

Artificial intelligence recommendation systems and consumer purchase intention: A systematic literature review and research agenda

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Abstract

Artificial intelligence recommendation systems now shape how consumers discover and evaluate products online, yet research on their influence on purchase intention remains scattered across theories, contexts and methods. This study presents a systematic literature review following the Scientific Procedures and Rationales for Systematic Literature Reviews protocol. A Scopus search covering January 2015 to March 2026 returned 1,779 records, which were screened to 397 and then to a final sample of 112 peer reviewed journal articles. The sample was analysed through bibliometric mapping in VOSviewer and Biblioshiny, including keyword co-occurrence, thematic maps and thematic evolution, and through the Theory, Context, Characteristics and Methodology (TCCM) framework. The literature draws mainly on the Stimulus Organism Response model, the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and trust theory. Most studies report that personalization, recommendation quality, transparency, explainability and trust are associated with stronger purchase intention, while privacy concerns, perceived manipulation and algorithmic bias weaken acceptance. Research is concentrated in e commerce and technologically advanced markets and relies mainly on cross sectional surveys and structural equation modelling. The review identifies gaps in explainable and ethical AI, consumer resistance, emerging market and cross-cultural evidence, and longitudinal and experimental designs, and it proposes a structured agenda for future research. Findings concern intentions rather than observed purchasing and reflect a single database.

Keywords: Artificial Intelligence, Recommendation Systems, Consumer Purchase Intention, Personalization, Consumer Trust, Explainable AI, Algorithmic Transparency, Systematic Literature Review, Bibliometric Analysis, TCCM Framework

JEL Classification: M31, D12, D83



1. Introduction

AI has revolutionized the way people buy and sell online (Dwivedi et al., 2021; Huang & Rust, 2021), and it has made shopping easier. AI's impact on digital commerce is ongoing (Han & Trimi, 2017). This is now a staple part of the business to consumer relationship and a critical factor in the consumer's buying process. One of the most important applications of AI is the recommendation system, which has revolutionized personalized shopping experience. By analysing user behaviour, transaction history, preferences, and contextual data, AI recommendation systems deliver personalized product and service suggestions, minimize information overload, assist users in finding the products they want to purchase, and facilitate the decision-making process (Han & Trimi, 2017). As a result, these systems have become much more than mere recommendations; they are becoming strategic marketing tools that will help boost customer engagement, user experience, and firms' competitive advantage in the ever-increasing digital marketplaces (Dwivedi et al., 2021; Huang & Rust, 2021). Machine learning, deep learning, natural language processing and generative AI have made remarkable advances, enabling the use of intelligent recommendation systems across multiple industries like e-commerce, social commerce, online retail, tourism, financial services and digital platforms. AI recommendation contexts go beyond collaborative filtering and include conversational agents, AI chatbots, explainable recommendation interfaces, and real-time personalisation to enable a highly adaptive consumer experience (Zimmermann et al., 2023; Chen et al., 2023). With the proliferation of AI-powered personalization, the question of how it might affect customer reactions to tailored experiences has emerged as a major research and practical challenge. As organizations aim to differentiate in the market through personalization, rather than simply product selection and pricing, predicting consumer response to personalized recommendations has become a primary area of concern in both research and practice. Since it reflects whether consumers turn AI recommendations into actual purchases, understanding purchase intent has become a major focus of research in AI recommendation systems.

There are several factors that affect consumers in the context of AI environments: recommendation quality, personalization, anthropomorphism, transparency, perceived usefulness, trust, perceived risk, and privacy concerns (Marriott & Williams, 2018; Pizzi et al., 2021; Hallikainen et al., 2022; Blut et al., 2023; Li et al., 2024). Further, AI conversational agents and personalized recommendation systems have received increased focus by researchers, transitioning from algorithmic performance analysis to cognitive, emotional, and behavioral aspects of consumer acceptance and resistance to AI recommendations (Ruan & Mezei, 2022; Cheng & Peng, 2024). Although this branch of research has expanded considerably, the literature is still scattered among a variety of theories, technologies, research contexts, and methodology. Previous research studies have tended to explore only one of the factors that can affect consumers' purchase intent, to conceptualize the AI recommendation system in various different ways, and to be conducted within a specific area of the industry or geography, thereby not gaining any cumulative knowledge.

Furthermore, new challenges like explainable AI, algorithmic transparency, ethical AI, consumer resistance, and human-centered AI have been gaining significant interest in the research community, but were often not combined in a single systematic review. This fragmentation makes it challenging to determine whether there are fundamental theoretical foundations, future research questions, methodological approaches, and gaps to knowledge that would support future research (Paul et al., 2021; Donthu et al., 2021). To overcome these limitations, the present study used Systematic Literature Review (SLR) methods, which are based on the Scientific Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) model (Paul et al., 2021), to systematically collect, organize, and analyses literature about the AI recommendation system and consumers' purchase intent. The objective of the review is to synthesize the intellectual structure of the field, explore the emergence of a research agenda, and develop a structured agenda for future research in the field, using a combined approach of bibliometric analysis and the Theory, Context, Characteristics, and Methodology (TCCM) framework, derived from 112 journal articles published from 2015 to 2026 in the Scopus database. The search involved a preliminary screening of 1779 studies and systematic screening and selection of 112 studies which satisfied the inclusion/exclusion criteria. In this study, the literature related to AI recommendation systems and consumer purchase intentions was reviewed systematically by combining the protocol SPAR-4-SLR and bibliometric analysis and the framework TCCM. The objectives are:

RO1: To synthesize the literature in a systematic way on the AI recommendation environment and consumer purchase intention by applying the SPAR-4-SLR methodology.

RO2: To review and understand the prevailing theories, contexts, characteristics and methodologies (TCCM) of the field.

RO3: To visualize the intellectual structure and development of the research field by using bibliometric analysis methods such as publication trends and thematic analysis.

RO4: To define gaps in research and to suggest a systematic research program for the future.

2. Theoretical Underpinnings and Literature Review

2.1 Evolution of Theoretical Perspectives

AI recommendation environments have been developing in tandem with the advancement of AI and digital commerce. While past research has primarily centered on measures of technology adoption and recommendation accuracy, recent research has started to consider consumers' cognitive, emotional, and behavioral reactions to AI recommendations. With the increasing personalization and interactivity of AI systems, theories from marketing, consumer behavior and information systems have been employed to understand the effects of AI on purchase intentions (Han & Trimi, 2017; Dwivedi et al., 2021).

2.2 Stimulus-Organism-Response (SOR) Framework

The most popular theory in AI recommendation research is Stimulus – Organism – Response (SOR). It describes how the personalization, recommendation quality, anthropomorphism, and transparency of AI can be external stimuli that affect the internal stimuli such as trust, perceived usefulness, satisfaction, and perceived risk that consumers experience during the evaluation process. These psychological responses subsequently determine purchase intentions (Pizzi et al., 2021; Wien & Peluso, 2021; Hallikainen et al., 2022).

2.3 Technology Acceptance Perspective

The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) help explain consumers' acceptance of AI recommendation systems. These theories highlight the roles of perceived usefulness, ease of use, performance expectancy and social influence in shaping behavioural intentions to use AI-supported shopping technologies. However, technology acceptance alone may not fully explain consumer responses without considering trust and privacy concerns (Bawack et al., 2022).

2.4 Trust and Information Processing Perspectives

Consumer confidence is a key element in the Trust Theory that affects the uptake of AI recommendations. However, transparency, accuracy, and explanations of recommendations boost consumers' trust in AI systems and privacy concerns and algorithmic bias reduce it (Marriott & Williams, 2018; Li et al., 2024). Similarly, in the realm of information consumption, consumers evaluate the quality and reliability of AI-produced information prior to purchasing a product, and during shopping, explainability is now playing an important role (Wien & Peluso, 2021; Chen et al., 2023).

2.5 Theoretical Synthesis

The literature reviewed shows that consumer behavior in the context of AI recommendation environments is still not comprehensively understood and explained by a single theory. There are two theories that explain consumers' confidence and evaluation of AI recommendations, which are Trust Theory and Information Processing Theory. Trust Theory and Information Processing Theory explain psychological responses of consumers towards AI recommender systems. These complementary views give a full picture of consumer intentions to purchase. However, there are a number of new challenges that have not yet been sufficiently researched, including explainable AI, algorithmic fairness, ethical AI, and consumer resistance (Zimmermann et al., 2023; Cheng & Peng, 2024).

2.6 Evolution of AI Recommendation Environments

Artificial intelligence (AI) recommendation environments are no longer limited to rule-based recommendation systems, but are now intelligent systems that can process vast amounts of

consumer information and provide tailored recommendations for products and services. The general approaches used in early recommender systems were collaborative filtering and content-based filtering, which were based on users' past behaviors or product features, respectively (Lu et al., 2016; Kabirmamdouh & K  k, 2025). These methods proved effective in enhancing the accuracy of recommendations but lacked flexibility and failed to capture consumers' shifting preferences. The emergence of machine learning, deep learning, natural language processing and big data analytics has revolutionized AI recommendation systems by empowering them to learn from consumer interactions, their context and constantly adapt their decisions (Hu et al., 2023; Jin et al., 2024). Nowadays, AI systems are more sophisticated, blending behavior, transactions and context to deliver highly tailored recommendations in various digital applications, such as e-commerce, social commerce, tourism, financial services, and conversational applications (Zimmermann et al., 2023; Hardcastle et al., 2025). Consequently, recommendation systems have evolved from optimizing the performance of the algorithm, to increasing the overall experience of the customer and assisting the consumers in their decision-making process. This has been shown in the literature that AI recommendation environments not only improve recommendation accuracy but also influence consumer behavior and decision-making. Psychological impacts such as trust, perceived personalization, satisfaction, transparency and consumer engagement have been identified as four key factors. Emerging as key facilitators of the impact of AI recommendations on purchase decisions, they are recent studies (Marriott & Williams, 2018; Hallikainen et al., 2022; He et al., 2024; Li et al., 2024). Meanwhile, in the research area, there is a transition from technology-centred to customer-centric thinking, as research has gone beyond a technology focus to one that is more consumer-centric, In the context of privacy, explainability, algorithmic bias and consumer resistance, explain (Cheng & Peng, 2024; Geyik & Weijo, 2025).

2.7 AI Recommendation Characteristics Affecting Purchase Intention

The utility of an AI's recommender is largely dependent on the recommender's nature. In all the studies analyzed, personalization is the feature that consistently stands out as being most significant, allowing AI systems to make personalized recommendations based on consumers' preferences, browsing behavior and purchasing habits. Personalized recommendations have the potential to improve the perceived relevance, shopping experience and purchase intention (Hallikainen et al., 2022; Yin et al., 2025). Likewise, the quality of the recommendations made which is determined by their accuracy, relevance, and timeliness – helps build consumer trust in the AI-based decision-making process (He et al., 2024). In addition to personalization, recent research has focused on the increased role of transparency, explainability, and anthropomorphism in consumer reactions. Consumers will be more willing to accept AI recommendations when they are aware of the methods behind their creation and feel that such a system is transparent and trustworthy (Li et al., 2024; Chen et al., 2023). AI chatbots contribute to increased engagement and purchase intention by providing more interactive shopping experiences, while also enhancing the experience of human-like communication (Chen et al., 2023). Some research underscores that

over-personalization and opaque algorithms can further heighten privacy concerns, diminish consumer autonomy, and foster algorithmic avoidance (Cheng & Peng, 2024; Geyik & Weijo, 2025). Research in recent years, therefore, recommends a balance between the effectiveness of recommendations and transparency, fairness and ethical use of AI to maintain consumer trust and long-term purchasing behavior.

2.8 Consumer Psychological Mechanisms

According to the literature, the psychological responses of the consumers to the AI recommendations have a significant influence on their purchase intentions, rather than the technological effects. Consistent with this, trust is also always found to be the most critical mechanism; AI recommendations are more likely to be trusted if users do not perceive a risk using them (Marriott & Williams, 2018; Li et al., 2024). Likewise, consumers' appraisals of AI recommendations that are perceived as useful and satisfactory increase their purchase intent and engagement in using the platform (Pizzi et al., 2021; Hallikainen et al., 2022; He et al., 2024). But it's not the case everywhere. Trust and resistance to AI recommendations can be undermined by several factors, such as privacy concerns, perceived manipulation, and algorithmic bias, and when the algorithms behind recommendation systems are opaque (Cheng & Peng, 2024; Geyik & Weijo, 2025). The results indicate that AI recommendations either support or hinder purchase behaviors based on psychological evaluations consumers make.

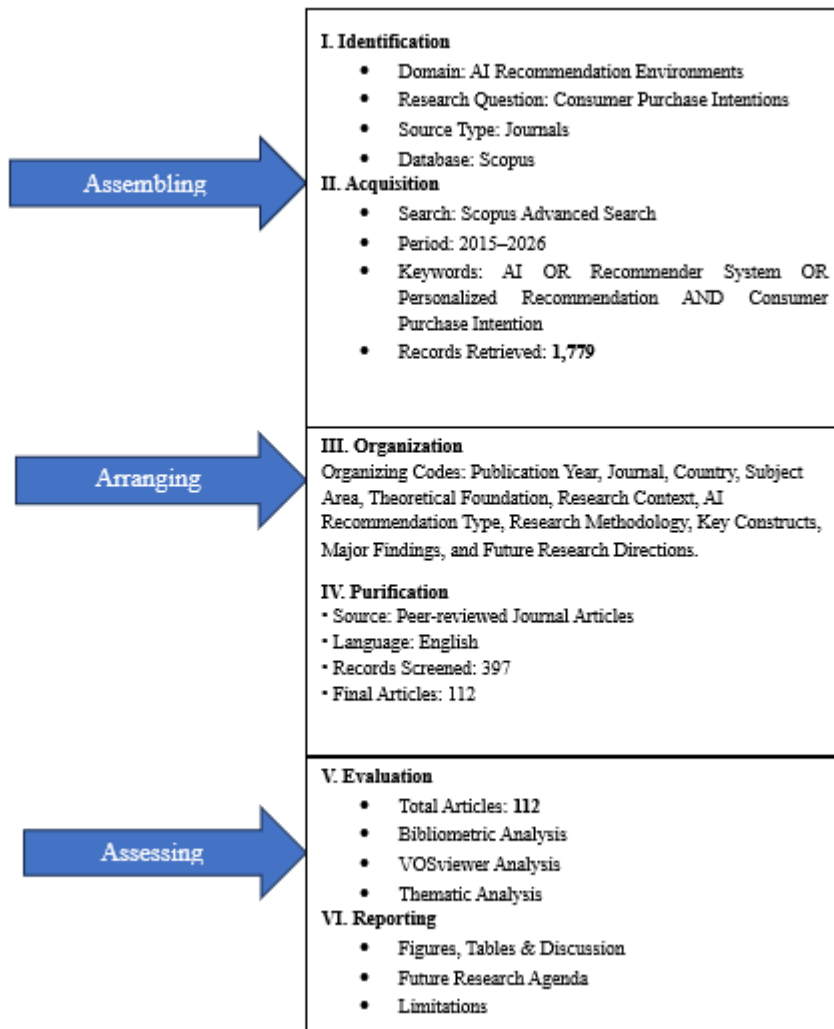
2.9 Research Gaps and Literature Synthesis

Although there are many studies on AI recommendation environments, there are still a few things that haven't been explored. The existing studies tend to adopt specific theories like Stimulus–Organism–Response (SOR) framework, Technology Acceptance Model (TAM), UTAUT and Trust Theory, which limits the diversity in theories that explain AI-enabled consumer behavior (Pizzi et al., 2021; Marriott & Williams, 2018; Bawack et al., 2022). E-Commerce has also been an area of research focus and for developed economies, sectors like healthcare, education, and financial services, and emerging markets have been relatively under-researched (Dwivedi et al., 2021). In terms of methodology, the literature is mainly characterized by cross-sectional surveys and structural equation modelling, and comparatively few studies are of longitudinal, experimental, qualitative, and mixed research designs. Secondly, there is a lack of empirical research in emerging topics such as explainable AI, algorithmic fairness, consumer resistance, digital well-being and ethical AI (Cheng & Peng, 2024; Zimmermann et al., 2023). Filling these gaps will help to advance understanding of consumer decision-making in AI-supported recommendation contexts.

3. Methodology

This systematic literature review follows the Scientific Procedures and Rationales for Systematic Literature Reviews proposed by (Paul et al., 2021) for systematically synthesizing the literature on AI recommendation environments and consumers purchase intentions.

Figure 1. SPAR-4-SLR Review Protocol



The SPAR-4-SLR protocol was chosen since it is a transparent, rigorous, and reproducible process for conducting a SLR using the iterative steps of assembling, arranging and assessing literature. The systematic approach helps researchers provide justifications for the decisions they make about the methodology and ensures consistency across review process (Paul et al., 2021). To offer a comprehensive synthesis of the studies selected, the review also incorporates the Theories, Contexts, Characteristics, and Methodologies (TCCM) framework developed by Paul and Rosado-Serrano (2019), which enables a systematic examination of the literature based on its theoretical

foundations, the contexts of the researched studies, the characteristics investigated, and the methodological perspectives adopted.

3.1 Search Strategy

Scopus was chosen for this review as it indexes peer-reviewed research from various disciplines relevant to the study such as marketing, information systems, consumer behavior and artificial intelligence. The multidisciplinary coverage facilitated the identification of research that investigated both the technical aspects of the AI recommendation system and how it affected purchase intentions (Paul et al., 2021). The following Boolean search string was used in Scopus: ("Artificial Intelligence" OR "AI Recommendation*" OR "Recommender System*" OR "Personalized Recommendation*") AND ("Purchase Intention*" OR "Consumer Purchase Intention*"). The review spanned publications between January 2015 and March 2026, offering an in-depth look at how AI recommendation technologies evolved within digital commerce and consumer decision-making. The search in Scopus was carried out on 29 June 2026 and found 1779 records. A search strategy, database selection, and review period were determined to ensure consistency in identifying literature. After the initial search, the records were checked with a set of inclusion and exclusion criteria following the SPAR-4-SLR protocol (Paul et al., 2021). Studies were selected if they (i) were published in peer-reviewed journals, (ii) were written in English, (iii) focused on consumer purchase intentions of AI recommendation systems, (iv) were indexed in Scopus, and (v) were within the scope of review. Studies were excluded if they were conference proceedings, book chapters, editorials, duplicate records, non-English publications, articles without accessible full texts, or studies that were not directly relevant to the research objectives. The author independently screened and selected the articles using the predefined inclusion and exclusion criteria. Each record was assessed for its relevance to the research objectives and its compliance with the established eligibility criteria. After initial screening, 1,779 records were narrowed down to 397 potentially relevant studies. Such studies were then further evaluated and a final sample of 112 peer-reviewed journal articles was determined for analysis. The chosen articles then were analyzed with the aid of bibliometric techniques and with the aid of the Theory, Context, Characteristics, and Methodology (TCCM) framework.

The review protocol presented in Table 1, comprising the selected database, search time, search strategy, inclusion and exclusion criteria, and the number of articles retained at each stage of the screening process.



Table 1. SPAR-4-SLR Review Protocol

Review Item	Description
Database	Scopus
Search Period	Published between January 2015 and March 2026.
Search Fields	Title, Abstract, and Keywords
Search Keywords	("Artificial Intelligence" OR "AI Recommendation*" OR "Recommender System*" OR "Personalized Recommendation*") AND ("Purchase Intention*" OR "Consumer Purchase Intention*")
Initial Records Identified	1,779
Records after Preliminary Screening	397
Final Studies Included	112
Inclusion Criteria	(1) Peer-reviewed journal articles; (2) Published in English; (3) Focused on AI recommendation systems and consumer purchase intentions; (4) Indexed in Scopus; (5) Published between 2015 and 2026

Exclusion Criteria	(1) Conference papers, book chapters, editorials, notes, and reviews; (2) non-English publications; (3) Duplicate records; (4) Studies not directly related to AI recommendations or consumer purchase intentions; (5) Inaccessible full-text articles
Review Protocol	SPAR-4 Systematic Literature Review (SLR) guidelines integrated with TCCM framework

3.2 Data Extraction

After final article selection, a structured data extraction process was performed to guarantee the uniformity of data across all reviewed studies. Systematic data collection of information such as publication year, journal, country of study, theoretical foundation, research context, AI recommendation type, research methodology, key constructs, and principal findings were performed. The coding of these variables made the descriptive analysis and qualitative synthesis in TCCM easier. The structured extraction process also allowed for comparisons between studies and minimized inconsistencies in the data interpretation phase.

3.3 Data Analysis

The selected studies were analysed using a combination of bibliometric techniques and qualitative synthesis. VOSviewer was used to visualise keyword co-occurrence relationships and examine connections among the principal concepts in AI recommendation research (Van Eck & Waltman, 2010). The overlay visualisation was used to examine the temporal distribution of keywords, while Biblioshiny, the web interface of the Bibliometrix package, was used to examine annual publication trends, thematic structure, and thematic evolution. The thematic map was interpreted in terms of the centrality and density of the identified themes. Finally, the TCCM framework was applied to synthesise the theoretical foundations, research contexts, characteristics examined, and methodologies adopted in the selected studies (Paul & Rosado-Serrano, 2019). These complementary methods were used to identify established research themes, relationships among concepts, and directions for future research. The results are presented in the following sections, beginning with the bibliometric profile of the selected literature, followed by a thematic synthesis and a future research agenda.

4. Results

In the systematic screening and eligibility process, 112 peer reviewed journal articles were retained for the final review. The studies as a whole provide a snapshot of the state of research in AI recommendation environments and consumer purchase intent, with information about the theoretical, contextual and methodological development of the field. The period of selected publications ranges from 2015 to 2026, which covers the current state of rapid development of AI technologies and their use in e-commerce. During this time, the amount of research has grown significantly, suggesting a shift in focus within the field of AI and recommender systems towards understanding their impact on consumer decision making and buying behavior.

Table 2. TCCM Framework Synthesis of AI Recommendation Research

Theory (T)	Context (C)	Characteristics (C)	Methodology (M)	Research Synthesis and Future Directions
Stimulus-Organism-Response (SOR)	E-commerce, online retail and AI-enabled shopping platforms	AI recommendation features, personalisation, anthropomorphism, trust, emotions and purchase intention	Predominantly quantitative surveys, experiments and structural equation modelling (SEM)	The SOR framework explains how AI recommendation features act as external stimuli that shape consumers' cognitive and emotional responses, which may influence purchase intentions. Future research could examine explainability, algorithmic transparency and longer-term consumer responses.

Technology Acceptance Model (TAM)	E-commerce, mobile commerce and AI shopping assistants	Perceived usefulness, perceived ease of use, behavioural intention and trust	Surveys using SEM and partial least squares structural equation modelling (PLS-SEM)	TAM helps explain consumers' acceptance of AI recommendation systems through perceived usefulness and ease of use. Future research could integrate privacy concerns and ethical considerations into technology acceptance models.
Unified Theory of Acceptance and Use of Technology (UTAUT)	AI-powered recommendation systems and digital commerce	Performance expectancy, effort expectancy, social influence and facilitating conditions	Quantitative surveys and structural equation modelling	UTAUT explains the acceptance of AI-enabled shopping technologies, with future research exploring cross-cultural differences in consumer responses.
Information Processing Theory	Recommendation systems, online shopping and digital decision-making	Information quality, recommendation relevance, cognitive processing and decision confidence	Experimental and survey-based studies	This perspective helps explain how consumers evaluate recommendation-related information before forming purchase intentions. Future research could examine information overload, information credibility and the role of explanations in AI-generated recommendations.

Trust Theory	AI recommendation environments and online retail platforms	Trust in AI, perceived risk, transparency, privacy concerns and purchase intention	Quantitative surveys and experiments	Trust is an important factor in understanding consumer responses to AI recommendations. Future research could distinguish trust in AI systems from trust in retailers and examine perceived fairness, privacy and transparency.
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Table 2 displays the TCCM synthesis of the research on AI recommendations, which has been interdisciplinary in the fields of marketing, information systems, e-commerce and consumer behaviour. The reviewed studies are based on theoretical models, namely SOR, TAM, UTAUT, Information Processing Theory and Trust Theory. They also examine the concepts of recommendation personalisation, perceived usefulness, trust, information quality and purchase intention. The literature can be found in a wide variety of digital shopping scenarios such as online retail, mobile commerce platforms and AI-powered shopping platforms. The representation of emerging economies and cross-cultural contexts should be explored to gain insight into the effect of cultural differences on consumers' reactions toward AI suggestions (Dwivedi et al., 2021).

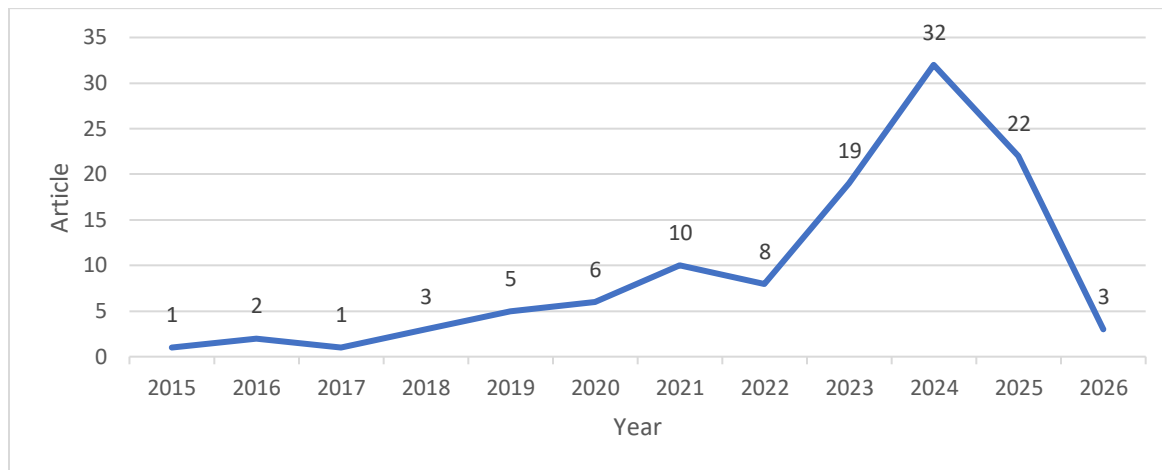
The literature reviewed mainly conducted quantitative studies based on surveys, experiments or structural equation modelling to investigate the relationship between AI recommendation attributes and the purchase intention of consumers. In addition to this, Information Processing Theory gives importance to the understanding of consumer evaluation of information related to recommendations, and Trust Theory brings attention to consumer trust, perceived risk and privacy concerns. The existing evidence can be expanded with the help of qualitative and mixed-methods research, as well as longitudinal studies and research that focuses on actual purchasing behaviour. Additionally, future research might examine the differences between various cultures, information overload, and the impact of transparency in AI-assisted shopping space

4.1 Annual Publication Trend

The annual trend of studies on the use of AI recommendation environments and consumer purchase intention in the period 2015–2026 is shown in Figure 2. From 2015 to 2018, the amount of research carried out remained limited. Since 2019, the number of publications has been increasing. This is akin to the rapid expansion of AI and the speed at which AI has grown. This trend is driven by the use of applications in digital commerce and the increasing focus on research

regarding personalization, trust, and purchase intention among the outcomes of AI for consumers (Huang & Rust, 2021; Dwivedi et al., 2021).

Figure 2. Annual Publication Trends in AI Recommendation Research, 2015–2026



The 2026 data cover January to March only and, therefore, represent a partial year. Consequently, the publication count for 2026 should not be compared directly with those of complete calendar years. In general, the publication trend reflects the evolution and the increasing relevance of AI recommendation research in the field of marketing and consumer behaviour.

4.2 Top Publishing Journals

Table 3 lists the top 10 journals, ranked by the number of articles published on AI recommendation environments and consumer purchase intentions. Journal of Theoretical and Applied Electronic Commerce Research had the highest number of publications (16) followed by the Journal of Business Research (9) and the Journal of Retailing and Consumer Services (7). The major themes of these journals are mainly related to electronic commerce, consumer behavior, digital marketing and information systems, thus showing that the field of AI recommendation research has gone multidisciplinary, covering both technical and behavioral elements. Moreover, the presence of famous publishers including Elsevier, Springer, Wiley, Taylor & Francis, IGI Global and MDPI, indicates that the research has gained academic importance and developed.

4.2 Top Publishing Journals

In Table 3, the clustering of publications in specific journals also indicates that there will continue to be a rise in future studies of consumer decision-making in the field of marketing, digital commerce, and artificial intelligence.



Table 3. Leading Journals Publishing Research on AI Recommendations and Consumer Purchase Intentions

Rank	Journal	No. of Articles	Publisher
1	Journal of Theoretical and Applied Electronic Commerce Research	16	MDPI
2	Journal of Business Research	9	Elsevier
3	Journal of Retailing and Consumer Services	7	Elsevier
4	Electronic Commerce Research and Applications	4	Elsevier
5	Electronic Markets	4	Springer
6	Cogent Business and Management	4	Taylor & Francis (Cogent)
7	Journal of Global Information Management	3	IGI Global
8	Technological Forecasting and Social Change	3	Elsevier
9	Tourism Management Perspectives	3	Elsevier
10	Psychology and Marketing	3	Wiley

4.3 Future Research Agenda Based on the TCCM Framework

Though research on artificial intelligence recommendation settings has grown significantly, the TCCM study reveals numerous gaps still exist at a theoretical, practical and methodological level. The majority of existing studies on consumer AI recommendations are based on consumer reactions to artificial intelligence suggestions, drawing on existing theories such as the Stimulus–Organism–Response (SOR) approach, the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and Trust Theory (Marriott & Williams, 2018; Pizzi et al., 2021; Bawack et al., 2022). While this thinking has enhanced knowledge about consumers, it has done less to boost the understanding of consumer behavior powered by AI, AI ethics and human-centered AI. Explainable artificial intelligence and consumer resistance still need to be investigated. Research is needed to extend the scope of e-commerce studies beyond traditional e-commerce settings and investigate numerous applications; including healthcare, where AI recommendation systems play a vital role. AI recommendation systems have a significant impact in various scenarios, including the healthcare sector. As can be observed in Table 4, the key sectors are financial services, travel, education and international digital trade. Furthermore, greater attention needs to be given to longer term behavioral outcomes and consumer welfare. privacy issues, fairness and algorithmic openness. In terms of methodology, future research would benefit from the use of longitudinal, mixed-method, behavioral and cross-cultural analysis procedures to provide a more complete picture of the impact of AI recommendation systems over time on the choice of the consumer. Combined, these lines of inquiry provide an organized plan for advancing theoretical development as well as the practical application of AI-driven recommendation systems.

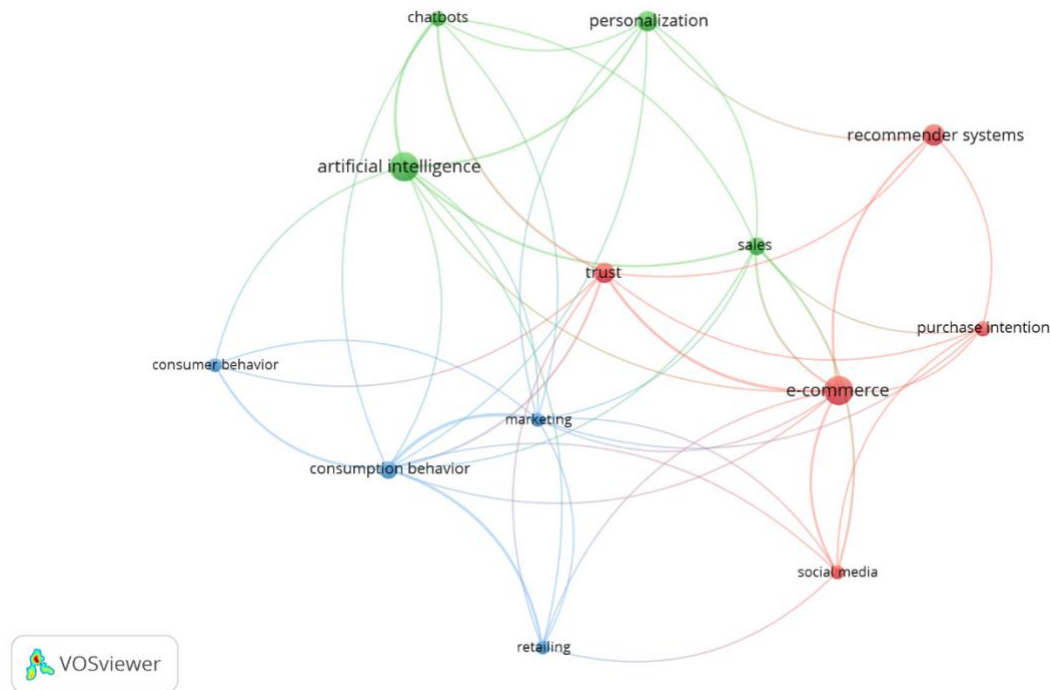
Table 4. Future Research Agenda Based on the TCCM Framework

TCCM Dimension	Current Research Status	Research Gaps	Future Research Directions
Theory	Predominant use of SOR, TAM, UTAUT, and Trust Theory (e.g., Pizzi et al., 2021; Bawack et al., 2022; Marriott & Williams, 2018).	Limited integration of emerging theories such as Consumer Reactance Theory and Ethical AI.	Develop integrated theoretical frameworks combining SOR, Trust Theory, Explainable AI (XAI), and Human-Centered AI (HCAI).
Context	Research is concentrated in e-	Limited research in emerging markets,	Examine AI recommendations

	commerce, mobile shopping, chatbots, and online retail environments (e.g., Pantano et al., 2019; Weith & Matt, 2023).	healthcare, banking, tourism, and B2B contexts.	across cross-border e-commerce, sustainable consumption, and omnichannel retailing.
Characteristics	Research mainly focuses on personalization, anthropomorphism, trust, perceived usefulness, and purchase intention.	Limited attention to algorithmic bias, privacy concerns, consumer reactance, dissatisfaction, and over-personalization.	Investigate AI transparency, fairness, explainability, privacy paradox, consumer resistance, digital well-being, and long-term customer loyalty.
Methodology	Most studies employ quantitative surveys, experiments, bibliometric analysis, and SEM-based approaches.	Limited use of longitudinal, mixed-method, behavioral analytics, and real-world experimental research.	Conduct longitudinal studies, field experiments, AI-driven behavioral analytics, mixed-method research, and cross-cultural comparative studies.
Overall Research Direction	Existing research demonstrates strong technological and marketing perspectives but provides limited understanding of long-term psychological, ethical, and societal implications.	Lack of cross-cultural, interdisciplinary, and longitudinal evidence.	Explore cultural differences, ethical AI governance, consumer well-being, and the long-term impact of AI recommendations on trust, loyalty, and decision-making.

4.4 Keyword Co-occurrence Analysis

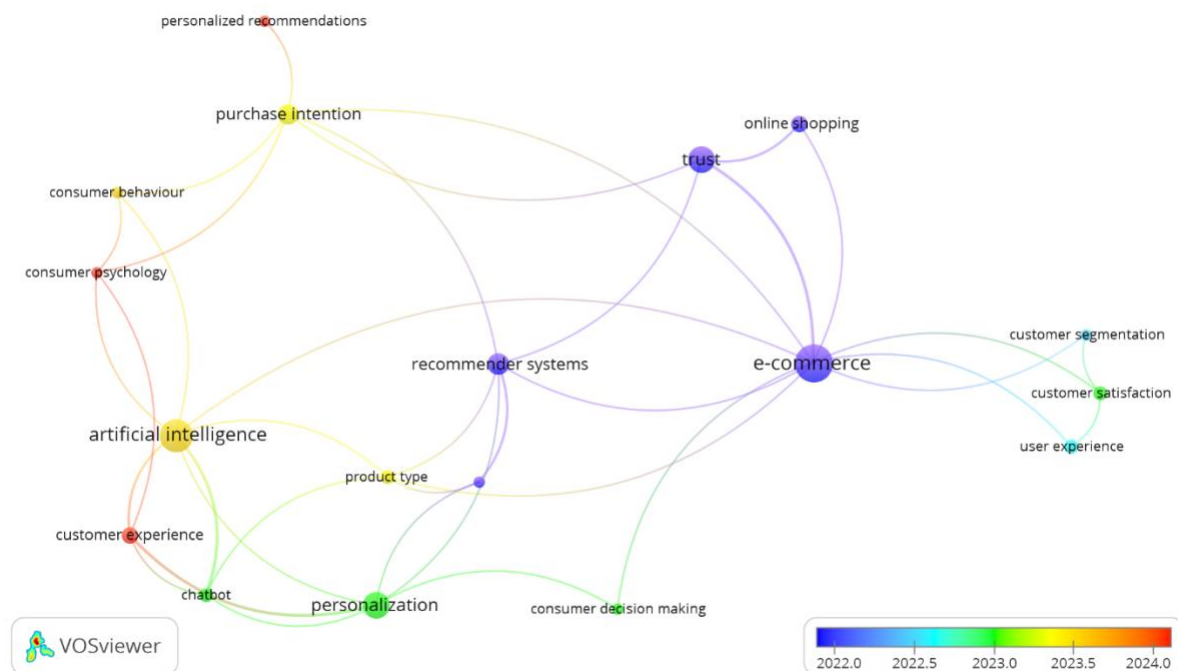
Figure 3. Keyword Co-occurrence Network of AI Recommendation Research



The keyword co-occurrence network (Fig. 3) indicates the conceptual structure of AI. In the case of the keywords, recommendation research is done by clustering them into themes where they are often found together. Artificial intelligence, purchase intent, e-commerce, trust, personalization, and recommendation systems have a high presence in the network, indicating the critical importance of these systems to the theoretical underpinning of the discipline. These close relationships between these keywords indicate that personalization with AI technology and the trust of the consumer are basic mechanisms through which recommendation systems can affect purchase decisions (Pizzi et al., 2021; Marriott & Williams, 2018). The network also shows the growth and development of related themes on the evolving scope of AI recommendation research, such as the use of chatbots, consumer behavior, user experience, and transparency. Recent research has begun to explore the behavioral, psychological and ethical aspects of AI-driven shopping journeys, in addition to just performance of the algorithms. The evolution reflects the interdisciplinary nature of the discipline and the increasing convergence between AI and marketing and consumer behavior research (Chen et al., 2023; Li et al., 2024).

4.5 Overlay Visualization Analysis

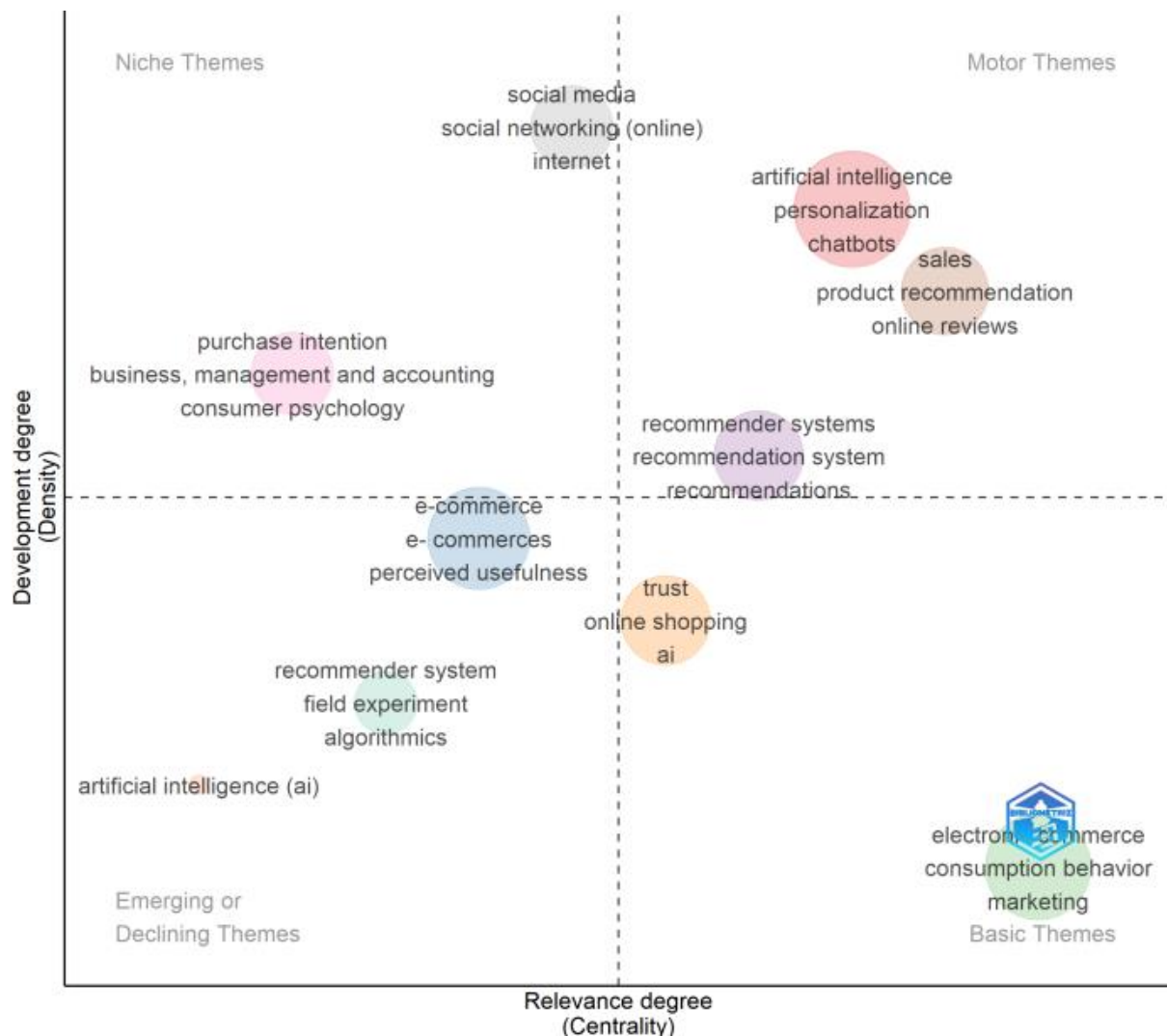
Figure 4. Overlay Visualization of Keywords in AI Recommendation Research



The visualization in Figure 4 is an overlay VOSviewer representation of the temporal distribution of the keywords in the field of AI recommendation research. The color gradient represents the difference in the average year of publication for the terms shown in the network. The keywords that are visible are: artificial intelligence, recommender systems, personalization, personalized recommendations, purchase intention, e-commerce, trust, online shopping, chatbots, customer experience, customer satisfaction and user experience. The terms reference the relationship between how AI recommendation technologies are developed and consumer reactions and digital shopping experiences. The terms of trust, customer satisfaction and user experience point to the significance of consumer-centered perspectives in this area. The overlay also maps the connections between the technical concepts and marketing outcomes such as purchase intention and online shopping. But the figure must be understood as a representation of the relationship of the keywords and their temporal distribution and NOT as evidence of cause and effect as far as consumer behavior.

4.6 Thematic Map Analysis

Figure 5. Thematic Map of AI Recommendation Research



The thematic map of the AI recommendation research (Fig. 5) illustrates the centrality and density of the themes. In the motor themes, the artificial intelligence theme, the personalization theme and the chatbot theme are identified as being relevant and developed within the researched motor map. Artificial intelligence, personalization and chatbots are identified as being relevant and developed in the motor map and as such are highlighted as being motor themes in the map. The basic themes seem to include electronic commerce, consumption behavior and marketing, indicating that they offer a good conceptual starting point for the study of electronic commerce. Purchase intention and consumer psychology are shown under the niche-theme area, showing that they are part of a more specific thematic cluster. Emerging and declining concepts of the map include other terms such as recommender systems, e-commerce, perceived usefulness and algorithms. These positions should be understood in the context of the map's centrality and density, but should not be taken as a measure of whether a topic is growing or declining in the long-term. Overall, the thematic map shows the link between AI recommendation technologies and outcomes of digital commerce and

consumers. Explainability, ethical AI and algorithmic transparency are relevant paths for future research, but are not explicitly identified as key themes in the labels on this map.

4.7 Thematic Evolution Analysis

Figure 6. Thematic Evolution of AI Recommendation Research, 2015–2024 and 2025–2026

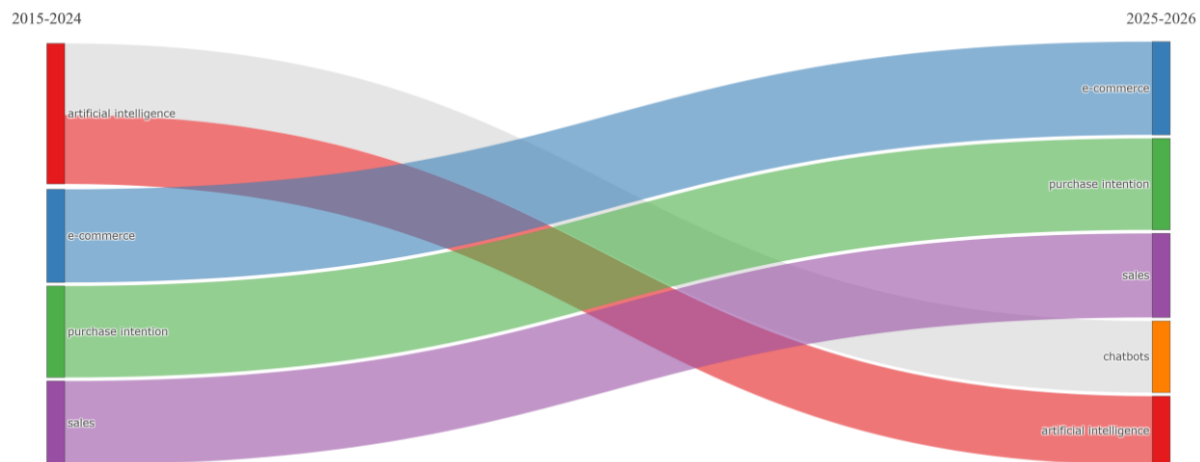


Figure 6 shows how the themes of AI recommendation research have changed from 2015-2024 to 2025-2026. The Sankey chart illustrates how the big themes of research have developed over time, but without losing the concepts. In the early days, the focus was mainly on artificial intelligence, e-commerce, personalization, and sales, with a strong emphasis on building recommendation systems and optimizing sales. In the contemporary era, these themes have developed into electronic commerce, purchase intention, artificial intelligence, and AI chatbots, which are more inclined towards consumer-based applications than research. Specifically, purchase intention and AI chatbots are emerging as key areas of interest, reflecting the increased focus on understanding consumers' behavioral reactions, interactive AI technology and conversational recommendation systems. In summary, the thematic overview highlights the growing maturity of the algorithmic component of the digital commerce landscape to a level that now includes aspects of consumer psychology, consumer experience, and intelligent human–AI interactions, signaling an increasing need for algorithmic assistance in decision-making for digital commerce.

4.8 Discussion

4.8.1 Theoretical Insights

Based on the review, there is a general agreement within the academic community on the influence of artificial intelligence recommendation characteristics on consumer behavior, based on the principles of Stimulus–Organism–Response theory, Technology Acceptance Model, Unified Theory of Acceptance and Use of Technology, and Trust Theory. Indeed, the academic community has demonstrated that a combination of psychological and technology-related factors can help understand how various attributes of artificial intelligence recommendations affect consumer purchasing intentions (Davis, 1989; Venkatesh et al., 2003; Marriott & Williams, 2018; Dwivedi et al., 2021).

4.8.2 AI Recommendation Characteristics and Consumer Behavior

Based on the findings of the review, personalization, recommendation quality, transparency, and explainability were determined as the main characteristics of artificial intelligence recommendation systems that affect consumer purchasing behaviour. For instance, personalization allows recommendation systems to assist customers in making faster and better purchase decisions. At the same time, the lack of transparency and explainability can prompt customers to develop negative perceptions towards such systems (Pizzi et al., 2021; Zimmermann et al., 2023; Cheng & Peng, 2024). Additionally, the findings of the review demonstrated that the increasing level of personalization of recommendation systems and the use of black-box artificial intelligence can make customers paranoid about potential privacy breaches and unfair treatment, which, in turn, can prompt negative consumer behaviours, such as avoidance (Aguirre et al., 2015; Hallikainen et al., 2022). Therefore, it is paramount that businesses implement recommendation systems that operate transparently and ethically to obtain consumer trust and avoid adverse consumer behaviours.

4.8.3 Research Gaps and Future Directions

As previously mentioned, the TCCM analysis revealed a number of research gaps related to the relationship between artificial intelligence recommendations and consumer purchasing intentions. Firstly, the majority of the studies included in the review followed an e-commerce framework, which prompts concerns regarding the ability to generalise the conclusions and findings of the articles included in the review. Moreover, most of the reviewed studies originated from developed countries, which, again, raises questions regarding applicability and generalisability (Ruan & Mezei, 2022; Chakraborty et al., 2024). Secondly, the majority of the reviewed studies followed a cross-sectional research design, which limits the possibility of determining cause-and-effect relationships (Zimmermann et al., 2023). Future research should focus on exploring the impact of artificial intelligence recommendations on consumer behaviour in different settings, utilising an array of research designs, including, but not limited to, cross-sectional, longitudinal, control-intervention, and mixed-methods. Moreover, future researchers should pay more attention to the role of such concepts as explainable artificial intelligence, ethical concerns, and human-related

issues in the design of recommendation systems that would increase consumer acceptance of artificial intelligence recommendations and, subsequently, consumer purchasing intentions.

4.9 Overall Contribution

To conclude, the reviewed articles demonstrate that the majority of them proved the influence of artificial intelligence recommendations on consumer purchasing intentions, with the characteristics of such recommendations playing a critical role in this relationship. In this study, the author used bibliometric methods to highlight the main themes that were explored in the analysed scholarly articles and provide an overarching perspective on the connection between artificial intelligence recommendations and consumer behaviour. The findings of this review have contributed to the growing body of research literature on consumer behaviour in the context of the impact of artificial intelligence, while also providing businesses with viable recommendations on the development of recommendation systems that would promote increased consumer trust and purchasing behaviours.

4.10 Managerial Implications

The results of the study indicate that the firms should develop the artificial recommendation system which will offer personalized options or services and increase overall satisfaction and loyalty of customers. At the same time, the businesses should ensure the transparency of the recommendation process and build consumer trust (Pizzi et al., 2021; Zimmermann et al., 2023). In addition, the companies should apply ethical AI practices, such as protecting consumer data and ensuring the absence of algorithmic bias and discrimination for achieving fairness and transparency. As a result, there is a possibility of improving customer satisfaction and lifetime value with the help of artificial intelligence recommendation systems. The review revealed that the researchers and managers should consider developing artificial intelligence recommendation systems which will offer personalization, as well as ensure the transparency of the recommendation process and ethical issues to maximize competitive advantage.

4.11 Limitations

The current article has several limitations, which are connected to the fact that the authors used the database of Scopus and analysed the articles published in the journals in English language only between 2015 and 2026. Besides that, there is a possibility that the results represent only the perspectives of 112 papers and do not reflect the realities of all researchers in the world. Moreover, the study does not consider cutting-edge innovations in artificial intelligence, such as the so-called generative AI and new trends in explainable AI, since they appeared recently. Thus, future researchers should consider using different databases and aim to include both the articles published in journals and magazines and the latest studies to improve the accuracy of their work.

5. Conclusion

This study provides a systematic review of research on AI recommendation systems and consumer purchase intention by integrating bibliometric analysis with the Theory, Context, Characteristics and Methodology (TCCM) framework. The findings identify the major research themes, theoretical perspectives, research contexts and methodological trends in this field. The review highlights the importance of examining consumer responses to AI recommendations while recognising research gaps relating to explainable and ethical AI, cross-cultural contexts and longitudinal research designs. These gaps provide directions for future studies to develop a more comprehensive understanding of consumer decision-making in AI-enabled shopping environments. Overall, this review offers a structured synthesis of the existing literature and a future research agenda for scholars and practitioners interested in developing trustworthy and effective AI recommendation systems. As the review primarily synthesises research on purchase intention, its findings should not be interpreted as direct evidence of actual purchasing behaviour.

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