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Artificial Intelligence Applications in Consumer Behaviour Analysis: A Systematic Review, Mapping Trends and Challenges

Adrián No-Pérez , Sandra Castro-González

Faculty of Business Administration, Universidade de Santiago de Compostela, Lugo, Spain

Corresponding author: Adrián No-Pérez (adrian.no.perez@usc.es)

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Abstract

Background: The vast amounts of data generated by consumers require new forms of processing, in which artificial intelligence stands out for its ability to analyse them more quickly and deeply. However, although there is abundant literature on artificial intelligence (AI) and consumption, most of it focuses on its impact on consumer behaviour rather than its usefulness in enhancing understanding.

Objective: The aim of this study is to conduct a thorough review of the existing literature on the use of AI to understand consumer behaviour.

Methods: This study uses the PRISMA protocol for the selection of the studies. Then, it combines bibliometric methods with a TCM-ADO framework to review articles. The Scopus database was used to gather peer-reviewed articles from 2014 to 2024. VOS Viewer and R-Studio were utilised for the analysis and visualisation of data.

Results: The study provides insights into publication trends, dominant theories, methods, antecedents, decisions and results in the literature about the use of AI to understand consumer behaviour. Furthermore, it identifies potential avenues for future research to advance the development of theory and methodology.

Conclusion: Research into the use of AI to understand consumers is still in its infancy. However, everything points to the application of AI in consumer behaviour continuing to expand, and its use for analysing attitudes and behaviour becoming more sophisticated and widespread.

Index Terms

AI; Consumer behaviour; Data processing; Bibliometrics; TCM-ADO; Theory context method; Antecedents decisions outcomes; Future research directions; AI applications in marketing.

1 INTRODUCTION

The growth of data available to understand and profile consumer behaviour has been exponential in recent years (Meizhi & Zhongzheng, 2024). Companies have a wealth of data on their customers, but at the same time, consumers now generate huge amounts of data and information through multiple digital channels (Cheung et al., 2021; Pyate & Srinivasan, 2024), such as social media or other review platforms (Xue et al., 2023). In this scenario, the exploitation of these data is also changing (Netsiri, 2023) and artificial intelligence (AI) plays a big role (Brenncke, 2024; Chaturvedi et al., 2025; Namysłowska, 2025). Conventional market and consumer research practices (Kopalle et al., 2022) are no longer as effective in exploiting vast amounts of complex information and data.

Furthermore, the use of new methods helps overcome some of the limitations of traditional methods (Smith, 2020), such as accuracy (Chang & Mukherjee, 2023) or the existence of subjectivity or biases when answering surveys or in group dynamics (Verma et al., 2021); thus, several studies have suggested using other methodologies to understand users' behaviour and feelings (Paul et al., 2023; Sun et al., 2022). Based on this, researchers and marketers need to employ AI techniques and tools to overcome this pitfall.

AI allows researchers to analyse large volumes of data in real time, faster than any human being, more accurately and with greater precision, going deeper where a human could not, thereby increasing the efficiency of the process. The use of AI therefore facilitates a deeper understanding of the consumer and much more accurate predictions of future behaviour. This has important implications for management as it leads to optimized marketing actions (Tian et al., 2018), hyper-personalization, real-time adaptation to the market and anticipating future needs and demands (Netsiri, 2023; Radu, 2023).

Thus, big data and machine learning have revolutionized research in consumer behaviour. Significant progress has been made in the literature in understanding the role of AI from consumers' perceptions of it and how they accept it (Kelly et al., 2023; Wong et al., 2023). In this sense, several studies conducted in recent years have concentrated on examining the influence of artificial intelligence on consumer behaviour (Huang & Rust, 2022), with a particular emphasis on attitudes and perceptions regarding AI interactions and utilization (Kopalle et al., 2022) or content generated by AI (Aljarah et al., 2025). For example, studies such as the one by Flavián et al. (2023) analyse the effect of voice assistant suggestions on consumer behaviour. The results, which consider how they influence the choice of different products, highlight the key role of credibility (Flavián et al., 2023). In this line, Oncioiu (2023) evaluated the attitudes of buyers and the use of chatbots or, in the case of Chin et al. (2022), the relationship between the intention to use certain artificial intelligence services in the field of sport and the factors that influence the predisposition to do so. The latter work highlighted the usefulness or ease of artificial intelligence services as one of the triggers for users to employ these applications (Chin et al., 2022). Therefore, the increasing use of AI services makes it crucial to understand how it affects behaviour as it will undoubtedly positively or negatively influence their decisions (Jain et al., 2024b). In addition, there are several systematic studies (Jain et al., 2024b; Mariani et al., 2022; Sánchez-Núñez et al., 2020; Ziakis & Vlachopoulou, 2023) on AI and consumer behaviour. Jain et al. (2024b) analysed 107 articles that had studied the interaction of AI with dimensions of consumer behaviour, such as consumer acceptance and trust, consumer interaction and engagement, attitude and personality, decision-making and adoption. Mariani et al. (2022), reviewing 198 papers, focused on analysing from a global perspective the intersection of artificial intelligence with three fields of knowledge: marketing, consumer research and psychology. They did so from an eminently theoretical point of view, identifying eight key thematic clusters and 412 theories and models. Ziakis & Vlachopoulou (2023), with an analysis of 211 articles, made a systematic review of the intersection between artificial intelligence and digital marketing with a focus on improving marketing strategies. Finally, Sánchez-Núñez et al. (2020) made a specific systematic review of opinion mining, sentiment analysis and emotion understanding. However, there is still a long way to go in using it to understand consumer behaviour. This study is distinguished from all previous studies by its emphasis on the nexus between AI and consumer behaviour, utilizing an entirely distinct focus.

Artificial intelligence offers various methods for analysing consumer behaviour, which can be classified into supervised, unsupervised and reinforcement learning. The choice between one or the other will depend on the objective of the study and the data source used (Taboada Villamarín, 2024). Supervised learning seeks to obtain expected results through labelled data (usually historical) (Liberos et al., 2024). Previously, it was required for its correct operation to learn the algorithms through training data (Giglio et al., 2020). Logistic regression, random forest, Bayes or SVM are commonly used algorithms (Liberos et al., 2024). An example of their use would be for analysing purchase history or satisfaction surveys to predict future behaviour; alternatively, customers could be segmented based on purchase history using classification trees.

In unsupervised learning, on the other hand, the data are not labelled because they do not follow any referent format (Giglio et al., 2020). The objective of using these unsupervised techniques is to explore the structure of the content to identify hidden patterns in behaviour (Liberos et al., 2024) and make predictions (Giglio et al., 2020) based on this. Today, much of the data is characterized by being in unstructured formats (Chang & Mukherjee, 2023), which is the case of data generated by consumers themselves on online platforms, so studies such as Taboada Villamarín (2024) have considered this type of learning the most suitable for textual analytics, which concerns the analysis of content originated by users. Another example could be cluster analysis (e.g., Katyayan et al., 2022), which allows customers to be grouped into segments based on shared characteristics, such as their purchasing habits or product preferences, without the need to know these categories in advance. In unsupervised methods, NLP is used to analyse unlabelled text and extract patterns or emergent themes, although it also plays an important role in supervised methods.

Finally, reinforcement learning seeks to elicit the most effective strategies from experience and training algorithms through rewards (Liberos et al., 2024). Consumer behaviour research can help discover how and why consumers respond differently to certain stimuli. For example, it can be valuable in understanding or delving into pricing dynamics (Ismail & Baysal, 2023; Lussange et al., 2023), response to promotional personalization (Liu, 2023) or interpreting how they act in a recommendation system (Keat et al., 2022).

This study analyses how AI is used to understand consumer behaviour, what techniques are used, what kinds of data are used for this and the contexts in which it has been carried out. Therefore, the conclusions and implications significantly differ from those of other systematic reviews, allowing progress in this field.

Accordingly, this literature review aims to answer the following research questions:

> **RQ1:** What are the prevailing trends and patterns in publication?
>
> **RQ2:** How has artificial intelligence been used to analyse consumer behaviour?
>
> **RQ3:** What research gaps exist in the application of artificial intelligence techniques to the study of consumer behaviour and what are the key future research directions?

To address these research questions, this paper is organized as follows. Section 2 describes the methodology. Section 3 describes some bibliometric results. Section 4 presents the results related to the classification of the reviewed papers in terms of theory, context, methodology, antecedents, decisions and outcomes obtained using the Theory-Context-Method (TCM) Antecedents-Decisions-Outcomes (ADO) framework (Ambika et al., 2023; Duggal et al., 2024; Jain et al., 2024a). Section 5 presents suggestions for future research. Finally, Sections 6 and 7 contain the conclusions and limitations of the study.

2 METHODOLOGY

2.1 Research method

Following the methodology previously employed in Ambika et al. (2023), Duggal et al. (2024) or Jain et al. (2024b), this study combines bibliometric methods with a TCM-ADO framework to review articles within the field of artificial intelligence literature for consumer behaviour analysis.

RQ1 is addressed through descriptive bibliometric analysis, which allows us to characterize publication patterns, main sources and keyword trends on the use of artificial intelligence in the study of consumer behaviour. RQ2 is analysed through a content synthesis based on the TCM-ADO framework, enabling a systematic mapping of how AI has been applied in this field. Finally, RQ3 is answered by integrating the findings from both phases to identify research gaps and future directions.

In this way, this work responds to Hulland's (2024) call for bibliometric analyses that add value by combining descriptive results and including an analysis of deep work. An objective evaluation is thus combined with bibliometric analysis and a qualitative evaluation using the TCM-ADO method (Ambika et al., 2023; Duggal et al., 2024; Jain et al., 2024b). This enables the identification of knowledge gaps that give rise to nascent trends in the area (Donthu et al., 2021).

To compile and analyse the research corpus, the PRISMA protocol is followed, supported by seminal and recent bibliometric articles (Mukherjee et al., 2022; Rasul et al., 2022). The protocol outlines a four-step corpus selection process: identification, screening, eligibility and inclusion. Figure 1 illustrates this review procedure based on the PRISMA protocol and the inclusion and exclusion criteria used in the study. These criteria help establish the study boundaries and communicate its limitations, including the possible omission of some relevant publications and articles.

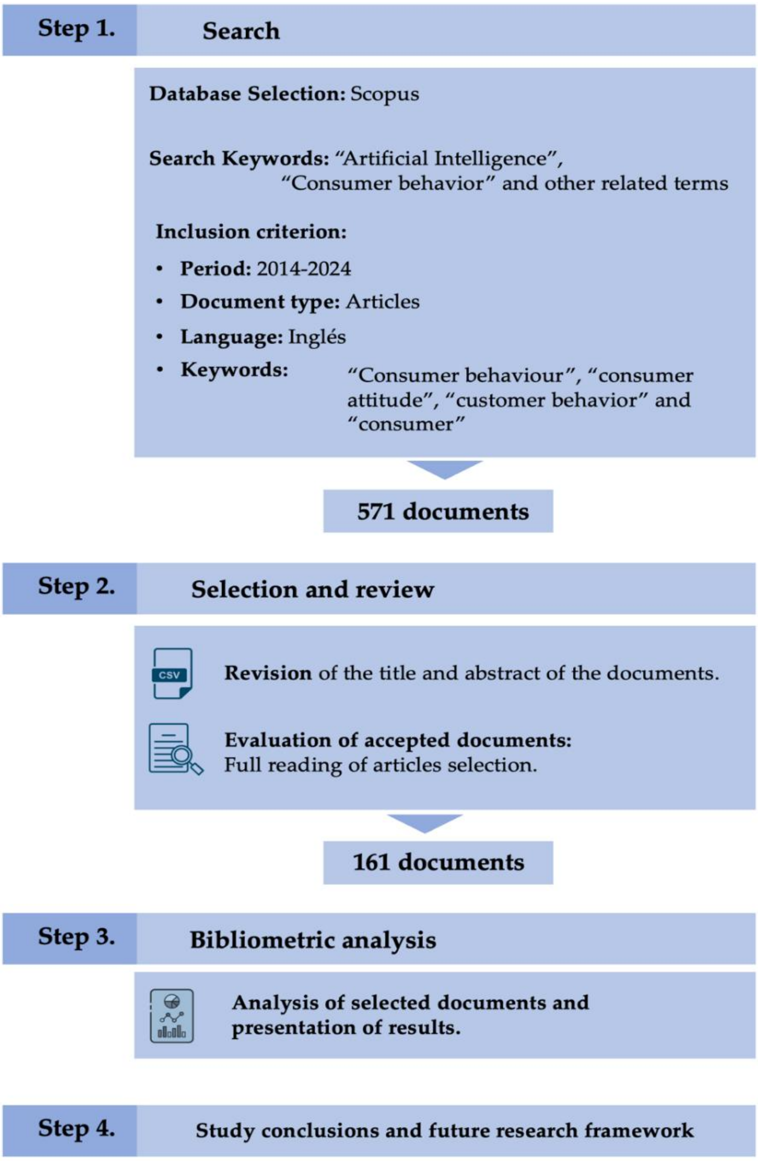

Figure 1. *PRISMA protocol applied to this study.*

2.2 Search strategy

2.2.1 Identification

The initial phase of the search strategy entailed using keywords to identify the works under study. The keywords for the search in the selected database were selected based on a previous review of the subject matter in articles (Jain et al., 2024b; Loureiro et al., 2021; Peltier et al., 2024; Singh et al., 2023), definitions and reviews in the literature on artificial intelligence and consumer behaviour. Concerning AI, the terms included "machine learning", "deep learning", "natural language processing", "artificial neural network" or "intelligent agent". These core technologies underpin AI and are widely recognized in the academic literature. The term "artificial intelligence" was also used to prevent excluding studies from the selection process due to the lack of explicit use of some of the abovementioned terms.

Regarding the terminology employed to describe consumer behaviour, it was resolved that the generic nomenclature would be utilized across all language variations ("consumer behaviour", "customer behaviour"). The term "consumer behaviour" is widely used in this field. As a result, the search would cover almost all, if not all, studies in the field. However, using keywords referring to specific consumer behaviour or attitudes could lead to the exclusion of interesting works, given the broad nature of this field.

With considerable expertise in this field, the authors engaged in a comprehensive discussion and selection process regarding these keywords. The keywords were entered into the Scopus databases using the "title, abstract and keywords" search rule to identify articles about the intersection of artificial intelligence and consumer behaviour. The use of Scopus is consistent with previous studies (e.g., Mariani et al., 2022); it was used due to its accessibility and capacity to store many documents and the ease with which they can be accessed and manipulated (Donthu et al., 2021). Furthermore, it is the largest and most comprehensive repository of peer-reviewed scientific literature (Morán et al., 2022) and has been widely used as a sole source in previous reviews in this field (e.g., Andarwati Kunharyanto et al., 2025; Guettala et al., 2024; Mysaka & Derun, 2024).

2.2.2 Screening

In light of the findings of preceding studies, the authors devised and deliberated upon the criteria for including or excluding pertinent manuscripts. The initial period under examination was 2014-2024, intending to monitor the evolution of publications in the descriptive analysis. In order to ensure the precision of the results and their focus on the field of study, only articles were selected for inclusion, while book chapters and conference papers were excluded (Donthu et al., 2021). Furthermore, given that most recent articles have been published in English (Jain et al., 2024b), the search was limited to this language.

Furthermore, several keywords about consumer behaviour were incorporated into the articles, including "consumer behaviour", "consumer attitude", "customer behaviour", "consumption behaviour" and "consumer". This approach allows considering linguistic differences and expanding the search to encompass a comprehensive range of articles pertinent to the subject matter under investigation. Consequently, 571 documents were collated and exported in .csv format for subsequent manual analysis and evaluation. This included the document title, abstract, authors, publication year, source and bibliographic references.

The complete search equation is therefore as follows:

> (TITLE-ABS-KEY ("artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing" OR "artificial neuronal network" OR "intelligent agent") AND TITLE-ABS-KEY ("consumer behavior" OR "customer behavior" OR "consumer behaviour" OR "customer behaviour")) AND PUBYEAR > 2014 AND PUBYEAR < 2024 AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (EXACTKEYWORD , "Consumer Behavior") OR LIMIT-TO (EXACTKEYWORD , "Consumer Attitude") OR LIMIT-TO (EXACTKEYWORD , "Customer Behavior") OR LIMIT-TO (EXACTKEYWORD , "Consumption Behavior") OR LIMIT-TO (EXACTKEYWORD , "Consumer Behaviour") OR LIMIT-TO (EXACTKEYWORD , "Consumer")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "j"))

2.2.3 Eligibility and inclusion

A selection and refinement process was conducted on the downloaded articles to determine their inclusion or exclusion in the subsequent analysis. The initial stage entailed reviewing the titles and abstracts of the documents in question. This is because the content of databases, such as Scopus, is not used exclusively for bibliometrics. Therefore, it is recommended that this check be carried out in order to avoid errors in the results (Donthu et al., 2021).

Following a manual review of the titles and abstracts, 270 articles were excluded either because they did not align with the specified research topic or because the focus of the study on artificial intelligence and consumer behaviour did not align with the objectives of this study. Subsequently, the full text of 301 potentially pertinent articles was analysed systematically. During this review, 140 articles were identified as irrelevant to the present study and were thus excluded. After completing both stages, 161 articles were identified and will be employed in the forthcoming bibliometric analysis.

3 RESULTS

3.1 Data sample

Figure 2 illustrates the growth in annual publications on the intersection of artificial intelligence and consumer behaviour over the past decade (2014-2024). A consistent increase in the number of papers published over the past ten years is evident. This trend, along with the observation that the maximum number of published papers was reached in 2024, indicates that examining consumer behaviour through the lens of AI technologies represents a contemporary and expanding area of scholarly inquiry.

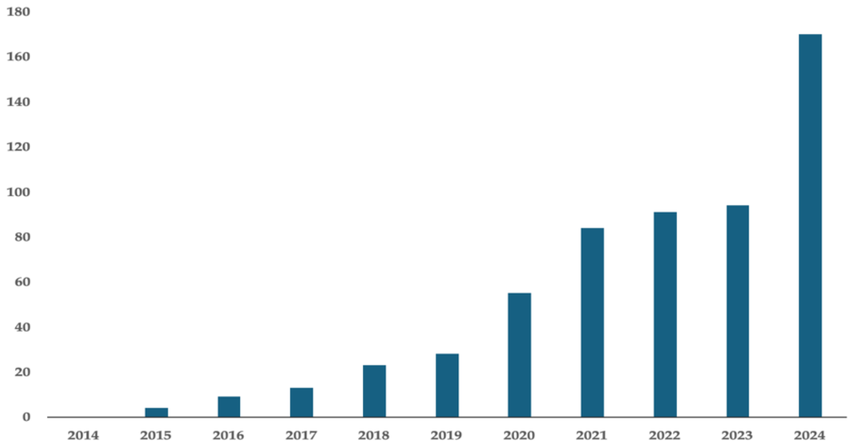

Figure 2. *Annual scientific production.*

As illustrated in Figure 3, the number of annual citations is rising in tandem with the volume of published papers. Furthermore, the high number of citations corroborates the relevance of the subject matter.

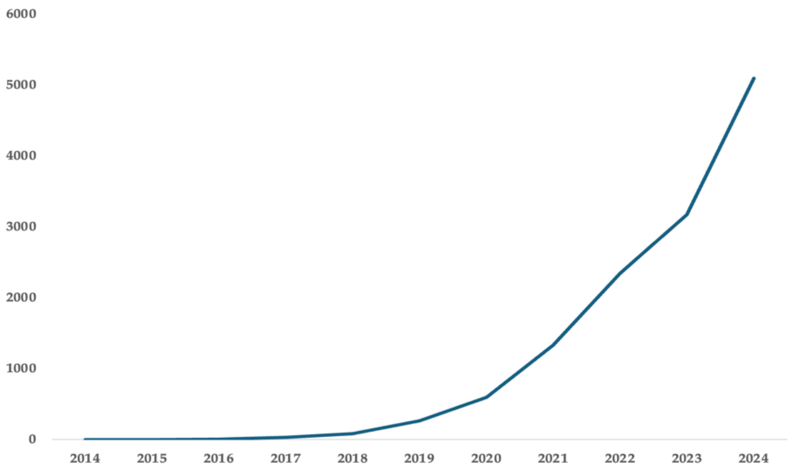

Figure 3. *Annual citations of documents.*

3.2 Keyword trends

The keyword co-occurrence map (Figure 4) illustrates the temporal evolution of usage trends, commencing in 2014 and concluding in the present. The network analysis encompasses the previous ten years. However, from 2020 onwards, there is a notable increase in the number of relevant publications on the subject.

The more obscure nodes refer to terms such as "behavioural science", "learning systems", "data analysis" or "decision making". These are early studies in the field, defined by the authors as innovative at the time (Tran et al., 2017). The vast majority address the evaluation of the shopping experience by presenting novel methodologies. For example, to avoid biases that could arise by collecting information through surveys, Tran et al. (2017) exposed a method supported by natural language processing that analyses food quality. Thus, the database is shaped by the purchase history of retail stores. In this vein, Akay et al. (2015) proposed to perform an analysis based on text mining. Their objective was to identify consumer behaviour relating to a set of drugs. Therefore, this first group of researchers focused on the study of consumer behaviour by primarily resorting to new AI learning techniques and systems.

The different greenish shades indicate that keywords related to consumer behaviour and AI techniques are some of the most commonly used by academics from 2021 to 2022. The publications focus on aspects such as consumer satisfaction or behaviour, putting into practice different techniques that artificial intelligence offers for these analyses. The terms associated with these technologies include, generically, “deep learning” or “machine learning” among others. For example, Urbancokova et al. (2020) applied machine learning algorithms to learn customer preferences and segment them into groups. Examples include the use of neural networks for the prediction of user loss or consumer abandonment intention (Liu & Zhao, 2021) or the classification of customers in the banking sector using LSTM networks according to their creditworthiness (Wang et al., 2019).

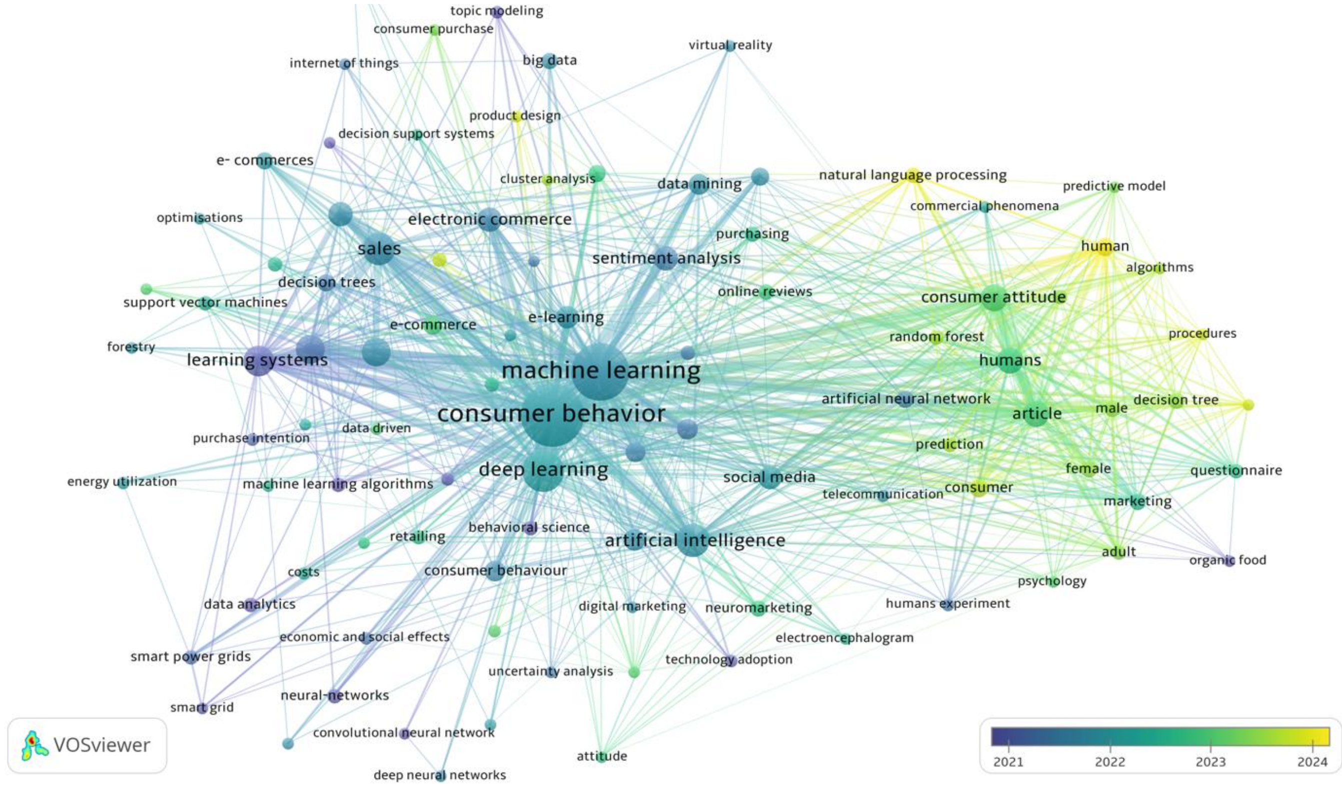

Figure 4. *Co-occurrence of keywords.*

Finally, the lightest colours, and therefore the most recent, are oriented to e-commerce and reviews, which coincides with the growing trend of online shopping (Maddalena, 2024). Numerous articles use reviews to understand customer behaviour in this type of shopping (Ma et al., 2024). In this sense, analysing user reviews becomes very important as users are increasingly conditioned by them (Olan et al., 2024).

It is worth noting the use of words such as “humans”, “adult”, “consumer attitude”, “neuromarketing” or “prediction”, as they are used in empirical studies with consumer samples. Using techniques such as the electroencephalogram, their predisposition to pay for a certain product is predicted according to the visualization of advertisements (Hakim et al., 2023) or the purchasing attitude regarding products with the presence of olfactory stimuli (Akbugday et al., 2024). Using the word cloud in Figure 5, a visual and simplified representation of the previous set of keywords is obtained, emphasizing the last year of publication.

Through this analysis, two major groups are extracted. The first, with a human component, refers to consumer attitudes, purchase intention or satisfaction. The publications study all these aspects of user consumption using AI algorithms. Wang et al. (2023) sought to identify the factors that influence purchases of electronic products through published reviews.

The second group combines the technological part, encompassing various currently applied techniques, proving that this is an emerging and growing area. Two strands are identified within the grouping. Some of the papers examine the impact of the relationship between consumers and chatbots or AI applications (Chin et al., 2022; Flavián et al., 2023; Li et al., 2024). On the other hand, others turn to algorithms for the treatment and processing of data that consumers have generated. Data, feature extraction, data processing and natural language processing are some of the most commonly used terms in the last year. There has been a growth in this type of research. The knowledge of this information helps improve the understanding of behaviour and sales in sectors such as medicine (Kita et al.,

2018) or allows organizations to improve their ability to adapt to the continuous changes in consumer preferences, which is an opportunity to anticipate and adapt to their needs (Lee & Lee, 2020).

Figure 5. *Keyword cloud.*

In addition to these preliminary analyses, a series of additional analyses was performed, which can be found in the Appendices. Specifically, they concerned co-authorship of principal authors (Appendix 1), bibliographic coupling of publications (Appendix 2) and citation analysis (Appendix 3).

4 GENERAL OVERVIEW: TCM-ADO FRAMEWORK

4.1 Theory

The theories used in the literature based on artificial intelligence to understand consumer behaviour are diverse. Much of the literature is based on consumer behaviour and psychology theories. In the former field, theories such as behavioural decision theory, theory of planned behaviour, theory of reasoned action, stimulus-organism-response (SOR) theory, RFM (recency, frequency, monetary value) theory, theory of loyalty and acquisition bias, CAB cognition-affect-behaviour theory, CBT cognitive load theory, theory of impulse buying or enduring involvement theory are used. In contrast, the theories coming from the field of psychology are expectation-confirmation theory, theory of social comparison, theory of interpersonal similarity, PAD model (pleasure, arousal and dominance), self-congruity theory, flow theory, theory of interpersonal behaviour or differential emotions theory. Computer science or mathematics theories are still used to a lesser extent, specifically theories such as graph theory, rough set theory, deep learning theory, statistical learning theory or clustering theory. Studies use the unified theory of acceptance and use of technology (UTAUT) and the technology acceptance model (TAM) for technology adoption. In addition, two theories overlap in psychology and technology: the uncanny valley theory and the uses and gratifications theory. Finally, a few studies have relied on management and communication theories, with the total quality management approach of Kano and communicative language teaching (CLT) theories. See Table 1 for more details.

Table 1. *Theories and works.*

Discipline	Theory	Works
Informatics, maths	Graph theory	Akay et al. (2015)
	Rough set theory	Mahfuza et al. (2022)
	Deep learning theory	Lin et al. (2021)
	Statistical learning theory	Pilone et al. (2023), Zhang (2022)
	Clustering Theory	Zhang et al. (2022)
Technology	Unified theory of acceptance and use of technology (UTAUT)	Luo (2021), Mustafa et al. (2022)
	Technology acceptance model (TAM)	Chin et al. (2022)

Discipline	Theory	Works
Psychology	Expectation-confirmation theory	Puspitasari et al. (2023)
	Theory of social comparison	Adamopoulos et al. (2018)
	Theory of interpersonal similarity	Adamopoulos et al. (2018)
	PAD model (pleasure, arousal and dominance)	Singh & Goyal (2019)
	Self-congruity theory	Gladstone et al. (2019)
	Flow theory	Zheng & Ding (2022)
	Theory of interpersonal behaviour	Taghikhah et al. (2021)
	Differential emotions theory	Pantano (2020)
Psychology and technology	Uncanny valley theory	Gerlich (2023)
	Uses and gratifications theory	Acquila-Natale & Iglesias-Pradas (2021)
	CBT cognitive load theory	Weiß & Pfeiffer (2024)
Consumer behaviour	Behavioural decision theory	Čufar et al. (2015)
	Theory of planned behaviour	Silva et al. (2023), Taghikhah et al. (2021), Ghosh et al. (2023), Jafari et al. (2022), Chiu et al. (2022), Yadav et al. (2022), Ali et al. (2023), Makarchev et al. (2022)
	Theory of reasoned action	Yadav et al. (2022): Ye & Huang (2022), Sukumaran & Majhi (2024)
	Stimulus-organism-response (SOR) theory	Ali et al. (2023), Adwan et al. (2022), Tohidi et al. (2023)
	RFM (recency, frequency, monetary value) theory	Hasumoto & Goto (2022), Mahfuza et al. (2022)
	Theory of loyalty and acquisition bias	Yang et al. (2021)
	CAB cognition-affect-behaviour theory	Ma et al. (2023)
	Theory of impulse buying	Taghikhah et al. (2021)
	Enduring involvement theory	Li et al. (2020)
Management	Total quality management approach of Kano	Čufar et al. (2015)
Communication	Communicative language teaching (CLT)	Zhang et al. (2023)

4.2 Context

The final sample of this study, comprising 161 articles, underwent a topic analysis of the abstracts. The method presented by Loureiro et al. (2021) was adopted for processing the texts using R software.

First, the text is converted into lowercase and any stopwords, or words that are considered empty, are removed in order to focus on the most meaningful words (Loureiro et al., 2021). Subsequently, the text is tokenized, resulting in the formation of sets of small words. In conducting this analysis, the R software employs the measures proposed by Cao et al. (2009) and Griffiths & Steyvers (2004). See Figure 6.

With the transformed corpus, the *k*-means algorithm is used, indicating the number of possible themes, which, in this case, is set to a range between 2 and 40 (Hair et al., 2022). The results show that from k = 5 onwards, the variability of the themes begins to stabilize, mainly in the measure of Cao et al. (2009). It should be noted that when working with a large number of publications, some of them may encompass several topics, which conditions the results (Loureiro et al., 2021).

Table 2 classifies the five themes identified and a series of significant words for each. These groups, together with those generated in the bibliographic coupling, allow us to establish groups of content that will be discussed in this section.

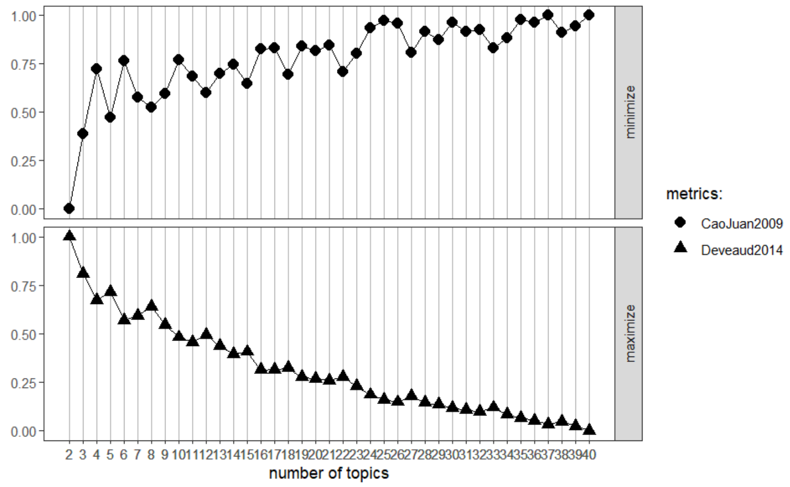

Figure 6. *Metrics of possible themes.*

Table 2. *Thematic groups and related authors.*

Topic	Keywords	Interpretation	Examples of related work
Topic 1. Consumer behaviour and preference detection	"custom" "behaviour" "import" "learn" "identifi" "social" "technolog" "effect" "aim" "prefer"	The studies in this group focus on analysing consumer behaviour to better understand consumer preferences. They are based on customer segmentation and the study of behavioural patterns.	Rajasekaran & Tamilselvan (2023)
Topic 2. Prediction of future behaviour	"data" "predict" "onlin" "busi" "result" "machin" "product" "network" "shop" "digit"	This group of studies focuses on analysing large amounts of data to develop predictive models of future consumer behaviour.	Das et al. (2022), Mustafa et al. (2022), Zhang (2022)
Topic 3. Use of advanced algorithms for digital consumer research	"consum" "studi" "research" "prefer" "algorithm" "analyz" "measur" "extract" "process" "digit"	This work aims to use efficient data processing algorithms to detect consumer behaviour patterns, preferences and trends.	Ghosh et al. (2023), Ma et al. (2024), Zhao et al. (2023), Zhou et al. (2024)

Topic	Keywords	Interpretation	Examples of related work
Topic 4. Consumer preferences and purchasing behaviour through reviews	"behaviour" "model" "data" "review" "base" "paper" "analysi" "platform" "time" "increas"	These studies rely on the study of online reviews to understand consumers' motivations, attitudes, preferences and purchasing behaviour.	
Topic 5. Personalization of the user experience	"market" "user" "method" "purchas" "inform" "evalu" "understand" "person" "approach" "factor"	This group of studies is based on using artificial intelligence to personalize consumer experiences based on personal data.	Li et al. (2024), Panda et al. (2024), Saha et al. (2022), Seo & Yoo (2023), Shah et al. (2022)

The thematic analysis revealed two main groups of articles, each with a distinct focus. The first group, comprising Topics 1, 4 and 5, explores the influence of AI on an organization's understanding of consumer knowledge. The second group, Topics 2 and 3, delves into predicting future consumer behaviour.

4.2.1 Impact of AI on the organization's knowledge of today's consumer

The accessibility of large amounts of data enables companies, through the use of AI technologies, to process very useful customer-generated information (Andrade & Cunha, 2023). This not only improves business relationships but also influences the internal operations of the organization, as AI enables more confident decision-making (Koç & Sevgili, 2020).

Consumer behaviour varies according to factors such as previous references, developed attitudes towards a product or brand or the context in which they are at a given moment (Akay et al., 2015). However, technological advances have transformed the methods of analysis and, as a result, have made it possible to deepen our understanding of consumer behaviour.

Nowadays, there is a wealth of data information, such as purchase history or content posted by users on social media. Studies such as Akay et al. (2015) have drawn on these sources to analyse the experience with health products. Furthermore, other consumers' opinions affect others' decisions, which confirms the use of these analyses to generate better experiences (Ghosh et al., 2023). In this line, Ghosh et al. (2023) studied attitudes and purchase intentions about refurbished products with a sample of customer reviews.

Today, there is a growing body of research measuring shoppers' polarity or personality traits. Emotions and ways of thinking or behaving influence issues such as purchasing certain brand products because of their image or the fact of entering a shop (Khatri et al., 2022). In conjunction with studying emotional responses using EEG or eye-tracking (Shah et al., 2022), psychological traits and their impact on a satisfactory experience are beginning to be assessed (Khatri et al., 2022).

4.2.2 Prediction of future behaviour

The second group brings together items that seek to predict future trends and behaviour. To this end, they use different AI techniques to analyse historical purchases or customer relationship data. The accuracy of AI algorithms makes it possible to extract useful information that improves the understanding of customer knowledge (Loureiro et al., 2021).

A wide variety of future actions can be predicted. For example, in the banking sector, these techniques are used to pre-minimize the risks of a loan default (Koç & Sevgili, 2020) or to predict, through customer history, whether they will apply for personal loans (Zhang, 2022). From a commercial point of view, Zhang et al. (2022) focused on finding potential customers and determining their buying possibilities to define a pricing strategy. Finally, Langen and Huber (2023) analysed the effect of coupon campaigns to reduce costs and improve their effectiveness. Among the advantages of AI tools is their ability to adapt, which is essential for meeting market needs and anticipating consumer behaviour (Aripin et al., 2023).

4.3 Methods

In the majority of studies, the primary method employed is primary data collection. Moreover, only 20 articles use samples of respondents, thereby underscoring the growing significance of user-generated data. The samples primarily comprise consumers or information that they have provided, either derived from previous purchases throughout the organization's history or databases or from opinions or reviews that users have posted. The utilization of data about users underscores the necessity for in-depth analysis, as this content enables the extraction of a wealth of information, thereby enhancing comprehension of their behaviour (Fernández-Rovira et al., 2021). The review of the articles has revealed a prevalent standard regarding the size of the study units, which is directly correlated with the specific objective and methodology employed. Papers that employ surveys as a source of data collection present smaller samples.

In contrast to the studies mentioned above, some studies exclusively apply AI techniques. In addition to a markedly larger sample size, their data sources are highly diverse. Consequently, data are derived from purchases (Sabbaghi et al., 2015), photographs (Giglio et al., 2020) or reviews and comments (Brzustewicz & Singh, 2021), the latter being the most frequently utilized source by academics. Ultimately, the smallest samples are those comprising neuromarketing techniques and AI integration.

4.4 Antecedents, decisions and outcomes

The papers address different aspects of consumer behaviour as dependent variables, ranging from purchase intention and loyalty to spending analysis, preferences and psychological factors. Concerning purchase intention, the papers analyse, for example, the purchase of financial products or housing, as well as the choice of services such as accommodation or transportation (Adwan & Aladwan, 2022; Gerlich, 2023; Wang et al., 2023; Zhang & Wang, 2023). In addition, they also study the preference for the type of channel (Acquila-Natale & Iglesias-Pradas, 2021). Concerning other aspects directly related to consumer behaviour, they analyse the consumption behaviour of certain products, such as electricity or water (Malinowski & Povinelli, 2022; Manandhar et al., 2023), the prediction of abandonment (Al-Mashraie et al., 2020; Hasumoto & Goto, 2022; Swetha & Dayananda, 2020), consumer comments and their impact on word of mouth (Adamopoulos et al., 2018; Ma et al., 2024) or the willingness to pay (Ribeiro et al., 2021). They also analyse emotions related to the shopping experience, satisfaction (Ribeiro et al., 2021) or loyalty (Puspitasari et al., 2023; Wassouf et al., 2020). Finally, some works aim to analyse psychological traits in consumer behaviour (Gladstone et al., 2019).

To analyse these variables, the studies use a variety of antecedents or explanatory variables of very different types. Firstly, they use variables related to consumption behaviour and preferences. Thus, they use satisfaction (Chiu et al., 2022; Oncioiu, 2023), perceived quality (Gerlich, 2023; Ma et al., 2023, 2024; Oncioiu, 2023; Puspitasari et al., 2023), personalization (Puspitasari et al., 2023) or user experience (Gerlich, 2023; Wang et al., 2023) as antecedents related to the consumer experience; they also use more behavioural variables such as spending (Kita et al., 2018), purchase intention (Garner et al., 2022), price sensitivity (Chen et al., 2021), use of chatbots (Oncioiu, 2023) or attitude towards marketing campaigns (Silva et al., 2023); they also intervene in the use of technological devices and services. Secondly, they analyse the intervention of psychological and social factors. Consumer attitudes, social influence

(Zhang et al., 2023), hedonic and utilitarian motivations (Chin et al., 2022) and the influence of positive and negative emotions (Ma et al., 2023) are analysed. Thirdly, the characteristics of the customers themselves are taken into account, such as length of time as a customer, income (Wong et al., 2018), type of account, credit score (Long et al., 2019), use of financial services, use of digital banking, products purchased, activity on social media (likes, followers) (Chaudhary et al., 2021) or choice of purchase. In addition, studies take into account sociodemographic variables: age, gender, income, occupation, education, status (rural/urban), geography, marital status, customer seniority, salary, educational level, eating habits, perception of diseases, etc. (Shen et al., 2021; Wong et al., 2018). Fourthly, explanatory variables relate to technology: browser, operating system, graphic type, network traffic, use of online services, device performance, battery, system, screen, user experience, audio/video quality and after-sales service (Wang et al., 2023). Finally, the studies also consider external factors such as GDP, educational level, culture or public policies (Kuo et al., 2023; Liu et al., 2019).

To systematize this section, a table is presented with the studies analysed (N=161) based on three ontological dimensions: (i) main AI techniques or tasks, (ii) consumer behaviour research approaches and (iii) sectors. This information can be found in Appendix 1.

5 FUTURE RESEARCH DIRECTIONS

This literature review aims to examine a topic currently emerging as a significant area of interest within the field of study under consideration: AI as a tool for consumer insight. The application of AI in consumer behaviour research will continue to expand and its use for attitude and behaviour analysis will become more sophisticated and pervasive. Furthermore, the analysis highlights potential avenues for future research derived from the systematic review and the authors' insights.

As demonstrated, the papers employ many theoretical frameworks, most centred on consumer behaviour. However, there is a dearth of convergence between the specific computer science and technology theories and those about consumer behaviour (Puspitasari et al., 2023). As has been demonstrated, there are instances of conjunction between psychological and technological theories (Acquila-Natale & Iglesias-Pradas, 2021; Gerlich, 2023). This evidence substantiates the feasibility of such an approach. It is important to note that consumer behaviour is being analysed within the context of systems and tools supported by machine learning. Combining the principles of these two fields can help build stronger frameworks that generate opportunities to further advance the knowledge of how AI can help understand consumer behaviour in the present and future.

The majority of studies focus on either supervised or unsupervised methods. However, there is potential for further research in the form of two-stage studies (Swenson et al., 2016) that consider both or studies that employ semi-supervised methods (Wang et al., 2022). Thirdly, it is somewhat surprising that reinforcement learning, one of the pillars of AI, has not been given more attention in this context. The reviewed papers have concentrated on techniques within the two branches of supervised and unsupervised learning but have omitted any reference to reinforcement learning techniques. Nevertheless, this could prove to be a highly intriguing avenue of inquiry, particularly in the context of research that employs experimentation as a methodological approach. The existing literature on consumer behaviour and experimentation is extensive (Ko et al., 2023) and the methodology has been used widely in recent times. Therefore, incorporating reinforcement learning techniques would represent a significant line of work. Finally, it is notable that the studies analysed have not yet considered the recent advances and popularization of generative AI, such as ChatGPT5 and Gemini. These tools, which are widely used among the population (Hyun Baek & Kim, 2023), can also be used to analyse large amounts of consumer data.

Conversely, concerning user-generated content analytics, the extant literature has either focused on images (e.g., Ye & Huang, 2022) or textual content (Yadav et al., 2022; Ziakis & Vlachopoulou, 2023), but to the best of our knowledge, there are no works that combine the analysis of both sources together. A joint analysis would facilitate the discovery of insights that might otherwise remain unidentified, such as consumers' emotional states, beliefs and values.

Sentiment analysis is closely linked to the topic mentioned above. There are two main approaches to sentiment analysis: dictionary-based and aspect-based sentiment analysis (ABSA) (Bi et al., 2024). The studies analysed are based on dictionaries (e.g., Akay et al., 2015), but ABSA methodology should be considered in the future. This methodology allows the extraction of aspect terms (Fu et al., 2020), which makes it possible to analyse both the explicit aspects contained in the texts and the implicit aspects.

Concerning the application of AI techniques to the analysis of consumer surveys, it is evident that surveys represent one of the most commonly utilized marketing tools, facilitating data acquisition. However, it is important to acknowledge that their use is not without inherent biases. Consequently, if surveys are to be employed in conjunction with AI for their analysis, one of the most significant considerations is the size of the samples. In light of this, it can be posited that one of the most promising avenues for future research would be to obtain larger sample sizes.

Conversely, a significant body of research explores the nexus between marketing and the metaverse (Kaur et al., 2024). Consumers engage with brands, products and companies in this domain, generating data that necessitate analysis. AI has the potential to play a pivotal role in the examination of metaverse data, facilitating the identification of potential opportunities within this domain.

The studies analysed highlight the necessity for a more expansive approach. There is a compelling requirement to employ existing models in disparate domains and cultures (Abdulqader et al., 2022; Pantano et al., 2021) and to utilize them in varied contexts and sectors (Hasheminejad & Reisjafari, 2017; Li et al., 2020; Senarath et al., 2022).

Ultimately, it is imperative to consider the potential adverse outcomes associated with AI, otherwise referred to as the “dark side” (Barari et al., 2024), within the scope of this study. Subsequent research should therefore address both the favourable and unfavourable aspects of using AI to understand consumers. We are referring here to opaque data collection (Martin & Murphy, 2017), the inference of psychological traits without prior consent (Kosinski et al., 2013), or the uniqueness neglect (Mou et al., 2023), among others.

6 CONCLUSIONS

This study makes an important contribution to the marketing literature by providing a review of existing work on analysis of consumer behaviour using artificial intelligence. It has been demonstrated that AI plays an essential role in consumer decision-making and in enhancing our understanding of current and potential consumer behaviour. Using bibliometric analysis and the TCM-ADO framework, the trends, theories, methodologies and variables under examination have been identified. This has led to the conclusion that significant progress remains to be made, particularly in theoretical advancement and methodological refinement. In particular, the need to develop theoretical frameworks that integrate theories of consumer behaviour with those from computer science and information systems is identified. Consumer behaviour theories provide insight into psychological and social variables – attitudes, norms, personal values, etc. – that can enrich technology acceptance models that focus more on studying utility or ease of use. For example, combining the theory of planned behaviour with the UTAUT can provide a deeper understanding of the motivating factors for the use of digital technologies. This theoretical integration broadens the explanatory scope of existing models and opens up new avenues of research.

Furthermore, the application of additional, more innovative marketing methodologies is recommended, such as reinforcement learning and generative AI techniques. The use of reinforcement learning can enable the modelling of adaptive patterns, that is, understanding how consumer behaviour changes in response to different experiences. Meanwhile, generative AI can be used more extensively for analysing online opinions, sentiment analysis and other analyses of consumer databases. There is already some evidence for this last point, although the results have not been entirely optimal to date.

Furthermore, the approach adopted in this study will advance this emerging field and provide a robust foundation for future research that may draw inspiration from it. Ultimately, from a managerial perspective, our study offers valuable insights for organizations seeking to use artificial intelligence to understand their consumers better. Firstly, managers should prioritize mature techniques such as those based on supervised learning. Although the general trend today is towards the use of generative artificial intelligence, there is, to date, insufficient scientific evidence to validate the robustness of these techniques for a deep understanding of consumer behaviour. Secondly, managers must invest in developing reinforcement learning methods, an area with great potential for understanding consumers that has, to date, been underestimated. Finally, the third major recommendation for managers arising from this study is to pay particular attention to the risks and unintended consequences of AI. To this end, they could implement general guidelines for application within the company or, explicitly for each project involving AI, specific ethical standards and risk assessments.

6.1 Limitations

This review sought to analyse artificial intelligence and consumer behaviour objectively. Despite the contributions, several limitations were identified. The articles were obtained from the Scopus database, using a specific time frame covering the last ten years. Although the database was updated to December 2024, some changes may still occur due to the standard indexing processes involved in database management. This information will be updated over time, affecting the research results. The authors' selection of search criteria may result in not obtaining relevant information, for example, from non-English publications. In addition, the approach to selecting and reviewing the sample of articles may condition the inclusion of papers despite the rigorous search process.

ADDITIONAL INFORMATION AND DECLARATIONS

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Author Contributions: A.N-P.: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Resources, Software, Visualization, Writing – original draft, Writing – review & editing. S.C-G.: Conceptualization, Data curation, Investigation, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing.

Statement on the Use of Artificial Intelligence Tools: The authors declare that they didn't use artificial intelligence tools for text or other media generation in this article.

Data Availability: The data that support the findings of this study are available from the corresponding author.

APPENDIX 1. CO-AUTHORSHIP OF PRINCIPAL AUTHORS

Figure A1.1 shows the collaborations between researchers. From a total of 534 authors, nine groupings are extracted. Although the authors collaborate, it should be noted that this collaboration occurs in small groups or individually, without major relationships. The number of clusters and the paucity of relationships demonstrate that the research topic is novel.

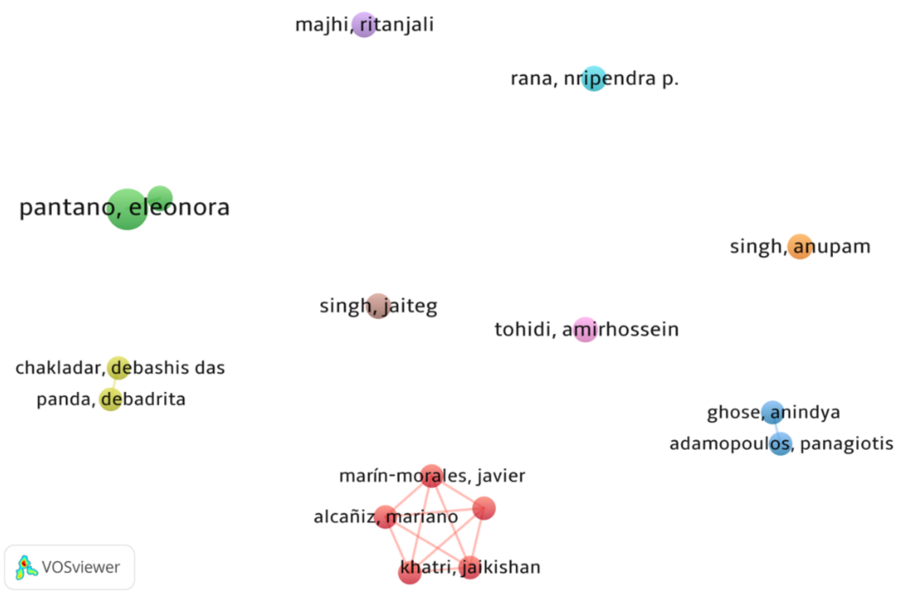

Figure A1.1. *Collaborations between researchers.*

The group of authors presented here has published at least two works in conjunction with one another. Furthermore, if the previously established limitation of two documents is disregarded, it becomes evident that a substantial number of works have been carried out individually (see Figure A.1.2).

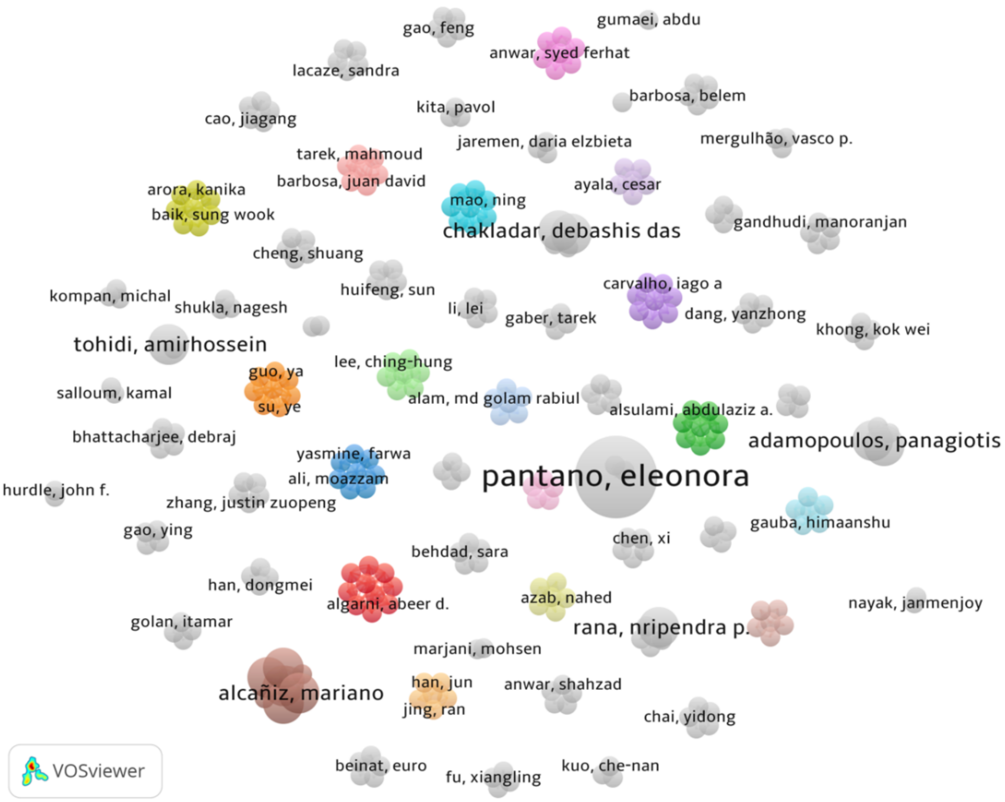

Figure A1.2. *Co-authorship of principal authors without restriction.*

Using the co-authorship analysis in Figure A 1.1, one of the main groups is the one formed by Adamopoulos and Ghose. This is a multi-thematic group where, on the one hand, they seek to predict consumer behaviour through purchase history (Sun et al., 2022) and, on the other hand, to determine how personality traits influence decision-making (Adamopoulos et al., 2018). Although they employ different AI techniques, both seek to process the data to improve consumer understanding.

The red group is the most numerous and is formed by authors such as Khatri, Moghaddasi, or Alcañiz. All the research focuses on the classification of customers according to purchase patterns (Khatri et al., 2022; Moghaddasi et al., 2021). In this case, the samples are similar, with 60 participants, and several studies use support vector machines (SVM).

Panda and Chakladar, lead authors of the yellow group, focus their research on predicting customer preferences. To do so, they use a supervised AI algorithm, which helps to more accurately interpret electroencephalograms while viewing a series of advertisements and product images from an e-commerce (Panda et al., 2024).

The blue group was formed by only two authors who developed works focused on retail buildings. They consider knowing the importance of commercial buildings, location, architecture, or tourist attractions as a key element in sales (Pantano & Dennis, 2019). The common feature is using unsupervised machine learning algorithms to analyse a set of tweets about consumer preferences in a shopping mall (Pantano et al., 2021) and more than a thousand photographs to evaluate the attractiveness of retail buildings (Pantano & Dennis, 2019).

Finally, there are five groups integrated by a single node, indicating a lack of connection with other authors in the analysed set. Rana examines consumer attitudes through reviews and comments on Amazon products (Kumar et al., 2024). Using machine learning algorithms, Jaiteg Singh focuses on predicting how emotions influence sales (Singh et al., 2022). The influence of word-of-mouth advertising on organic products for subsequent customer segmentation is the topic studied by Tohidi et al., (2023). The thematic classification of comments and the identification of consumption patterns are the topics analysed in the studies by Singh et al., (2022), and Sukumaran et al., (2024).

Table 1 presents a list of the most relevant authors on consumer behaviour and AI techniques, ordered by the number of total citations. Adamopoulos and Ghose are the most prolific authors in this field.

Table A1.1. *Most influential authors / most cited authors.*

Authors	Total citations
Adamopoulos, Pangiotis	122
Ghose, Anindya	122
Todri, Vilma	113
Pantano, Eleonora	106
Han, Dongmei	106
Liu, Qigang	83
Luo, Suguan	83
Wang, Chongren	83
Dogra, Debiprosad	80
Gauba, Himaanshu	80

The citations are not concentrated on a specific author but present similar and low numbers. This could indicate that this field is in its infancy, but with the significant growth in publications (Figure 3), it represents an opportunity for future exploration. In addition, the diversity among the most cited authors concerning the purpose of their research when applying different AI techniques is worth noting.

An evaluation of the H index complements this analysis of the first four authors, indicated in Google Scholar in October 2025. The results show that the number of citations in this area and the valuation of academic production have no apparent direct relationship.

Table A1.2. *H-index and total citations of authors.*

Authors	No. of citations	H-index
Adamopoulos, Pangiotis	122	22
Ghose, Anindya	122	60
Todri, Vilma	113	11
Pantano, Eleonora	106	50

However, if the Google Scholar profile of each of them is analysed (Table A1.2), certain publication patterns can be deduced. On the one hand, Ghose and Pantano are academics with long careers, starting in 2002 and 2014, respectively, focusing on the subject under analysis in recent years. On the other hand, it should be mentioned that Adamopoulos and Todri were incipient authors in their research careers. Given that authors with a long research career have focused on this subject and that others with few publications are very often mentioned, this proves the relevance of this one.

APPENDIX 2. BIBLIOGRAPHIC COUPLING OF PUBLICATIONS

Figure A 2.1 illustrates the interconnections between publications with analogous references in their bibliographies (Mukherjee et al., 2022). The format is distinctive, with a preponderance of papers that share few references.

The right margin suggests that the articles do not share many references. These papers analyse aspects of consumer behaviour from various methodological approaches. The green cluster applies a methodology that combines supervised and unsupervised learning techniques to determine customer value (Zhao et al., 2023). The grey cluster, where Hung is the most prolific author, focuses research on discovering emotions and preferences as a component in decision-making. They use machine learning algorithms to predict purchase and payment preferences (Carbo-Valverde et al., 2020; Shen et al., 2021) or sentiment analysis to identify how it affects digital word-of-mouth (Hung & Chen, 2016). Finally, Boccia et al. (2024) segment consumers according to the influence of advertising on the purchase of organic products.

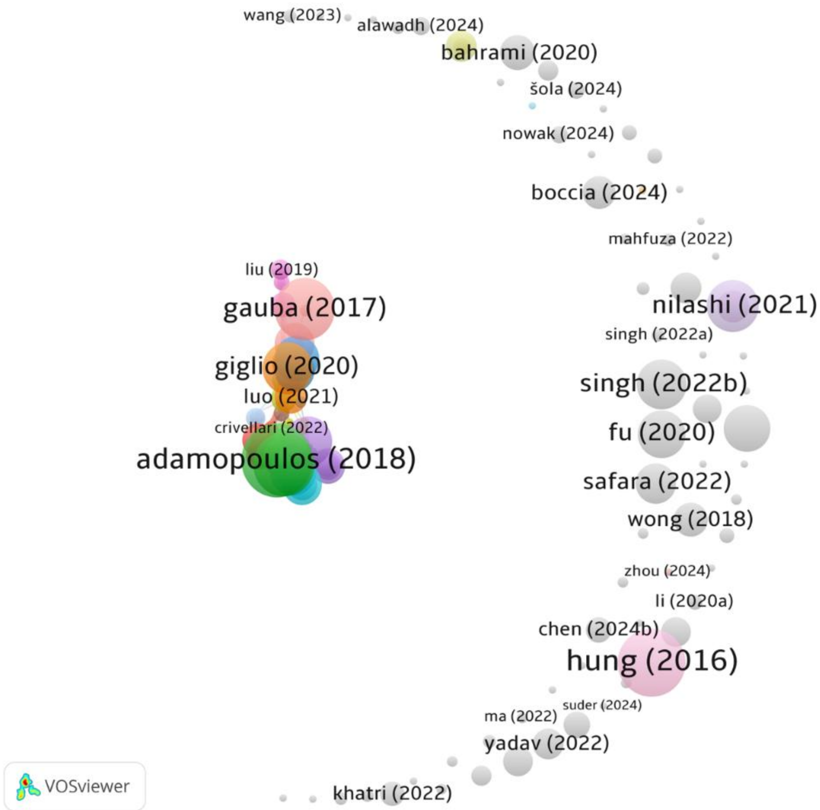

Figure A2.1. *Bibliographic coupling of publications (1).*

A set of papers occupying the left margin exhibits a greater number of shared references. Figure A 2.2. illustrates a series of clusters, classified according to their subject matter.

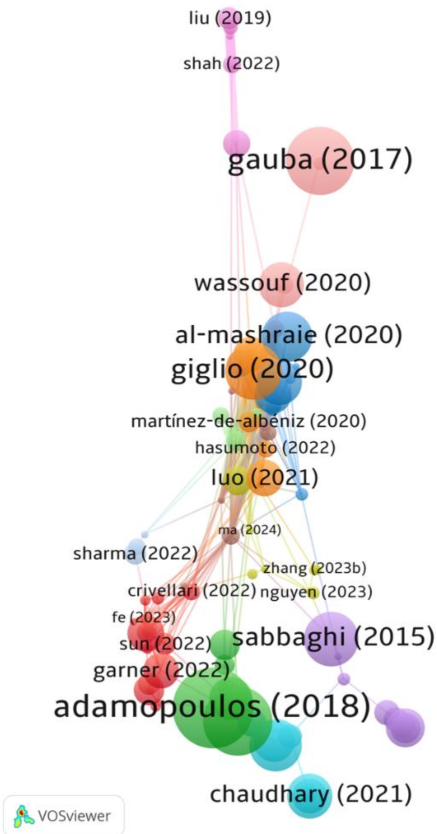

Figure A2.2. *Bibliographic coupling of publications.*

The common variable among the articles in the red cluster, comprised of the largest number of publications, is the typology of the sample and the techniques they apply. They all employ user opinions about products on Yelp (Fe, 2023) or reviews and tweets (Brzustewicz & Singh, 2021). Unstructured user-generated content is analysed to provide answers to different objectives, such as evaluating a tourist destination (Garner et al., 2022).

The green cluster studies consumer behaviour linked to personality aspects. This is the case of Adamopoulos et al., (2018) or Carbo-Valverde et al. (2020) who assess its impact through machine learning in sectors such as electronic banking.

The primary objective of the blue group is to determine consumers' purchase intentions or attitudes using unstructured data analysis and classification methods. Pantano and Dennis (2019) use AI techniques to process photographs (Silva et al., 2023), which determine people's intention to manage waste and classify it through their previous consumption.

The purple cluster integrates a series of articles that analyse consumer behaviour, such as when they have purchased a product and/or service and have had previous experience. This is the case of Ribeiro et al. (2021), which seeks to predict future food product consumption based on data from previous purchases. In this line, Liu & Zhao (2021) predict loyalty towards a milk brand or Sabbaghi et al. (2015), which is the storage of technological devices through a sample of data stored on hard disks.

The orange cluster covers the classification and segmentation of consumers. Pilone et al. (2023) perform classification according to their willingness to pay for craft beer among more than 400 consumers, and Zhao et al. (2023) perform segmentation based on age, time of access, or usage in the telecommunications sector. Both use random forest as the main technique. Finally, the yellow cluster refers to consumer preferences, which Rajasekaran and Tamilselvan (2023) analyse based on the properties of e-commerce products.

APPENDIX 3. CITATION ANALYSIS

Citation analysis of documents

Table A 3.1. presents a ranking of the ten most influential articles in the field of study, aiming to assess the impact of these publications. It is noteworthy that the number of citations among the principal publications is highly variable, which suggests that this subject is still in its infancy.

The most cited article in this period determines how consumer personality affects word-of-mouth in the digital domain (Adamopoulos et al., 2018). Second, Wang et al. (2019) assess creditworthiness through the history of bank loans granted in China. Next, Gauba et al. (2017) predict advertising preferences by combining electroencephalograms with sentiment analysis and random forest on a sample of users. The fourth article describes a method that seeks to improve the understanding of user comments for their correct analysis (Hung & Chen, 2016). Next, Giglio et al. (2020) focus on identifying brand attributes in the tourism sector by visualizing photographs.

The application of neural networks for purchase prediction in the electronics sector is the focus of the sixth most cited paper (Sabbaghi et al., 2015). Gladstone et al. (2019) seek to establish personality traits as a function of customer transactions in a British bank.

The last three researches aim to analyse the tourism sector by resorting to textual analytics (Nilashi et al., 2021), adopt a method to predict the abandonment of electronic product usage (Al-Mashraie et al., 2020), and understanding consumer attitudes through topic analysis of published tweets (Singh et al., 2022).

Table A3.1. *10 most cited published articles.*

Article title	Authors	Year	No. of citations
The impact of user personality traits on word of mouth: Text-mining social media platforms	Adamopoulos, P.; Ghose, A.; Todri, V.	2018	113
A Deep Learning Approach for Credit Scoring of Peer-to-Peer Lending Using Attention Mechanism LSTM	Wang, C.; Han, D.; Liu, Q.; Luo, S.	2019	83

Article title	Authors	Year	No. of citations
Prediction of advertisement preference by fusing EEG response and sentiment analysis	Gauba, H.; Kumar, P.; Roy, P.; Singh, P.; Dogra, D.; Raman, B.	2017	80
Word sense disambiguation based sentiment lexicons for sentiment classification	Hung, C.; Chen, S.	2016	78
Branding luxury hotels: Evidence from the analysis of consumers' "big" visual data on TripAdvisor	Giglio, S.; Pantano, E.; Bilotta, E.; Melewar, T.C.	2020	57
An investigation of used electronics return flows: A data-driven approach to capture and predict consumers storage and utilization behavior	Sabbaghi, M.; Esmaeilian, B.; Raihanian, M.; Behdad, S.; Cade, W.	2015	52
Can Psychological Traits Be Inferred From Spending? Evidence From Transaction Data	Gladstone, J.; Matz, S.; Lemaire, A.	2019	48
What is the impact of service quality on customers' satisfaction during COVID-19 outbreak? New findings from online reviews analysis	Nilashi, M.; Abumalloh, R.; Alghamdi, A.; Minaei-Bigdoli, B.; Alsulami, A.	2021	47
Customer switching behavior analysis in the telecommunication industry via push-pull-mooring framework: A machine learning approach	Al-Mashraie, M.; Chung, S.; Jeon, H.	2020	45
Modeling the public attitude towards organic foods: a big data an text mining approach	A., Singh, Anupam; A., Glinska-Newes, Aldona	2022	42

Impact analysis of journals

The present study also reviews the impact factor of the journals in which the ten most cited articles have been published. Table 4 illustrates the evolution of these data points according to the information available in Clarivate until December 2024 (inclusive).

Table A3.2. *Impact factor of leading journals.*

Source	Quartile evolution	
	Year of publication	2024
Information Systems Research	Q1 (2018)	Q1 (2024)
IEEE Access. Institute of Electrical and Electronics Engineers Inc.	Q1 (2019)	Q2 (2024)
Neural Networks	Q1 (2017)	Q1 (2024)
Knowledge-Based Systems	Q1 (2016)	Q1 (2024)
Journal of Business Research	Q1 (2020)	Q1 (2024)
Waste Management	Q1 (2015)	Q1 (2024)
Psychological Science	Q1 (2019)	Q1 (2024)
Telematics and Informatics	Q1 (2021)	Q1 (2024)
Computers and Industrial Engineering	Q1 (2020)	Q1 (2024)
Journal of Big Data	Q1 (2022)	Q1 (2024)

All of them are in the first quartile, indicating that they are journals of high importance in their field. Also, since the research publication, they have maintained their position, except for IEEE Access. Institute of Electrical and Electronics Engineers Inc., which has dropped to the second quartile.

Regarding the categories, there are journals oriented towards business, management, or marketing, such as Information Systems Research and Journal of Business Research, and others linked to technological aspects of AI and computer science, such as Knowledge-Based Systems or Journal of Big Data. In addition, the study developed by Gladstone et al. (2019), investigating the personality traits of bank customers, was published in a journal that deals with psychological aspects in a generalized way.

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