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REVIEW PAPER

AI-powered consumer behavior analysis: A review of applications, techniques, and ethical implications

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Abstract

Artificial Intelligence (AI), Machine Learning (ML), and Big Data Analytics have converged, changing how companies gain insights into, predict, and respond to consumer behavior. This paper will discuss the theory, methodology, and commercial applications of interpreting consumer behavior using AI-driven data analysis, including technologies such as recommendation systems, sentiment analysis, predictive customer behavior, and computer vision. The research, using supervised, unsupervised, and deep learning techniques, highlights the potential of AI to segment customers, personalize marketing strategies, forecast demand, implement dynamic pricing, and predict churn across various sectors such as retail, banking, healthcare, and entertainment. The paper also highlights the advantages of using AI, including enhanced personalization, increased conversion rates, and real-time consumer insights, as well as ongoing issues with data privacy, algorithmic bias, transparency, and ethical oversight. The paper is a research proposal that presents a conceptual framework, research questions, and testable hypotheses related to AI personalization, consumer trust, and purchase intention; outlines a mixed-methods design for future empirical validation; and identifies research directions for further investigation, including Emotion AI, generative AI, and Metaverse-integrated commerce. The literature synthesis suggests that AI is moving organizations away from reactive to predictive and prescriptive decision-making.

1. Introduction

Consumer behavior has, for the most part, been examined using survey analysis, focus groups, and post-purchase analysis, which are informative but lack predictive power, speed, and scale. This has led to an unprecedented amount of behavioral data generated by e-commerce platforms, mobile applications, social media, and connected devices. The increasing access to data and the development of computational power and algorithmic complexity have led to the emergence of AI-powered consumer behavior analysis, which involves analyzing, predicting, and, to a certain degree, influencing consumer purchasing patterns and decision-making processes using AI, machine learning, big data analytics, and natural language processing [1, 2]. Artificial Intelligence, in its simplest sense, is the ability of computer systems to carry out tasks that normally require human mental activity, including pattern recognition, learning from experience, and decision-making. In the context of consumer behavior, AI is not used to dictate or manipulate consumer decisions, but rather to provide a big-picture analytical assistant to detect patterns across millions of consumer interactions that would be impossible for humans to detect manually [3]. If an AI system detects customers who looked at running shoes, read reviews, spent time on a specific brand, and left without buying, it can predict that customers are likely price-sensitive and interested in the shoe, and suggest a discount as a countermeasure. The same principle applies to systems that power platforms such as Amazon, Netflix, Spotify, and YouTube, which provide personalised content and

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product recommendations based on historical behaviour [4].

On a methodological level, AI-driven consumer behavior analysis relies on several complementary methods [1, 2]. Many supervised learning techniques, such as decision trees, random forests, support vector machines, and neural networks, are employed for classification and prediction problems, such as churn prediction. Unsupervised learning methods like K-Means Clustering, Hierarchical Clustering, Association Rule Mining, etc enable Customer Segmentation and Market Basket Analysis. In sentiment analysis, for more complex tasks such as image-based consumer analysis or large-scale natural language understanding, deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer models can be used [5]. They are used in various business applications like customer segmentation, personalizing marketing efforts, predicting demand, dynamic pricing, predicting churn, and recommending products across different industries such as retail, banking, healthcare, e-commerce, hospitality, entertainment, education, etc. [2].

While AI can offer numerous advantages, such as customer satisfaction, higher conversion rates, better personalization, and demand forecasting, there are also many challenges to overcome when implementing AI in consumer behavior analysis [1, 3]. Academic and practitioner discussions have focused on data privacy and regulatory compliance (such as GDPR), algorithmic biases, data quality, algorithmic explainability, security, and the ethical boundaries of consumer monitoring [6-8]. With the growing reliance on AI for marketing and customer engagement strategies, it is crucial to understand its capabilities, limitations, and impact on consumer trust and welfare [7, 9].

The purpose of this paper is to present a structured review of the use of AI in consumer behavior analysis, highlighting the various components, data sources, applications, and techniques used in this field, and putting these advancements into perspective in terms of their benefits, challenges, and ethical implications. To inspire empirical research, the paper offers a research framework with five research questions and hypotheses exploring the impact of personalization using AI on purchase intention, the mediation effect of consumer trust, the effectiveness of sentiment analysis in marketing, the impact of recommendation systems on impulse purchases, and ethical issues influencing consumer acceptance of AI-based services. The paper reviews the literature on the use of AI in consumer behavior, outlines the proposed research framework and research hypotheses, and discusses future directions, including Emotion AI, generative AI, and the integration of AI with Metaverse and Internet of Things (IoT) technologies.

2. Literature Review

2.1 Machine Learning and Its Application in Consumer Behavior Analysis

Numerous studies and publications illustrate the evolution of marketing from a rule-based strategy to one that relies on AI and data to understand consumers better. AI-based applications identified 12 types applications in marketing [1]. They found that AI is increasingly used across all areas of marketing, including advertising, sales forecasting, and customer relationship management (CRM), to support accurate decision-making and improve operational efficiency. Kumar et al. (2024) [2] outlined the definition of AI-driven marketing, its use throughout the customer journey, and the implementation of AI in business marketing activities. They added that AI has become a key marketing strategy tool, even though it was originally a marketing support tool for analysis. Moving to the customer contact level, explored how AI-powered personalization is reshaping customer experiences, revealing that AI-driven personalization can lead to more relevant, efficient, and fulfilling interactions between businesses and customers [3]. As a whole, this literature confirms that AI has revolutionized the way firms sense, interpret, and respond to consumer behavior, thereby taking organizations closer to predictive and prescriptive capabilities.

2.2 Personalization, Recommendation Systems, and Purchase Intention

Much of the research has focused on the impact of AI personalization on consumer purchase intent and decisions. In the context of the purchase behavior, Alsaffarini and Awwad (2026) [10] used an explanatory sequential mixed-methods design. They showed that exposure to AI-personalized messages strongly influences purchase behavior, especially when they perceive AI recommendations as relevant, timely, and emotionally appealing. Trust in AI positively influences purchase behaviour and moderates the relationship between personalisation and purchase behaviour. This result aligns with the study on how AI influences consumers' buying decisions when shopping online [11], which concluded that AI recommendations and search tools can significantly impact purchase decisions. Similarly, AI-powered recommendation systems are regarded as a fundamental element of personalization, as they use behavioral and preference data to identify products that consumers may not be aware of, broadening the scope and impact of marketing communications [4]. This collection of studies demonstrates that algorithmic complexity is not the sole driver of AI-driven personalization but also relies on perceived relevance, trust, and transparency in data governance.

2.3 Sentiment Analysis and Marketing Effectiveness

Word of mouth, particularly its sentiment component, has become the primary focus for firms seeking to understand consumer opinion at scale, and NLP techniques are making this possible. In an overview of sentiment analysis and emotion detection methods [5], discussed the application of text-mining techniques to categorize consumer-generated content (CGC), such as consumer reviews and social media posts, into polarity and emotion categories for use in product development and campaign evaluation. When looking at social media specifically, Teepapal (2025) [12] investigated how consumer perceptions are affected by AI-driven personalization in social media marketing environments and concluded that personalization efforts based on sentiment and behavioral signals are linked to better engagement and brand interaction outcomes, as long as they are perceived as non-intrusive. The results indicate that sentiment analysis is not a stand-alone tool but rather one that can enhance the accuracy and emotional impact of the personalization and recommendation approaches.

2.4 Recommendation Systems and Impulse Buying

There have been a few studies exploring the behavioral impact of AI-driven recommendations, specifically on impulsive buying. Amin (2025) [13] examined the effects of AI-powered functions on impulse buying. He concluded that algorithm-driven exposure to personalized content can streamline the decision-making process, thereby increasing impulsive shopping when content recommendations closely match a user's historical browsing patterns. Alongside this behavioral approach, Acharya et al. (2022) [14] investigated the process of "cognitive absorption" – the level of cognitive involvement of the consumer with an AI-powered recommender system – as a factor influencing continued usage intention in e-commerce contexts, concluding that user immersion within a more engaging recommender interface can lead to increased susceptibility to decision-making impulsiveness. Taken as a whole, these results suggest that the purpose of recommendation systems is to make decision-making more efficient, but they can also exacerbate impulsive consumption behavior, a topic investigated in both marketing and consumer welfare contexts.

2.5 Chatbots, Trust, and Customer Loyalty

One key application of AI in consumer behavior analysis is conversational agents, AI-powered chatbots designed to interact with customers. Another significant application of AI in consumer behavior analysis is the use of conversational agents, or AI-powered chatbots, in customer service and engagement. Rohit et al. (2024) [15] examined consumer interaction with chatbots and voicebots. They found that trust was the key mechanism linking consumers' acceptance or rejection of conversational AI, with consumers who trusted it more willing to share information and rely on automated recommendations. Varying the problem-solving ability of an AI agent in an e-commerce setting, Gao et al. (2025) [16] adopted an expectation-confirmation model to explore the impact of the AI agent's ability to resolve issues on its own on consumer continued use intentions, concluding that the AI agent's problem-solving is positively related to satisfaction and repeat interactions with AI-based service channels. The findings of these studies indicate that the behavioral value of chatbots is less a function of how sophisticated they are at conversation and more a function of the user's perception of their reliability and ability to establish and maintain consumer trust during interactions.

2.6 Ethics and Privacy, Bias, and Transparency

Alongside this, there exists a parallel body of literature regarding the ethical implications of using AI to analyze consumer behavior. There is also a growing body of research on the ethical concerns surrounding AI-driven consumer behavior analytics. Karami et al. (2024) [7] performed a thorough investigation of the ethical considerations associated with the use of AI in digital marketing. They outlined five main ethical issues: privacy concerns due to the large-scale data collection, the risk of algorithmic bias and its potential to produce discriminatory outcomes, the possibility of consumer manipulation, and the overall lack of transparency, which hinders accountability. Algorithmic bias is not only relevant to marketing contexts; as Ge et al. (2021) found in their study of AI tools for recruitment, it can be demonstrated by systematically unfair results stemming from biased training data, a pattern directly applicable to AI-driven customer segmentation and targeting. Ghasemaghaei and Kordzadeh (2024) [17] also explored how algorithmic injustice can result in discriminatory decisions made by an organization and, based on the obedience-to-authority perspective, explained why algorithmic outputs are sometimes accepted uncritically by decision-makers. On the privacy dimension specifically, Morić et al (2024) [8] conducted a review of challenges related to personal data protection in e-commerce and found that regulatory compliance (e.g., with GDPR framework) and robust data-governance practices all had an impact on consumer trust; Teodorescu et al (2023) [9] conducted a case study on consumer trust in AI algorithms used in e-commerce, and found that perceived data-handling practices and algorithmic transparency significantly shape consumer trust. Regarding organizational aspects, Shahzad et al. (2024) [18] examined the ethical challenges of AI development from the perspective of a marketing employee, emphasizing that internal governance is as crucial to safeguarding data security and privacy as external consumer-facing protections in AI-driven marketing practices. These studies all highlight the need for technology development alongside the parallel development of mechanisms for fairness, transparency, and accountability to ensure the long-term viability of AI-driven consumer behavior analysis.

2.7 Fundamental and Applied Synthesis and Research Gap

Across all of these research streams, there is a clear one. In each of these cases, consumer attitudes and purchase-related behavior are demonstrably affected by each of the four streams of research, but in every case, these variables are moderated by consumer trust, transparency, and privacy concerns [7, 9, 10]. The current literature, however, focuses on these AI applications individually, such as studying personalization and purchase intention [10, 11], sentiment analysis and engagement [5, 12], or chatbot trust and loyalty [15, 16], with comparatively little literature incorporating these mechanisms and the associated ethical risks in a single explanatory framework. This fragmentation reduces the field's capacity to describe how various AI-enabled touchpoints come together to influence the consumer decision pathway and to design applicable ethical boundaries for AI applications. The present paper overcomes this shortcoming by consolidating these threads of literature into a single research framework, that treats personalization, trust, and ethical governance as interdependent factors influencing consumer response to AI-driven marketing.

3. Research Gap

- The fragmentation gap exists, as studies tend to focus on individual AI applications, for instance, personalization, or conversational agents, without modeling their interaction on the one consumer journey. Single-application studies underestimate or miscredit the combined behavioral impact of AI-powered touchpoints, since real-world consumers receive recommendations, sentiment-driven content, and chatbots all at the same time, not one after another.
- There is a gap between trust and the integration of ethics. Although studies like [7, 9] have confirmed the relationship between trust and ethical perceptions (privacy, transparency, fairness) with a customer's response to AI, this ethical aspect is not typically integrated formally in the purchase-intention literature and is instead more commonly discussed descriptively This segregation limits the field's ability to statistically explain the degree of dependence between AI personalization and customer behavior with reasonable accuracy, while accounting for the influence of trust and ethical governance.
- This paper proposes a new methodology that addresses this methodological gap as it integrates both the quantitative survey-based method to study purchase intention and the qualitative/conceptual method to examine ethical risk, with a few studies bridging both methods to explain not only the effectiveness of AI-driven consumer behaviour analysis, but why and under what conditions it is effective or ineffective.
- There exists a currency/technological gap in the research literature. Although some of the latest and emerging technologies, such as Emotion AI, AI-powered content generation, and AI-powered Metaverse/IoT-based shopping environments, have garnered some practitioner interest, they have received less empirical research. The above four gaps, fragmentation in AI applications, weak integration of ethical constructs in behavioral models, limited use of mixed methods, and thin coverage of emerging AI technologies, are the goals and methodology outlined below.

4. Research Objectives

After studying these two algorithms, I conclude that Dijkstra’s algorithm is most relevant to the research questions, and the following objectives are set for the study:
RO1: To explore the impact of personalization and recommendation systems on consumer purchase intention and purchase behavior due to the use of AI.
RO2: To understand how exposure to AI-driven personalization and recommendations relates to purchase-related outcomes and how consumer trust acts as a mediator between them.
RO3: To assess the impact of using AI sentiment analysis to enhance the relevance and effectiveness of marketing communications.
RO4: To explore how the recommendations system can influence impulsive buying compared to deliberate buying intent using AI.
RO5: To identify consumer acceptance or resistance to AI-based marketing and service systems and the ethical issues that affect this decision, such as issues with privacy, bias, and transparency.
RO6: To conceptualize and empirically validate a unified model of how personalization via artificial Intelligence, consumer trust, and ethical perceptions relate to purchase behavior and customer loyalty.

5. Research Methodology

5.1 Research Design

The study uses an explanatory sequential mixed-methods design, similar to that used in a related study [10]. The first (quantitative) phase will evaluate the hypothesized relationships among AI personalization exposure, sentiment-informed content, trust, privacy concerns, and purchase behavior (H1–H5, as proposed in the paper's framework) through a structured online survey. During the second phase (qualitative), semi-structured interviews with a purposive sample of survey respondents will be conducted to illuminate and contextualize the quantitative findings, including emotional reactions, perceived manipulation, and ethical issues not adequately addressed by closed-ended questions. In this type of sequencing, the qualitative phase can help to clarify why certain quantitative relationships are strong, weak, or unexpected.

5.2 Population and Sampling

The target audience is adult consumers who have interacted with AI-driven personalization, recommendations, or chatbots during their online shopping experiences in the last year. The quantitative phase is recommended to use stratified random sampling to ensure good representation across age, gender, income, and frequency of online shopping, as the same sampling procedure was adopted in similar studies [10]. Based on conventional sample size recommendations for models with multiple predictors, a minimum sample size of about 350-500 subjects is recommended for multiple regression or structural equation modeling. Based on qualitative research guidelines on thematic saturation, a purposive subsample of about 15-20 participants, representative of the sample's diversity, should be selected for the qualitative phase.

5.3 Data Collection Instrument

The structured, self-administered online questionnaire will be divided into Demographic information about the respondent, exposure to AI-driven personalization and recommendation systems, perceived sentiment-responsiveness of marketing content, trust in AI systems and privacy concerns; and purchase behavior, impulse buying tendency, and customer loyalty. The measurement items will be adapted from scales previously validated and reported in the literature. Personalization-exposure and purchase-behaviour items [10] and will be responded to on a five-point Likert-type scale (1 = Strongly Disagree to 5 = Strongly Agree). Pilot testing should be conducted with a sample of about 25-30 respondents before full deployment to evaluate item clarity and internal consistency (the minimum acceptable level is Cronbach's alpha ≥ 0.70).

5.4 Variables and Measurement

The proposed model treats the AI-based personalization exposure and AI-based sentiment responsiveness approaches as independent variables, and purchase intention, purchase behavior, and impulse buying as dependent variables, with consumer trust mediating the relationship between personalization and purchase outcomes. The moderating effect of privacy concerns and perceived algorithmic transparency on the personalization-purchase relationship was modeled, with privacy concerns expected to diminish and perceived algorithmic transparency to enhance this relationship, following prior research [7, 10].

5.5 Data Analysis Techniques

Quantitative data will be analyzed using descriptive statistics to characterize the sample and key constructs (means, standard deviations, and frequency distributions) and Pearson correlation analysis to examine bivariate associations among variables. Analytical approaches adopted in similar studies [10] will be employed to test the hypothesized relationships, using multiple regression analysis or Partial Least Squares Structural Equation Modeling (PLS-SEM), in which mediation and moderation effects are assessed simultaneously. Before hypothesis testing, the variance inflation factor (VIF) will be used to assess multicollinearity, and Cronbach's alpha will be used to assess internal consistency reliability. To allow for the emergence of themes across the qualitative interview data, the data will be transcribed verbatim and analyzed using Braun and Clarke's (2006) [19] six stages of thematic analysis, aided by qualitative data analysis software, focusing on themes of trust, emotional response, and ethics. Finally, quantitative and qualitative results will be combined through a connecting approach in which qualitative themes are linked to quantitative constructs to explain the strength or weakness of the statistical relationships.

5.6 Ethical Considerations

The proposed study will follow standard ethical protocols in conducting research. All participants will sign an informed consent form that includes an explanation of the study, the right to withdraw at any time, and information about the confidentiality and anonymization of their data. Data collection and storage will be structured to comply with relevant data-protection laws (such as GDPR principles) and align with the data-governance issues [8, 18]. Ethical clearance will be obtained from the relevant institutional review body before collecting the data

6. Scope of the Study

The scope of this study is intentionally restricted to four dimensions to make it feasible and representative of the phenomena identified in the literature review.

6.1 Conceptual Scope

The study addresses only four of the most popular categories of AI consumer behavior analysis identified. AI for personalization, recommendation systems, sentiment analysis, and conversational AI (chatbots). This paper does not address applications in consumer marketing and services (e.g., facial-expression analysis for marketing campaigns), nor does it cover purely offline computer-vision applications (such as in-store face recognition with autonomous cameras in marketing. In the context of supply-chain optimization, inventory forecasting, HR analytics, and autonomous B2B procurement agents are beyond scope.

6.2 Population and Contextual Scope

The proposed empirical work focuses on adult online consumers who have interacted with personalization, recommendation, or chatbot systems during their online shopping. While the study could be applied to digitally intensive sectors such as retail and service sectors , it does not aim to be generalizable across low and non-digital retail and service outlets.

6.3 Temporal Scope

The literature reviewed in this study covers the period from around 2015 to 2026, a time when personalization, recommendation, and conversational technologies powered by AI began to become common marketing tactics [1, 2]. The proposed primary data collection is cross-sectional, meaning that it measures consumer attitudes and behavior at a single time point, specifically within the 12 months preceding data collection, rather than examining changes over time. Longitudinal extensions are suggested as a direction for future research.

6.4 Thematic Boundaries

The study does not delve into a comprehensive legal or regulatory analysis of AI governance frameworks or algorithmic or technical evaluation of specific machine learning models, but extends to the ethical dimensions of AI-powered consumer behavior analysis and how these affect consumer trust and acceptance [7, 8]. Other applications, such as Emotion AI, Generative AI-related content, and shopping using the Metaverse and IoT, are discussed in concept as future scope and are beyond the empirical scope of the proposed study.

7. Conceptual Framework

This study proposes an integrated conceptual framework of "AI-driven personalization exposure," "AI-based recommendation exposure," and "Sentiment-informed Content" as independent variables, which directly affect the "Purchase-related outcomes" and indirectly through the "Consumer trust in AI systems" in the process of consumer purchasing decision. Perceived algorithmic transparency and privacy concerns are positioned as moderators to weaken and strengthen these relationships, respectively. Purchase intention/behavior, impulse buying behavior, and customer loyalty are all dependent variables. The proposed framework is shown in Figure 1.

Based on the assumption that both exposure types, personalization exposure (H1) and AI-based recommendation exposure (H2), affect the purchase intention/behavior directly as well as indirectly via consumer trust, the hypothesis is presented in Figure 1.

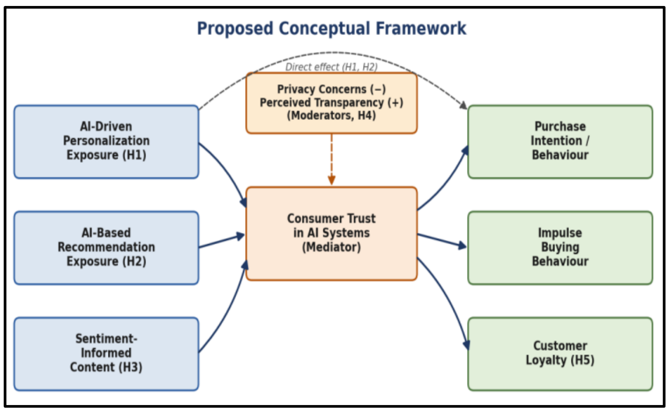

Figure 1: Proposed conceptual framework linking AI-driven inputs, consumer trust, and purchase-related outcomes.

Based on the assumption that AI-based personalization exposure (H1) and AI-based recommendation exposure (H2) affect purchase intention/behavior directly, and indirectly via consumer trust, the hypothesis is presented in Figure 1. Sentiment-informed content (H3) is expected to further build trust, due to its perceived emotional relevance and attunement in interactions with AI. As the main mediating construct, consumer trust is predicted to impact all three outcome variables positively, purchase intention/behavior, impulse buying, and customer loyalty (H5), aligning with the results of the trust-centered studies [10, 15]. Personalization–privacy concerns and personalization–perceived transparency are expected to moderate the relationship between personalization and trust, respectively: privacy concerns are expected to dampen the positive effect of personalization on trust, whereas perceived transparency is expected to amplify it, consistent with the personalization–privacy paradox reported by [7, 9].

8. Future directions and discussion

This paper is in the proposal and literature-synthesis phase, with no primary data was collected. The pattern of expected outcomes, in light of the conceptual framework and the empirical background literature, is discussed in this section rather than the results of the implemented study. The expected results listed are meant to help guide hypothesis testing when the proposed survey and interviews are administered and should not be interpreted as empirical results.

Table 1 summarizes the five hypotheses derived from the framework, their anticipated directions, and the literature supporting each expectation.

In addition to the individual hypotheses, the framework as a whole is expected to be supported by the study results, indicating that consumer trust is the strongest single predictor of purchase-related outcomes [10], who found that trust can be a stronger predictor of purchase decisions than personalization exposure alone. When it comes to the direct impact on purchase intention, it is believed that personalization and recommendation exposure will still have a direct effect, albeit less pronounced, given the documented decreases in search effort and increases in relevance [4, 11], respectively. As anticipated, consumers with greater data-privacy sensitivity are expected to experience stronger moderating influences of privacy concerns and transparency [7].

Table 1: Hypotheses and supporting literature for the proposed AI-driven consumer behavior framework.

Hypothesis	Statement	Expected Direction	Ref.
H1	AI-driven personalization exposure positively influences purchase intention/behavior.	Positive (direct & indirect via trust)	[3, 10, 11]
H2	AI-based recommendation exposure positively influences purchase intention/behavior.	Positive (direct & indirect via trust)	[4, 14]
H3	Sentiment-informed content strengthens consumer trust in AI-driven marketing.	Positive	[5, 12]
H4	Privacy concerns negatively, and perceived transparency positively, moderate the personalization–trust relationship.	Negative (privacy) / Positive (transparency)	[7-9]
H5	Consumer trust positively influences purchase behavior, impulse buying, and customer loyalty.	Positive	[10, 15, 16]

However, the themes that emerge from the interviews should be similar, at a qualitative level, to those found in other mixed methods studies [7]: trust and skepticism towards AI recommendations, emotional reactions (appreciation/discomfort), heterogeneous awareness of data collection practices, and a connection between highly personalized recommendations and impulse buying. If the results of the empirical testing in the future do not confirm the pattern anticipated in this paper, but rather diverge from it (e.g., if the privacy concerns exhibited no significant moderating effect), that divergence would also be a noteworthy finding that would require a deeper inquiry into the contextual or cultural factors not fully covered in the proposed framework.

9. Conclusion

This paper explored artificial Intelligence and how it can be used to analyze, anticipate, and respond to consumer buying habits through the analysis of consumer behaviour and the application of artificial Intelligence, machine learning, big data analytics, and natural language processing. The paper presented a structured literature review tracing the evolution from rule-based marketing to AI-driven personalization, recommendation systems, sentiment analysis, and conversational agents. It showed that these technologies are consistently effective not only when they involve cutting-edge technology but also when consumer trust, perceived transparency, and privacy concerns are considered. Based on this review, the paper identified a set of specific gaps, including (1) the lack of integration of AI applications in different strands of research and the (2) lack of integration of ethical constructs into behavioural models; (3) limited use of mixed-methods designs; and (4) thin empirical coverage of emerging AI technologies, and developed a corresponding set of research objectives, a conceptual framework, and a mixed-methods research methodology designed to address them.

In theory, the paper provides an integrated framework in which consumer trust emerges as the key factor linking AI-driven personalization, exposure to recommendations, sentiment, purchase intention, impulse purchase, and customer loyalty. At the same time, privacy concerns and perceived transparency serve as boundary conditions. Theoretically, the paper provides an integrated framework in which consumer trust emerges as the key factor linking AI-driven personalization, exposure to recommendations, sentiment, purchase intention, impulse purchase, and customer loyalty. At the same time, privacy concerns and perceived transparency serve as boundary conditions. In practice, as suggested by the proposed framework and the hypothesized relationships, the sophistication of an organization's personalization algorithms is not the only aspect that should be invested in, but rather the integration of transparent and trust-building data practices, as the literature reviewed in this article confirms that trust, rather than the sophistication of the algorithm alone, is what makes AI-driven insights result in purchase behavior and long-term loyalty. The following propositions, however, shall be tested empirically by the mixed methods design.

The restrictions of this stage bind the paper. The literature-based character of the proposal means that its conceptual framework and expected outcomes have not yet been empirically tested; the hypotheses must be tested using the mixed-methods design before any firm conclusions can be drawn. The scope of the review also did not include empirical discussion of emerging application types such as Emotion AI, generative AI-based content, or AI-augmented Metaverse/IoT shopping environments. The proposed framework should therefore be tested empirically with a variety of consumer groups and industries, longitudinally over time as AI systems increase in capability, in the context of personalization through Emotion AI and generative AI, and through creating and testing ethical AI governance frameworks for consumer-facing marketing contexts. Following these directions would help ensure that AI-powered consumer behavior analysis delivers commercial value and protects consumer trust, autonomy, and welfare.

Data Availability Statement

This paper is submitted in the literature review and proposal phase – no primary data have been collected yet. Once data collection, has been completed, data will be made available upon reasonable request by participants, subject to participant consent and institutional ethical approval.

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