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Human-AI Collaboration and Trust in AI-Supported E-Commerce Marketing: A Systematic Literature Review

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Abstract

This systematic literature review aims to synthesise the findings of 15 studies (2022–2026) that examined human-AI collaboration and trust in the use of AI in e-commerce marketing and decision-making. It outlines applications, advantages, problems, and variables of human-AI collaboration in accordance with PRISMA 2020 guidelines. According to the results, human-AI collaboration involves personalisation, recommendations, CRM, chatbots, predictive analytics, and advertising. AI accuracy, explainability, trust, human expertise, task complexity, data quality, and organisational governance could improve the outcomes of decisions. However, there can be risks of automation, such as automation bias, over-reliance, and lack of transparency. Based on the conceptual framework proposed in the review, the application of AI should be as a complement to the decision-making process, not a substitute. Trust, accountability, and governance are all essential for successful collaboration between humans and AI. These insights could help inform AI's implementation in e-commerce marketing for managers, theorists, and policymakers. The review gives an idea of the conceptual framework and directions for future research.

Keywords: *Human-AI collaboration, Trust, E-Commerce marketing, Decision-making, Explainable AI, Automation bias*

Introduction

With the evolution of e-commerce and the growing role of artificial intelligence (AI), customer data analysis, personalisation, recommendation, advertising, forecasting, and customer relationship management are some of the operations that are supported by the use of AI (Rane et al., 2024). Recent reviews suggest that AI and machine learning are increasingly being integrated into the e-commerce space to analyse consumer behaviour, personalise the customer experience, engagement, and support commercially relevant decisions. AI-driven marketing tools like chatbots, personalisation engines, and predictive analytics have been linked to enhanced customer acquisition, conversion, and other e-commerce metrics, particularly improving customer acquisition, conversion, and other e-commerce metrics (Madanchian, 2024; Bulut & Taşkın, 2024). As AI becomes more prevalent, the applications of marketing automation have grown, too (Dhawas et al., 2024). AI can handle vast amounts of customer and transaction information, recognise patterns, make recommendations, and aid in marketing strategies—tasks that would be difficult to accomplish manually. But as AI becomes more powerful, that doesn't automatically mean that marketing decisions would be entirely automated. A recent study on the human–AI collaboration in marketing suggests that when humans combine their judgment with the insights provided by AI, it could enhance decision-making results, with the degree of improvement depending on contextual conditions and the specific nature of the task (Ngo, 2025).

This has led to greater interest in human-AI collaboration, where humans continue to play a part in AI-enhanced tasks, like supervision, evaluation, feedback, interpretation, and decision-

making. In addition, human-AI is defined as a process that involves the use of AI at various points within an AI system, in combination with human judgment, and notes several challenges such as trust calibration, cognitive load, scalability, and the right timing of human intervention. This view is especially significant in e-commerce marketing, as AI can provide recommendations or predictions, which marketing teams might want to review to see if they are relevant to customer context, business goals, ethical guidelines, and market conditions.

Problem Statement

While artificial intelligence (AI) has come a long way, there are clear drawbacks to making fully automated marketing decisions. The accuracy of data fed into AI systems is crucial, and the suggestions they can make are technically viable but contextually irrelevant for individual customers, markets, or the organisation. The results of human–AI cooperation also rely on the decision authority and responsibility of the human–AI system (Gaczek et al., 2026). Human judgment is therefore crucial to consider and filter, validate and adjust, and reject or override AI-generated recommendations, if needed. The challenge is then how to leverage AI capabilities and human knowledge to create sound and well-informed e-commerce marketing decisions.

Research Gap

The applications of AI in e-commerce have been discussed in previous research in the fields of personalisation, customer analytics, customer recommendations, predictive analytics, and customer relationship management (CRM) (Madanchian, 2024; Bulut & Taşkın, 2024). But there is limited research that systematically explores the human role in AI-driven e-commerce marketing decisions. While human-AI collaboration research spans across multiple fields, it is not yet well connected to the e-commerce marketing context. In addition, evidence on human–AI collaboration is still scattered in terms of applications, the role of humans, benefits, challenges, and influencing factors (Ngo, 2025). Thus, this review offers a comprehensive integration of human-AI collaboration in e-commerce marketing and decision-making.

Aim of the Study

The review aims to systematically synthesise literature on human-AI collaboration and trust in AI-Supported e-commerce marketing. It specifically examines how collaboration is applied and evaluated in practitioner contexts, alongside the factors that influence consumer trust in AI-supported e-commerce environments.

Research Questions

RQ1: How is human-AI collaboration applied in e-commerce marketing and decision-making across practitioner and consumer contexts?

RQ2: What advantages, challenges, and factors influence the effectiveness of human-AI collaboration for practitioners, and what factors influence consumer trust in AI-supported e-commerce marketing?

Research Objectives

- To examine and synthesise how human- AI collaboration is applied across e-commerce marketing and decision-making across both practitioner and consumer contexts.
- To identify the benefits, challenges, and factors that influence the trust and the effectiveness of human–AI collaboration for practitioners, and factors that influence consumer trust in AI-supported e-commerce.

Literature Review

Artificial Intelligence in E-Commerce

Artificial Intelligence (AI) has become an indispensable part of an e-commerce system that utilises user behaviour data, tailors shopping journeys, aids in recommendations, and helps

with purchase decisions (Lari et al., 2022). Specifically, AI-driven tools have been shown to enhance Customer Relationship Management (CRM) by improving personalisation and analytics; this still requires human oversight to align with business goals (Bulut and Taskin, 2024). Recent empirical research demonstrates the ability of AI personalisation to shape consumers' spending habits and their purchasing decisions, as well as concerns regarding transparency and data governance. Similarly, Hassan et al. (2025) discovered that personalised recommendations can influence the relationships between trust, satisfaction and loyalty in AI-powered e-commerce. Shah et al. (2025) concluded in Pakistan that the use of AI personalisation, the effectiveness of chatbots and predictive analysis were linked to the purchase decisions of online consumers. The results suggest that the use of AI in the e-commerce space isn't limited to automation of business operations, but rather to systems that actively assist in customer analysis and decision-making.

AI in E-Commerce Marketing

AI has also revolutionised e-commerce marketing by personalising marketing, engaging customers, recommending products, advertising, and predicting customer behaviour (Raji et al., 2024). In recent studies, it has been proposed that personalisation delivered through AI could influence consumer decisions to buy, and that trust and transparency are key components in digital marketing (Alsaffarini & Awwad, 2026). For instance, research into personalisation and AI found correlations between personalisation and purchase intent, and consumer trust in the purchase process, especially when there is more transparency and control (Teodorescu et al., 2023). Similarly, Mumtaz et al. (2025) explored the use of AI technologies such as recommendation engines, chatbots, dynamic advertising, and voice assistants across the context of consumer decision-making in digital marketing. These capabilities have been expanded through emerging generative AI applications to advertising and content creation. Madathil (2025) makes a point of the ongoing necessity of human involvement in the creation of marketing ads using AI. So, AI is now aiding in the decision-making process and optimisation of marketing strategies, not just routine tasks.

Human-AI Collaboration in E-Commerce

Human-AI collaborative systems involve humans in AI-assisted processes by monitoring, assessing, providing feedback, correcting, or approving (Ottun & Flores, 2025). Human oversight and decision-making at various points in the AI pipeline are described as key features of human-AI collaborative systems. The process in e-commerce marketing can be depicted as: Data is fed into AI that then analyses it and recommends it, which is then evaluated by humans, who accept, modify, or override the recommendations, which then goes to marketing decision. This is unlike the fully automated decision-making process, which is depicted as AI → Decision, where the human element is still there between AI output and the final decision. The recent evidence suggests that the combination of human effort and AI can enhance marketing decision-making by complementing human judgment with AI insights, but the effectiveness of this synergy hinges on contextual factors (Ngo, 2025). There is also a chance that human involvement can shape the trustworthiness of AI to the consumer. Moreover, the analysis examines how perceived human oversight can impact the trustworthiness of AI systems. Thus, human-AI collaboration serves as a valuable framework for exploring the interplay between AI recommendations and human judgment in e-commerce marketing decision-making.

Trust in Human- AI Collaboration

Human–AI collaboration can be viewed as the enhancement of human analytical power with AI rather than the outright replacement of human judgment. In marketing research, AI delivers computational power, quick analysis, pattern recognition, prediction, and recommendations, while humans bring in the context, strategic judgment, interpretation, and responsibility. AI-aided human judgment, in general, leads to better marketing decision outcomes, with the

effectiveness of collaboration depending on the task and contextual conditions (Ngo, 2025). However, Pokorny (2025) emphasizes that human readiness for AI collaboration is not automatic; it requires specific cognitive and metacognitive competencies to overcome barriers such as trust miscalibration and communication inflexibility. Similarly, a systematic review reveals various types of human–AI decision-making and underscores the importance of integrating human expertise and AI capabilities to produce outcomes (Ali et al., 2025). The results of the e-commerce analysis also reveal that the effectiveness of recommendations depends on the product's characteristics and the trustworthiness of the AI-generated and human-generated recommendations, indicating that neither of these sources is more effective in all cases (Mazzù et al., 2025). These results also highlight that human-AI collaboration can be a complementary choice to a decision architecture, with AI complementing the analytical capabilities while humans maintain contextual interpretation, strategic control, and accountability.

Explainable AI and Trust

Appropriate evaluation and trust in AI-powered outputs by decision makers and users is also critical for human-AI collaboration effectiveness (Etuk & Omankwu, 2025). Evidence suggests that an explainable and transparent AI can help to drive greater understanding and trust, depending on the method of AI suggestions and the users' interactions with them. Conversations in e-commerce recommendations led to an increase in perceived transparency, interpretability, and trust, which differed depending on the decision context and the device that was used (Chen et al., 2025). Research on AI chatbots in e-commerce indicates that perceived interactivity and humanness are associated with users' trust in AI systems and their intention to adopt AI chatbots (Ding & Najaf, 2024). Similarly, dialogic communication by AI chatbots has been associated with AI-technology trust and consumers' intention to adopt chatbot-based decisions (Hui et al., 2025). But when mistrust becomes an issue, it is when it gives rise to automation bias or overreliance. Excessive use of AI recommendations was shown to depend on the AI literacy of the user, their professional experience, the verification requirements, and the complexity of explanations given (Romeo & Conti, 2026). Thus, a calibrated level of trust and human activity is essential in human-AI collaboration, whereby the decision-makers can accept, question, alter, or reject the recommendations made by AI, as opposed to blindly.

Methodology

Research Design and Approach

A systematic literature review (SLR) was used in this study for synthesising recent evidence relating to human–AI collaboration and trust in AI-supported e-commerce marketing and decision-making. The review was conducted according to PRISMA 2020 guidelines for literature identification, screening, eligibility and study selection. The following two research questions were used to guide the review: RQ1:How is human-AI collaboration applied in e-commerce marketing and decision-making across practitioner and consumer contexts? RQ2: What advantages, challenges, and factors influence the effectiveness of human-AI collaboration for practitioners, and what factors influence consumer trust in AI-supported e-commerce marketing? Due to the differences in design, application of AI, participants, contexts, and outcomes, a thematic synthesis was conducted instead of meta-analysis. This conceptual framework was then created from the synthesised evidence.

Information source

The literature search was conducted across ScienceDirect, Emerald Insight, Wiley Online Library, and Google Scholar between 5 December and 25 January 2026. The individual search dates for each information source are reported separately in Table 1. The raw searches yielded a total of 55,527 records: ScienceDirect (n=361), Emerald Insight (n=1,079), Wiley Online Library (n = 15,687), and Google Scholar (n = 38,400).

This relevance-ranked cut-off was applied because the raw returns from Wiley Online Library (n=15,687) and Google Scholar (n=38,400) were too large for feasible title/abstract screening within the review timeline, and because relevance ranking places the most topically aligned records first. The cut-off is acknowledged as a limitation (section 6.3), as relevant studies ranked below the top 100 may not have been captured. Therefore, the PRISMA records report a total of 1,640 exported records: ScienceDirect (n = 361), Emerald Insight (n = 1,079), Wiley Online Library (n = 100), and Google Scholar (n = 100).

Table 1: Information source and search characteristics

Information source	Search period	Publication filter	Language filter	Source filter	Records retrieved
Science Direct	5 Dec - 25 Jan 2026	2022-2026	English	Peer-reviewed literature	361
Emerald Insight	5 Dec - 25 Jan 2026	2022-2026	English	Peer-reviewed literature	1,079
Wiley Online Library	5 Dec - 25 Jan 2026	2022-2026	English	Peer-reviewed literature	15,687
Google Scholar	5 Dec - 25 Jan 2026	2022-2026	English	Any	38,400
Total	-	-	-	-	55,527

(Note: indicates sources where only the top 100 records by relevance were exported for screening due to volume).

Search strategy

The search strategy was designed as 4 concept groups: (1) human involvement and human-AI collaboration, (2) AI, (3) e-commerce and digital marketing, and (4) decision-making and recommendation. Logical operators OR and AND were used to combine synonymous terms within each concept group and to combine the four concept groups, respectively. The overall search period was 5 December 2025 to 25 January 2026, and the publication period was limited to 2022–2026.

The following was the Boolean structure of the core:

("human-in-the-loop" OR "human-AI collaboration" OR "human oversight") AND ("artificial intelligence" OR "generative AI" OR "machine learning") AND ("e-commerce" OR "e-commerce" OR "digital marketing" OR "online marketing") AND ("decision making" OR "marketing decision" OR "recommendation" OR "personalisation")

The search syntax was modified depending on the search features of the sources.

Table 2 Database-Specific Search Strategy

Source	Search string	Filters	Search Time
Science Direct	*("human-AI collaboration" OR "human oversight" OR "human-in-the-loop") AND ("artificial intelligence" OR "generative AI" OR "machine learning") AND ("e-commerce" OR "e-commerce" OR "digital marketing" OR "online marketing") AND ("decision making" OR "marketing decision" OR "recommendation" OR "personalisation")*	Publication years: 2022–2026; English; document/source filters as documented in search history	5 Dec 2025 to 25 January 2026
Emerald Insight	*("human-AI collaboration" OR "human oversight" OR "human-in-the-loop") AND ("artificial intelligence" OR "generative AI" OR "machine learning") AND ("e-commerce" OR "e-commerce" OR "digital marketing" OR "online marketing") AND ("decision making" OR "marketing decision" OR "recommendation" OR "personalisation")*	Publication years: 2022–2026; English; document/source filters as documented in search history	5 Dec 2025 to 25 January 2026
Wiley online library	*("human-AI collaboration" OR "human oversight" OR " human-in-the-loop") AND ("artificial intelligence" OR "generative AI" OR "machine learning") AND ("e-commerce" OR "digital marketing" OR "online marketing") AND ("decision making"OR "recommendation" AND "personalisation")*	Publication years: 2022–2026; English; document/source filters as documented in search history	5 Dec 2025 to 25 January 2026
Google scholar	*("human-AI collaboration" OR "human oversight" OR "human-in-the-loop") AND ("artificial intelligence" OR "generative AI" OR "machine learning") AND ("e-commerce" OR "e-commerce" OR "digital marketing" OR "online marketing") AND ("decision making" OR "marketing decision" OR "recommendation" OR "personalisation")*	Publication years: 2022–2026; English; document/source filters as documented in search history	5 Dec 2025 to 25 January 2026

Overall search period: 5 December 2025 to 25 January 2026.

Eligibility Criteria

The inclusion criteria were set before screening of the studies to ensure consistency with the research goals.

Table 3 Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Publication type	Peer-reviewed research articles	Editorials, commentaries, opinion papers, abstracts
Language	English	Non-English
Period	2022-2026	Outside the specified period
Context	E-commerce, digital commerce, online marketing, digital marketing, or related marketing decision-making.	Unrelated context
Topic	AI, human-AI collaboration, AI recommendation, AI-supported marketing or assisted decision-making	AI applications unrelated to marketing, e-commerce, or decision-making.
Evidence	Empirical, experimental, meta-analyses, theoretical, or review evidence relevant to Conceptual	Insufficient evidence
Human Involvement	Studies addressing human evaluation, oversight, collaboration, intervention, or decision-making.	Fully automated AI studies with no relevant human role
Full text	Full text article available	Full text article not available
Relevance	Addressed at least 1 research question	Unrelated to the research questions

The criteria were designed to align study selection with the review questions and PRISMA 2020 reporting principles, which require explicit eligibility criteria and explanation of how studies were grouped for synthesis.

Protocol Registration

The systematic review protocol was not prospectively registered in PROSPERO. A structured review process was followed using predefined eligibility criteria, search concepts, data-extraction fields, quality-appraisal procedures (AMSTAR 2 for systematic reviews, SARNA for narrative/critical reviews, JBI checklist for quantitative cross-sectional studies, MMAT for mixed-methods studies, and design-specific checklists for experimental studies) and synthesis categories. The lack of prospective protocol registration is recognised as a methodological limitation. This is because it reduces the transparency of decisions made before study selection and synthesis. This is Limitation is further discussed in Section 6.3.

Study selection/screening

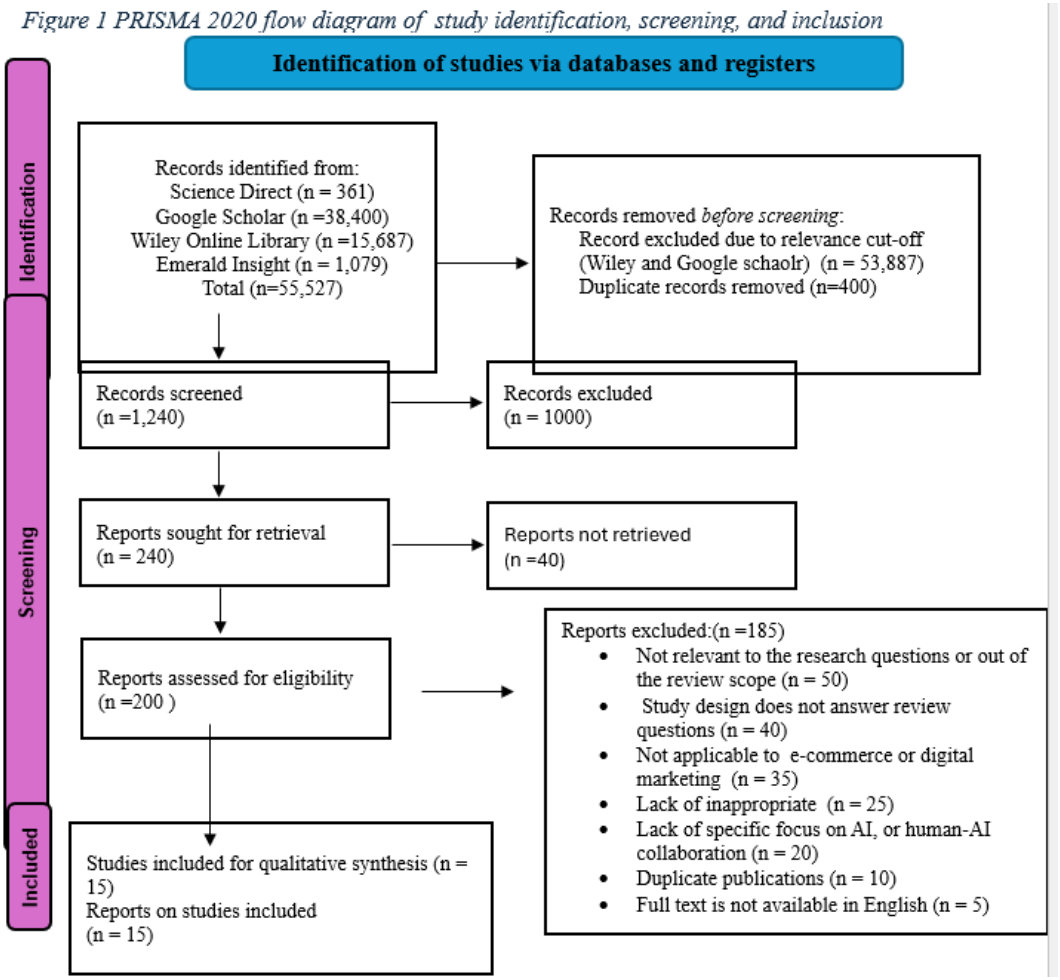
The PRISMA 2020 was followed in the process of study selection. Records were gathered in all four information sources from 5 December 2025 to 25 January 2026, and then duplicate records were eliminated. The other records were then reviewed by title and abstract against the predefined eligibility criteria listed in Table 3. Full-text reports were then downloaded as potentially eligible reports and then evaluated against the eligibility criteria, before being included in the qualitative synthesis. The searches yielded 1,640 records: ScienceDirect (n = 361), Emerald Insight (n = 1,079), Wiley Online Library (n = 100), and Google Scholar (n = 100). After removing 400 duplicate records, 1,240 records were left for title and abstract screening. Screening at both the title/abstract and full-text stages was performed by a single reviewer (the first author). No independent second screener was involved, and therefore inter-rater agreement (e.g Cohen's kappa) could not be calculated. Any uncertainties were resolved by the reviewer re-checking the record against the eligibility criteria in Table 3. This single-

reviewer process is acknowledged as a limitation in section 6.3. These were excluded, leaving 240 reports to be retrieved. Of the 240 reports retrieved, 40 were not retrieved, and 200 full-text reports were assessed for eligibility. 185 reports were excluded from the full-text assessment, with 15 studies included in the qualitative synthesis.

The 185 full-text exclusions reported were due to the following reasons:

- Not relevant to the research questions or out of the review scope (n = 50)
- Study design does not answer the review question (n = 40)
- Not applicable to e-commerce or digital marketing environment (n = 35)
- Insufficient empirical or conceptual evidence (n = 25)
- Lack of specific focus on AI or human-AI collaboration (n = 20)
- Duplicate publications (n = 10)
- Full text is not available in English (n = 5)

Figure 1 PRISMA 2020 flow diagram of study identification, screening, and inclusion



Screening Reliability

The primary reviewer conducted the study screening. A second-screener assessment was not performed independently of the first one for the present review, and hence Cohen's kappa could not be calculated. It is recognised that there is no independent duplicate screening. There are further discussions of this in the Limitations section (6.3).

Data extraction

The information from 15 of the studies included in the study was extracted and recorded according to a structured matrix by author/year, country, type of study, context, sample/data source, AI use, human involvement, marketing use, main results and methodological quality. Two sets of human roles were separated: those within the organisation who make decisions

and those who use AI systems as consumers. The entire matrix is included in the supplementary information (Supplementary Table S1). The extraction was done by one reviewer without duplicate extraction or inter-reviewer agreement assessment.

Methodological Quality Appraisal

Several methodological differences among these studies resulted in the choice of appropriate design tools. The AMSTAR 2 tool was used to evaluate systematic reviews, the SANRA checklist was used to appraise narrative and critical literature reviews, JBI checklists were used for quantitative cross-sectional studies; MMAT was used for mixed methods studies; and experimental studies were evaluated using the appropriate design-specific checklists. Appraisal included design appropriateness, sampling, measurement, analysis, bias, transparency, and evidence credibility. There were no studies that were automatically excluded, but rather, results were interpreted and reported in Supplementary Table S2. Appraisal was done by one Reviewer. Studies were classified as "High" if they met the following criteria: AMSTAR 2- high confidence if zero critical weaknesses were found; moderate confidence if one critical weakness was found; low confidence if more than one critical weakness was found; JBI - ≥80% of checklist items were met; MMAT - all five quality criteria were met. According to these thresholds, 12 studies were rated "High" (including Hui et al., 2025, which scored 7/8 JBI items), two studies were rated "Moderate" (Mumtaz et al., 2025; Shah et al., 2025), and one studies rated "Moderate-high" (Hui et al., 2025). No studies were rated "Low".

Quality appraisal was not used as an exclusion criterion; rather, it was used to interpret the strength of the evidence. These three studies did not describe the sampling procedures and/or used a cross-sectional design, making causal inferences impossible. The item-level scores (e.g., "JBI 6/8") and the critical weaknesses found on the AMSTAR 2 (e.g., "AMSTAR 2 critical weaknesses: 0") are available in Appendix B for readers to re-score the studies if they choose. In summary, the methodological quality of the included evidence was adequate; no study was excluded on quality grounds, but the two cross-sectional studies (Mumtaz et al., 2025, Shah et al., 2025) were interpreted cautiously because their designs preclude causal inference.

Thematic Synthesis

This was not possible in the current study as data were too heterogeneous to conduct a statistical meta-analysis; therefore, thematic synthesis was used. All the findings were extracted, coded, and classified based on the research questions. Four themes emerged: (1) the use of AI in e-commerce marketing and decision making; (2) human-AI cooperation and decision augmentation; (3) the advantages, obstacles, and risks of human-AI collaboration; and (4) factors that affect trust and the effective collaboration between humans and AI. Convergent and contrasting findings were taken into consideration.

Conceptual Framework and Transparency

Thematic synthesis was used as a conceptual framework, which was designed inductively and based on the evidence. It included AI capability, explainability, trust, human expertise, AI literacy, data quality, oversight and organisational governance. The framework is an evidence-informed interpretation and not a validated causal model. Records of searches, screening, extraction, and appraisal were kept for transparency. The review protocol was not prospectively registered; screening, extraction and appraisal were done by a single person. In the study, these restrictions have been recognised.

Results

Study Selection

The systematic search was conducted across four scholarly information sources from 5th December 2025 to 25th January 2026. Total no of 1,640 records: ScienceDirect (n = 361), Google Scholar (n = 100), Wiley Online Library (n = 100), and Emerald Insight (n = 1,079). After removing 400 duplicate records, 1,240 records remained for title and abstract screening. Of these, 1000 were excluded, leaving 240 reports for retrieval. The 40 reports were not retrieved, and 200 full-text reports were assessed for eligibility. Of these, 185 were excluded for pre-defined reasons, and 15 studies were included in the systematic review. The selection process is shown in the PRISMA 2020 flow diagram (Figure 1).

Characteristics of included studies

Although the search covered 2022-2026, all 15 included studies were published between 2024 and 2026. These were identified through a systematic search covering the period 2022 to 206. The synthesis is explicit and makes a separation of evidence into two streams to overcome the mismatch between the broad research questions and the narrow focus of the included studies. The practitioner side stream focuses on human oversight, human collaboration, and human decision responsibility in organisations (Ngo, 2025; Li & Tian, 2026; Romeo & Conti, 2026; Gaczek et al., 2026; Madathil, 2025). The consumer side stream focuses on consumer trust, transparency, and reactions to AI recommendations (Hassan et al., 2025; Chen et al., 2025; Mumtaz et al., 2025; Mazzù et al., 2025; Shah et al., 2025; Nagpal & Cotte, 2026; Najaf, 2024; Hui et al., 2025). There are two more reviews that give the context of the general use of AI in marketing (Bulut & Taşkın, 2024; Madanchian, 2024). The studies covered different aspects of AI applications in e-commerce marketing, consumer decision-making, recommendation systems, customer relationship management, advertising, etc., and human-AI collaboration. The methodological designs were systematic literature reviews, quantitative surveys, experimental research, multi-method research, and meta-analyses. The characteristics of each of the included studies are summarized in Table 4.

Table 4 Characteristics of Included Studies

Study	Country/ Region	Year	Study design	Human role	Key findings	Quality
Bulut & Taşkın	International	2024	Systematic literature review	Marketer	AI can improve CRM in e-commerce by personalization, analytics, engagement, and retention.	High
Madanchian	Canada / International literature	2024	Critical literature review, 50 scope documents	Marketer	AI marketing tools such as chatbots, personalisation, and predictive analytics can enhance e-commerce performance.	High
Hassan et al.	Egypt	2025	Quantitative survey and used SEM	Consumer	Personalised AI recommendations can impact trust, satisfaction, and loyalty in AI-powered e-commerce.	High
Chen et al.	China / South Korea	2025	Three experiments, N=1,429	Consumer	Tailored explanations increase transparency, interpretability, and trust in conversational recommendations.	High
Mumtaz et al.	Pakistan	2025	Quantitative survey	Consumer	Recommendation engines, chatbots, dynamic advertising and voice assistants. Recommendation engines, chatbots, dynamic advertising and voice assistants shape consumers' decision-making.	Moderate-high
Madathil	International	2025	multi-method empirical study,	Marketer	finds that human–AI collaborative advertisements elicit better audience reactions than AI-only ads	High
Mazzù et al. (2025)	Italy	2025	Experimental studies	Consumer	Consumer responses to human versus AI recommendations vary across product and recommendation contexts.	High
Ngo	International	2025	Meta-analysis; 132	Both	Human–AI collaboration yields better decision outcomes, but contextual factors are necessary for achieving synergy.	High
Shah et al.	Pakistan	2025	Quantitative research study with 400 online buyers in Pakistan	Consumer	Finding that AI personalisation, chatbot effectiveness, and predictive analysis all have a significant impact on online purchase decisions.	Moderate high
Gaczek et al.	United Kingdom	2026	Three vignette experiments and 587 marketing managers	Marketer	found that human–AI collaboration impacts responsibility attribution and ethical decision-making.	High
Hui et al.	Pakistan	2025	Quantitative survey SEM	Consumer	Dialogic communication by AI chatbots positively influences AI-technology trust, which increases consumers' intention to adopt chatbot decisions. Perceived self-threat moderates this relationship weakness the link between trust and adoption.	High
Ali et .,al	International	2025	Systematic review	Both	AI–human collaboration Improves decision making and innovation but risks deskilling, power imbalance and opacity.	High
Sele & Chugunova	Canada/USA	2024	Two experimental studies	Consumer	Perceived adequacy of human oversight as one of the mechanisms that affect the trust of AI.	High
Ding & Najaf	China	2024	Quantitative survey SEM	Consumer	Interactivity and perceived humanness significantly influence trust toward AI chatbots; trust mediates the relationship between these factors and the intention to adopt AI chatbots for e-commerce.	High
Romeo & Conti	Italy	2026	Systematic review	Both	Automation bias can lead to relying too heavily on AI, underscoring the need for transparency and human oversight.	High

Applications of AI in E-Commerce Marketing and Decision Making

The first research question explored the uses of AI and human-AI collaboration. The 15 studies identified some specific applications that are closely related to each other, such as personalisation, recommendation systems, customer relationship management, predictive analytics, chatbots, advertising and decision support. There was strong evidence of personalisation and recommendation systems throughout the evidence base. With respect to personalisation and analytics, Bulut and Taşkın 2024 highlighted this as a significant application of AI in CRM, whereas Hassan et al. 2025 discussed the relationships between personalised recommendations, customers' trust, satisfaction and loyalty. Additionally, Mazzù et al. (2025) showed that the reactions of consumers to the human and AI recommendations depend on the product and the recommendation. There was also a high frequency of AI as a tool for customer engagement. Madanchian (2024) pointed out applications of chatbots, personalisation and predictive analytics, and Mumtaz et al. (2025) discussed recommendation systems, chatbots, dynamic ads and voice assistants in consumer decision-making. Similarly, Shah et al. (2025) explored the concepts of AI personalisation, bots and predictive analysis within the context of an online purchasing scenario. AI is also being used in the fields of

advertising and content creation, as shown in the literature. Madathil (2025) explored the collaborative partnership between human and AI in generative AI advertising and how humans can be part of the process to review and guide AI-generated marketing materials. All this suggests that AI isn't just being used for mundane tasks like automation; it's also being deployed in analytical, customer-facing, creative, and decision-making functions.

Human-AI Collaboration in Marketing Decision-Making

The second big issue was the human's involvement in AI-driven decision-making. Several studies, however, did not consider AI as an autonomous decision-maker, but rather a process of collaboration between AI and human decision-makers, where AI provides information, predictions, or recommendations, which are then assessed by the humans. A meta-analysis of 132 experiments across 27 studies conducted by Ngo (2025) revealed that human–AI collaboration may enhance the outcomes of marketing decisions, with some effects depending on the task and the context. Moreover, there are various types of AI–human decision-making configurations, and the level of expertise, task characteristics, and collaboration structure are crucial. Evidence also found that human involvement is crucial in ethical and strategic decision-making. Gaczek et al. (2026) looked at the impact of human–AI interaction on responsibility attribution and ethical decision-making by marketing managers. In a similar discovery, Madathil (2025) found that people are also a vital part of judging whether AI-generated ad content is effective. In summary, the reviewed research shows that e-commerce decision-making has not been fully automated. Instead, human-AI collaboration supports decision augmentation, in which AI provides analytical capabilities, pattern recognition, prediction, and recommendations, while humans retain responsibility for contextual interpretation, strategic judgement, and supervision.

Benefits of Human-AI Collaboration

Some advantages came out of the studies that were reviewed. AI can handle and ingest lots of data quickly and can help with personalised marketing and recommendations, customer engagement, and predictive decision-making. The findings of Hassan et al. (2025), Mumtaz et al. (2025) and Shah et al. (2025) suggest that these applications are pertinent to consumer responses and purchase-related decisions. Human involvement provides an additional layer of interpretation and control. There is a need for opportunities to enhance marketing decision outcomes using human-AI collaboration, as highlighted by Ngo (2025), and opportunities for complementary human and AI inputs, as emphasised. Another possible benefit was explained. In conversational recommendation scenarios, Chen et al. (2025) reported that customised explanations can enhance the transparency, interpretability and trust in the system. The results in this study indicate that AI systems can offer more decision support when they give results that are comprehensible and can be meaningfully judged by humans.

Research challenges and risks of human–AI collaboration

It was also found that there were some challenges as per the reviewed literature. Automation bias and reliance on AI were key issues noted. Romeo and Conti (2026) pointed out that there was potential for AI recommendations to be overused by decision-makers without proper verification. This discovery is further proof of the importance of a human presence. Other important aspects were trust, transparency, and perceived control. In addition, the human oversight experience can impact AI credibility. There are also indications that AI-generated content is context-specific. Mazzù et al. (2025) discovered that there are different types of human and AI recommendations, and that consumers react to these differently, depending on the type of recommendation and product. This means that the AI-driven recommendations might not be directly applicable and may need some interpretation before they are put into practice.

Factors Influencing Trust and Effective Human-AI Collaboration

Across 15 studies, five recurring factors associated with effective human–AI collaboration were identified as follows:

1. **The accuracy and function of AI**: To provide meaningful support to decision-making, accurate and capable AI outputs are needed.
2. Explainability and transparency: Decision-makers must have information in a way that is easy to understand to make the right decisions about AI recommendations.
3. **Human expertise + AI literacy**: Users need enough knowledge to comprehend, ask questions, and support the output of AI.
4. **Task and contextual properties**: AI assistance may be effective depending on the complexity of the task, properties of the products, and properties of the context.
5. **Human oversight and governance**: Decision makers need opportunities to accept, adapt, question, or reject AI suggestions.

These factors are consistent with the findings of Ngo (2025) and Romeo and Conti (2026).

Overall results synthesis

The analysis of the 15 studies included supports that AI is becoming even more present in e-commerce marketing, including personalisation, recommendation systems, CRM, chatbots, predictive analytics, advertising, and decision support. Concurrently, the extent to which human skills and expertise are integrated into the decision-making process has been shown to affect the effectiveness of AI. Therefore, the results suggest a framework that may be tested in future research by identifying recurring relationships among AI capability, human oversight, explainability, trust, task characteristics, and governance. The evidence also suggests there are conditions that need to exist to collaborate effectively: Explainability, Trust, Human Expertise, Task Characteristics, AI Capability, and Governance. On the contrary, other potential challenges of increased automation, lack of transparency, and automation bias are important issues that need to be monitored and observed by humans.

Discussion

This systematic review is a synthesis of evidence from 15 studies that explored the use of human -AI collaboration in e-commerce marketing and decision-making. Overall, the results show that the collaboration between human -AI collaboration is a continuum of collaborative models where AI can be used to make recommendations or act as a decision support tool in collaboration with humans. The effectiveness of AI implementation was not determined solely by AI capability; rather, the reviewed evidence indicates that it was associated with human expertise, task characteristics, and organisational context. These results align with the findings of Ngo (2025), who conducted a meta-analysis of 15 studies on human–AI collaboration in marketing and reported that the effectiveness of human–AI collaboration varied with contextual and task-related conditions; task configurations and human expertise are important.

Human-AI Complementarity

The results are in line with complementarity as opposed to a substitution view. While AI excels at processing large amounts of data, recognising patterns, making predictions, personalising content, and processing data quickly, human beings are better at interpretation, strategic thinking, ethical considerations, and accountability (Ngo, 2025; Gaczek et al., 2026). However, human-AI complementarity may not be equally effective across all contexts. The study by Mazzù et al. (2025) revealed that the reactions of consumers to the recommendations of humans and AI vary, depending on the category of the product and the context of the recommendation. So, human involvement is essential for tasks depending on the tasks' characteristics. While some decisions could be made entirely by AI – for low complexity, or

when the context is limited, and the stakes are small – more complex decisions and decisions with higher stakes or where the context is richer will need more human oversight (Gaczek et al., 2026). The evidence thus suggests a contingency approach in which the level of human involvement may vary according to task complexity and risk. However, recent meta-analytic evidence from Vaccaro et al. (2024), which was not included in the present review, indicates that human-AI combination may perform worse than the better-performing human-only or AI-only condition in some decision-making tasks (Hedges' g = -0.23). These findings highlight that the effectiveness of collaboration depends on task characteristics and contextual conditions. particularly true in decision-making tasks.

Decision Quality and Efficiency

The synthesis also splits the concepts of decision speed and decision quality. AI can significantly improve the processing of information and the generation of recommendations; however, these capabilities do not necessarily ensure effective strategic decisions. Romeo and Conti (2026) pointed out automation bias, where decision makers might accept the recommendations of AI without proper checking. Therefore, the quality of a decision made by human-AI collaboration should be evaluated in several ways, such as accuracy, fit, ethical suitability, and outcomes for stakeholders. When users feel like they have enough transparency and control, their trust, satisfaction, and loyalty are likely to increase when there are personalised AI recommendations, according to Hassan et al. (2025). This indicates that the e-commerce decision quality benefits are not just short-term, but also long-term concerning customer experience.

Trust, explainability and oversight

The conditions that were found to be important for the successful collaboration were trust and explainability. Tailored explanations in conversational recommendation systems were found to improve the perceived transparency and interpretability of the system and trust in it by Chen et al. (2025). The perceived sufficiency of human control is also an important mechanism that affects the credibility of AI. However, excessive reliance on AI recommendations can contribute to automation bias, highlighting the importance of appropriate human verification and oversight trust is put in place, this can lead to automation bias (Romeo & Conti, 2026). This sets up a tension: Trust of AI enables AI adoption, but too much of it can lead to a reduction of human oversight. Calibrated trust, backed by explainability, AI literacy, and professional qualifications, as well as organisation verification mechanisms, is therefore essential for successful human-AI collaboration (Romeo & Conti, 2026).

Automation versus Augmentation

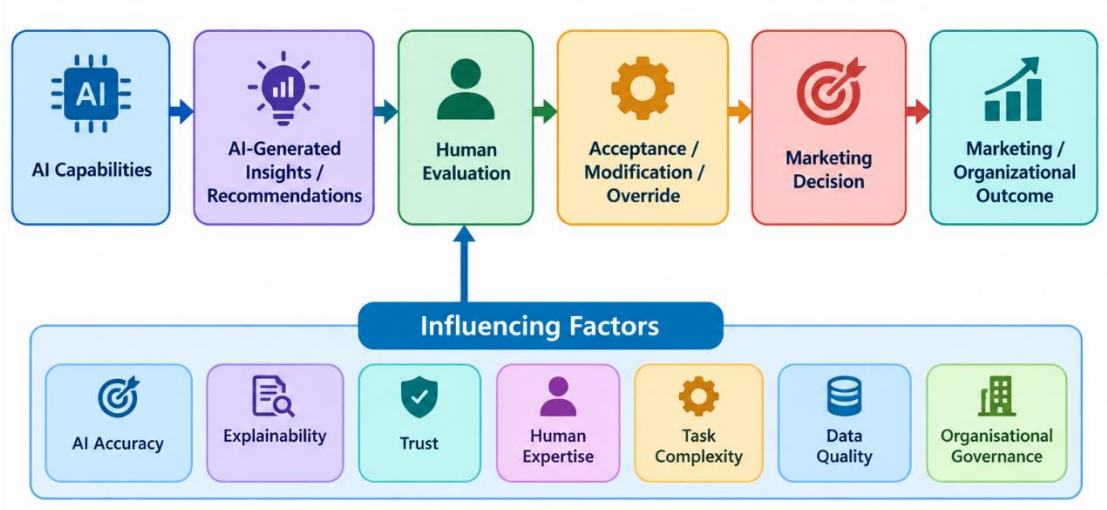
The evidence that has been reviewed suggests that there will be a transition from automation to augmentation (Ngo, 2025). While some of the functions of personalisation, recommendation, customer relationship management (CRM), chatbots, predictive analytics, and advertising content generation are being largely automated by AI, there is a steady rise in the literature that highlights the need to maintain human judgment.

While it significantly enhances capabilities in personalization, CRM, and predictive analytics (Bulut & Taşkın, 2024; Madanchian, 2024), it does not replace the need for human collaboration Teodorescu et al., 2023); however, the literature is increasingly calling for the maintenance of human judgment. Ngo (2025) found the benefits of human-AI collaboration and demonstrated that collaborative configurations are different depending on the expertise and the characteristics of the task. Similarly, Madathil (2025) discovered that while AI-led ads gave a more positive reaction from the audience, human-AI collaborative ads showed even more positive results. The results show that human involvement could be used as a source of value and not just be a limitation on automation.

Conceptual Framework Derived from Synthesis

The proposed conceptual framework illustrates how human -AI collaboration operates in e-commerce marketing. Insights and recommendations generated by the AI capabilities are assessed by human decision makers who can take, alter, or dismiss the results and then make marketing decisions. This process is impacted by the accuracy of AI, its explanations, its trust, human skills, the complexity of the task, the quality of the data, and the governance of the organisation. The framework is backed by research that suggests the successful integration of human–AI collaboration relies on the nature of the task, human expertise, AI capabilities, and how the decision-making responsibility is shared between the human and AI. Research indicates that successful human–AI collaboration is influenced by the characteristics of the task, the expertise of the human, the capabilities of the AI, and the distribution of decision-making roles between the human and the AI (Ngo, 2025; Li & Tian, 2026).

Figure 1 Conceptual Framework of AI-Human Collaboration and Trust in E-Commerce Marketing



The results overall support the previous studies, which indicate that AI can be used to aid personalisation, engagement, prediction, and recommendation in e-commerce (Bulut & Taşkın, 2024; Madanchian, 2024). Additionally, they are related to evidence on the role of collaboration, transparency, explainability, and trust (Ngo, 2025; Chen et al., 2025; Li & Tian, 2026). This review, however, is innovative as it focuses on the role of humans at the heart of the analysis and identifies some of the conditions that are creating a more collaborative approach, such as the accuracy of the AI model, its explainability, trust, human expertise, task complexity, data quality, and organisational governance. The synthesis questions the premise that the higher an AI's ability, the better the decisions that it can make. Mazzù et al. (2025) found that AI recommendations do not always seem to be preferred across the different contexts, and Romeo and Conti (2026) demonstrated that greater use of AI can lead to higher levels of automation bias. The findings indicate that there is a contingent and non-linear relationship between the involvement of AI and decision quality. Decision architectures, not automation, are critical for e-commerce organisations to ensure they're using AI most effectively, based on the complexity of the task and the level of risk, AI reliability, and context.

Conclusion

The purpose of this systematic literature review was to synthesise evidence from 15 studies that investigate how human-AI collaboration and trust in AI-assisted marketing and decision-making in e-commerce are related. The findings indicate that AI is being adopted more in personalised customer experiences, recommendation systems, CRM, chatbots, predictive analytics, advertisements, and marketing assistance. This study suggests that there is a need

to do more than just the technology to achieve successful AI adoption. AI can create content, but human oversight is required for interpretation of results, determining relevance, ethical considerations, and accepting, adapting, or discarding AI-suggested content. The review also identified several factors that influence human-AI collaboration: explainability, transparency, trust, human expertise, AI literacy, task characteristics, AI accuracy, data quality and organisational governance. Automation bias can occur when human decision-makers rely excessively on AI-generated recommendations without adequate verification, potentially weakening independent judgment and decision-making. The suggested human-AI collaboration model suggests that AI should not replace human decision-making but rather serve as a tool to assist with it. Overall, the review offers a thorough overview of the possibilities of AI capabilities and the need for responsible use, appropriate governance, and human involvement in e-commerce marketing, highlighting the importance of human skills. The suggested relationships must be further explored with empirical studies in other markets, tasks, and organisational contexts.

Implications and Recommendations

Managerial Implications:

- Have manual review procedures in place for AI-provided marketing ideas.
- Define boundaries and specify what decisions will be automated, and what human approval will be required.
- Run marketing personnel AI-literacy & training programmes.
- Ensure there are clear override procedures to enable decision makers to review and rectify content generated by AI that is inappropriate.
- Compare and contrast AI recommendations and customer context, business objectives, and market conditions.
- Be aware of automation bias and do not assume that the suggestions provided by AI are always correct.

Theoretical Implications:

- The study is an extension of the application of human-AI collaboration in e-commerce marketing and decision-making.
- It doesn't just think of human-AI interaction as technology replacement; it sees it as a way to leverage and extend decision-making.
- The framework integrates AI capabilities with human expertise, with explainability, trust, task characteristics, and governance.
- It provides a baseline for subsequent empirical testing of the relationships among AI capabilities, human oversight, and marketing decision outcomes.

Governance and Ethical implications:

- There should be clear accountability processes within organisations when decisions are made using AI.
- AI systems must be clearly explained and transparent in a suitable way.
- There should be meaningful rather than just procedural human oversight.
- Organisations need to take care of privacy, fairness, data quality and responsible governance when implementing marketing systems based on AI.

Recommendations (Based on findings):

- To make high-impact marketing decisions, e-commerce organisations should consider implementing structured human-AI collaboration processes that are structured (Ngo, 2025).
- Marketing teams should have the ability to disagree, tweak, or overrule AI recommendations (Gaczek et al., 2026).

- Continuous training on AI literacy of marketing personnel should be provided (Romeo & Conti, 2026).
- Recommendations from AI should be well-explained and applicable to the situation (Chen et al., 2025).
- Managers need to establish measurable indicators for assessing the effectiveness of AI in decision-making (Li & Tian, 2026).
- Consider the risk of automation bias and over-reliance on AI regularly by organisations (Romeo & Conti, 2026).
- Roles and responsibilities of AI, marketers, and decision-makers need to be well-defined (Gaczek et al., 2026).
- The application must be grounded in principles of privacy, fairness, transparency, and accountability when using AI.
- The process of decision-making needs to be adjusted according to task complexity and risk (Mazzù et al., 2025).
- Use of both business outcomes and responsible-AI indicators should be used (Nagpal & Cotte, 2026).

Future Research

- Conduct longitudinal studies to track the development of human-AI partnerships and relationships.
- Run experiments comparing the decision-making process using AI only, human only, and collaborative human-AI decision-making.
- Examine how the quality of marketing decisions varies across different levels of human involvement.
- Understand the issues of automation bias, overreliance, and trust calibration in marketing research.
- Use the suggested framework in quantitative testing of larger and/or more diverse samples.
- Talk about how AI can be used to create ads, content, recommender systems, and marketing strategies.
- Discuss the human-AI collaboration across different e-commerce markets, products, and verticals.
- Start research in underrepresented markets of developing and emerging economies.
- Discuss issues that affect the effectiveness of collaboration, including AI literacy, professional skills, and organisational culture. Explain the implications of explainability and interface design on the acceptance, modification, and rejection of AI recommendations.

Limitations

There are several limitations to this review. First, the protocol was not registered in PROSPERO or OSF, reducing transparency in terms of pre-specified methods. Second, screening and appraisal took place entirely by the author alone, and an independent second screener was not employed. Third, the review focused on the English-language literature, which might not reflect the work done in other languages.

Fourth, only the top 100 relevance-ranked records from Wiley Online Library and Google Scholar were screened, so some relevant studies may have been missed. Fifth, there is a small sample of included studies (n=15) and the studies included are also heterogeneous in design, context and outcome measures, reducing the extent to which they can be generalised. Sixth, the search of grey literature was not performed; this could lead to publication bias. Seventh, several of the studies included in the review do not specifically address the issue of human oversight and may reduce the impact of the study on the review. Lastly, the proposed

framework is conceptual and has not yet been empirically tested; further research involves testing the proposed relationships. Moreover, a significant limitation is that 53,887 of the 55,527 identified records (97.0 percent) were never screened. Due to the high volume of results, only the top 100 records from Wiley and Google Scholar were exported. Because relevance ranking differs on each platform, the review should not be treated as an exhaustive capture of all available literature.

Conflict of interest: The author declares no conflict of interest.
AI-Use Statement: Generative AI was used to assist with locating and checking references. It was not used for screening, data extraction, quality appraisal, thematic synthesis, or the writing of the review's substantive arguments. All AI- assisted references were verified against the sources by the author.
Data-Availability statement: All extracted data are presented in the supplementary tables.
Ethics statement: Ethical approval was not required for this systematic review as no human participants were involved.
Protocol Registration: The review protocol was not registered in a public database (e.g., Prospero or OSF)

References

Ali, I., et al. (2025). Human–AI collaboration in knowledge ecosystems: A multidisciplinary review, integrative framework and future directions. *Journal of Knowledge Management*, 1–22.https://doi.org/10.1108/JKM-03-2025-0431

Alsaffarini, E., & Awwad, B. S. (2026). Artificial intelligence in sustainable marketing: How AI personalisation impacts consumer purchase decisions. *Sustainability, 18*(2), 1123. https://doi.org/10.3390/su18021123

Bulut, Y. E., & Taşkın, N. (2024). Exploring the role of artificial intelligence in enhancing CRM activities within e-commerce: A systematic literature review. *MCIS 2024 Proceedings*, 28.

Chen, Q. Q., Lin, L. M., & Yi, Y. (2025). Tailoring explanations in conversational recommendations: The impact of decision contexts and user interfaces. *Journal of Retailing and Consumer Services, 85*, 104281.https://doi.org/10.1016/j.jretconser.2025.104281

Dhawas, P., Bondade, A., Patil, S., Khandare, K. S., & Salunkhe, R. V. (2024). Intelligent automation in marketing. In *Hyperautomation in business and society* (pp. 66–88). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-3354-9.ch003

Ding, Y., & Najaf, M. (2024). Interactivity, humanness, and trust: A psychological approach to AI chatbot adoption in e-commerce. *BMC Psychology, 12*(1), 1–14. https://doi.org/10.1186/s40359-024-02083-z

Etuk, E. A., & Omankwu, O. C. B. (2025). Human-AI collaboration: Enhancing decision-making in critical sectors. *Communication in Physical Sciences, 12*(2), 426–433. https://doi.org/10.4314/ggb6wr66

Gaczek, P., Leszczyński, G., Wei, Y., & Sun, H. (2026). The bright side of AI in marketing decisions: Collaboration with algorithms prevents managers from violating ethical norms. *Journal of Business Ethics, 204*, 771–794. https://doi.org/10.1007/s10551-025-06083-w

Hassan, N., Abdelraouf, M., & El-Shihy, D. (2025). The moderating role of personalised recommendations in the trust–satisfaction–loyalty relationship: An empirical study of AI-driven e-commerce. *Future Business Journal, 11*, 66. https://doi.org/10.1186/s43093-025-00476-z

Hui, Z., Khan, A. N., & Khan, N. A. (2025). Unveiling the influence of dialogic communication on AI-technology trust in e-commerce. *Aslib Journal of Information*

Management. Advance online publication. https://doi.org/10.1108/AJIM-11-2024-0563

Lari, H. A., Vaishnava, K., & Manu, K. S. (2022). Artificial intelligence in e-commerce: Applications, implications and challenges. *Asian Journal of Management, 13*(3), 235–244. https://doi.org/10.52711/2321-5763.2022.00041

Madanchian, M. (2024). The impact of artificial intelligence marketing on e-commerce sales. *Systems, 12*(10), 429. https://doi.org/10.3390/systems12100429

Madathil, J. C. (2025). Generative AI advertisements and human–AI collaboration: The role of humans as gatekeepers of humanity. *Journal of Retailing and Consumer Services, 87*, 104381. https://doi.org/10.1016/j.jretconser.2025.104381

Mazzù, M. F., Andria, A., Baccelloni, A., & De Angelis, M. (2025). The impact of humans vs. AI recommendation on consumer reactions to product exposure. *Electronic Commerce Research*. https://doi.org/10.1007/s10660-025-10048-6

Mumtaz, F., Qaisar, M. N., Zahid, A., & Ahmed, N. (2025). The impact of artificial intelligence on consumer decision-making in digital marketing. *Journal of Asian Development Studies, 14*(2), 372–387. https://doi.org/10.62345/jads.2025.14.2.30

Ngo, V. M. (2025). Human–AI collaboration for marketing capabilities: A meta-analysis. *Marketing Letters, 36*, 839–855. https://doi.org/10.1007/s11002-025-09783-5

Ottun, A.-R. O., & Flores, H. (2025). *Trustworthy AI in practice: A comprehensive review of human oversight and human-in-the-loop approaches*. TechRxiv. https://www.techrxiv.org/doi/abs/10.36227/techrxiv.176118749.93102582/v1

Pokorny, L. (2025). *Human-AI collaboration in high-stakes decision-making environments.* DOI: 10.5281/zenodo.18011475

Raji, M. A., Olodo, H. B., Oke, T. T., Addy, W. A., Ofodile, O. C., & Oyewole, A. T. (2024). E-commerce and consumer behaviour: A review of AI-powered personalisation and market trends. *GSC Advanced Research and Reviews, 18*(3), 66–77. https://doi.org/10.30574/gscarr.2024.18.3.0090

Rane, N., Choudhary, S., & Rane, J. (2024). *Artificial intelligence and machine learning in business intelligence, finance, and e-commerce: A review*. SSRN. https://doi.org/10.2139/ssrn.4843988

Romeo, G., & Conti, D. (2026). Exploring automation bias in human–AI collaboration: A review and implications for explainable AI. *AI & Society, 41*, 259–278. https://doi.org/10.1007/s00146-025-02422-7

Sele, D., & Chugunova, M. (2024). Putting a human in the loop: Increasing uptake, but decreasing accuracy of automated decision-making. *PLOS ONE, 19*(2), e0298037. https://doi.org/10.1371/journal.pone.0298037

Shah, G. M., Joyo, A. S., & Memon, N. A. (2025). Determining the effect of artificial intelligence on online buying behaviour of consumers: A case study of retail buyers in Karachi, Sindh. *Journal of Development and Social Sciences, 6*(1), 86–96. https://doi.org/10.47205/jdss.2025(6-I)09

Teodorescu, D., Aivaz, K.-A., Vancea, D. P. C., Condrea, E., Dragan, C., & Olteanu, A. C. (2023). Consumer trust in AI algorithms used in e-commerce: A case study of college students at a Romanian public university. *Sustainability, 15*(15), 11925. https://doi.org/10.3390/su151511925

Vaccaro, M., Almaatouq, A., & Malone, T. (2024). When combinations of humans and AI are useful: A systematic review and meta-analysis. *Nature Human Behaviour*, *8*(12), 2293-2303. https://doi.org/10.1038/s41562-024-02024-1

Appendix 1: Extraction Matrix of included studies (supplementary Table S1)

Study	Country/ Region	Year	Study design	AI Application context	Human role	Key findings	Quality
Bulut & Taşkın	International	2024	Systematic literature review	AI for CRM	Marketer	AI can improve CRM in e-commerce by personalisation, analytics, engagement, and retention.	High
Madanchian	Canada / International literature	2024	Critical literature review, 50 scope documents	Chatbots, personalisation, predictive analytics	Marketer	AI marketing tools such as chatbots, personalisation, and predictive analytics can enhance e-commerce performance.	High
Hassan et al.	Egypt	2025	Quantitative survey and used SEM	Personalisation AI recommendations	Consumer	Personalised AI recommendations can impact trust, satisfaction, and loyalty in AI-powered e-commerce.	High
Chen et al.	China / South Korea	2025	Three experiments, N=1,429	Tailored explanations in conversational AI	Consumer	Tailored explanations increase transparency, interpretability, and trust in conversational recommendations.	High
Mumtaz et al.	Pakistan	2025	Quantitative survey	Recommendation engines, chatbot dynamics, ads, voice assistants	Consumer	Recommendation engines, chatbots, dynamic advertising, and voice assistants. Recommendation engines, chatbots, dynamic advertising, and voice assistants shape consumers' decision-making.	Moderate
Madathil	International	2025	multi-method empirical study,	Generative AI advertising	Marketer	finds that human–AI collaborative advertisements elicit better audience reactions than AI-only ads	High
Mazzù et al. (2025)	Italy	2025	Experimental studies	Human vs AI recommendations	Consumer	Consumer responses to human versus AI recommendations vary across product and recommendation contexts.	High
Ngo	International	2025	Meta-analysis; 132	Human-AI collaboration	Both	Human–AI collaboration yields better decision outcomes, but contextual factors are necessary for achieving synergy.	High
Shah et al.	Pakistan	2025	Quantitative research study with 400 online buyers in Pakistan	AI personalisation, chatbots, predictive analysis	Consumer	Finding that AI personalisation, chatbot effectiveness, and predictive analysis all have a significant impact on online purchase decisions.	Moderate
Gaczek et al.	United Kingdom	2026	Three vignette experiments and 587 marketing managers	Human-AI Collaboration	Marketer	Found that human–AI collaboration impacts responsibility attribution and ethical decision-making.	High
Ding & Najaf	China	2024	Quantitative survey SEM	AI chatbot in e-commerce	Consumer	Interactivity and perceived humanness significantly influence trust toward AI chatbots; trust mediates the relationship between these factors and the intention to adopt AI chatbots for e-commerce.	High
Ali et al.	International	2025	Systematic review	AI-human collaboration	Both	AI–human collaboration Improves decision making and innovation but risks deskilling, power imbalance and opacity.	Moderate
Sele & Chugunova	Canada/USA	2024	Online experimental studies	Perceived human oversight	Consumer	Perceived adequacy of human oversight" as one of the mechanisms that affect the trust of AI.	High
Hui et al.	Pakistan	2025	Quantitative SEM	AI chatbot dialogic communication	Consumer	Dialogic communication by AI chatbots positively influences AI-technology trust, which increases consumers' intention to adopt chatbot decisions. Perceived self-threat moderates this relationship weakness the link between trust and adoption.	High
Romeo & Conti	Italy	2026	Systematic review	Explainable AI, human oversight	Both	Automation bias can lead to relying too heavily on AI, underscoring the need for transparency and human oversight.	High

Appendix B Methodological Quality Appraisal of included studies (supplementary Table S2)

Study	Study design	Appraisal tool	Item level result	Overall Rating
Bulut & Taşkın	Systematic literature review	AMSTAR 2	Critical weakness 0	High
Madanchian	Critical literature review, 50 scope documents	SANRA (Narrative review checklist)	10/12	High
Hassan et al.	Quantitative survey and used SEM.	JBI Cross-sectional	8/8	High
Chen et al.	Three experiments, N=1,429	JBI experimental	10/10	High
Mumtaz et al.	Quantitative survey	JBI Cross-sectional	5/8	Moderate
Madathil	Multi-method empirical study	MMAT	5/5 criteria meet	High
Mazzù et al. (2025)	Experimental studies	JBI experimental	9/10	High
Ngo	Meta-analysis; 132	AMSTAR 2	Critical weakness 0	High
Shah et al.	Quantitative research study with 400 online buyers in Pakistan	JBI Cross-sectional	6/8	Moderate
Gaczek et al.	Three vignette experiments and 587 marketing managers	JBI experimental	10/10	High
Ding & Najaf	Quantitative survey SEM	JBI Cross-sectional	7/8	High
Li and Tian	Systematic review and conceptual framework	AMSTAR 2	Critical weakness 1	Moderate
Nagpal & Cotte	Two experimental studies	JBI experimental	9/10	High
Hui et al.	Quantitative SEM	JBI Cross-sectional	7/8	High
Romeo & Conti	Systematic review	AMSTAR 2	Critical weakness 0	High