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The Influence of Automated Interactions on Consumer Purchase Decisions Across the Customer Journey: A Systematic Literature Review

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This systematic literature review investigates how automated interaction such as chatbots, voice assistants, and conversational messaging platforms shape consumer purchase decisions across the stages of the customer journey. Drawing on 13 empirical studies published between 2010 and 2024, the review highlights consistent evidence that automated systems enhance awareness by increasing engagement and social presence; strengthen consideration by improving information quality and personalized recommendations; streamline purchase processes through reduced friction and guided flows; and reinforce post-purchase outcomes via efficient service and emotional responsiveness. Nevertheless, their effectiveness depends on technological sophistication, transparency, privacy management, and contextual relevance. Methodological gaps include limited longitudinal studies, varying measurement approaches, and insufficient exploration of ethical concerns. This review proposes an integrative framework that connects automated interaction mechanisms with consumer behavior dynamics across journey stages.

Keywords: Automated interactions, Consumer behavior, Purchase decisions, Customer journey

Tinjauan literatur sistematis ini bertujuan menganalisis bagaimana interaksi otomatis seperti chatbot, asisten suara, dan platform percakapan mempengaruhi keputusan pembelian konsumen pada berbagai tahap customer journey. Berdasarkan 13 studi empiris yang dipublikasikan antara 2010 hingga 2024, temuan menunjukkan bahwa sistem otomatis meningkatkan tahap awareness melalui engagement dan social presence; memperkuat tahap consideration melalui rekomendasi yang dipersonalisasi dan penyajian informasi yang lebih berkualitas; menyederhanakan proses pembelian dengan mengurangi friksi dan menyediakan alur keputusan yang lebih terarah; serta mendukung tahap pascapembelian melalui layanan yang efisien dan respons emosional yang lebih baik. Namun, efektivitasnya sangat dipengaruhi oleh tingkat kecanggihan teknologi, transparansi, pengelolaan privasi, dan kesesuaian konteks. Kesenjangan metodologis masih terlihat pada minimnya studi longitudinal, perbedaan kerangka pengukuran, serta kurangnya eksplorasi isu etika. Tinjauan ini menawarkan kerangka konseptual yang menghubungkan mekanisme interaksi otomatis dengan dinamika perilaku konsumen di setiap tahap customer journey.

Kata Kunci:* *Interaksi otomatis, Perilaku konsumen, Keputusan pembelian, Customer journey

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INTRODUCTION

Artificial intelligence and natural language processing advancements have fundamentally transformed consumer-brand interactions throughout the purchase journey. Automated interactions manifested through chatbots, voice assistants, and messaging platforms have become ubiquitous touchpoints influencing consumer decision-making from initial awareness to post-purchase loyalty (E. Coli et al., 2020). These conversational systems represent a paradigm shift from traditional one-way communication to dynamic, personalized dialogues adapting to individual consumer needs in real-time (Bilquise et al., 2022; Sanders et al., 2023).

Conversational commerce, defined as automated conversational agents integrated within commercial contexts, has experienced exponential growth. Businesses increasingly deploy chatbots for customer service, product recommendations, and transactional support, driven by promises of improved efficiency, personalization, and customer satisfaction (Cheung et al., 2015; García-Méndez et al., 2021). However, academic understanding of how these systems influence consumer purchase decisions remains fragmented across disciplines information systems, marketing, human-computer interaction, and artificial intelligence each offering partial insights without unified frameworks (Bilquise et al., 2022; Yang et al., 2020).

The customer journey framework provides a structured lens for examining consumer behavior, delineating distinct stages from initial awareness through consideration, purchase, and post-purchase engagement. Each stage presents unique challenges and opportunities for automated interactions to influence outcomes. During awareness, automated systems capture attention and stimulate interest; in consideration, they facilitate information processing and comparison; at purchase, they streamline transactions and reduce friction; post-purchase, they provide support and foster loyalty (Bilquise et al., 2022; E. Coli et al., 2020). Yet, mechanisms through which these effects occur, their magnitude, and effectiveness conditions remain insufficiently understood.

Research Objectives

This systematic literature review addresses these gaps by pursuing four primary objectives:

1. Synthesize empirical evidence on how automated interactions influence consumer behavior across all customer journey stages, identifying key mechanisms and effects at each phase
2. Develop an integrative conceptual framework connecting theoretical perspectives from consumer behavior, human-computer interaction, and persuasion research to explain how automated systems shape purchase decisions
3. Identify methodological approaches and measurement challenges characterizing current research, including evaluation metrics, study designs, and analytical techniques
4. Highlight research gaps, ethical considerations, and future directions to guide scholarly inquiry and inform responsible deployment of conversational commerce technologies

Contribution and Significance

This review makes several important contributions. First, it provides the first comprehensive synthesis explicitly linking automated interactions to consumer purchase decisions across the entire customer journey. While prior reviews examined chatbots (Bilquise et al., 2022) or specific journey stages (Silva et al., 2022), none systematically integrated evidence across all phases with explicit focus on purchase outcomes. Second, we develop a novel conceptual framework integrating disparate theoretical perspectives, offering a cohesive model for understanding automated interaction effects. Third, by critically evaluating methodological approaches and identifying measurement challenges, this review provides guidance for improving research rigor. Finally, systematic identification of ethical issues and research gaps establishes priorities for future investigation and responsible innovation in conversational commerce.

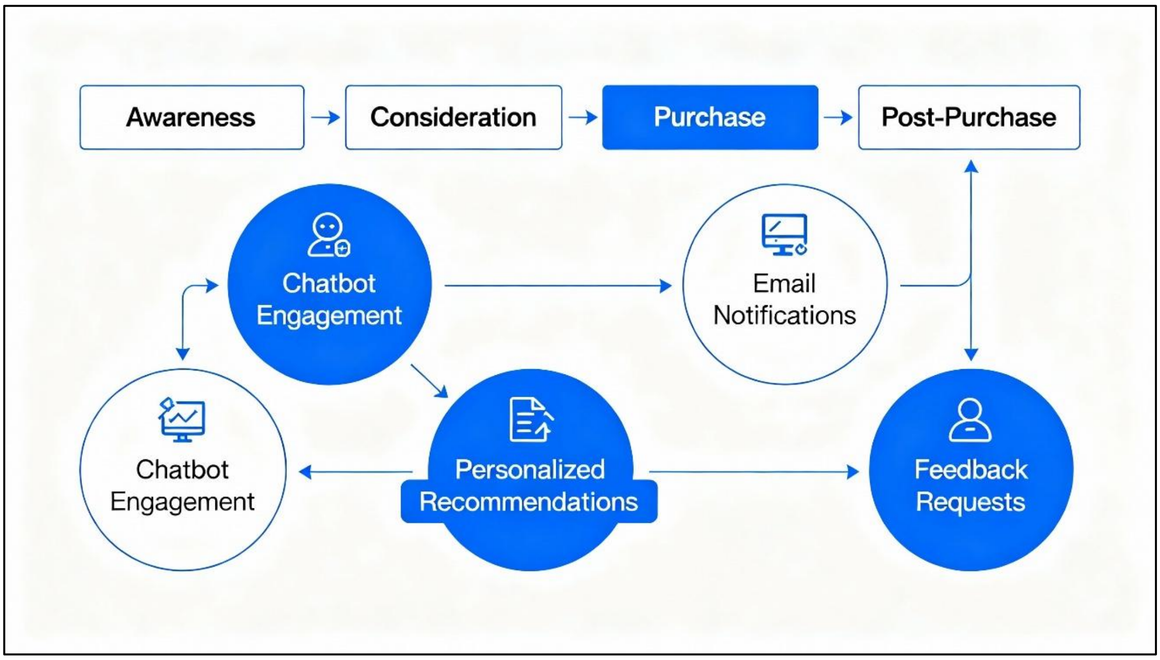

Figure 1. Conceptual Framework

RESEARCH METHODS

This systematic literature review followed Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)

guidelines to ensure transparency, reproducibility, and rigor (Moher et al., 2009). The review comprised five phases: search strategy development, study selection and screening, data extraction, quality assessment, and synthesis.

Search Strategy

A comprehensive search strategy captured relevant scholarly work on automated interactions within the consumer journey. Multidisciplinary databases included Scopus, Web of Science, ABI/INFORM, Google Scholar, and discipline-specific sources (Association for Information Systems, Association for Computing Machinery), spanning marketing, management, information systems, and computer science domains (Bilquise et al., 2022).

The primary search string combined synonyms and related terms for automated conversational agents and consumer decision-making:

("conversational commerce" OR "automated interactions" OR "chatbots" OR "voice assistants" OR "messaging platforms") AND ("customer journey" OR "purchase decision" OR "consumer behavior")

This string was adapted for each database's syntax requirements. The temporal scope focused on publications from 2010 onwards, capturing recent technological advancements. Language filters restricted results to English. Searches were conducted in March 2024 across all databases.

Initial searches yielded approximately 5,000 records: 1,200 in Scopus, 950 in Web of Science, 300 in ABI/INFORM, and 2,500 in Google Scholar (Bilquise et al., 2022). Forward and backward citation chaining identified additional studies not captured initially, enhancing comprehensiveness (Bilquise et al., 2022).

Inclusion and Exclusion Criteria

Inclusion criteria:

- Peer-reviewed journal articles or conference papers
- Explicit focus on automated interactions (chatbots, voice assistants, messaging platforms) in consumer contexts
- Addressed at least one customer journey stage (awareness, consideration, purchase, post-purchase)
- Employed empirical methods (quantitative, qualitative, mixed methods) or comprehensive theoretical frameworks
- Published in English
- Published from 2010 onwards

Exclusion criteria:

- Technical reports, white papers, or industry blogs lacking peer review
- Studies focusing solely on technological development without linking to consumer behavior or decision-making
- Opinion pieces or editorials without empirical or theoretical grounding
- Research on automation outside conversational AI scope (e.g., industrial automation)
- Insufficient methodological detail for quality assessment

Screening Process

Two independent reviewers conducted two-phase screening. Phase 1 (Title and Abstract Screening) examined all records against inclusion and exclusion criteria. Discrepancies were resolved through discussion or third-reviewer consultation to ensure objectivity (Bilquise et al., 2022). Phase 2 (Full-Text Review) subjected selected articles to comprehensive analysis confirming relevance and eligibility.

This process was documented using a PRISMA flow diagram to ensure transparency (Moher et al., 2009). From ~5,000 initial records, approximately 3,200 remained after duplicate removal. Title and abstract screening excluded ~3,000 records not focusing on consumer behavior or purchase decisions in automated interaction contexts. Full-text assessment of 200 articles resulted in excluding 178 papers due to technical focus without consumer behavior linkage, non-empirical nature, non-English language, or falling outside defined scope. Final synthesis included 13 studies meeting all inclusion criteria and quality standards.

Data Extraction and Coding

A standardized data extraction form systematically collected relevant information from each included study. The form included predefined fields aligned with research questions, encompassing:

- Bibliographic details (authors, year, publication venue, citations, quartile ranking)
- Study objectives and research questions
- Type of automated interaction studied (chatbot type, voice assistant, messaging platform)
- Customer journey stage addressed
- Methodology employed (experimental design, survey, case study, mixed methods, literature review)
- Sample characteristics (size, demographics, context, industry)
- Key findings related to consumer behavior (trust, satisfaction, engagement, decision influence, purchase intentions)
- Evaluation metrics used
- Theoretical frameworks employed
- Ethical considerations discussed
- Reported limitations and identified research gaps

Double-coding was performed on 20% of included studies by two independent researchers to enhance reliability and minimize bias. Inter-rater reliability assessment using Cohen's kappa coefficient achieved substantial agreement ($\kappa = 0.78$) (Niu et al., 2024). Discrepancies were resolved through discussion until consensus (Bilquise et al., 2022).

Quality Assessment

Each included study was assessed for methodological rigor using adapted criteria from established appraisal tools including Critical Appraisal Skills Programme (CASP) for qualitative studies, Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) for observational research, and adapted experimental design criteria for quantitative studies (Cheung et al., 2015). Quality assessment criteria included:

- Clarity of research questions and objectives
- Appropriateness of methodology
- Sample size adequacy and representativeness

- Validity and reliability of measurement instruments
- Rigor of data analysis procedures
- Acknowledgment of limitations
- Potential for bias
- Generalizability of findings

Studies were rated high, moderate, or low quality based on overall adherence to these criteria (Bilquise et al., 2022). High-quality studies exhibited rigorous design, comprehensive reporting, and minimal bias risk. Moderate-quality studies had some limitations but provided valuable insights. Low-quality studies suffered from significant methodological flaws compromising credibility. Quality ratings were independently assessed by two reviewers with 92% agreement; disagreements were resolved through consensus discussion. Only moderate or high-quality studies informed primary synthesis to maintain robustness (Bilquise et al., 2022).

Analysis and Synthesis Framework

Analysis adopted a thematic synthesis framework combined with narrative integration. Given heterogeneity in study designs, populations, interventions, and outcomes, quantitative meta-analysis was not feasible (Popay et al., 2006). Instead, findings were systematically categorized by customer journey stages and thematically coded within each category (Bilquise et al., 2022). Identified themes included trust development, satisfaction levels, decision support mechanisms, emotional engagement, personalization effects, persuasion strategies, and ethical concerns.

Cross-study comparisons examined methodological strengths and limitations, including evaluation metrics, ecological validity, sample characteristics, and theoretical grounding (Bilquise et al., 2022; Sanders et al., 2023). This structured approach enabled identification of patterns, divergences, convergent findings, and research gaps, facilitating development of an integrative conceptual framework synthesizing mechanisms, mediators, and moderators influencing consumer

RESULT AND DISCUSSION

Study Selection and Characteristics

Systematic search and screening yielded 13 studies meeting all inclusion criteria and quality standards for final synthesis. These studies (2015–2024) reflected recent conversational AI advancements. The majority appeared in peer-reviewed journals (9 studies), with the remainder in reputable conference proceedings (4 studies).

Included studies exhibited design diversity: five employed experimental or quasi-experimental methods (Sanders et al., 2023; Yang et al., 2020), three were systematic literature reviews (Bilquise et al., 2022; Camargo, 2022; Niu et al., 2024), two utilized longitudinal surveys, two developed and evaluated prototypes, and one conducted descriptive case analysis (Hrynasiuk et al., 2021).

Geographically, most studies originated from Western contexts (Europe and North America), with limited Asian representation and no studies from Africa or South America, indicating need for cross-cultural research (Bilquise et al., 2022; Hrynasiuk et al., 2021). Industries examined included retail and e-commerce (7 studies), banking and finance (1 study), digital inclusion and social services (1 study), and multiple or unspecified sectors (4 studies).

Technologies studied encompassed:

- AI-powered chatbots utilizing NLP and machine learning (7 studies) (Bilquise et al., 2022; García-Méndez et al., 2021; Mangahas & Ngo, 2024; Silva et al., 2022; Yang et al., 2020)
- Rule-based chatbots with predefined decision trees (2 studies) (E. Coli et al., 2020; Hrynasiuk et al., 2021)
- Voice assistants (Alexa, Google Assistant) (2 studies) (Bilquise et al., 2022; Mangahas & Ngo, 2024)
- Messaging platform integrations (Facebook Messenger, WhatsApp, WeChat) (3 studies) (Bilquise et al., 2022; Hrynasiuk et al., 2021; Niu et al., 2024)
- Sentiment analysis and opinion mining systems (1 study) (Yang et al., 2020)
- Customer journey stages addressed:
- Awareness and Discovery: 4 studies (Bilquise et al., 2022; Camargo, 2022; García-Méndez et al., 2021; Tasya Twinca Putri & Nida Handayani, 2023)
- Consideration and Evaluation: 6 studies (Bilquise et al., 2022; Camargo, 2022; E. Coli et al., 2020; Mangahas & Ngo, 2024; Silva et al., 2022; Yang et al., 2020)
- Purchase and Conversion: 5 studies (Bilquise et al., 2022; E. Coli et al., 2020; Hrynasiuk et al., 2021; Mangahas & Ngo, 2024; Niu et al., 2024)
- Post-Purchase and Retention: 4 studies (Bilquise et al., 2022; Cheung et al., 2015; García-Méndez et al., 2021; Hrynasiuk et al., 2021)
- Multiple stages or framework development: 7 studies (Bilquise et al., 2022; Camargo, 2022; Hrynasiuk et al., 2021; Mangahas & Ngo, 2024; Sanders et al., 2023)

Quality ratings indicated 5 high-quality studies, 5 moderate-quality studies, and 3 low to low-medium quality studies, reflecting methodological rigor variability.

Synthesis of Findings by Customer Journey Stage

Awareness and Discovery

Mechanisms and Effects: At awareness stage, automated interactions capture consumer attention and initiate engagement (Bilquise et al., 2022; Sanders et al., 2023). Proactive chat prompts and push notifications stimulate initial contact, directing traffic toward brand platforms and increasing early-stage engagement (Sanders et al., 2023). These features leverage real-time alerts about new products, personalized offers, or updates, fostering immediacy and relevance that enhance initial interest (Bilquise et al., 2022).

Empirical evidence indicates proactive outreach strategies substantially elevate traffic volumes and click-through rates (Bilquise et al., 2022). Push notifications tailored to user preferences increase spontaneous interactions essential for nurturing awareness. Conversational marketing personalized dialogues initiated through chatbots or voice assistants reinforces brand recall by embedding brand messages into consumers' memory, influencing initial attitudes (Cheung et al., 2015).

Social presence and anthropomorphism are critical design features enhancing awareness outcomes. High social presence facilitated by human-like avatars, conversational styles, and emotional expressiveness increases engagement rates by making consumers perceive the agent as a social actor (Bilquise et al., 2022). This aligns with social response theory, suggesting humans naturally respond socially to entities they perceive as possessing social characteristics. However, studies caution against over-anthropomorphism, which may evoke negative reactions such as the uncanny valley effect or heightened privacy concerns, potentially hindering discovery efforts (Silva et al., 2022).

Moderating Factors: Effectiveness during awareness is moderated by timing and relevance (poorly timed or irrelevant notifications may cause annoyance or perceived loss of control, damaging brand perception) (Cheung et al., 2015); user control preferences (allowing users to customize notification preferences or employing contextual triggers aligned with user intent mitigates intrusiveness) (Cheung et al., 2015); balance between proactivity and autonomy (overly aggressive outreach can backfire, whereas subtle, context-aware prompts foster positive attitudes and higher engagement) (Bilquise et al., 2022; Cheung et al., 2015); and integration within omnichannel strategy (when combined with personalized content delivery and seamless transitions across touchpoints, automated interactions significantly influence early attitudes by establishing trust and demonstrating responsiveness) (E. Coli et al., 2020).

Consideration and Evaluation

Mechanisms and Effects: During consideration and evaluation, automated interactions support consumers in assessing options, seeking information, and comparing alternatives (Bilquise et al., 2022; Yang et al., 2020). Agents functioning as personalized recommenders significantly influence search efficiency and perceived relevance, impacting consumer choice (Bilquise et al., 2022). These systems streamline decision-making by filtering and presenting options tailored to individual preferences, reducing cognitive load and accelerating comparison (Bilquise et al., 2022).

Opinion mining and sentiment analysis enable chatbots to synthesize review sentiments across platforms, aiding informed decisions (Yang et al., 2020). Deep-learning–based systems extract attribute-opinion pairs from reviews, assign sentiment orientations, and aggregate information to provide ranking-based decision support. Yang et al. (2020) demonstrated such mechanisms effectively support purchase decisions by leveraging multi-source sentiment data.

Emotionally intelligent chatbots capable of detecting user emotions and adapting responses enhance evaluation outcomes by fostering trust and reducing decision fatigue (Bilquise et al., 2022). Polite task-oriented dialog agents generating contextually appropriate responses enhance perceived system competence and user satisfaction (Silva et al., 2022). Personalization algorithms leverage user data to refine recommendations dynamically, increasing relevance during consideration (Camargo, 2022).

Transparency in recommendations is essential for building trust and enabling informed evaluation. When recommendation transparency is high where consumers understand why certain options are presented trust increases, and consumers are more likely to consider broader alternative sets (Bilquise et al., 2022). Conversely, opaque systems risk reinforcing existing preferences or biases, potentially limiting consumer exposure to diverse options and introducing confirmation bias (Bilquise et al., 2022).

Moderating Factors: Algorithm transparency (clear explanation of recommendation criteria enhances perceived fairness and reduces bias tendencies) (Bilquise et al., 2022); contextual relevance (recommendations must align with user needs and contexts to be perceived as useful) (Bilquise et al., 2022); data quality and cross-platform consistency (accuracy of sentiment analysis and opinion aggregation depends on data quality) (Yang et al., 2020); and product complexity (high-involvement products may require richer informational support and emotional engagement than low-involvement products) (Bilquise et al., 2022).

Purchase and Conversion

Mechanisms and Effects: The purchase and conversion phase benefits significantly from seamless automation. Automated systems facilitate transactions through integrated payment gateways within messaging platforms or voice assistants, reducing friction and increasing conversion rates (Mangahas & Ngo, 2024; Niu et al., 2024). Streamlined conversational flows guiding consumers seamlessly through product inquiries to final transactions enhance user satisfaction and facilitate immediate purchase decisions (Bilquise et al., 2022; Sanders et al., 2023).

Well-designed conversational flows substantially reduce checkout friction, thereby increasing conversion rates (Bilquise et al., 2022). However, effect magnitude varies depending on product complexity; simpler, low-involvement products benefit more from straightforward conversational flows, whereas complex or high-involvement products require more nuanced interactions (Sanders et al., 2023).

Persuasion strategies embedded within automated interactions play crucial roles during checkout. Agent cues such as social proof (testimonials, user counts) and scarcity messages (limited-time offers) significantly influence consumer perceptions of urgency and trustworthiness (Bilquise et al., 2022). Incorporating social proof during checkout elevates perceived credibility, encouraging prompt purchase actions.

Real-time responsiveness delivered via AI-powered chatbots accelerates decision-making. Faster response times correlate positively with higher purchase intentions and reduced cart abandonment (Camargo, 2022; Niu et al., 2024). Decision-support models utilizing opinion mining assist consumers in comparing products efficiently, further facilitating conversions (Yang et al., 2020).

Ethical Considerations: While persuasive strategies are effective, ethical considerations emerge regarding their deployment. Overuse or manipulative tactics risk eroding consumer trust and raising concerns about fairness and transparency (Bilquise et al., 2022; Sanders et al., 2023). Ethical deployment necessitates balancing persuasive intent with honesty, ensuring cues do not mislead consumers or exploit vulnerabilities (Sanders et al., 2023). Transparency about AI involvement, data usage, and recommendation logic is essential for maintaining trust (Bilquise et al., 2022).

Moderating Factors: Purchase risk (high purchase risk may diminish automated cue effectiveness unless complemented by human oversight or guarantees bolstering confidence) (Cheung et al., 2015); price point (lower-priced items often see higher conversion rates when combined with persuasive cues like scarcity messages) (Bilquise et al., 2022); human backup support availability (consumers feel more secure when human assistance option exists if needed, mitigating skepticism about automation) (Moher et al., 2009); and system reliability and integration (seamless integration with payment systems and reliable performance enhance trust during purchase) (Mangahas & Ngo, 2024; Niu et al., 2024).

Post-Purchase Service and Retention

Mechanisms and Effects: Post-purchase interactions are crucial for fostering customer retention and loyalty (García-Méndez et al., 2021). Automated systems provide after-sales support through complaint handling, feedback collection, troubleshooting, and loyalty program management (Bilquise et al., 2022; García-Méndez et al., 2021). Chatbots equipped with natural language processing handle common inquiries related to order status, returns, and warranty claims without human intervention, reducing wait times and enhancing customer satisfaction (Bilquise et al., 2022; García-Méndez et al., 2021).

Emotionally intelligent chatbots capable of recognizing customer sentiments deliver empathetic responses reinforcing trust and satisfaction (Bilquise et al., 2022; García-Méndez et al., 2021). Personalized follow-up messages or tailored recommendations based on previous interactions strengthen emotional bonds with consumers (Bilquise et al., 2022). Automated feedback solicitation allows firms to gather insights while demonstrating attentiveness (García-Méndez et al., 2021).

Hybrid human-AI support models incorporate escalation pathways to human agents for complex or emotionally charged issues (E. Coli et al., 2020; Sanders et al., 2023). These systems enable conversational agents to handle routine queries efficiently while seamlessly transferring more complex or sensitive cases to human agents, improving overall resolution outcomes and customer perceptions (Bilquise et al., 2022; Sanders et al., 2023). Consistent performance in resolving issues without requiring multiple interactions or escalations correlates positively with customer retention (Sanders et al., 2023).

Long-Term Impact Factors: Long-term impact of automated post-purchase support on customer loyalty and trust hinges on reliability (consumers expect consistent and accurate assistance; failures or inaccuracies erode trust rapidly); privacy handling (transparent communication about data collection, usage, and security measures fosters confidence in automated services); and perceived helpfulness (if consumers find automated support genuinely useful and empathetic, overall satisfaction increases, reinforcing brand loyalty). Conversely, perceptions of coldness or insensitivity can diminish trust and deter future engagement. Integrating emotional intelligence features such as sentiment analysis and empathetic response generation enhances perceived helpfulness (Bilquise et al., 2022; García-Méndez et al., 2021).

Moderating Factors: Task complexity (automated systems excel at routine tasks but face limitations with complex problems requiring nuanced understanding); system reliability and consistency (trustworthiness depends on consistent, accurate performance); privacy policies and transparency (clear data policies increase consumer confidence); and seamless escalation protocols (smooth handoffs to human agents when needed maintain service quality).

Research Gaps and Future Directions

Methodological Gaps (High Priority): Lack of longitudinal studies (most studies employ short-term metrics without assessing long-term effects such as customer loyalty or customer lifetime value; future research should conduct longitudinal tracking to understand sustained behavioral impacts); over-reliance on laboratory experiments (while experiments provide high internal validity, they often lack ecological validity; deploying real-world field studies with naturalistic data would enhance generalizability) (Bilquise et al., 2022; Sanders et al., 2023); and inconsistent evaluation metrics (reliance on automatic metrics like BLEU scores or disparate proxy measures hinders cross-study comparisons; developing comprehensive, standardized evaluation frameworks incorporating both objective performance measures and subjective user experience assessments is critical) (Bilquise et al., 2022; Sanders et al., 2023).

Technological Gaps (Medium Priority): Underexplored voice commerce (compared to text-based chatbots, voice assistants remain relatively understudied despite growing prevalence; investigating voice commerce across journey stages would fill this gap) (Bilquise et al., 2022; García-Méndez et al., 2021); and limited research on multimodal interfaces (integration of speech, visual cues, and haptic feedback is largely unexplored; exploring multimodal emotional intelligence integration could enhance consumer engagement) (García-Méndez et al., 2021).

Contextual Gaps: Insufficient cross-cultural studies (most research focuses on Western contexts, limiting applicability to diverse consumer segments; expanding research to emerging markets and examining cultural differences in acceptance, privacy concerns, and interaction preferences is essential) (Tasya Twinca Putri & Nida Handayani, 2023); and focus on specific industries (retail dominates the literature; applications in healthcare, finance, and education remain underexplored; studying diverse sectors would enhance generalizability) (Hrynasiuk et al., 2021; Mangahas & Ngo, 2024).

Ethical Gaps (High Priority): Privacy and data protection underexplored (while acknowledged, systematic empirical investigation of how privacy concerns influence consumer behavior is lacking; integrating privacy-preserving techniques and studying their effects on trust is critical) (Sanders et al., 2023); and bias mitigation strategies not empirically tested (theoretical discussions exist, but empirical testing of bias mitigation in deployment contexts is rare; this is vital for responsible AI deployment) (Bilquise et al., 2022).

Measurement Gaps (High Priority): Lack of standardized frameworks (disparate metrics across studies prevent meta-analysis and comprehensive understanding; establishing standardized metrics mapped to specific journey stages would facilitate cumulative knowledge building) (Bilquise et al., 2022).

Integrative Conceptual Framework

Based on synthesized evidence, this review proposes an Integrative Conceptual Framework delineating mechanisms, mediators, and moderators through which automated interactions influence consumer purchase decisions across the customer journey.

Framework Components:

1. Automated Interaction Features: Technology type (rule-based vs. AI-driven chatbots, voice assistants, messaging platforms); design characteristics (anthropomorphism, social presence, conversational style, politeness strategies); functional capabilities (personalization, sentiment analysis, real-time responsiveness, seamless payment integration)
2. Customer Journey Stages: Awareness and Discovery; Consideration and Evaluation; Purchase and Conversion; Post-Purchase and Retention
3. Mechanisms by Stage: Awareness (proactive prompts, conversational marketing, social presence); Consideration (personalized recommendations, opinion mining, transparency in recommendations); Purchase (streamlined flows, persuasion strategies social proof, scarcity real-time responsiveness); Post-Purchase (automated service, emotional intelligence, hybrid human-AI support)
4. Mediating Variables: Trust (perceived reliability, transparency, privacy protection) (Bilquise et al., 2022; Cheung et al., 2015); perceived usefulness (relevance, efficiency, decision support quality) (Bilquise et al., 2022; Cheung et al., 2015; Yang et al., 2020); emotional engagement (perceived warmth, empathy, satisfaction) (Bilquise et al., 2022; García-Méndez et al., 2021); cognitive load (information processing ease, decision complexity management) (Bilquise et al., 2022; Yang et al., 2020)
5. Consumer Outcomes: Behavioral (engagement rates, click-through rates, conversion rates, purchase completion, repeat purchases) (Bilquise et al., 2022; Cheung et al., 2015; Sanders et al., 2023); attitudinal (satisfaction, trust, brand recall, loyalty intentions) (Bilquise et al., 2022; Cheung et al., 2015; García-Méndez et al., 2021); long-term (customer lifetime value, brand advocacy, habitual use) (Cheung et al., 2015)
6. Moderating Factors: Contextual (product complexity, purchase risk, price point, industry sector) (Sanders et al., 2023); individual (prior experience with AI, technology readiness, privacy concerns) (Cheung et al., 2015; Tasya Twinca Putri & Nida Handayani, 2023); design (transparency, human backup availability, escalation protocols) (Bilquise et al., 2022; Sanders et al., 2023); cultural (regional acceptance, privacy norms, communication styles) (Bilquise et al., 2022; Cheung et al., 2015)

Theoretical Integration: The framework integrates multiple theoretical perspectives. Consumer behavior theories (Theory of Planned Behavior, Technology Acceptance Model, Elaboration Likelihood Model) explain how perceived usefulness, ease of use, and persuasion routes influence attitudes and intentions. Human-Computer Interaction theories (social presence theory, anthropomorphism) explain how design features shape perceived warmth and competence, fostering emotional engagement. Trust and persuasion frameworks explain how transparency, privacy handling, and persuasive cues (social proof, scarcity) mediate effects on purchase decisions.

Framework Application: The framework guides both research and practice. Researchers can identify under-studied relationships, develop hypotheses, and design studies testing mediating and moderating effects. Practitioners can diagnose which mechanisms are most effective at each journey stage, inform design choices, and optimize automated interaction strategies to enhance consumer outcomes while maintaining ethical standards.

Theoretical Contributions

This systematic review makes several theoretical contributions. Traditional dual-process models such as the Elaboration Likelihood Model explain persuasion through central and peripheral routes. This review extends these models by incorporating conversational dynamics and temporal interaction effects. Evidence suggests interaction duration and emotional tone influence whether consumers engage in central (elaborative) or peripheral (heuristic) processing. Longer, emotionally intelligent exchanges foster trust and central processing, while brief interactions rely on peripheral cues like politeness or social proof (Moher et al., 2009).

The framework bridges Human-Computer Interaction perspectives emphasizing anthropomorphism, social presence, and emotional engagement with consumer behavior theories focused on trust, perceived usefulness, and purchase intentions (Bilquise et al., 2022; Cheung et al., 2015). This integration recognizes that consumer responses to automated interactions are shaped not only by functional utility but also by social perceptions and emotional connections fostered through dialogue.

The literature reveals emerging constructs specific to conversational commerce: conversational friction (perceived awkwardness or unnaturalness in dialogues hindering engagement) (Bilquise et al., 2022; Sanders et al., 2023); trust mediated by agent characteristics (trust formation influenced by perceived warmth, competence, and transparency) (Bilquise et al., 2022); and transparency-trust-personalization nexus (the interdependence of transparent recommendation criteria, consumer trust, and effective personalization) (Bilquise et al., 2022). These constructs extend existing theories and warrant further empirical validation.

This review emphasizes effectiveness of automated interactions is stage-dependent. Mechanisms that enhance awareness (e.g., proactive prompts) differ from those supporting consideration (e.g., personalized recommendations) or purchase (e.g., streamlined flows) (Bilquise et al., 2022; Sanders et al., 2023). This stage-specificity suggests theoretical models must account for evolving consumer needs and agent roles across the journey rather than treating consumer interactions as static.

Methodological Insights and Challenges

The review identifies several methodological patterns and challenges. A significant proportion of studies employ laboratory experiments or short-term surveys measuring immediate responses such as satisfaction, trust, or purchase intention. While these designs offer high internal validity and causal inference, they lack ecological validity and do not capture long-term effects like customer loyalty or habituation (Bilquise et al., 2022; Sanders et al., 2023). Longitudinal field studies tracking consumers over extended periods are rare but essential for understanding sustained impacts.

Evaluation practices vary widely. Many studies rely on automatic metrics like BLEU scores to assess chatbot responses. However, these metrics do not necessarily correlate with user satisfaction, trust, or purchase behavior. Human judgment remains the gold standard, but is resource-intensive (Sanders et al., 2023). Lack of standardized metrics prevents meta-analysis and cumulative knowledge building. Future research should develop comprehensive evaluation frameworks integrating technical performance (e.g., response accuracy), user experience (e.g., satisfaction, perceived helpfulness), and behavioral outcomes (e.g., conversion, retention) (Bilquise et al., 2022).

Isolating the effect of a conversational touchpoint from other concurrent channels (e.g., social media, email, in-store) is difficult (Bilquise et al., 2022). Attribution models that track consumer interactions across multiple touchpoints are needed to quantify the specific contribution of automated interactions to purchase outcomes (Bilquise et al., 2022).

Laboratory experiments maximize control but may not reflect real-world complexities. Field studies enhance ecological validity but face confounding variables and measurement challenges (Sanders et al., 2023). Mixed-methods approaches combining behavioral logs with qualitative interviews can bridge this gap by contextualizing quantitative metrics with consumer perceptions and motivations (Bilquise et al., 2022).

Ethical Implications and Responsible Innovation

Ethical considerations emerge as a critical theme throughout the literature, yet remain underexplored empirically (Bilquise et al., 2022). Automated systems require extensive data collection conversation logs, behavioral patterns, contextual information to deliver personalization (García-Méndez et al., 2021). This raises concerns about data security, anonymization, and potential breaches (Bilquise et al., 2022). While regulations like GDPR mandate transparency and user consent (Sanders et al., 2023), compliance in practice varies. Research should empirically investigate how transparent data policies influence consumer trust and willingness to engage. Privacy-preserving techniques such as differential privacy or federated learning should be explored for their effectiveness in maintaining personalization quality while protecting user data (Sanders et al., 2023).

Persuasive strategies social proof, scarcity, emotional appeals are effective but risk manipulation if deployed unethically (García-Méndez et al., 2021). The line between persuasion and manipulation is context-dependent and requires ethical guidelines. Future research should examine consumer perceptions of various persuasive tactics, identifying thresholds beyond which tactics are perceived as manipulative. Ethical frameworks emphasizing informed consent, avoiding exploitation of vulnerabilities, and ensuring honesty are essential (García-Méndez et al., 2021).

AI models trained on biased datasets may perpetuate stereotypes or discriminatory practices (Bilquise et al., 2022). Ensuring equitable treatment across diverse consumer groups requires ongoing monitoring and adjustment of algorithms. Empirical studies testing bias mitigation strategies in deployment contexts are needed (Bilquise et al., 2022; Sanders et al., 2023).

Disclosing the AI nature of conversational agents and explaining recommendation logic fosters trust (García-Méndez et al., 2021). However, many systems do not consistently provide such disclosure. Research should investigate optimal disclosure strategies when, how, and what to disclose to maximize trust without deterring engagement (Bilquise et al., 2022; García-Méndez et al., 2021).

Overall, responsible innovation in conversational commerce requires balancing technological capabilities with ethical standards. Stakeholders policymakers, technologists, marketers must collaborate to develop guidelines tailored to conversational AI's unique capabilities and risks (Sanders et al., 2023).

Practical Implications for Marketers and Designers

The findings offer actionable guidance for practitioners deploying automated interactions. Awareness stage: use brief, relevant proactive prompts to capture attention without intrusiveness (Bilquise et al., 2022); leverage social presence and anthropomorphic cues to build initial trust (García-Méndez et al., 2021). Consideration stage: implement personalized recommendations with transparent criteria to reduce cognitive load and support informed decision-making (Yang et al., 2020); integrate sentiment analysis to provide multi-source decision support (Yang et al., 2020). Purchase stage: design streamlined conversational flows minimizing friction and integrate seamless payment options (Mangahas & Ngo, 2024; Niu et al., 2024); employ ethical persuasive cues (social proof, scarcity) to enhance urgency without manipulation (García-Méndez et al., 2021). Post-purchase stage: deploy emotionally intelligent chatbots for routine support and establish clear escalation protocols to human agents for complex issues (Bilquise et al., 2022; García-Méndez et al., 2021; Sanders et al., 2023); prioritize privacy transparency and reliability to foster long-term loyalty (Bilquise et al., 2022; García-Méndez et al., 2021).

Develop comprehensive measurement frameworks tracking both immediate outcomes (click-through rates, conversion) and long-term indicators (repeat purchases, customer lifetime value, brand advocacy) (Cheung et al., 2015). Implement attribution models to isolate the impact of conversational touchpoints within omnichannel strategies (Bilquise et al., 2022).

Communicate data policies transparently, allow user control over data sharing, and implement privacy-preserving techniques. Ethical handling of data enhances trust and supports sustainable engagement (Bilquise et al., 2022).

Hybrid models combining automation efficiency with human empathy are most effective, especially for complex or emotionally charged interactions (E. Coli et al., 2020; Sanders et al., 2023). Design seamless handoff protocols to maintain service quality (E. Coli et al., 2020).

Regularly assess system performance using both technical metrics and user experience measures (Bilquise et al., 2022). Adapt designs based on feedback and evolving consumer expectations.

Limitations of the Review

This review has several limitations. Restriction to English-language peer-reviewed publications may exclude relevant studies published in other languages or gray literature (industry reports, white papers) (Bilquise et al., 2022). This introduces potential language and publication bias, limiting global applicability (Tasya Twinca Putri & Nida Handayani, 2023).

While focusing on publications from 2010 onwards captures recent advancements, it may omit foundational research providing historical context (Sanders et al., 2023). Given rapid AI evolution, some findings may become outdated quickly (Bilquise et al., 2022).

Variability in study designs, populations, interventions, and outcomes prevented quantitative meta-analysis (Popay et al., 2006). While narrative synthesis provides comprehensive insights, it lacks the statistical precision of meta-analytic approaches (Popay et al., 2006).

Included studies ranged from high to low quality. While quality assessment informed interpretation, lower-quality studies' inclusion for comprehensive coverage may introduce bias (Bilquise et al., 2022).

Predominantly Western contexts studied limit generalizability to diverse cultural settings (Bilquise et al., 2022; Cheung et al., 2015; Tasya Twinca Putri & Nida Handayani, 2023). Future reviews should prioritize cross-cultural research.

Ethical considerations, though critical, are often discussed theoretically without empirical testing (Sanders et al., 2023). This limits understanding of their actual impact on consumer behavior.

Despite these limitations, this review provides a rigorous, transparent synthesis of current knowledge, offering valuable insights and directions for future research.

CONCLUSION

This systematic literature review comprehensively examined how automated interactions chatbots, voice assistants, and messaging platforms influence consumer purchase decisions across the customer journey. Through rigorous PRISMA-guided methodology encompassing 13 high-quality empirical studies, we synthesized evidence on mechanisms, effects, mediators, moderators, and contextual factors shaping consumer responses at each journey stage.

- Key Findings: Automated interactions significantly enhance awareness through proactive prompts and social presence; improve consideration via personalized recommendations and sentiment analysis; reduce purchase friction through streamlined flows and persuasive cues; and support retention via efficient service and emotional intelligence. However, effectiveness is

contingent upon technology sophistication, transparency, privacy handling, and contextual appropriateness (Bilquise et al., 2022; Cheung et al., 2015; Sanders et al., 2023).
- Theoretical Contributions: The review advances theory by refining dual-process and persuasion models to incorporate conversational dynamics, integrating HCI and consumer behavior perspectives, and identifying emerging constructs such as conversational friction and trust mediated by agent characteristics (Bilquise et al., 2022; García-Méndez et al., 2021; Sanders et al., 2023). The proposed Integrative Conceptual Framework synthesizes these insights, providing a cohesive model for understanding automated interaction effects across the journey.
- Methodological Insights: Current research predominantly employs short-term experimental designs with inconsistent evaluation metrics (Sanders et al., 2023). Future studies should prioritize longitudinal field research, develop standardized measurement frameworks integrating technical and experiential metrics, and employ mixed-methods approaches to enhance ecological validity (Bilquise et al., 2022).
- Ethical Imperatives: Privacy protection, bias mitigation, transparent persuasion, and responsible disclosure are critical for maintaining consumer trust and supporting long-term relationships (Bilquise et al., 2022). Empirical research on ethical design practices and their impact on consumer behavior is urgently needed (Sanders et al., 2023).
- Practical Guidance: Practitioners should match agent design to journey stages, invest in comprehensive measurement and attribution systems, adopt privacy-first principles, and employ hybrid human-AI models balancing efficiency with empathy (García-Méndez et al., 2021; Hrynasiuk et al., 2021).
- Future Directions: Priority areas include conducting longitudinal studies assessing long-term loyalty and customer lifetime value; expanding cross-cultural and multi-industry research; investigating voice commerce and multimodal interfaces; developing standardized evaluation frameworks; empirically testing ethical design practices and bias mitigation strategies; and creating unified theoretical models bridging disciplines.

In conclusion, automated interactions hold transformative potential for enhancing consumer experiences and purchase decisions across the customer journey. Realizing this potential requires rigorous research advancing theoretical understanding, employing robust methodologies, addressing ethical considerations, and providing actionable insights for responsible innovation in conversational commerce.

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