

Artificial Intelligence Agents and Consumer Behavior: A Bibliometric Analysis of an Emerging Research Field

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Article Info

Received: 24.06.2026

Revised: 10.09.2026

Accepted: 23.09.2026

Published: 15.10.2026

Keywords:

Artificial Intelligence Agents, AI Agents, Consumer Behavior, Bibliometric Analysis, Anthropomorphism.

Jel Code:

M31, O32, D11

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Review Article

<https://doi.org/10.5281/zenodo.23373211>

Abstract

Recent dynamic advances in AI technologies have brought about profound transformations in the marketing paradigm and in consumer behavior and interactions. At the heart of this transformation, the relationship between AI agents and consumer behavior stands out as a timely area calling for in-depth investigation in the literature. This study constitutes a bibliometric analysis undertaken to reveal the intellectual accumulation of knowledge in this conceptual domain and to examine the evolution of the literature systematically. To this end, 438 articles indexed in the Web of Science (WoS) database between 2020 and 2026 were subjected to a comprehensive examination. The research first conducted a performance analysis to resolve the quantitative structure of the field, mapping annual publication distributions, the most prolific authors, the most highly cited studies, leading countries, and institutional collaborations. It then carried out citation, co-citation, and co-occurrence analyses using science mapping techniques in order to structure the intellectual framework of the field. The findings show that the AI agent literature emerging in the context of consumer behavior is following a growth trend that is gaining momentum in both quantitative and qualitative terms. Thematically, the literature was found to concentrate on the transparency and interpretability of AI algorithms, the implications of these algorithms for consumer attitudes and behavior, the strengthening of human-AI interaction through anthropomorphic design elements, the dark side encompassing ethics, privacy, and trust, and sectoral reflections in the service industry.

1. Introduction

Over the past few years, AI has moved to the center of business innovation, owing to its capacity to anticipate consumer behavior and optimize organizational processes. By delivering operational efficiency across a wide range of domains, from logistics to customer relationship management, the technology is fundamentally reshaping how firms and consumers interact (Haque et al., 2024; Hoyer et al., 2020; Ma & Sun, 2020). In the course of this shift, AI has ceased to be merely a mechanical tool that executes routine tasks and has evolved into autonomous agents capable of making their own decisions and engaging in social interaction (Humberd & Latham, 2026; Li et al., 2026).

The evolution of generative AI (GenAI) and large language models (LLMs) has made agent-based systems the new reality in the marketplace, systems that can perceive, reason, and form an emotional connection with the customer, thereby exhibiting “feeling AI” and “artificial empathy” (Huang & Rust, 2022; Liu-Thompkins et al., 2022). The growing prevalence of natural language interfaces has reshaped human-computer interaction by giving rise to autonomous entities that can act on behalf of users (Rothschild et al., 2025). The hyper-personalization these systems afford is fundamentally transforming how firms approach market segmentation and targeting (Haque et al., 2024). By enabling the right offer to reach the right customer at the precise moment of need, this capacity maximizes both immediate and future consumption opportunities (Raja et al., 2026).

The launch of ChatGPT marked a turning point in the commercial adoption of AI, and the retail and e-commerce sectors, with their rich data infrastructures, have become primary testing grounds for these technologies (Khoi & Phuc, 2026: 13). The consumer journey has become an active cognitive-support mechanism that AI optimizes in real time (Acar & Schweidel, 2026; Ma & Sun, 2020). Concerns about algorithmic transparency, together with the belief that AI lacks the capacity to “feel” in emotionally charged hedonic contexts, nonetheless sustain a continued preference for human advice (Huang et al., 2025: 1415-1416; Nizette et al., 2025: 50-51). As purchase decisions are delegated to autonomous systems, traditional frameworks have proven inadequate, ushering in a new era that Taşkın (2025: 43) terms the “agentic customer experience.” This evolution offers operational efficiency and personalization across diverse sectors (Dwivedi et al., 2026; Parthiban & Adil, 2023) and is shaped by multidimensional psychological dynamics, including

consumers' preference for receiving bad news from AI (Garvey et al., 2023) and their susceptibility to artificial emotional cues (Han et al., 2023).

Bibliometric and systematic review studies on the role of AI in business and marketing have made notable contributions to the literature. This body of work has examined market research (Loureiro et al., 2021), retail applications (Haque et al., 2024), e-commerce (Zhang & Liu, 2026), banking (Parthiban & Adil, 2023), and customer experience from a sensory marketing perspective (Mouammine, 2026). Consumer-AI interaction (Riandhi et al., 2025) and the use of GenAI in retail (Khoi & Phuc, 2026) have likewise been examined in detail. However, most studies treat conventional automation processes as equivalent to agentic AI. They investigate how variables such as anthropomorphism, artificial empathy, and perceived intelligence shape consumer attitudes toward AI agents, yet they do so within a fragmented framework (Pillai & Sivathanu, 2020; Adam et al., 2021; Moussawi et al., 2021; Riandhi et al., 2025). A comprehensive mapping of how autonomous, decision-making AI agents affect consumer behavior has yet to appear. Addressing this gap, the present study sets out to map the role and theoretical contributions of AI agents within the consumer behavior literature in a holistic manner through bibliometric analysis. To this end, it seeks to answer the core research questions presented below, with the aim of revealing the intellectual structure of the existing literature.

RQ1: What are the research trends and performance patterns in the study of AI agents within the context of consumer behavior?

RQ2: What insights does the literature on AI agents in the context of consumer behavior offer to academic scholarship and practitioners?

RQ3: Which research gaps have been identified in the literature examining AI agents in the context of consumer behavior, and in what areas and in what ways might researchers contribute to this field in the future?

To address the research questions outlined above, the remainder of the study is organized as follows. The second section, following this introduction, presents the conceptual framework. The third section sets out the research methodology and the data collection process. The fourth section reports the results of the performance analysis and science mapping conducted as part of the bibliometric analysis. The study concludes with a discussion section that interprets the findings in light of the existing literature.

2. Conceptual Framework

2.1. The Concept of an Artificial Intelligence Agents

AI rests on transferring distinctively human cognitive faculties to machine systems (Ma & Sun, 2020: 482) and on the capacity of computational machines to emulate the multifaceted abilities of humans. With the rise of ChatGPT in particular, GenAI has become a focal point of intense interest in both academic circles and society at large. Underlying this interest is the fact that such systems have begun to surpass human performance along certain dimensions. Indeed, as Hermann & Puntoni (2024) emphasize, efforts to grasp the capacity of GenAI and its socioeconomic implications remain in their early stages.

AI agents are defined as a concrete instantiation of programs, algorithms, and systems endowed with the capacity to exhibit intelligence (Lei et al., 2025: 599). Having gained visibility, tools such as ChatGPT, DeepSeek, and Google Gemini have moved into the mainstream (Hasselwander et al., 2026), and autonomous AI agents have become technological entities that perceive and interpret environmental data without external oversight and carry out their assigned tasks independently (Gonzalez et al., 2026). Conceptualizing AI agents as representations of the digital human is closely tied to the notion of the digital twin. A digital twin is a virtual counterpart of a physical object, system, or process; sustained by a continuous flow of data, it updates in synchrony with its real-world equivalent and affords real-time monitoring, analysis, and optimization (Korzynski et al., 2025).

The purchase journey of today's consumers is shaped by the multilayered coordination of AI agents operating in the background. From digital search engines to dynamic pricing systems, every touchpoint is optimized in real time through machine learning algorithms. Through this systemic integration, AI ceases to be a tool that passively observes consumer behavior and becomes an active infrastructure that steers and reconfigures behavioral patterns at scale (Ma & Sun, 2020: 481-482). Such a transformation sets the stage for reassessing this emerging body of literature through a range of theoretical lenses.

AI systems, whose economic and functional impact is expanding rapidly, are taking on an increasingly anthropomorphic character across a broad range of domains from education to retail, displaying human-like appearances, emotional expressions, and personality traits (Alabed et al., 2022: 1-2). The “digital humans” that have emerged with the rise of LLMs in particular blur the human-AI boundary in roles ranging from business representation to brand ambassadorship. This shift points to a fundamental paradigm change, one in which AI moves beyond being a purely functional tool and evolves into a social entity capable of forming emotional bonds with users (Kim & McGill, 2025: 363-364). In the specific case of chatbots, however, it should be borne in mind that linguistic anthropomorphism can exert adverse effects on persuasiveness, and that machine language may prove more effective than human language in utilitarian contexts. This calls for designers to deploy anthropomorphic features deliberately and in moderation (Yang et al., 2026). By attributing human qualities to non-human entities, anthropomorphism offers users a multidimensional experience. Anthropomorphic conversational AI is profoundly reshaping how firms manage customer relationships and interactions (Chaturvedi et al., 2025). Anthropomorphic features integrated into AI systems, such as gender, voice, and appearance, positively influence consumers’ brand perceptions and attitudes. Among these features, gender plays a particularly decisive role. Female AI agents tend to be perceived as warmer and more trustworthy, whereas male agents are associated with rationality and task performance. Female agents also appear more persuasive for hedonic products, and male agents for utilitarian ones (Huang et al., 2025: 1416-1417).

Within Social Cognitive Theory, the dimensions of warmth and competence provide a foundational basis for explaining human-robot interaction. Under Social Response Theory and the Computers as Social Actors (CASA) paradigm, users approach these systems according to human norms even when they are aware that the systems possess no consciousness. From the standpoint of Social Presence Theory, the personalized responses and anthropomorphic features that AI provides strengthen the user’s sense of social connection. Alongside these, acceptance models such as the Technology Acceptance Model (TAM), the Service Robot Acceptance Model (SRAM), and the Extended Unified Theory of Acceptance and Use of Technology (UTAUT-2) indicate that perceived ease of use, social interaction, benefit, and trust play a decisive role in the adoption of service robots (De Keyser & Kunz, 2022: 173-174). The proliferation of AI agents has led consumers’ relationship with technology to acquire an emotional dimension that extends beyond functional use. Consumers turn to AI to meet needs such as companionship, support, and personal growth, a development that is transforming expectations of human relationships and patterns of social behavior (Alabed et al., 2024). AI, in transforming both business and society, thus enhances personalization while improving efficiency (Loureiro et al., 2021: 911). It should not be overlooked, however, that excessive reliance on algorithms dulls individual skills and weakens decision-making capacity (Theoharakis & Mylonopoulos, 2026).

2.2. Artificial Intelligence Agents in Consumer Behavior

Across a broad spectrum of sectors such as retail, e-commerce, healthcare, and finance, AI is restructuring corporate decision-making mechanisms and the ways in which value is created (Khoi & Phuc, 2026: 12; Zhang & Liu, 2026). The integration of this technology into advisory and decision-support processes is likewise transforming the dynamics of how consumers interact with the digital service ecosystem (Tang & Son, 2026). Agents powered by GenAI and LLMs in particular, unlike traditional recommendation systems and static platforms, can interpret user intent in real time and synthesize contextual data. Integrated across all channels, from websites to smart devices, these systems are coming to occupy an increasingly central place in consumers’ search, decision-making, and post-purchase experiences (Nguyen et al., 2026).

AI-based recommendation mechanisms optimize consumers’ access to personalized products and services (Huang et al., 2025: 1415). Because agent design directly affects the service experience and decision-making processes, understanding the psychological dynamics of user-system interaction has become critical for the marketing field (Nguyen et al., 2026). Avatar-based assistants tailored to individual expectations serve as effective tools in personalized advertising strategies and in driving the adoption of new products (Park et al., 2025). This turns AI into a guiding reference point that shapes consumer behavior (Theoharakis & Mylonopoulos, 2026). Consumers who form an emotional bond with AI agents ultimately exhibit greater satisfaction and loyalty, along with a sustained orientation toward the service provided (Yim et al., 2024).

The impact of agent technology on consumer behavior is particularly evident in price tracking and agent-assisted payment applications. AI agents can autonomously perform specific stages of the purchasing process, such as price tracking, identifying suitable alternatives, and completing purchases after approval, within the

goals and boundaries set by consumers (Srinivasan, 2025). Moreover, a recent example of AI agents' potential influence on consumer behavior is Universal Cart, introduced by Google on May 19, 2026. This system consolidates products encountered across platforms such as Google Search, Gemini, YouTube, and Gmail into a single smart shopping cart and tracks prices, deals, and stock status. By making decisions aligned with consumer preferences and executing actions at various stages of the purchasing process on the consumer's behalf, Universal Cart highlights the active role of AI agents (Srinivasan, 2026).

Although AI's acquisition of anthropomorphic features enables more natural interaction with consumers, once this process crosses a certain threshold, it can evoke unease and discomfort in users (Poushneh & Gearhart, 2025). Voice-based AI, in this respect, can mitigate such discomfort and heighten purchase intention by creating a stronger sense of independence and social closeness than text-based systems (Poushneh & Gearhart, 2025). AI's capacity to remember past preferences (memory), for its part, strengthens favorable attitudes by fostering a sense of uniqueness, yet in privacy-sensitive domains such as health and personal care, it can have the opposite effect, prompting discomfort and adversely affecting service evaluations (Chai et al., 2026). When service failures occur, consumers appear more forgiving of algorithmic systems than of human representatives (Chacon et al., 2025). These attitudes toward AI are not uniform, however. Indeed, while consumers welcome the pursuit of efficiency, they may display marked resistance in service encounters that involve self-relevant judgments bearing on appearance, identity, or personal competence (Anagha et al., 2026). A study by Wang et al. (2026) shows that consumers favor AI over humans in situations that require the disclosure of highly sensitive data, such as financial and health information, while prioritizing human warmth and advice in low-sensitivity situations.

The Internet, self-service technologies, and AI have substantially altered consumer behavior, and consumers now expect faster, easier, and more personalized shopping experiences. Businesses, in turn, draw on these technologies to anticipate consumer needs more accurately. Privacy concerns, distrust of algorithms, and a sense of discomfort with automated systems nonetheless complicate technology adoption. This transformation has also created conditions conducive to a rise in certain negative behaviors, such as consumer theft (Giroux et al., 2022: 1027-1028).

3. Research Methodology

This study aimed to provide a comprehensive mapping of the role and theoretical contributions of AI agents within the consumer behavior literature through bibliometric analysis. Frequently adopted to analyze the intellectual, conceptual, and social network dynamics of a research field (Aria & Cuccurullo, 2017), this methodology offers researchers a holistic perspective by identifying the historical development and thematic trends of disciplines (Rojas-Lamarena et al., 2022). In contrast to the subjective nature of traditional literature reviews, this technique approaches the subject within a quantitative framework and, at the same time, eliminates the operational and temporal constraints entailed by manual screening (Li et al., 2017). In light of the reasons outlined, bibliometric analysis was therefore identified as the method best suited to the aim of the study, and the research design was structured accordingly.

3.1. Literature Review Strategy and Data Collection

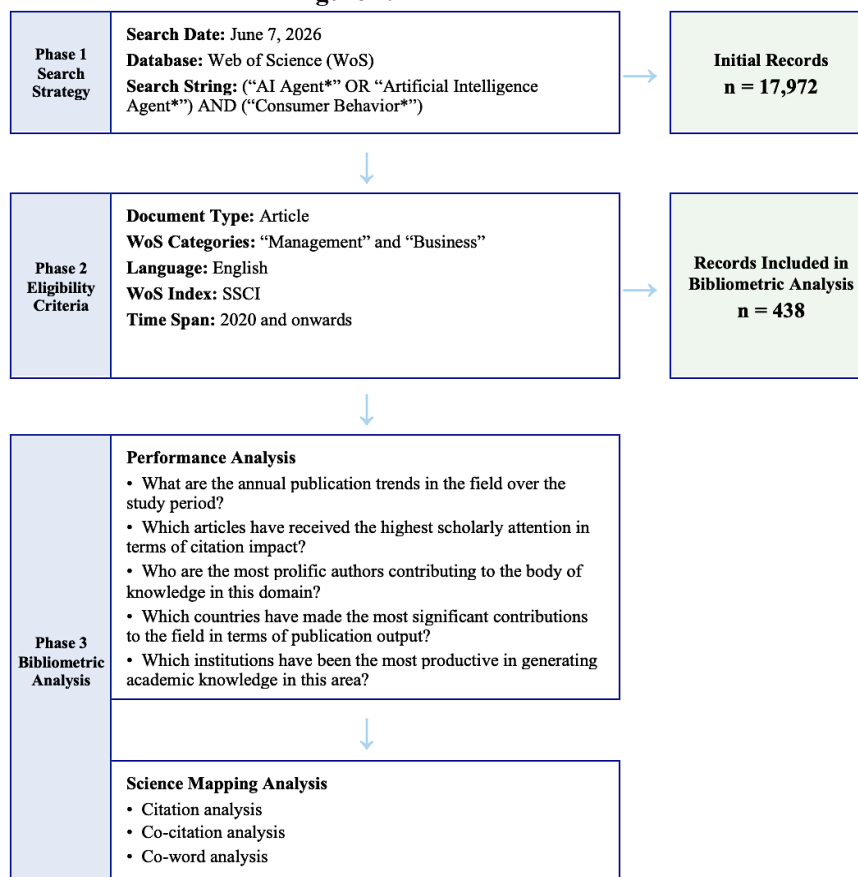
Constructing a dataset for bibliometric research and identifying pioneering studies, influential researchers, and dominant themes in a field begins with a comprehensive literature search (Kayhan & Arslan, 2024; Baştuğ & Kayhan, 2023). This process involves two main stages: first, identifying relevant studies using specific databases and keywords; and second, screening studies based on predefined inclusion and exclusion criteria (Ozturk, 2021). The choice of database is critically important for a reliable bibliometric analysis. Platforms such as WoS, Scopus, Google Scholar, Microsoft Academic, and Dimensions are particularly widely preferred in the literature (Moral-Muñoz et al., 2020). Accordingly, the databases and keyword combinations adopted in comparable studies were examined and are presented in Table 1.

As shown in Table 1, although prior studies have predominantly favoured the Scopus database, WoS is the platform most frequently consulted for bibliometric studies in the field of management and organization (Zupic & Čater, 2015). Moreover, WoS is one of the most comprehensive interdisciplinary citation indices worldwide (Van Raan, 2014). For the present study, framed within the context of consumer behavior, WoS was therefore determined to be the most appropriate database.

Table 1. Databases and Search Parameters Used in Previous Studies

Article	Database	Keywords
Zhang & Liu, 2026	Scopus and WoS	((ai OR (generative AND ai) OR (artificial AND intelligence) OR (intelligence) OR (large AND language AND model) OR (machine AND learning)) AND TITLE-ABS-KEY (fashion OR apparel OR clothes OR clothing OR textile*OR outfit OR wardrobe OR garment*))
Khoi & Phuc, 2026	Scopus	((“generative AI” OR “generative artificial intelligence” OR “large language model*” OR “LLM” OR “ChatGPT” OR “GPT-3” OR “GPT-4” OR “BERT” OR “transformer*” OR “retrieval augmented generation” OR “agentic AI”) AND (“retail*” OR “e-commerce” OR “electronic commerce” OR “online shopping” OR “consumer” OR “customer experience” OR “recommender system*”))
Badiu et al., 2025	Scopus	(“AI agent” OR “chatbot” OR “virtual assistant” OR “intelligent agent”) AND (“business performance” OR “organizational performance” OR “efficiency” OR “productivity”) AND (“customer support” OR “customer interaction” OR “customer service” OR “customer experience”)
Riandhi et al., 2025	Scopus	“AI” OR “Artificial Intelligence” AND “Consumer Behavior” OR “Consumer Behaviour”
Haque et al., 2024	Scopus	“Artificial Intelligence” OR “AI” AND “Retail Marketing”

Once the database had been determined, the search string executed on the WoS platform was structured, with reference to the studies in Table 1, as (“AI Agent*” OR “Artificial Intelligence Agent*”) AND (“Consumer Behavior*”). In addition, to ensure the reliability of the selected keywords, the opinions of four independent researchers specializing in consumer behavior and artificial intelligence were obtained, and the search string was revised accordingly. An initial search conducted on this basis on 07.06.2026 retrieved a total of 17,972 documents from the database. The methodological flow followed throughout the research process is depicted in Figure 1.

Figure 1. Research Process

To obtain a more homogeneous dataset in keeping with the aim of the research, specific filtering criteria were applied within the WoS database. These restrictions narrowed the focus and scope of the present study in line with the relevant literature (Bilgiseven & Arslan, 2025). Accordingly, the document type was limited to “Article,” the language to “English,” the WoS index group to the “Social Sciences Citation Index (SSCI),” and the research categories to “Business” and “Management.” To ensure the relevance of the search results to the scope of this study, the WoS category filter “Business” and “Management.” Since “AI” and “consumer behavior” are an interdisciplinary fields, unfiltered searches also return publications from unrelated areas such as engineering, computer science, psychology. As this study focuses specifically on the business and management literature, the search was restricted to these two categories. Furthermore, one of the most tangible precursors of the paradigm shift in AI research from 2020 onward was OpenAI’s GPT-3 model, which, with

its 175 billion parameters, can perform a wide variety of language tasks without additional training and exhibits the potential to generate text at a human level (Mucci, 2026). With reference to this radical development and acceleration in the AI literature, only articles published in 2020 or later were included in the analysis. Following application of the inclusion and exclusion criteria, analyses were conducted on the 438 articles evaluated for the bibliometric analysis.

3.2. Bibliometric Analysis of the Literature on Artificial Intelligence Agents and Consumer Behavior

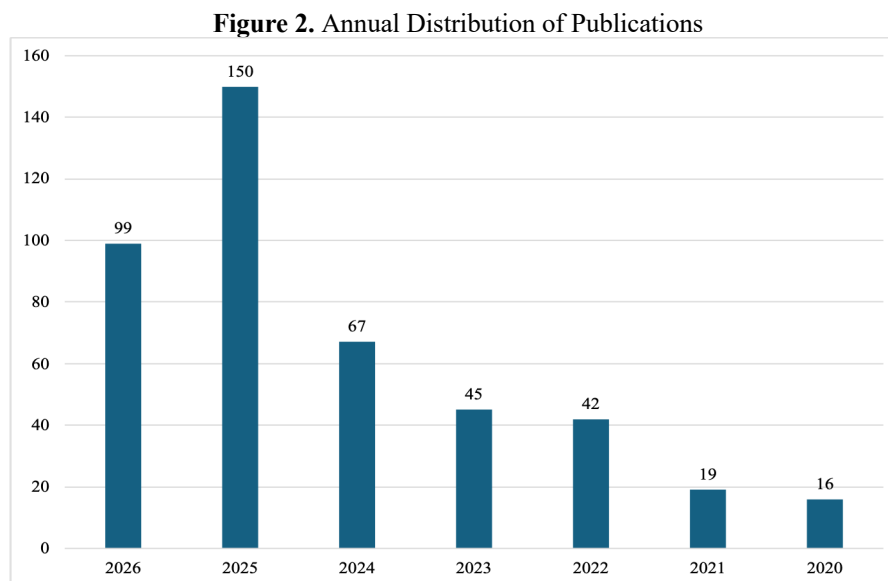
The bibliometric analysis process of this research, which sought to examine the role of AI agents within the consumer behavior literature, comprised two principal methodological stages. A performance analysis was conducted to quantify publication trends in the literature, and science mapping was carried out to reveal the intellectual and conceptual structure of the discipline (Zupic & Čater, 2015). The bibliometric method was ultimately adopted in this study for its considerable capacity to delineate the boundaries of intellectual structure, identify mainstream themes, and trace the historical development of the literature in business and social science research (Ozturk, 2021).

3.2.1. Performance Analysis

A performance analysis was conducted on the 438 articles obtained from the WoS database. Within this scope, assessments were made on the basis of core bibliometric indicators, including annual publication trends, the most highly cited articles, the most prolific authors, and the leading countries and institutions.

3.2.1.1. Annual Publication Trend

The annual publication productivity and distribution trend of the articles included in the analysis between 2020 and 2026 are visualized in Figure 2.



When the annual distribution of publications in the relevant literature (2020-2026) is examined, academic interest is seen to follow a pattern of steady growth. The relatively limited number of publications during the 2020-2022 period, which constituted the field's nascent phase, indicates that the topic was still in the early stages of development. Publication productivity gained appreciable momentum from 2023 onward, however, reaching levels of 45 and 67 respectively. In 2025, it peaked at 150 publications, thereby attaining mainstream status. Even in 2026, an incomplete year, the 99 publications recorded so far (up to 07.06.2026) demonstrate that the high output trend of recent years is continuing robustly.

When the annual distribution of publications is considered, the 2020-2021 period may be regarded as the formative phase of the relevant literature. The pioneering studies published during this period primarily examined the transformative effects of AI, machine learning, and chatbots on customer experience and business, bringing phenomena such as chatbot adoption onto the discipline's core research agenda (Pillai & Sivathanu, 2020; Ma & Sun, 2020; Hoyer et al., 2020; Adam et al., 2021; Moussawi et al., 2021; Loureiro et al., 2021).

The 2022-2023 period of the literature concentrated on the emotional dimension of human-AI interaction, analyzing AI's role in service (Song et al., 2022), artificial empathy (Liu-Thompkins et al., 2022), emotional expressions (Han et al., 2023), and the effects of service messages (Garvey et al., 2023). The 2024-2025 phase, in turn, witnessed considerable growth in publications driven by the momentum of GenAI. During this period, contemporary topics such as feeling AI (Huang & Rust, 2024) and chatbot-based information sharing (Al-Emran et al., 2024) came to the fore.

The 2026 literature points to a paradigmatic shift in AI from an instrumental role toward agentic systems defined by a capacity for autonomy and collaboration. During this period, the research agenda for agentic systems (Dwivedi et al., 2026), human acceptance in the transition from tool to agent (Li et al., 2026), and the organizational dimensions of this transformation within the framework of agency theory (Humberd & Latham, 2026) were examined in depth. These temporal patterns make concrete how the field has evolved from concerns centered on simple adoption toward questions of trust and empathy, and from there toward a new analytical frontier in which human-AI collaboration takes center stage. This reflects both technological progress and the broadening conceptual depth of AI agents within the consumer behavior literature.

3.2.1.2. Most Cited Articles

On the assumption that citation count reflects scholarly impact and significance in the relevant field, the top 10 articles with the highest WoS citation counts among the 438 examined are presented in Table 2.

Table 2. Top 10 Most Cited Articles

Articles	WoS Citation Count
Pillai & Sivathanu, 2020	633
Adam et al., 2021	630
Hoyer et al., 2020	588
Moussawi et al., 2021	302
Jussupow et al., 2021	298
Loureiro et al., 2021	291
Ma & Sun, 2020	280
Song et al., 2022	244
Liu-Thompkins et al., 2022	241
Schanke et al., 2021	237

In the literature addressing the impact of AI technologies on business and consumer behavior, a pioneering group of studies has shaped the field by developing broad conceptual frameworks. Hoyer et al. (2020), in this regard, proposed an integrated taxonomy that links the role of technologies such as IoT (Internet of Things), AR (Augmented Reality), VR (Virtual Reality), and chatbots across three distinct stages of the shopping journey to the cognitive, sensory, and social value dimensions. In a similar vein, Loureiro et al. (2021) analyzed 404 articles compiled from WoS and Scopus through text mining, focusing on a structural and conceptual examination of the AI literature in business. The analysis identified 18 latent topics representing the conceptual structure of the literature. These themes were classified into four main strategic clusters that provide analytical coherence: the social and organizational impact of AI, AI systems, and AI methodologies. On the methodological side, Ma & Sun (2020) compared machine learning approaches with traditional econometric models and presented an integrated, innovative analytical framework for marketing research.

Studies addressing adoption behavior have enriched TAM with AI-specific variables. In this context, Pillai & Sivathanu (2020) analyzed chatbot adoption in the hospitality and tourism industry using Partial Least Squares Structural Equation Modeling (PLS-SEM) and showed that anthropomorphism and perceived intelligence exerted a positive influence on acceptance, whereas stickiness toward traditional agents exerted a negative moderating effect. In an experimental study examining the adoption of the Personal Intelligent Agent (PIA), Moussawi et al. (2021) analyzed laboratory data using Structural Equation Modeling (SEM). That research sought to determine the role of perceived intelligence and anthropomorphism in acceptance. Its distinctive contribution lies in positioning PIAs as “dual-purpose systems” that combine task-oriented and social dimensions, and in integrating these two dimensions within a single model for the first time. Drawing on the CASA paradigm, Song et al. (2022) examined the effects of different service agents on communication quality and the perception of privacy risk, along with the moderating role of users' need for human interaction in this process. Findings from five scenario-based experiments revealed that the type of service agent directly affected adoption intention, while perceived communication quality and privacy risk mediated this relationship.

In the area of chatbot design, Adam et al. (2021) demonstrated that anthropomorphic design cues and the Foot-in-the-Door (FITD) technique enhanced user compliance through social presence. Schanke et al. (2021), for their part, provided causal evidence that humanizing robots benefited the firm by increasing transaction conversions and information sharing, yet also heightened price sensitivity by inducing a bargaining mindset in consumers. Investigating the role of artificial empathy, Liu-Thompkins et al. (2022) modeled perspective-taking, empathic concern, and emotional mimicry as holistic design inputs and offered a framework aimed at closing the human-AI gap. Finally, Jussupow et al. (2021) examined physicians' interactions with AI-assisted systems through a mixed-methods approach and developed a typology of five distinct decision-making patterns.

When the reflections of AI agents in the consumer behavior literature are assessed as a whole, the publications examined are seen to address the multidimensional effects of AI on customer interactions, adoption dynamics, design features, and decision-making processes through a variety of theoretical frameworks. This methodological diversity, ranging from conceptual reviews and bibliometric syntheses to field experiments, reflects both the theoretical depth and the methodological pluralism of the existing literature. These articles are regarded, for this reason, as important cornerstones in the relevant research field.

3.2.1.3. Most Prolific Authors

To identify the leading researchers shaping the consumer behavior literature focused on AI agents, scholars with at least 4 publications are listed in Table 3 according to their academic output and citation performance.

Table 3. Most Prolific Authors

Authors	Number of Publications	Total Citation Count
Alan R. Dennis	6	195
Debolina Dutta	5	125
Yogesh K. Dwivedi	4	162
Jochen Wirtz	4	122

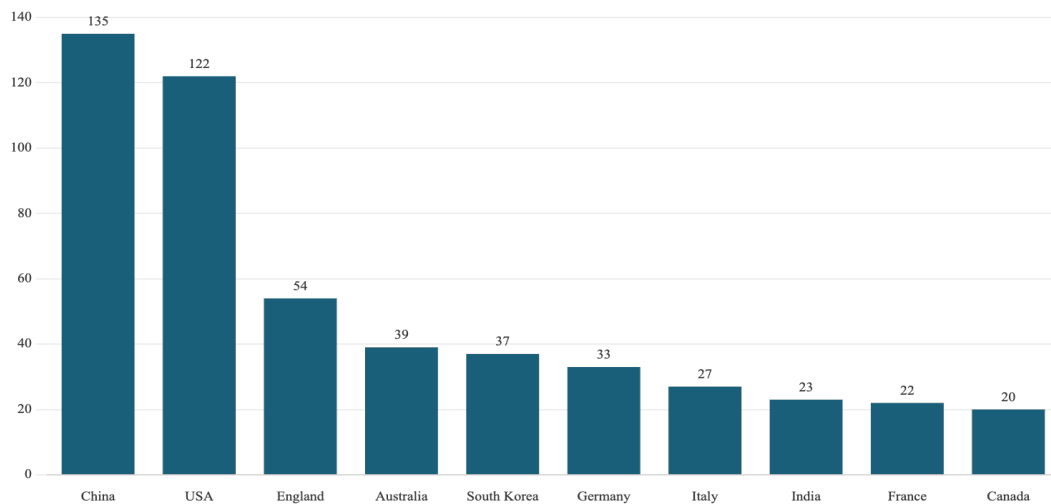
In line with the findings in Table 3, Alan R. Dennis stands out as the most dynamic and central figure in the field, with 6 publications and 195 citations. Debolina Dutta ranks second with 5 publications (125 citations), while Yogesh K. Dwivedi (162 citations) and Jochen Wirtz (122 citations) continue to contribute to the literature with 4 publications each. The high citations-per-publication ratio of Yogesh K. Dwivedi, in particular, attests to the conceptual and theoretical depth of his work in this field.

Overall, Table 3 shows that the intellectual accumulation of this emerging field is in the process of clustering around a handful of pioneering authors. At the same time, the fact that even the most prolific authors cluster within the range of 4 to 6 publications indicates that the literature remains in an “early growth and maturation” phase. This reveals that the field under examination has not yet reached saturation; on the contrary, it retains an exploratory and niche character.

3.2.1.4. Leading Countries

The countries to which the articles assessed in the study belong were examined in terms of the number of publications. In this regard, the top 10 countries with the most publications in this field are shown in Figure 3.

When the geographical distribution of the studies assessed in the analysis is examined, the literature is seen to be shaped largely by China (135) and the United States (122). The fact that these two countries account for roughly half of all publications indicates that knowledge production is being driven from a particular geographical perspective. The strong position of China and South Korea (37) on the list draws attention to an Asia-centered acceleration in AI research and to the research capacity generated by these countries' national AI policies.

Figure 3. Leading Countries in the Literature

The comparatively limited contribution of European countries, which possess well-established research infrastructures, by contrast, suggests that the continent has yet to make full use of its potential in this area. Moreover, the presence of India (23) and Australia (39) on the list shows that research interest is spreading across an increasingly broad geography.

3.2.1.5. Leading Institutions

The institutional distribution of studies examining the consumer behavior literature focused on AI agents was analyzed. Accordingly, a list of the most productive universities that have contributed at least 8 publications to the field is presented in Table 4.

Table 4. Institutional Distribution of Publications

Institutions	Number of Publications	Country
University of London	19	United Kingdom
The Indian Institutes of Management IIM System	14	India
State University System of Florida	11	USA
University System of Georgia	10	USA
California State University System	9	USA
University of Texas System	9	USA
Renmin University of China	8	China
Sichuan University	8	China
Sun Yat-Sen University	8	China
Sungkyunkwan University	8	South Korea
University of Cambridge	8	United Kingdom

When the most productive institutions are examined, the University of London stands out clearly with 19 publications, followed by the Indian Institutes of Management (IIM) System with 14, confirming India's strong research capacity at both the national and institutional levels. The United States is represented through broad-based university systems rather than individual central institutions, namely the State University System of Florida (11), the University System of Georgia (10), the California State University System (9), and the University of Texas System (9). From China, Renmin University of China, Sichuan University, and Sun Yat-Sen University each contribute 8 publications, extending the country's national dominance to a polycentric institutional structure. The presence of Sungkyunkwan University (8) and the University of Cambridge (8) further shows that scholarly leadership is shared by long-established institutions on a global scale. Encompassing both large state university systems and elite research universities, the list indicates that consumer behavior research focused on AI agents exhibits no tendency toward institutional monopolization.

3.2.2. Scientific Field Mapping

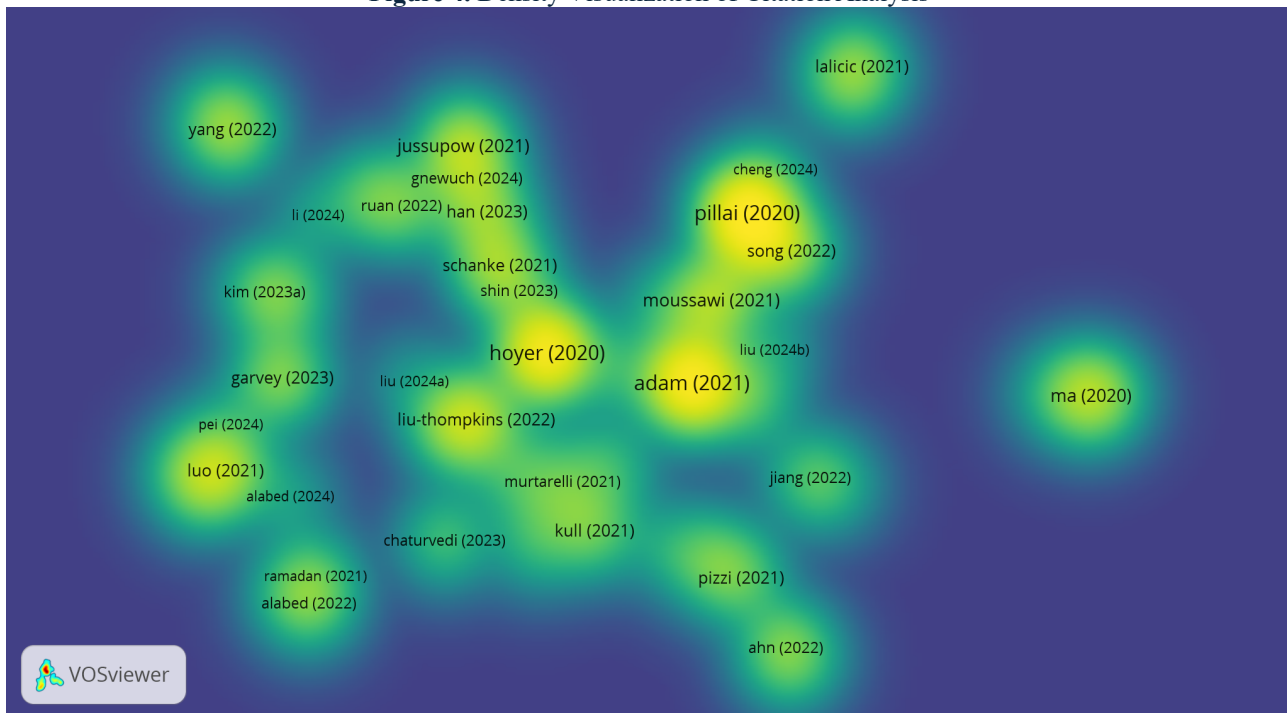
Science mapping, alongside performance analysis, is one of the two principal processes of bibliometric research. By analyzing the relationships between the components of a research field and its intellectual structure (Baker et al., 2021: 1028; Donthu et al., 2021: 288), it reveals the evolutionary dynamics of the relevant literature and exposes the relational network among disciplines, areas of specialization, studies, and

authors (Passas, 2024), thereby making hidden patterns visible, revealing gaps, and offering a guiding framework for future research. Among the various software programs available for this purpose, including CitNetExplorer, SciMAT, BibExcel, Pajek, and Bibliometrix (Gutierrez-Salcedo et al., 2018; Orhan, 2022: 111), VOSviewer was preferred for its high-quality visualization and its capacity to process large datasets (Sinkovics, 2016: 332). Citation, co-citation, and keyword co-occurrence analyses were carried out using the software.

3.2.2.1. Citation Analysis

Publications form mutual citation relationships because they share similar theoretical content and methodologies or assume similar roles in the flow of knowledge (Pieters & Baumgartner, 2002). In this respect, citation data enable identification of the leading article, author, and journal in a given field (Block & Fisch, 2020). As a fundamental technique of science mapping, citation analysis rests on the assumption that the intellectual link between publications is reflected through citations (Donthu et al., 2021).

Figure 4. Density Visualization of Citation Analysis



To construct the network map of the 438 articles assessed within the scope of the citation analysis, a specific threshold was applied. Accordingly, 56 articles meeting the criteria of having received at least 50 citations and possessing a minimum total link strength of 1 were included in the analysis. The density map produced with the VOSviewer software, which displays the link density of these studies, is presented in Figure 4. On the basis of this map, a list of publications connected to at least 5 articles is provided in Table 5.

When the studies in Table 5 with the highest citation and link strength are examined, the literature follows a clear theoretical trajectory anchored by umbrella studies that map the field holistically. Through the Theory-Context-Characteristics-Methodology (TCCM) approach, De Keyser & Kunz (2022) map agent-based AI technologies, such as service robots and chatbots, within the consumer behavior literature. Drawing together 88 articles and 79 expert opinions, they identify the field's dominant theories (Anthropomorphism Theory, the CASA paradigm, Algorithm Aversion Theory, Uncanny Valley Theory, and others), contexts, and methodological preferences. Their study summarizes the theoretical foundation underlying major empirical investigations (Adam et al., 2021; Pillai & Sivathanu, 2020; Schanke et al., 2021; Moussawi et al., 2021; Song et al., 2022) and flags a key research gap: the need to move beyond robot-human comparison toward collaboration. Similarly, Hoyer et al. (2020) argue that emerging technologies such as AI, IoT, AR, VR, and Mixed Reality (MR) are transforming customer experience across all business lines, reconfiguring existing dynamics by generating new touchpoints throughout consumers' pre-transaction, transaction, and post-transaction journeys.

Table 5. Most Linked Articles in the Citation Analysis

Article	Number of Links	WoS Citation Count
Adam et al., 2021	16	630
Pillai & Sivathanu, 2020	9	633
Hoyer et al., 2020	6	588
Li et al., 2024	6	63
Liu-Thompkins et al., 2022	5	241
Garvey et al., 2023	5	231
Murtarelli et al., 2021	5	119
De Keyser & Kunz, 2022	5	108
Gnewuch et al., 2024	5	93
Mari et al., 2024	5	56

The second group of high-impact studies focuses on the adoption dynamics of AI-based agents. Drawing on TAM, Pillai & Sivathanu (2020) examine the adoption of AI-based chatbots in hospitality and tourism. Interviews with travel agency managers and customer surveys reveal that perceived ease of use, benefit, trust, intelligence, and anthropomorphism directly determine usage intention, whereas attachment to traditional agencies and human representatives negatively affects the intention to use chatbots.

A further set of studies turns to the persuasion mechanisms that secure user compliance. Adam et al. (2021) examine the integration of Natural Language Processing (NLP)-equipped AI chatbots into customer service in place of human representatives, showing that verbal anthropomorphic design leads users to perceive chatbots as social entities in line with social response theory, while small confirmations elicited through the FITD technique increase compliance with larger requests in accordance with commitment-consistency theory. Similarly, Gnewuch et al. (2024) find that, in hybrid systems, users adopt a more human-oriented communication style when they know a real person is involved, which raises background staff workload and undermines automation.

Anthropomorphism, lying at the center of persuasion processes, constitutes a distinct thematic axis in the literature. It is defined as the attribution of distinctively human qualities (voice, image, gestures and facial expressions, action, or emotion) to non-human entities or products (Epley et al., 2007; Airenti, 2015), becoming concrete when consumers name the products they own, assign them a gender, and form bonds with them (Sönmez & Nart, 2022). As technology advances, software, robots, and chatbots are likewise humanized through anthropomorphic design and human-like forms and voices. Liu-Thompkins et al. (2022) and Mari et al. (2024) showed that endowing AI-based technologies with emotional empathy improved the user experience and influenced purchase decisions. Garvey et al. (2023), in turn, found that users infer intentions from AI agents much as they do from humans, evaluating price offers differently by their nature (favorable/unfavorable or good/bad) and by whether the source is an AI agent or a human representative.

Finally, the spread of anthropomorphic and persuasion-oriented applications opens up a debate over the ethical dimension. Li et al. (2024) focus on the potential of AI technologies to trigger unethical consumer behavior, showing that users engage in more unethical behavior in the absence of identity disclosure than when their identities are evident. Murtarelli et al. (2021), in turn, note that two principal frameworks, the technological and the anthropomorphic, have so far been adopted in the value-creation processes arising from human-chatbot interaction. They emphasize, however, that AI applications also introduce new ethical challenges, including information asymmetry, heightened consumer risk perception, loss of trust and reputation, network security, and privacy, and accordingly formulate a holistic model that incorporates an ethical approach alongside the technological and anthropomorphic dimensions to create value through chatbots.

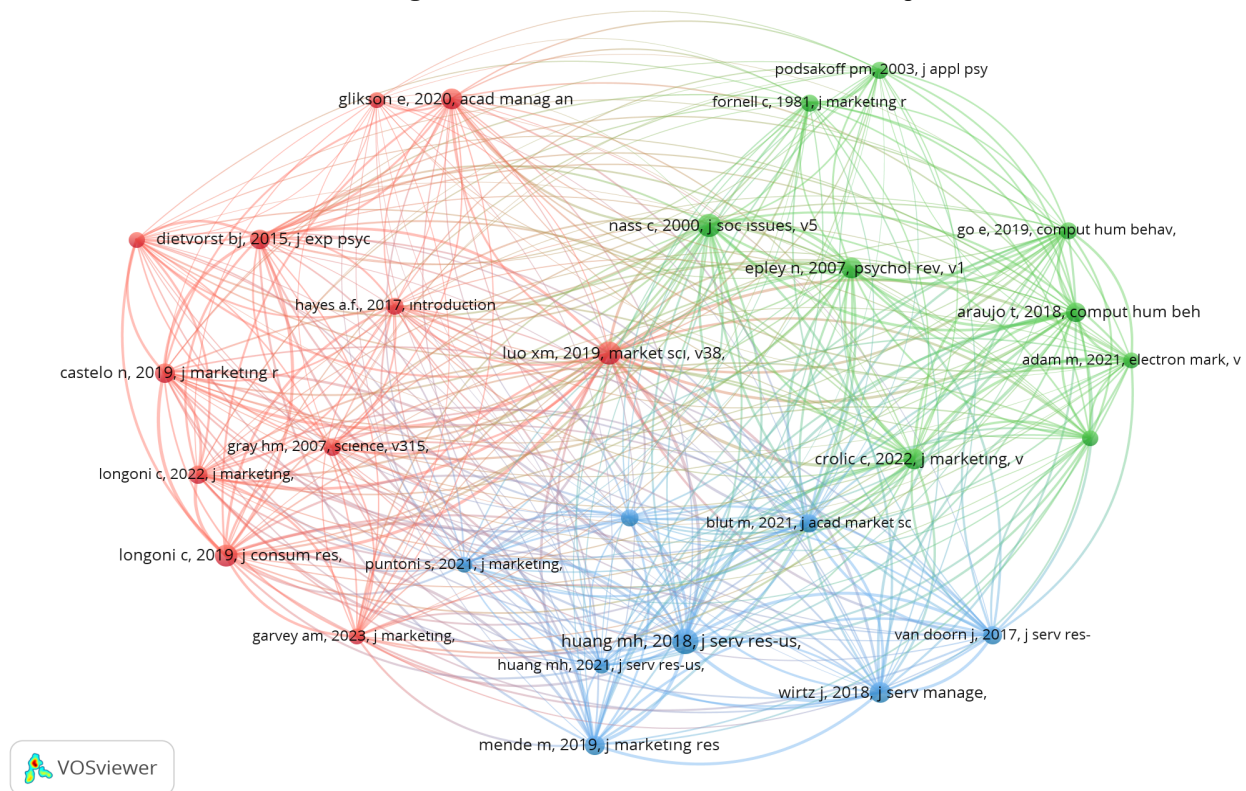
3.2.2.2. Co-citation Analysis

Co-citation analysis reveals the themes and similarities in a given field through the frequency with which two studies are cited together (Small, 1997) and maps scholarly relationships and interdisciplinary interactions (Leydesdorff, 1998). An increase over time in the number of co-citations between studies signals conceptual similarity between them and likewise produces a higher co-citation link strength (Zan, 2019). This analytical method makes it possible to identify the most influential publications in the literature and to uncover thematic clusters (Donthu et al., 2021).

A total of 25,962 references were identified in the bibliographies of the 438 articles examined within the scope of the co-citation analysis. To derive meaningful and interpretable patterns from this extensive citation

matrix, the network map of the 28 seminal studies meeting the threshold criterion of at least 30 co-citations is visualized in Figure 5.

Figure 5. Co-citation Network Visualization Map



When the visualization presented in Figure 5 is examined, the studies in question are seen to cluster into three principal groups. Summary information and details regarding these clusters are presented in Table 6.

The studies within Cluster 1 (Red) in Table 6 focus predominantly on user attitudes and behaviors toward algorithms, whose perception triggers mechanisms of either trust in or resistance to AI technologies. Dietvorst et al. (2015) examined the concept of “algorithm aversion,” finding that users lose trust in a system the moment they encounter an error, even when they know its predictive performance exceeds that of humans; individuals show far lower tolerance for machine errors than for human ones, even when algorithms remain the more consistent performers. Examining the nature of algorithmic tasks, Castelo et al. (2019) argue that resistance depends on whether a task is objective or subjective, with individuals turning to algorithms for data-driven processes while seeking human expertise in emotional and personal domains. Longoni et al. (2019), by contrast, relax the assumption of an innate resistance, holding that individuals place greater trust in algorithm-generated suggestions and rationalize them, though experts caught between their own prediction and an algorithm’s output approach such guidance with greater reserve.

Beyond these studies of basic algorithm-user interaction, Longoni et al. (2019), Luo et al. (2019), Raisch & Krakowski (2021), Longoni & Cian (2022), and Garvey et al. (2023) have problematized the effects of human-machine design in AI algorithms on user judgments. Longoni et al. (2019), for instance, found that patients prefer human doctors to algorithms in diagnosis and treatment despite the AI revolution in medicine. Chatbots, among the most frequently simulated tools in the literature, illustrate this: the moment consumers recognize that they are interacting with an artificial agent, they restrict or terminate the dialogue, since chatbots, though seen as successful in objective tasks, are perceived as lacking empathy and accumulated knowledge on the subjective plane (Castelo et al., 2019; Luo et al., 2019). Similarly, Longoni & Cian (2022) noted that users endorse AI competence in utilitarian and practical decisions but resist AI recommendations in hedonic domains oriented toward emotional gratification.

Table 6. Co-citation Analysis Clusters

Clusters	Main Point of The Clusters	Number of Items	Articles	Keywords and Themes
Cluster 1 (Red)	Investigation of users' attitudes toward AI and algorithms (trust, resistance, aversion, etc.)	10 ¹	Glikson & Woolley (2020); Dietvorst et al. (2015); Castelo et al. (2019); Gray et al. (2007); Longoni & Cian (2022); Longoni et al. (2019); Logg et al. (2019); Garvey et al. (2023); Luo et al. (2019); Raisch & Krakowski (2021)	Algorithms, AI, technology, consumer behavior, aversion, trust
Cluster 2 (Green)	Anthropomorphism and humanization in AI-based technologies	7 ²	Adam et al. (2021); Araujo (2018); Crolie et al. (2022); Epley et al. (2007); Go & Sundar (2019); Nass & Moon (2000); Sheehan et al. (2020)	AI, antropomorphism, social presence, humanizing, chatbots
Cluster 3 (Blue)	Examination of AI-based service robots from the perspective of consumer experience and behavior	8	Blut et al. (2021); Davenport et al. (2020); Huang & Rust (2018); Huang & Rust (2020); Mende et al. (2019); Puntoni et al. (2021); van Doorn et al. (2017); Wirtz et al. (2018)	Service robots, consumer behavior, AI, customer experience, antropomorphism, service strategy, replacement

Garvey et al. (2023), in turn, demonstrated that perceived value differs according to whether an offer originates from AI or from a human: because consumers regard AI as devoid of free will and intention, they find AI offers less “self-interested,” while interpreting a better human offer as motivated by “goodwill.” To synthesize, this cluster yields strategic insights into how firms should integrate algorithms and humans. Glikson & Woolley (2020) treat trust as the principal determinant of human-AI collaboration, showing that systems built with reliable, transparent, and real-time feedback mechanisms enable far more successful human-AI teaming. Raisch & Krakowski (2021) likewise stress that sharp, dichotomous distinctions should be avoided; faced with these two organically interconnected approaches, firms should adopt a holistic organizational perspective rather than reductively focusing on a single methodology.

When the studies within Cluster 2 (Green) are examined, common themes come to the fore: anthropomorphic designs for AI applications, the endowment of systems with human-like qualities, and the attribution of a social-entity dimension to these technologies. Anthropomorphism, one of the literature's core concepts, is generally defined as the process by which individuals attribute human characteristics to non-human figures to reduce surrounding uncertainty and relieve loneliness. Epley et al. (2007) treated this tendency as a psychological process that gave theoretical direction to subsequent work, while Nass & Moon (2000), in their pioneering early study, observed that individuals project human behavioral patterns onto computers and perceive them almost as social actors. More recently, Araujo (2018) revealed that human-like names and conversational styles heighten users' tendency to view chatbots as human. Designed with appropriate human-like features, such technologies yield critical outcomes for the user, including brand loyalty and satisfaction.

Similarly, Go & Sundar (2019) found that e-commerce chatbots designed in a more human-like fashion, through visual figures, identity cues, and interactive dialogue structures, evoked a strong sense of social presence and closeness in consumers. Even when they commit an operational error, chatbots incorporating human cues are tolerated more readily than mechanical ones when they attempt to repair it. Firms should therefore develop interactive error-repair capabilities rather than pursue perfection in AI technologies (Sheehan et al., 2020).

In parallel with earlier studies, Adam et al. (2021) likewise proposed that verbal anthropomorphic designs build a sense of social presence and strengthen users' motivation to cooperate with the system. Offering an antithetical view, Crolie et al. (2022) contend that excessive humanization raises user expectations asymmetrically, so that when chatbots fail to meet these heightened expectations, users are inevitably seized by negative emotions such as dissatisfaction, disappointment, and anger.

The final group, Cluster 3 (Blue), concentrates on consumer experience and behavior in the context of service robots (Davenport et al., 2020; Puntoni et al., 2021; Blut et al., 2021). In advancing the SRAM, Wirtz

¹The co-citation analysis identified 11 studies belonging to Cluster 1 (Red). One of these, however, the study by Hayes et al. (2017), is concerned specifically with scientific analysis methods rather than the AI agent literature. It has therefore been excluded from this table.

² The second cluster (Green) obtained from the co-citation analysis contains 9 studies in total. Two of these, by Fornell & Larcker (1981) and Podsakoff et al. (2003), have been kept outside this table, which was constructed within the scope of the AI agent literature, since they are studies concerned with scientific analysis methods.

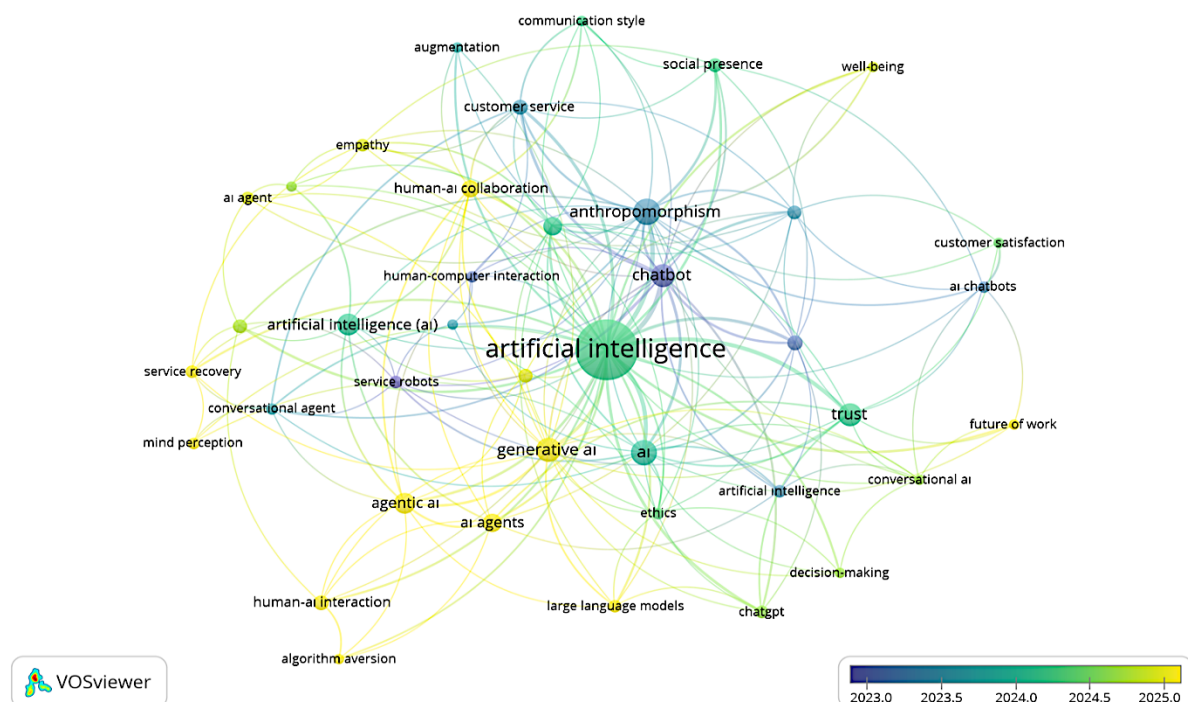
et al. (2018) emphasized that social norms and trust are at least as critical as functional benefit, noting that firms must dynamically reassess their strategies and service processes to build sustainable competitive advantage.

Huang & Rust (2018), for their part, sketched a theoretical roadmap in which service robots pass through a four-stage hierarchy of mechanical, analytical, intuitive, and empathetic intelligence toward full human-machine integration. Mende et al. (2019) then empirically examined the psychological effects of humanoid service robots on consumer behavior and their strategic consequences for firms, while Huang & Rust (2020) clarified how AI technologies should be positioned strategically to enhance customer loyalty and optimize the user experience in services.

3.2.2.3. Keyword Co-occurrence Analysis

Co-occurrence analysis is a type of bibliometric analysis based on words that appear together in studies, aimed at revealing the semantic structure of the literature and constructing the relationships among themes (Aria & Cuccurullo, 2017). Whereas other analyses link studies indirectly through citations, it draws on the direct, original content of the articles as a measure of similarity (Callon et al., 1983), assuming that frequently co-occurring words stand in a thematic relationship (Donthu et al., 2021). Carried out to determine the conceptual structure of the literature, the analysis yielded 1,739 unique keywords across the 438 articles examined. To derive more focused themes, a layered network map formed by the 40 keywords appearing in at least 5 studies is visualized in Figure 6.

Figure 6. Co-occurrence Network Overlay Visualization of Keywords



The overlay visualization in Figure 6 shows the evolution of keywords over time through their average publication year, which indicates the chronological periods in which the co-occurring words are concentrated (Van Eck & Waltman, 2023). The 2023-2025 range thus reflects where the examined terms cluster: the rapid development and proliferation of AI technologies and AI agents in recent years drove work in this area to gather momentum across these years. The network map further shows that “artificial intelligence” and “artificial intelligence agent,” along with their variants “ai” and “ai agent,” are frequently used together. The dense connections around these terms indicate that the field still revolves around what artificial intelligence is and how it should be defined, with the effort to conceptualize the technology carrying appreciable weight in the literature.

Another central phenomenon prominent in the literature is anthropomorphism, that is, humanization: the use of human elements such as image, voice, emotion, and empathy in AI-based software, AI agents, and

robots. The effects of such designs on consumer behavior rank among the field's most important research topics, and endowing AI technologies with "social presence" so as to bring them into interaction and collaboration with humans recurs frequently as a theme. It is unsurprising that chatbots and ChatGPT are the two most heavily used AI applications in consumer behavior research, since they are the most visible examples in which debates over anthropomorphism and social presence take concrete form. Yet, like every technological development, artificial intelligence has dark sides of its own. Figure 6 shows ethics and trust appearing on the map as two elements representing this dark side: the ethical concerns AI raises among consumers, and the attendant trust problems, are being investigated with steadily growing interest.

Assessed as a whole, the map reveals that the agent-based AI literature has undergone a rapid paradigm shift within a short span. The center of gravity of research is moving from the classical chatbot toward agentic AI capable of autonomous decision-making and toward large language models. Anthropomorphism retains its theoretical centrality throughout, but is now reinterpreted in terms of human-like decision-making and intention rather than appearance. That behaviorally critical concepts such as trust, ethics, and decision-making remain at the periphery, by contrast, shows that the literature still tends toward defining the technology, with research grounded in consumer psychology relatively in the background. The growing prominence of ethics and algorithm aversion nonetheless suggests that, as AI agents proliferate, these debates are maturing into a distinct axis of research. The literature is thus advancing toward a new agenda, one evolving from how to converse with artificial intelligence toward how much decision-making authority it should be granted and how consumers come to trust autonomous agents.

4. Conclusion and Discussion

This research set out to provide a holistic mapping of the role and theoretical contributions of AI agents in the consumer behavior literature through bibliometric analysis. A two-stage examination was conducted to decipher the field's quantitative ecosystem and intellectual structure. The performance analysis identified chronological publication productivity, citation leaders, the most prolific authors, and the pioneering countries and institutions, while the subsequent science mapping, drawing on citation, co-citation, and co-occurrence analyses, made visible the mainstream debates and latent thematic relationships within the literature.

The citation analysis shows Adam et al. (2021) leading in both link strength and total citations, followed by Pillai & Sivathanu (2020) and Hoyer et al. (2020). Overall, the literature converges on several theoretical axes: TCCM-based umbrella studies, adoption dynamics, persuasion mechanisms, anthropomorphic design strategies, and ethical risks. The co-citation clusters sharpen this picture. Cluster 1 (Red) examines trust in versus resistance to algorithms, indicating that users tolerate machine errors poorly, resist AI in their areas of expertise, and view it as lacking genuine empathy and intention, which supports a symbiotic, interdependent model of human-machine design over rigid distinctions. Cluster 2 (Green) shows that anthropomorphic cues evoke social presence and closeness, enhancing satisfaction, loyalty, and error tolerance, yet warns that over-humanization breeds unmet expectations and negative responses, underscoring balanced design and interactive repair capabilities. Cluster 3 (Blue) addresses service robots, holding that social norms and trust matter as much as functional benefit, and traces AI's developmental hierarchy from mechanical to analytical, intuitive, and ultimately empathetic intelligence.

The co-occurrence analysis reveals a high frequency among the keywords "artificial intelligence," "artificial intelligence agents," "ai," and "ai agents," suggesting that this emerging field remains oriented toward ontological inquiry, conceptual definition, and theory-building. Anthropomorphism stands at the center of this map. Notably, the literature attends not only to optimization-oriented benefits but also to the "dark side of technology," where unethical behavioral tendencies, perceived risk, and trust-building recur as clustered themes.

4.1. Theoretical Contributions

By tracing the dynamic evolution of the AI agent and consumer behavior literature in recent years through a bibliometric approach, this study aims to redraw, restructure, and map the conceptual boundaries of the field. The empirical findings obtained bring together the human-AI interaction literature, which presents a rather scattered, fragmented, and siloed appearance in the existing body of work, within a holistic, integrated, and multidimensional theoretical framework. In this respect, the study clarifies the field's intellectual structure by organizing the cumulative body of knowledge. The results of the analysis conducted reveal, in an original

manner, the algorithm-based processes, anthropomorphic design features, and service-experience-oriented thematic clusters that constitute the literature's fundamental building blocks and ontological ground. Moving beyond presenting these thematic structures as static data, the research dynamically traces conceptual shifts and paradigmatic transformations over time, thereby addressing RQ2 by offering scholars a structured conceptual map to guide future theory-building on the algorithmic and anthropomorphic dimensions of AI agents, and providing multidimensional theoretical contributions to both the historical trajectory of the literature and its future conceptual orientations.

4.2. Practical Implications

The bibliometric findings presented by this study offer important strategic roadmaps for firms, market analysts, marketers, and technology managers seeking to integrate AI applications and AI agents into their business processes. The empirical research examined in the literature clearly shows that focusing solely on developing a “flawlessly functioning technology” in technical and operational terms is not sufficient for commercial and sustainable success. Real success lies in proactively managing users' psychological barriers, the limits of their trust, their inclination to accept the technology, and their perceptual dynamics. Accordingly, the study provides practitioners with concrete, actionable insights for optimizing the customer experience in AI integration processes, building consumer trust, and overcoming the potential consumer resistance that may develop toward technological innovations.

One of the most critical issues that must be managed with strategic precision at the institutional and operational levels is the paradoxical nature that anthropomorphic design strategies hold within market dynamics. Endowing virtual assistants and chatbots with human-like names, conversational styles, language patterns, or visual figures triggers a sense of social closeness and psychological bonding (social presence) in consumers, and this directly and positively affects customer satisfaction and brand loyalty. Indeed, findings in the literature reveal that potential operational errors an AI system displaying human cues may make during a process can be tolerated by users more readily and with greater empathy. The greatest risk factor managers face at this point, however, is falling into the error of “over-anthropomorphism.” If an interface asymmetrically fosters the perception that the user is interacting with a real person, thereby creating an inflated architecture of expectations, and then proves inadequate in meeting that expectation, an “expectancy disconfirmation” scenario comes into play, and the consumer's disappointment, alienation, and anger increase exponentially. In this context, rather than attempting to mislead the user through a flawless imitation of a human, managers' adoption of “algorithmic explainability” and “ethical transparency” policies that clearly declare from the outset that the system is an AI application emerges as a strategic imperative for long-term trust-building and crisis management.

4.3. Limitations and Future Research Directions

Although this study offers a comprehensive theoretical framework for revealing the intellectual structure and historical evolution of the AI agent and consumer behavior literature, it carries certain methodological constraints stemming from the nature of bibliometric methods and from the data selection process. It is of considerable methodological importance that future researchers bear these limitations in mind when evaluating the present findings and when building new empirical or theoretical models upon this work. The most salient constraint of the research concerns the restrictions placed on the database, index type, subject category, language, and time span included in the analysis. The bibliometric data in this study were obtained from the WoS database, which houses the most prestigious indices of international academic scholarship, by filtering for journals indexed within the SSCI alone and by selecting only the “Business” and “Management” subject categories from among the WoS categories. The dataset was further limited to studies published in “English” alone and covering the period from 2020 onward.

This filtering strategy shapes the macro-level constraints of the study and, in turn, the new avenues of inquiry it opens for future work. First, owing to the database and index restriction, qualified scholarly studies, book chapters, sectoral reports, and articles written in other languages that fall outside the scope of WoS, in indices such as Scopus or Google Scholar, could not be incorporated into the analysis set. In this respect, it would be valuable for future studies to conduct cross-database bibliometric analyses encompassing platforms such as Scopus and Google Scholar rather than relying on the WoS database alone, so as to minimize publication bias in the literature. Second, because of the WoS category restriction, the output of multidisciplinary fields that make substantial contributions to the human-machine interaction and AI agent

literature, such as Computer Science, Information Systems, and Psychology, fell outside the scope of the study. This may have confined the technological and deeper psychological dimensions of consumer behavior to a business-centered perspective. Future bibliometric and systematic review studies would therefore do well to adopt an interdisciplinary filtering strategy that also encompasses the computer science and psychology categories, in order to map the technical dimension of AI and algorithm design together with user psychology; this stands out as a critical requirement for the intellectual depth of the literature.

The third and methodologically most dynamic constraint is the restriction on the time span. The analysis's focus on 2020 onward precluded a longitudinal tracking of the early phases of AI and chatbot technologies; while it successfully captured the literature's current and disruptive period of technological transformation, it gave rise to the risk that the field's historical, cumulative line of development might not be fully reflected. To overcome this constraint, future studies are encouraged to conduct longitudinal analyses with a broad temporal projection covering the past 15 to 20 years from the very emergence of the AI agent literature. The theoretical ruptures between the field's paradigmatic roots and today's GenAI revolution could thereby be traced more clearly. Finally, to complement the macro-level map of the literature that this bibliometric analysis provides, it is anticipated that empirically testing prominent themes such as "over-anthropomorphism" and "interactive repair capabilities" through laboratory or field experiments (experimental designs) or mixed-methods research in future studies would support the theoretical depth of the literature with practical and empirical findings.

Acknowledgements

This research received no specific support from funding agencies in the public, commercial, or not-for-profit sectors. The authors additionally made use of Claude Opus 4.8 High and Grammarly for Turkish-to-English translation and grammatical correction during the preparation of the article.

Author Contributions

All authors contributed equally to the conceptualization, methodology, data analysis, and writing of this article. All authors have read and approved the published version of the article.

Declaration of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical approval

Ethical approval was not required for this study as it is based entirely on the review and synthesis of published literature.

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