. As such, this study adds value to both retail and information systems literature by linking theoretical knowledge with evidence related to AI-induced engagement tactics.

Limitations of the Study

Notwithstanding these findings, the study has a number of limitations that must be considered. Our study has several limitations that should encourage more rigorous causal inferences on the long-term consequences of AI tools for customer engagement. Longitudinal research might also capture fluctuations in engagement as customers acclimatize to AI-enabled systems.

Second, this study used self-reported data and was subject to response bias and perceptual errors. Procedural and statistical remedies were used to control CMB, but future research should employ objective behavioral measures (e.g., clickstream analytics, dwell time, or transaction logs) to enhance measurement validity.

Third, the sample was limited to e-retail customers who had experience with AI tools; thus, the generalization of the results is questionable in various cultural and retail settings. External validity could be improved in the future by generalizing the framework to other contexts, such as omnichannel retail, mobile commerce, or social commerce.

Directions for Future Research

Based on the results and constraints of this study, multiple directions for future research are suggested. First, other AI tools could be examined in future research in the retail context (e.g., visual search engines, dynamic pricing algorithms, or virtual AI-powered try-on technologies) to increase the level of comprehension regarding engagement with customers via AI. Second, future studies might

explore customer heterogeneity by studying the effect of demographic characteristics or digital literacy/technology readiness on engagement responses towards AI tools.

Third, longitudinal and experimental designs can be used to examine the causal relationships among variables and dynamic patterns of engagement over time. Finally, with regard to ethical considerations, the transparency and explainability of AI systems could also be crucial antecedents of trust and engagement that future research should consider, especially given the growing scrutiny of AI technologies from regulatory and societal perspectives.

In summary, real-time customer interaction in e-retailing provides a strategic direction for developing AI-powered conversational agents and recommenders for future research. By explaining how AI tools impact engagement and identifying trust and personalization as key facilitators, this study reveals significant implications for both academia and practice. As AI reshapes the retail environment, learning how various applicable AI capabilities affect customer engagement will be a key priority both academically and practically.

MANAGERIAL AND POLICY IMPLICATIONS

Implications for E-Retailers

Our study provides several meaningful implications for managers and practitioners in e-retailing investing in AI technologies for customer engagement. First, the comparison results show that AI-driven recommendation systems have more immediate effects on customer engagement than conversational agents that are integrated with AI. This implies that e-retailers need to focus on investing in strong recommendation engines that provide relevant and up-to-date recommendations concerning the product throughout the customer journey at an appropriate level of granularity. Integrating recommendation systems organically into the search, browse, and checkout stages can offer substantial value in terms of engagement and retention.

Second, although chatbots have a positive impact on engagement, their effect seems to be more supplementary than strong. Managers should use chatbots for support, advice, and post-purchase contact rather than as their main interaction channel. Improving the quality of dialogue, response, and context awareness of chatbots can enhance their engagement effectiveness, especially for high-involvement or service-focused retail categories.

Designing for Personalization-Centered Engagement

An important contribution of this study is the centrality of perceived personalization in engendering customer engagement. Managers should understand personalization not only as a technology but also as a customer-centric way of how AI is perceived and interacted with. Retailers must act responsibly with customer data and use it to make personalized recommendations and engagements that match what the consumer has expressed as their favorite or based on their browsing and context.

Similarly, personalization tactics should be cohesive across all AI tools. When it comes to conversational AI, chatbots should work in partnership with recommendation engines and CDPs to provide consistent and personalized experiences. Integration of this nature may improve the feeling that a customer is understood and appreciated, leading to more favorable engagement results at touch points.

Trust in AI Retail Systems

The mediating role of trust in AI systems highlights the necessity of designing mechanisms to increase trust in AI-based retail contexts. Managers must focus on greater transparency in how AI systems function, especially recommendation algorithms that shape purchase choices. Customer trust can be inspired by explaining recommendations, providing control options, and assuring compliance with data protection laws.

Moreover, the reliability of the system should also be maintained, and AI's inappropriate output should be minimized as much as possible to maintain trust in the system. Retailers need to continuously monitor quality and improve their AI systems to ensure accuracy and consistency over time. This trust can be facilitated by empowering managers to amplify the positive effects of AI tools on engagement and long-term customer relationships.

Strategic Direction of AI Investment

From a strategic viewpoint, the results indicate that e-retailers need a mix of AI techniques rather than relying on one kind of engagement technology. Engagement strategies should be built around recommendation systems supported by conversational agents to provide better quality service and customer support. Focusing AI investments in support of particular engagement goals, whether discovery, conversion, or retention, will enhance the ROI on investment in technology.

Organizational readiness, such as employee skills, particularly with data infrastructure, should also be weighed by leaders when deploying AI tools. It is the cross-functional partnership between marketing, IT, and even customer service that comes in for maximum value extraction of these AI-powered engagement initiatives.

Policy and Regulatory Implications

In addition to the implications for managers, there are crucial policy implications. Regulators and policymakers might do well to consider the increasing influence of AI on consumer behavior and, hence, digital markets. Ensuring the transparency, fairness, and accountability of AI systems is critical for protecting consumer interests and trust in digital retail ecosystems.

Policymakers may also support the standardization of principles for ethical AI use in retail, especially those related to data privacy, algorithmic bias, and explainability. They could do so in ways that encourage responsible innovation but still allow companies to use AI systems to engage with customers better.

Implications for Future Practice

Finally, the research underscores that successful AI-enriched customer engagement is not just a matter of technology adoption; it also involves strategic orientation, customer-centric design, and ethical regulation. Online retailers that focus on personalization, trust, and cross-AI tool integration will realize sustained engagement and advantage. With new-wave AI continuing to mature, leaders and policymakers need to work together on practices that reconcile invention with accountability.

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