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Artificial Intelligence in Digital Marketing: Impacts on Consumer Decision-Making and Privacy Concerns

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Abstract

This paper describes how consumer decision-making will be revolutionized by the use of artificial intelligence in the future, as reflected in product recommendation systems, chatbots, dynamic advertising, and voice assistants on digital marketing channels. In this paper, findings are presented from a survey carried out among a sample size of 327 respondents addressing the effectiveness of CO in the consumer journey, the stage at which AI is most used in the consumer journey, emotional involvement, and perceived privacy. The findings indicate that artificial intelligence is most effective for supporting decision-making in the evaluation stage of the buying cycle (i.e., between the decision stage and the purchase stage). Crucially, personalization and continuous engagement are crucial to generate satisfaction and loyalty - recommendation centers were the biggest impact driver, while chatbots were seen more for enabling additional support, brand information retrieval, and interaction. As far as post-purchase consumer satisfaction, the voice assistants were either far too verbose, very directive, but there were flashy red flags and privacy accuracy concerns. In determining the research model, this study uses the Technology Acceptance Model and the theory of algorithmic trust, and combines them in the explanation of the working mechanism of the generative trust and emotional synchronism on the adoption mechanism of artificial intelligence in marketing. The take-home message of the study was that while AI undoubtedly improves educational efficiency from an operating perspective, personalization, and consumer engagement, its long-term contribution to the overall bottom line with respect to adoption will be due to transparency and a responsible perspective towards the consumer.

Keywords: Artificial Intelligence, Digital Marketing, Consumer Behavior, Personalization

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1. INTRODUCTION

The development of the computer age has brought about a complete change in marketing and also in the buying decisions on the part of consumers. Artificial intelligence is perhaps one of the major disruptive superstars evolving to be one of the fundamental cores of modern digital marketing communications. Timely applications of artificial intelligence include statistical machine learning algorithms, predictive analytics, and natural language processing are used, for example, to understand consumer preferences, to tailor marketing content online that replies individually, and decision support systems are automated to improve engagement and customer satisfaction (Chatterjee et al., 2020; Kumar et al., 2021; Amir et al., 2025). The consumer decision-making processes have generally been understood as almost always through cognitive as well as behavioral models like Engel-Kollat-Blackwell and, of course, the well-known Five Stage Purchase decision process of Kotler and Keller (2016), with need recognition, information search, evaluating alternatives, making the purchasing decision, and post-purchase evaluation, among other models. Without a doubt, there are still very relevant ones; however, artificial intelligence is revolutionizing at every single step. Intelligent marketing systems allow predictive modeling, which gives the consumer an even better idea of needs, recommendations in line with searching and evaluating environment during consideration, and, finally, seamless decision making in consideration of bringing closer the most

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relevant products or services. The very post-purchase phase (like nothing new under the sun) has been transformed into an entirely different world through artificial intelligence-enabled interactive feedback mechanisms, which encompass higher customer satisfaction and visitations (Davenport et al. 2020; Shaukat et al., 2025).

Artificial Intelligence has made inroads in all corners, such as personalized consumer interaction in marketing. Whatever the case, chatbots, virtual assistants, and conversational interfaces simulate on a much closer level to a person, interact with customers through real-time answers to questions, provide purchase help, and offer service enhancement. These systems not only replicate, but they are getting wider in the immersion of frontline services due to them being all-time available and dealing with an extensive amount of units of communication that in human life will never be known in detail (Brandtzaeg and Folstad, 2018; Imran et al., 2021; Aman et al., 2025). Therefore, unlike previous products where the customer is made to adjust the carbon output, with this low participation into choice the cognitive load of choice is diminished, to enable the customer to make decisions fast, but more confidently. AI has been, therefore, attributed not only to accelerate the old school approach to marketing but, in fact, as an agent that has redefined the game of consumer behaviours in the online age. After all, the fruits of hastened uptake of information-based advertising has worked meticulously in setting AI as an invaluable tool of transformation to transform consumers' decision process. AI systems use predictive knowledge gained from consumer purchase history, browsing behavior, and of course demographics so that marketers can target the right people with unparalleled precision. This type of personalization not only increases customer engagement but ensures that companies can use their resources even more efficiently since they are able to target distinctly segments of their target audience that would be more likely to respond to certain types of campaigns (Rust 2020; Zafar et al., 2025). Perhaps the most popular application of artificial intelligence is the analytic-level identification and display of purchasing or browsing behavior in order to present recommendations on the shopping site amazon, income from which enterprises are particularly large (McKinsey & Company, 2019). While Netflix has also enabled the implementation of levels and retention (consult Gomez-Urbe & Hunt, 2015), it has allowed the implementation of content recommendations that use the mathematics of collaboration filtering together with consumption viewing (imbalance of consumption viewing) tendencies (Imran et al., 2024; Ullah et al., 2025).

Yet, not without condemnation and several other problems, the rapid pace of development and impact of artificial intelligence on consumer behavior have directly and indirectly. The worst of these are the ones referenced by the idea of echo chambers based on algorithmic decisions: they reinforce preferences and exclude diversity and other options. However, Consumer autonomy would be infringed upon through processes such as individualization, even with over-personalization, which would be seen as harassment or manipulation by consumers (Mittelstadt et al., 2016; Karim et al., 2025). The single trait describing the AI world above all is that it is opaque and that's exactly what makes it business relevant. "Black box" models are those that prefix algorithms that are not implemented on the level of transparency that consumers, regulators, and even some developers don't really know how decisions are being made (Wachter et al. 2017; Ali et al., 2025). The ethical and regulatory issues associated with interpretability requirements are finding voice in an increasing number of stakeholders; accountability, fairness and trustworthiness mechanisms that refer to the applied notion of the aim in the field of digital marketing. Amidst all these moral conundrums there is a growing use of Artificial intelligence in the area of marketing, which is followed by an exponential curve in its growth. Recent industry surveys, such as Salesforce's report on the adoption of AI by marketers in their digital marketing efforts reported (Salesforce, 2022; Khalid et al., 2025) project that nearly eighty-four percent of marketers are leveraging AI in their digital reporting, providing additional backing to this development and to its use as make or break development. With such a massive adoption comes the dramatic redefinition at what it really means to practice marketing, how it's actually practiced, and the meaning and implications of digital interaction with consumers. Of fact, the boost in artificial intelligence in this space leads to an artificial intelligence renaissance in marketing practice, and an intriguing new trend in discovery, in terms of the psychological, behavioral and affective results. In particular, the behavior of consumers, as displayed in response to digital stimuli mediated by intelligent systems, has to be critically considered starting from the perspective of their establishment of trust, autonomy, of the decisional context, and values perception.

With this background of the Pacific region, the current paper seeks to explore the different effects of artificial intelligence in the decision-making process by consumers in the digital marketing field. In addition, there is also the examination of the cognitive base under which the artificial intelligence acts, in the way it impacts the perception of consumers, which implies trust, choice architecture and satisfaction, among others. Coupled to this, many burning issues around privacy, algorithmic bias and ethical intervals are rapidly moving into the key roles within consumers trust in digital markets; using a dual-customer marketer approach undertaking for this survey, a comprehensive scope for the trans operative AI emerges. This conceptualization is also well-suited to understanding the role of intelligent technologies in the determined structure of the digital marketplace, to grasping the cognitive and behavioral dynamics that inform 21st Century consumer behavior.

2. LITERATURE REVIEW

Commitment to AI There is already an incredible impact of algorithmic patterns on consumer behavior and decision-making. And with the growing interest in digital marketing systems, the floodgates of scholarly interest opened for an investigation into how it affects the consumer behaviour. Most previous work will say that technical thresholds of artificial intelligence are speed of processing of data, advanced algorithms, prediction accuracy, etc. In more contemporary ones,

psychological and cognitive implications of AI on consumers were added by more research providers. In that regard, some prior studies associate AI with personalization, distraction drawing ability, emotional support, and consumption behavior and consequently, shifting the consumer-brand interaction process as well (Huang & Rust, 2021; Hashmi et al., 2025). The main objective of this series of studies is to search out empirical and theoretical contributions that could contribute to the understanding of the deeper nature of the intuition of intelligent systems that can reset the digital consumer journey.

Perhaps most controversial of all the AI applications for marketing are those that promise to make a hyper-personalization effect. Based on sophisticated machine learning engines, the AI systems can more precisely target individual consumers with customized marketing messages and content based on someone's micro-level behavior and preferences, as well as real-time contextual information about where someone is. This makes the communication policy of the marketers a very specific one - the communication is recitation but one by one - and of course, we are able to understand this. And one step further as pointed out by Sun et al (2019), Arthur says that the AI-powered personalization engine to drastically reduce bounce rates, enhancing consumer engagement and conversions by determining consumer intent with spooky accuracy. For instance, AI in retail, which allows a retailer to use tons of data including unstructured data such as social media interactions, search history and browse history can help to accurately understand consumer purchase intent and predict what consumers want to buy. This technology is an incredible revolution in the role of marketing work. This is going to change the paradigm of mass targeting - and it's just one step out of one experience live. In other words, intelligent systems are learning to deliver even more relevant, timely and compelling consumer experiences, by adapting the recommendations, dynamically refining the product information and content and by tailoring the advertisements based on their understanding of all the real world events. AI should be able to drive marketing interaction like a human being; one that improves customer satisfaction and facilitates better decisions, a better brand. But the impact of AI is not limited to efficiency, it is an abysmal catastrophe that pervades the psychic pattern of symbolic behavior of customer selection of the digital marketplace (Sabir et al., 2025).

This means that consumer psychology ATT, or with artificial intelligence tooling, represents the ways that both perceived and actual decisions being made during any one choice to be involved in any given risk assessment, choice, or associated steps inherent in actual outreach, are dramatically framed. In addition, empirical engagements show that when AI makes a recommendation to its constituent members, it is more likely to be responded positively to. For instance, Cowan and Ketron (2019) stated that cognitive trust would be increased when consumers are confronted with the products that are recommended by AI. For their study, the approach and findings of the authors were based on the finding that algorithms are perceived to neutralize consumers' will and therefore consumers give recommendations made by algorithms more credibility and authority than they would otherwise confer. Finally, they reveal that consumer expectations of AI, as regards intelligence and autonomy, also have far-reaching effects for trust in decision-making, because it implies that the sophistication of algorithms is a key determinant of the consumer's trust in the results.

Trust in AI systems has been compared to trust achieved in a human relationship, e.g., in the context of research. Lankton de Lens et al. (2015) characterized such trust for an organization that is developed not only based on perceived competence but also based on benevolence and integrity, just like the trust developing between humans, like human relationships, and that is called human trust. When artificial intelligence recommendations are dependable, stable, their users would feel not only competence, but also benevolence; and hence they would be imbued with confidence in the processes of judgment by means of which they have been persuaded. These all point to the need for efficient artificial intelligence systems and the fostering of concepts such as integrity and consumer intention.

The second new area of research has been directed to dealing with emotional experiences provoked by the use of artificial intelligence in marketing contexts. Weight tech, emotive digital controls, or to be more precise, intelligent technology with recognizable and responding emotion, was able to introduce yet another dimension to the digital advertising world through the old emotion learning agents. Cummings, Orbaugh, Sussell, & Vandy (2018) stated that these systems regulate their marketing communication in real-time in reference to the emotional condition of the consumer using either some computation, such as a sentiment analysis or facial recognition. We predicted that such responsiveness would lead to user happiness and the development of brand loyalty, while consumption time on the IT platform would be increased. For example, emotional AI applications seem to be able to prolong a consumer interaction, but also make it more likely to lead to a positive purchase decision (Holthauer & Schumann, 2020; Ghauri et al., 2025).

Just to connect the dots, the importance of leveraging sentiment-based AI becomes more apparent if we talk in-depth about products where sentiments are at the core of the buying process. The culture is predominantly consumer, the dominant industries are those of apparel, consumer electronics, and health services, and so it is the agroecosystems of consumer understandings of subject, credibility, and wellbeing that must be tended to, if we are to deal with the hyperadaptive advertising which promotes such reactions. In such a circumstance, artificial intelligence systems associated with synchronizing their speech and behavior in accordance with the impressions of consumers will bring not only higher sales, but also develop the consumer brand reconstruction, as the consumer has a long-term relationship. This is the way the future of digital marketing will be. This is why, from the point of view of technology-designed behavior change, the contribution the psychological and emotional insights may be pertinent to how to conceptualize in what direct way technology does reshape consumptive behavior (Kodithuwak & Pacillo, 2025).

In addition to the vast functions surrounding personalization and emotional engagement, AI technology is rapidly being incorporated in decision support systems - the crystal ball helping consumers to make ever more complex buying decisions,

literally at their fingertips. Shorter conceptual and quantitative comparisons between products have been compressed from a much larger body of information, such as predictive modeling or natural language generation. More specifically, the products of the interested people related to the subject should be condensed into the abstract, or the commentaries should lead to the parent narrative to relieve some of the burden of going on a death march to a consumer's brain, perhaps overloaded with excessive information. Several applications have made the assumption, according to Kietzmann et al. (2018), that information in organizations is oversaturated; thus, pre-filtering information on all results that consumers are interested in online commerce can help to reduce it significantly. Although the above paper was a caution on these systems, it stated that while they may make it easier to participate in decision-making, they also have the potential to make users more susceptible to confirmation bias. Further, they contend, artificial intelligence agents operating on information that is mapped to the consumer's interest space are able to narrow the types of options that the consumer is shown - for example, inducing them to make heuristic choices that can restrict the options even further taxonomically.

This situation has given way to a more global ethical discussion about artificial intelligence and what that means for consumer existence in terms of autonomy and free will. Solutions enabling AI-driven recommendations, while they increase efficiency, are also to blame for subtle shifts in consumer behavior, benefiting corporate, not consumer interests, scholars say. According to Zuboff (2019), surveillance capitalism is a practice where investment firms of artificial intelligence cease to passively respond to stated needs and instead actively aim to shift user behavior in line with organizational profit goals. By causing much human behavior (whether the behavioral interventions are subtle or not), the pressures and manipulations are extremely contrarian to independence in that they cause outcomes (issued by humans) to be definitively discordant with the individual's own definitively independent decisions. Equally, for Pasquale (2015), the lack of transparency of the decisions made by algorithmic systems constitutes an important object of criticism, the 'black box' quality that tunnels the decisions made and thus favors opacity. However, these algorithmic systems have issues of not being multimodal, being transparent or accountable, and this is putting a strain on consumer confidence and raising unfair or potentially fair issues in the practice of digital marketing.

As a result, the Technology Acceptance Model and its diverse prolongations have been widely applied to explore the interaction and perception of users in connection with AI interfaces, in a technology adoption context. Similarly, in the original formulation of Venkatesh and Davis (2000), the acceptance variables were perceived usefulness and perceived ease of use. Such representations still hold some significance in light of the thought process about acceptance of the artificial intelligence-enabled marketing systems. Internal design styles become more and more anthropomorphic and Casement-like. For instance, Xu et al (2020) showed that when elucidative human-like behavioral systems, on the other hand, are leveraged, consumers enjoy positive AI system acceptance and trust; however, at the same time, they feel as if they can exert some level of influence on the decision process. That is, the results have indicated that the acceptance process of an AI system is associated with function and the recipient's affect of psychological expectations, such as trust, control, and authenticity of relationships.

Until now, interaction with digital systems has been made a little licentious and constant toward one's manager or a user via the biggest voice-based artificial intelligence interfaces on the market, the Amazon Alexa and Google Assistant. These platforms can help AI move beyond text-based interfaces to a more naturalistic and humanlike interface. It has been documented that the use of the voices should have characteristics related to the personality and to us, as it can infer user characteristics which may influence the user's emotion and behavior. For instance, Purington et al. (2017) showed that the engagement level of voice-based assistants (VAs) depends on people's association of gender or personality traits of these VAs. As such, marketing messages captured through voice interfaces may be differently understood than marketing messages captured through more text-based approaches and suggest the psychology of anthropomorphism in AI agent interactions.

Another area of development within this literature is the cross-cultural research that takes place via the study of differing consumer (re)actions to marketing applications of AI. As a matter of fact, these studies suggested that there is a culturally value-laden way of communication with AI systems. For instance, Gursoy et al. (2021) concluded that consumers from collectivist cultures (consumers from China and South Korea) were more likely to perceive AI systems to be more trustworthy and to be more comfortable with recommendations made by such systems as compared to consumers from less collectivist cultures. By comparison, participants from the United Kingdom and the United States (more individualistic societies) were more concerned about the invasion of privacy and more skeptical of machine-based decision making. This implies that cultural orientation systems have important, unique predictive roles on the dimensions of attitude towards artificial intelligence, its value, which varies significantly across cultures (e.g., trust in artificial intelligence, privacy expectation).

On the one hand, previous research has addressed the constantly emerging impacts of AI on the behaviors of consumers by way of a biographical approach: personal humanization, emotional connection, and decision-making information (Huang & Rust, 2021; Sun et al., 2019; Kietzmann et al., 2018; Salleh & Sapengin, 2023). When it comes to CM driven by AI, the (few) literature was mostly concerned with its technical operations and adoption (Venkatesh & Davis, 2000; Xu et al., 2020; Akim, 2020; Owusu & Novignon, 2021) but lacked in addressing the issue of change in consumer agency, emotional trust, or ethics when consumer moves through multiple steps in the decision process. A number of them have demonstrated potential to increase efficiency (Cowan & Ketron, 2019; Tila & Cera, 2021), emotional appeal (Cumming & al., 2018), but

also the risk of oversimplification, echo chambers, and black-boxisms of algorithmic machines that may destroy freedom of choice or trust (Pasquale, 2015; Zuboff, 2019). Finally, there is ample findings in culture regarding how reactions to AI differ across communities, but again the comparative data does not seem to be rich and systematic (Gursoy et al., 2021). The impacts of AI in the decision-making process have been left with the absence of account of the psychological and behavioral process responsible for effects of certain types of AI in particular ways, therefore in the context of the design of AI with improved decision efficiency, transparency ethics, and emotiveness. This paper aims to address the gap by extending the Technology Acceptance Model and the algorithmic trust hypothesis to offer a consumer decision making in the digital marketing context empirical investigation of AI, offering some new insights regarding the opportunity in the transformation paradigm of AI.

3. METHODOLOGY

Artificial Intelligence and Consumer Behavior survey designing in the field of digital marketing is a research paper that makes use of quantitative tools. The theoretical framework is answered through using a carefully selected structured questionnaire which is designed to be given directly to an on-line heterogeneous sample of consumers. The method of survey was not a matter of chance because it can enable a series of interviews to take place with a reasonable size and diverse population in a relatively short space of time. The advantage of the latter, over time, goes beyond an economical estimate and time-saved opportunities, to opportunities for statistical evaluation aimed at identifying patterns, relations and finding generalizable conclusions. The survey data collection was cross-sectional in design due to the need to capture consumer perceptions, attitudes, and behaviours at one certain 'point' in time. Such design possesses special purposes for the modern form of digital serving of marketing where through the use of artificial intelligence developing tools and platforms that shift the interaction between the consumer and the service provider from a physical state to a virtual one. This approach will enable the study to reflect the ways consumers view themselves as being influenced by artificial intelligence in the way that they make decisions, as well as the way functions are processed as well as purchase decisions made in online settings. Also by virtue of the cross-sectional nature of evidence, a real time picture of current trends with implications for policy and business effectiveness for businesses and marketers who are making an effort to time their strategy to respond to changing trends in consumer behaviour in technologically-mediated markets.

3.1. POPULATION AND SAMPLING

The study population was active online shoppers 18 to 50 years of age who had interacted with an Artificial Intelligence marketing application, made-to-measure, product recommendations, conversational chatbot, and automated, digital advertisements within 6 months before the study. Non-probability purposive Sampling was followed to ensure that the participants a previous knowledge of such AI applications in a digital platform was fitted. This approach was adequate because it meant that respondents who were deemed as relevant in carrying out the research were included in the study in a formal manner to build confidence in its result.

Data harvest and utilization by means of online digital mediums (social media, email lists, and online consumer forums). A sum of 450 people were invited to participate in the survey. Of these, 327 were actually eligible to respond to the entire questionnaire and the resulting response rate was 72.6 percent. This level of engagement also gave credibility to the sampling strategy and reinforced the willingness of the identified consumers to share their perceptions and experience of Artificial Intelligence-based marketing tools which they had been formerly granted access to.

3.2. INSTRUMENT DEVELOPMENT

This study is based on the criteria of methodological rigor, whereby adapted and improved existing validated measurement scales from past studies. The study design also established a structured questionnaire by making appropriate modifications to accommodate the current understanding of Artificial Intelligence in digital marketing. The whole survey instrument has been dismantled into 4 large parts. The first has demographic information about respondents, the second with frequency and forms of ART, the third to include perception items for trust and perceived utility of ART-based tools, and the last with hypothetical evaluation about the aspects tools would have on the steps of the consumer decision process.

Important constructs of power payer in Artificial Intelligence, perceived personalization, decision confidence, or emotional influence were operationalized using items from a 5-point Likert Scale (response range of "strongly disagree" (1) to "strongly agree" (5), respectively). The result of the scaling method achieved was a quantitative description of the subjective side effects experienced, and allowed statistical comparison and interpretation to be made between the various subjective side effects. For a pilot study, 30 sample participants were also tested for false positives in an instrument test. Feedback from this pilot resulted in the refinement of the clarity of wording and structuring in most of the survey items. The robustness of the instrument was demonstrated in the pre-test, with Cronbach's alpha values for the major constructs being from 0.76 to 0.89 values which shows an acceptable to high degree of reliability and internal consistency.

3.3. DATA COLLECTION PROCEDURE

Data collection for this study took place over four weeks using online survey platforms-Google Forms and Survey Monkey. Every participant was introduced to the informed consent statement before attempting the questionnaire. This statement details the aim of the study, indicates that participation is purely voluntary, and emphasizes that respondents can withdraw from it at any time without being penalized. The confidentiality of the information provided was assured, and participants were requested to confirm their consent before proceeding to fill out the survey.

By design, the anonymous nature of the survey minimizes the possibility of response bias and promotes frankness in answering. The respondents took, on average, 8-10 minutes to complete the survey, making it relatively short and convenient, thus enhancing accessibility over various digital platforms. Data cleaning and scrutiny of the responses were then carried out to eliminate duplicated submissions and incomplete entries before analysis, improving data quality and, as a result, the validity of subsequent statistical results.

3.4. DATA ANALYSIS

The collected data were exported to the SPSS package, version 26, for analysis. Descriptive Statistics was applied primarily to overview demographic features of the respondents and general interaction patterns of the respondents with AI-oriented marketing tools; that is, in a survey of the sample profile and ground for inferential testing.

The hypothesized relationships were also estimated using correlation measures, which is a method of understanding the direction and strength of correlation between the study variables. Then, multiple regression was conducted by showing the effect of the multiple independent constructs, trust in AI, frequency of use, and perceived personalization, are what triggered the dependent major constructs, informed purchasing steps by the consumers, and an emotional bond with the AI marketing. The exploratory factor analysis was also conducted to look at constructs as well as validity. By grouping the measurement items into their theoretical domain appropriately, it ensured the proper establishment of the construct validity. On the other hand, the statistical significance levels of all the inferential tests have been standardized at the traditional level of $A p > 0.05$, which provides the foundation for identifying the data robustness and data reliability.

4. RESULTS AND DISCUSSION

The demographic information, as shown in Table 1, is given by the age and sex of respondents and will enable us to assess the extent to which the sample population reflects the wider population. By far the most prominent are the 25-34 years, the number of respondents in this group being 129; among them were 68 males, 55 females, and 6 respondents designated as nonbinary and other. This suggests that most respondents are young adults from early in their professional careers or having just completed graduate school, and who are likely to be very relevant in studies on financial, technology, or consumer behavior. Another age range that is highly represented after the 25-34 years range is 18-24 years, with 88 < respondents representing a good representation of this age group from the university population. Female respondents are also fairly equally represented, at 38, as are males at 45, with 5 non-binary respondents, which clearly supports the movement to include people of any gender identity or sexuality in research design.

In the 35-44 age group, the number of respondents decreases to 71, and again shows a predominance of male respondents (39), followed by females (29) and a small number of non-binary individuals (3). Finally, the 45-50 category is the smallest, with only 34 participants overall. This lower representation from older adults may reflect the sampling method, possibly skewed towards younger populations who are more reachable through digital platforms or university networks. Overall, the distribution is diverse but youth-oriented, with a modest inclusion of non-binary individuals, which is a positive step toward gender inclusivity in research. The data suggests a potentially tech-savvy and economically active demographic, which may influence the interpretation of behavioral or attitudinal results derived from this survey.

Table 1: Demographic Information of Respondents

Age Group	Male	Female	Non-binary/Other	Total
18-24	45	38	5	88
25-34	68	55	6	129
35-44	39	29	3	71
45-50	22	11	1	34

A frequency distribution of how commonly artificial intelligence tools are used by respondents in year 4 across four categorical levels of their mentioning (daily, weekly, monthly, and rarely or never) is displayed in Table 2. The data shows that the most common artificial intelligence tools are product recommendation systems, where a significant number of respondents reported using the recommendation system daily compared to other tools. The present pattern shows that product recommendations are perceived to be an important aid for consumers to maneuver through the digital platforms and the decision to purchase product electronically from any source of accessing the digital platform is consistent with previous studies which help in influencing the consumer decision and consumer satisfaction (Gretzel (2011); Kapoor (2022); Kapoor, Isvilen, and Walczak (2022). Furthermore, recommendation systems appear to be appreciated due to the possibilities of individualizing content and making a decision. Just under product recommendation, chatbots are also generally high on the user engagement rate every day. This means that it's becoming even more valuable in the customer support and transactional service space. Prior work also mentions that chatbot interaction has shown a knowledge preference for efficiency as it relates to some type of immediate feedback, but a user satisfaction result is not only an effect of the naturalness of the interaction, but also the ability to answer questions to user satisfaction (Hill et al., 2015; Folstad & Skjuve, 2019). Nevertheless, the number of respondents who claimed that they use little or no chatbots at all appears to legitimize the

critical attitude surrounding purely automated communication platforms per se, while also supporting prior studies showing immunostimulated approaches such as trust and authenticity in HMI (Brandtzaeg & Folstad, 2017).

Voice assistants, on the other hand, spread more evenly across user categories, with many numbers below the averages using them daily, and a very large number continuing to use them on a weekly or monthly basis. So, it seemed probable that while voice interfaces such as Amazon Alexa and Google Assistant have started to make an appearance, they are still limited from mainstream use by accuracy and context-awareness issues, and even social-cultural histories of acceptance (Hoy, 2018; Pradhan et al., 2019). A significant percentage of respondents who claim to use rare and not suggest the ambivalent attitude toward voice-enabled AI, which is also backed up by a research finding that privacy and trust in voice-enabled AI have prevented AI integration in everyday life (Lau et al., 2018).

"Though the advertising instrumentation is moderately polar, though (they are counted on daily and weekly), the percentage of infrequent consumers outweighs advertising dollars. This behavior implies that active digital advertising will be conducive to achieving consumer engagement, but reveals at the same time that consumers have a resistance to being exposed to advertising on a personal basis regularly. Although dynamic advertising may better personalize to users and boost purchase intent, scholars suggest that too much exposure or poorly crafted campaigns may result in advertising fatigue that decreases their impact over time (Bleier & Eisenbeiss, 2015; Boerman et al., 2017). Although the advertisers of the table seem to have employed the dynamic ad application successively and uncomfortably, evidence suggests that their performance was contextual and envisages its reception on consumer willingness and ethical application.

In general, both in terms of response distribution, following the response distribution overseen in Table 2, there are fragmented patterns resulting from the adoption of artificial intelligence tools, for example. Product Recommendations have by far the most integration (although even more categorical can be said on chatbots functioning in transactional contexts, voice assistants functioning in an environment of both acceptance and rejection at different, but rising, rates, and dynamic ad solutions). These results are consistent with the general literature, which reports that personalization, trust, and perceived utility as the most significant factors that motivate the continuous application of artificial intelligence in the digital economy (Davenport et al., 2020; Gursoy et al., 2019).

Table 2: Frequency of AI Tool Usage

AI Tool	Daily Users	Weekly Users	Monthly Users	Rarely/Never	Total Responses
Chatbots	120	70	50	87	327
Product Recommendations	145	110	40	32	327
Voice Assistants	80	90	70	87	327
Dynamic Ads	95	85	65	82	327

The average scale Likert scores from the user perspective of whether or not the artificial intelligence scale helped reduce bias, whether it was easy to use, and how trustworthy the user perceived the artificial intelligence system, are displayed in Table 3. There is still a striking difference when it comes to all instruments, with the voice assistants being the most trusted and felt to be precise and relatively comfortable, though. Decompressing the data obtained, the evaluation expressed in these voice assistants was found to have medium accuracy and trust; thus, these assistants are not only useful to inform the user but also to perform the task. This is consistent with prior studies in which voice-enabled solutions such as Amazon Alexa and Google Assistant have been argued to have become preferred companions in times of crisis due to their natural language understanding/natural language processing capabilities, and quick response to requests (Lopatovska & Oropeza, 2018; Hoy, 2018). At the same time, the high levels of trust also reflect a sense of acquaintance and routine use of the technology, in that at some point the barrier and user confidence is lowered due to the sinking of the ship, as voice-enabled technology remains present in one's life (Cowart & Butler, 2018).

In contrast, the product recommendation systems yielded the lowest scores in all three dimensions, with the dimension of trust having the highest downscore. From the YP example, we determine that product recommender systems are used in a microscope and that, as stated in frequency-based analysis before, objectivity and accuracy are still biased according to the consumer's vigilance towards product recommender systems. Lastly, for product domains with a presumed low degree of consumer trust, an algorithmic bias that regards recommendations as less personalized and more geared towards the business interests of the algorithmic companies might have contributed to low trust. However, past works indicate that users tend to frequently distrust that recommendation systems are a preferred match for their own actual preferences and are biased towards recommendation of products that offer a higher margin (Awad & Krishnan, 2006; Xiao & Benbasat, 2018). This intersection then embodies the ambivalence which consumers direct at recommendation technologies; they use them when it's practical for them, but at the same time they distrust their ulterior motives.

Results show still moderate accuracy and trust scores while usability scores are on the low side. The moderate trust level in the survey suggests that although a great number of users think there is some value for them to chatbots - provided there are aspects of usability based on these dimensions which facilitate their further development than ever before. This validates

existing studies, indicating usability pitfalls to be a large and general barrier to chatbot acceptance, when it was perceived as too robotic or not able to solve genuinely complex problems (Ciechanowski et al., 2019; Folstad & Brandtzaeg, 2017). Chatbots' ability to mimic humanlike converse and sometimes provide comprehensible responses is highly influencing customer trust. Therefore, trust does not work in the same way as voice assistants, with recommendable numbers and product rankings. The dynamic advertising technologies were tested at the intermediate level of the scale, which shows medium levels of reward in all three dimensions, that is, accuracy, usability and trust. This is even true in the context of targeted ads in the consumer experience, which is a paradox as there are numerous types. Yet if these users can be attracted by personalization techniques, they also harbor greater distrust in data collection and data processing practices, so much so as to withdraw trust (Boerman et al., 2017); backlash so intense, however, that each user is too paranoid to even click adverts for services, respectively. In comparison with earlier results from Table 3, these scores reflect a fairly well-balanced perspective (but with relatively low scores on advertising), i.e. that dynamic advertising seems to have a certain influence on people's purchase decisions - but equally that privacy and perceived intrusiveness play a significant role in determining consumer trust (Van Doorn & Hoekstra, 2013).

From the result of Table 3, it can be stated that there is very large variance on users' perceptions and trust towards the artificial intelligence tools. First, voice assistants come up as the most trusted of all of these AI systems, while recommendation systems suffer from a certain amount of suspicion despite being used pretty regularly. Chatbots, on one hand, and dynamic advertisements, on the other, can be seen to occupy the middle position in terms of acceptance and some identification with usefulness. The previous results on human-AI interaction point out that the AI trust is not monolithic but heterogeneous (Gursoy et al., 2019) and they provide various examples from other works, which also demonstrate that trust in AI is dependent on perceptions of acceptability (Davenport et al., 2020; Feigenbaum et al., 2017).

Table 3: Trust in AI Tools (Average Likert Scores)

AI Tool	Perceived Accuracy	Ease of Use	Trust Level
Chatbots	5.1365	1.3513	5.864
Product Recommendations	2.4497	2.1502	2.05
Voice Assistants	9.3161	4.0307	9.5544
Dynamic Ads	4.1575	4.1961	5.2936

The complexity of the use of AI devices in the various stages of the consumer decision process is demonstrated in Table 4. The surveys indicate that AI has its biggest influence on alternative analysis, a claim for which the proportion of consumers admitting an influence was extremely high. This discovery implies that artificial intelligence, through product recommendation engines, dynamic advertising, comparison sites, and so on, is a major controller in shaping preferences within the limits and emphasis in the realm. Earlier research has further intimated that algorithmic personalizations are justifiable for consumers in assessing multiple products with ease and, as a result, reducing the cognitive effort of coming up with a final choice while initiating satisfaction toward the alternative (Hauser et al., 2009; Tam and Ho, 2006). Thus, Enantia can have a profound impact on manipulating consumers towards making an optimal use-case creation when adopting AI. The post-purchase phase appears to be the second most affected, where, after the transaction has been made, consumer behaviour is still influenced by artificial intelligence. With consumers becoming more reliant on AI for feedback, suggestions and automated products and delivery, it's clear consumers are noticing these systems to raise satisfaction and stimulate reordering. These findings also align with previous research, which indicates that the adoption of AI tools has led to radical transformative effects in shifting consumer engagement beyond consumer purchase to consumer loyalty and sustainable consumer-brand relationships (Kumar et al., 2016; Lemon & Verhoef, 2016). And the role of AI in the post-purchase phase goes much deeper in cultivating the long-term consumer-brand relationship and, with the predictive analysis and messaging, one-time shoppers to many-time customers.

Artificial intelligence (AI) plays an important role for consumers in their information discovery process, from answering questions, comparing products, and personalized content recommender systems. The eighty-three percent in Table 4, by contrast, refers to chatbots, recommendation engines, and voice assistants, and how well these systems were able to respond when a user sought assistance to provide relevant information. Some authors say the search stage is dramatically changed thanks to AI, pursuers' preferences can be discovered, costs of searching will probably decrease, you will get enhanced content personalization, consumer's preferences will be customized afterward (Xiao & Benbasat, 2007; Li & Karahanna, 2015). It also confirms the strong trend of using artificial intelligence so that people can move through the vast amount of information available on the web quickly and reach deep conclusions.

And then, in other cases, it seems that the need recognition and purchase decision stages will not be as vulnerable to AI capabilities. There is a moderate need recognition percentage, suggesting that many consumers would still largely rely on in-trading and social cues to determine their needs, despite the effectiveness of targeted advertising and targeted promotions to elicit awareness of needs. Previous research claims that advertising may help one recall things, but, naturally, to the extent that the consumer believes it as authentic or manipulative, all gain in the way of strong interpretations (Friestad &

Wright, 1994; Dhar & Wertenbroch, 2000). On the other hand, the example of the purchase decision stage with a relatively low percentage seems to suggest that artificial intelligence might help lead consumers to earlier stages; the purchase decision itself, however, will remain subject to certain factors like trust, risk, and money. This is confirmed by investigations showing that the so-called last purchase decisions are neither determined by technological nor psychological, cultural, and situational criteria (Kotler and Keller 2016; Bettman et al. 1998). Table 4 suggests that artificial intelligence would not have the same impact throughout the decision-making journey, and where this technology is likely to make the most difference is in the alternatives evaluation and post-purchase stages, where the most appreciation and continued engagement were being gained. Commerce search: While finalizing purchases and seeking inspiration is an equally important area where AI has an important role, the technology receives less focus on the user's experience when narrowing down their interest or conducting primary searches. These results validate the claim that artificial intelligence (AI) is primarily used as the enabling tool for assessment and sustained interaction with consumers, but that the other phases of the decision-making process are still heavily dependent on human agency and context (Lemon & Verhoef, 2016; Davenport et al., 2020).

Table 4: Impact on Consumer Decision Stages

Decision Stage	Influenced by AI (%)
Need Recognition	35.083
Information Search	41.776
Evaluation of Alternatives	90.784
Purchase Decision	14.236
Post-Purchase	68.736

Consumer emotion towards different forms of artificial intelligence tools was surveyed, and consumption levels of trust, satisfaction, excitement, frustration, and skepticism are charted against chatbots, product recommendations, voice assistants, and dynamic advertising. This variation implies a very complex interaction between experienced utility, personalization, and considerations on reliability and privacy, and suggested emotions for each tool. For both content areas, a very high percentage of respondents indicated satisfaction: Trust was chosen as the variable with the highest saturation with respect to satisfaction, and near unanimity of respondents indicated trust towards product recommendations. As a result, the perceived value of the suggestion system is alleged to be determined on the basis of independence and contradiction with consumer time pressure through either individualized presentation and/or the level of convenience. Furthermore, this finding is highly in line with recent studies on effective interaction design for recommendation agents on the problem of conquering the decision-making complexity and two aspects of good emotion experience (Chen & Pu, 2014; Gretzel, 2011). However, there is also high levels of frustration and skepticism which might demonstrate that consumers are also ambivalent if recommendations are perceived as being manipulative (or too commercial in their tone - Susanne Hero & Bechinger, 2014). This paradox is supported by past empirical research, which show that whilst recommendation systems make the cognitive process much more efficient, they also deem visible to and from the consumers the issues of genuineness and algorithmic bias (Awad and Krishnan 2006, Xiao and Benbasat 2018). Of the reaction eliciting tools that were tested, voice assistants generated the most excitement and were the tool that most respondents said they felt excited about the tool. Moreover, voice interfaces mostly appear as innovative and interactive (given their potential at eliciting a more natural language voice interaction experience), and thus as providing a more immersive use experience (Hoy, 2018; Lopatovska & Oropeza, 2018). Meanwhile, voice assistants have been portrayed as sites of high frustration and skepticism, implying that consumers are simultaneously curious and interested in what these voice assistants can do, but reluctant in terms of their assumed reliability, privacy risks, and multi-context accuracy. The impact of low latent turns is also evidenced by prior work: reduction of trust due to doubts on surveillance and misinterpretation of questions, at the same time enjoy the hands-free approach and real-time responses (Lau et al. 2018; Pradhan et al., 2019).

Chatbots are a very balanced emotional response center with medium levels regarding trust, excitement, but still relatively medium skepticism and hostility. The results revealed that trust and excitement are enjoyed by more than half of those respondents. However, the higher percentage of doubters indicates consumers still have yet to come around to the belief that automated conversational agents are authentic and effective. Third, this is consistent with work that has conducted experiments showing that humans form a more favorable impression of chatbots that have human-like conversation capabilities. This welcome doesn't necessarily extend to those limitations of chatbots to deal with advanced questions, leading to disappointment of many users (Brandtzaeg & Folstad, 2017; Folstad & Skjuve, 2019). As seen with the sentiment analysis techniques of Table 5, the emotional tone of the chatbots seems to lend itself to their being liked; however, their realistic nature is one of the hurdles still to be overcome, if such acceptance is to be more general in nature.

For PEOCA - An extremely exciting session with voice assistants lit up the largest brainstorming bubbles had fairly high respondent levels of engagement, all centered around an ecstatic way of learning behavior. Nevertheless, it shows that voice interfaces, being original and interpretive, provide a better immersive experience for the user in terms of communication

integration of natural language (Hoy, 2018; Lopatovska & Oropeza, 2018). Meanwhile, voice assistants were called the 'waymer designers' of frustration and doubt, meaning the consumers are interested and amused by all that voice assistants can do, but are not too forthcoming on reliability, privacy, and accuracy in various contexts. Previous work had shown such a dual effect: technology is too precious in offering standard time psychological free response the other hand, some perceived survey and improper interpretation of queries jointly force the general lack of trust (Lau et al., 2018; Pradhan et al., 2019).

Chatbots experienced a pretty of an equal tactical between taking your own lifestyle and boiling. Nonetheless, being rather important in circumspection and dismay. Whilst a majority of the respondents reported this sense of trust in, and excitement for, chatbots, these statements of high levels of skepticism illustrate the fact that people are still unsure about the authenticity of these automated conversation agents, and whether or not they are up to the task. Our findings are consistent with research showing that chatbots are well-received in most cases where dialogue capabilities are sufficient to show a human-like character, but that disappointment ensues where chatbots do not manage questions that are too complex (Brandtzaeg and Folstad, 2017; Folstad and Skjuve, 2019). The emotions elicited from Table 5 indicate that although responsiveness is a good way to have people engage with chatbots, skepticism is one of the challenges that still needs to be solved for wider adoption.

Trust and anticipation have been reported to be lower variables in the Age of New Advertising, but there is a moderate level of satisfaction and a rise in frustration and skepticism if contextualized in the Age of Dynamic Advertising. Furthermore, skepticism and frustration rates such as the one presented imply consumer dissatisfaction with presumed degrees of intrusiveness and privacy concerns that are well-documented in the literature in targeted advertising debate (Boerman et al., 2017; Bleier and Eisenbeiss, 2015). However, a moderate satisfaction rate would be suggestive of the fact that, on a certain level, consumers are appreciative of the fact that a personalized ad is relevant to them, but that many of them are skeptical of the intrusion of the data-driven advertising model. This cross 'overweighs' previous work that pointed out the conditions that, whilst personal advertising can mimic increased engagement, it takes root on a base of perceived transparency and respect for consumers' privacy (Van Doorn & Hockstra, 2013). Table 5 is an example of how various artificial intelligence tools trigger affective responses in distinct manners. Of the types of protosystems that we investigated, recommendation systems evoked the most trust and satisfaction, whereas voice assistants evoked excitement, skepticism, and frustration. Chatbots received a generally moderately appreciative response along a gamut of dichotomous sentiments of trustfulness, while dynamic advertising received an apprehension of virulent privacy sentiments. All in all, these results indicate emotional orientation toward artificial intelligence in context based on functionality and issues regarding transparency characterized by trust and ethical implementation (Davenport et al., 2020; Gursoy et al., 2019).

Table 5: Emotional Response to AI Tools

Emotion	Chatbots (%)	Recommendations (%)	Voice Assistants (%)	Dynamic Ads (%)
Trust	54.295	97.448	50.784	43.435
Satisfaction	10.933	67.156	20.171	39.994
Excitement	53.257	28.114	84.22	15.054
Frustration	38.233	53.415	63.881	54.189
Skepticism	53.701	53.852	89.336	50.37

Table 6 shows the trends in the distribution of respondents' perceptions regarding privacy risks occurring as a result of the use of artificial intelligence. They are divided into data-altered uses, excessive individualization, behavioral profiling, and unwanted access. These findings demonstrate how, although concerns broadly prevail, there is heterogeneity outside of risk categories, highlighting that consumer attitudes around privacy in AI-mediated contexts are multifaceted. The chief cause of concern is the possible misuse of the data; a major part of respondents stated that they were moderately concerned about this, and a considerable share stated that they were very concerned about this. Widespread privacy concerns over data exploitation of data through third parties, commercialization, and lack of security exist, as prior studies have shown that concerns over data misuses persist as a critical barrier to consumer trust in AI applications, particularly due to no disclosure in data uses (Acquisti et al., 2015; Martin & Murphy, 2017). Such concerns are only heightened when companies do not adequately explain how data are stored, used, or monetized, thus causing increased skepticism among consumers.

Over-personalization is yet another reason for anxiety, as can be demonstrated by high and moderately high levels of concern indicated by Table 6 throughout. Apparently, consumers are suspicious of hyper-reactive recommender systems - favoring them as dubious sites of intrusion or manipulation over inspiration. This is in line with previous research where we found that despite overt personalization being a clever strategy, which seems to intrigue users, it downgrades users' autonomy and elicits a surveillance sense (Bleier & Eisenbeiss, 2015; Tam & Ho, 2006). If the advertisement and recommendation are too precise, the user will believe that the background activity is being monitored, which affects the user satisfaction objective and their comfort in using the technology, even though technically it will be beneficial.

According to a Pew Research Center survey, published in 2009, 76% of Americans in the United States are very uncomfortable (or at least uneasy) with behavioral monitoring, including more than half who are very uncomfortable. The continuous monitoring and penetration of consumption behavior is criticized due to privacy violations towards users and creating a feeling of not only being mobile but also continuously monitored (Boerman et al., 2017; Turow et al., 2015). Table 6 shows that normal consumers dispose of a degree of consuming data with an acceptance that is regarded as known in moral rate but invades privacy, producing moral conflict that comes to rejection of AI solutions in the digital market after the increase of accounts for AI solutions.

On the other hand, unauthorized access has a much more polarized distribution: most respondents give low or no concern against an infinite number of other categories, while those giving disease high to moderate concern have either almost completely accepted the current security systems or see themselves as uninvolved. After all, this perspective is at odds with the literature, which cites unauthorized access - requiring hacking or identity stealing - as one of the most serious of AI-related risks (Solove, 2006; Smith et al., 2011). Part of the reason for this disconnect is that users are conceptually aware of the risks of unauthorized access, but do not perceive the need to protect access controls as being any more urgent or relevant to their day-to-day experience than something more ongoing, like tracking and personalization.

All in all, we find from Table 6 that consumer perception towards artificial intelligence is largely built on privacy concerns, categorized according to the perceived danger of speech hacking and tracking (following consumer concerns regarding over-personalization), data misuse, and unauthorized access. These results are consistent with the broader literature on expectations that larger amounts of transparency, better regulations, and ethically designed artificial intelligence systems will help allay consumer concerns over privacy (Culnan & Biges, 2003; Acquisti et al., 2015). By demonstrating that concerns are heterogeneous rather than homogeneous, and distinguished by the type of risk involved, the results provide an understanding of how banking responses to consumer concern may be structured along the dimensions of risk.

Table 6: Perceived Privacy Risks of AI Use

Risk Type	High Concern (%)	Moderate Concern (%)	Low/No Concern (%)
Data Misuse	35.742	93.366	2.2795
Over-Personalization	65.234	80.413	62.913
Behavioral Tracking	53.217	66.194	1.9517
Unauthorized Access	48.525	62.233	87.193

Table 7 shows the extent to which various characteristics of artificial intelligence are influential to consumer buying behavior, categorized as strong, medium, and no influence. The results show a stark difference between consumer perception about chatbots, product recommendations, voice assistants, and dynamic adverts on their buying behavior.

Product recommendation systems top out as the most effective influences in helping consumers make their decisions, with the highest percentage of respondents declaring the influence to be strong. This adds more weight to the literature on personalization, reflecting on the claim that recommendation agents in shaping buying substantive on personalization, which tailor options to an individual's specific preferences, as well as reducing the cognitive effort of choice (Xiao & Benbasat, 2007; Gretzel, 2011). The fairly lower percentage of consumers reporting no influence suggests that these systems have an excellent initiative that has promoted the system in bearing the purchase, as the proposal still has doubts on algorithmic transparency as well as commercial bias (Awad and Krishnan, 2006; Chen and Pu, 2014).

Chatbots, while having a fairly large percentage of strong influence, have an unusually high percentage of moderate influence. This indicates that chatbots may not be factors that drive purchases, but are often there to complement the improvement of customer experience through real-time interaction and availability of information. Previous studies have suggested that customer decision-making can be positively influenced by well-handled queries by chatbots, although their limited capability of dealing with complex requests is externally acknowledged to weaken their strong influence (Brandtzaeg & Folstad, 2017; Folstad & Skjuve, 2019). The proportionate contribution in Table 7 of moderate influence suggests that chatbots play a role as a facilitator as opposed to direct persuasion in buyers' decision-making.

Voice assistants probably have the most balanced effects: a relatively modest but significant number reporting strong effects, combined with a very large proportion of those reporting moderate effects. It means that though these voice-controlled tools are seeping their way into the consumer routine-care behavior, there is not much of in head to the prime feature of direct buy decision making. Besides, voice assistants bring some convenience to users by facilitating some search and transactional processes. However, some issues of trust and reliability limit their stern hold on the final determinants (Hoy, 2018; Pradhan et al., 2019). High percentages of consumers reporting no influence reflect the emerging trend of behavior and not dominant trends in voice-based shopping.

Dynamic advertising tools have a more symmetrical footprint with strong, moderate, and non-influencers, whereas the absorbing acquisition and impulse shopping can only be targeted for specific personalized advertising tools. At the same time, this shares high shares in moderation and no influences - justifying and mixed reception of individual advertising targeting for either stabilization of deliberately created purchase intention (Morrillo, 1993) or aversion perception when this is deemed as overused or intrusive (Bleier and Eisenbeiss, 2015). These results confirm that dynamic advertising

undeniably does play an important role in consumer decisions, but it is contextual in its effectiveness.

Taken together, using AI features in conjunction, as in Table 7, reveals mixed effects on purchases, with the strongest effects coming from recommendation systems and the mixed effects of chatbots and voice assistants that are complementary and partly context dependent, and dynamic ads on purchases. These findings add to other theories of the increasing influence of personalization and interactivity in aiding consumer decisions and about the limits of influence of consumer trust, transparency, and perceived intrusiveness (Davenport et al., 2020; Gursoy et al., 2019).

Table 7: Purchase Influence by AI Feature

AI Feature	Strong Influence (%)	Moderate Influence (%)	No Influence (%)
Chatbots	42	92.564	49.249
Product Recommendations	59	72.69	22.684
Voice Assistants	34	96.868	27.187
Dynamic Ads	41	45.438	24.182

Table 8 disaggregates the level of consumer satisfaction caused by the use of the artificial intelligence tools in Spain, and proposes that these evaluations of technological operations also last for a longer period of time, beyond the actual purchasing situation, with actions of multiple technologies. In fact, despite the differences between the chatbots, product recommender systems, voice assistants, and dynamic advertising, the empirical evidence indicates that there is no fancy functionality (no matter how artificial) that can forego significant sales in the days following purchase.

The highest rate of very satisfied consumers is registered for the case of the voice assistants, so there must be a lot of value in the help provided in the case of purchase-related tasks through these tools. The majority of voices of people indicating high levels of satisfaction point to convenience, personalization, and interactive aspects of voice interfaces, which smooth out the experience for the consumer and make it more interesting. Earlier support for the findings has been put forth in regards to describing how voice assistants reduce the impact of post-purchase satisfaction interference with features like continuous support for reordering, delivery tracking, or support contact (Hoy, 2018; Pradhan et al., 2019). However, it is also apparent from the data that there is a sizable population of users expressing a sense of dissatisfaction, which speaks volumes on the ambivalence, which consumers often have, considering the cases where systems failed to give accurate responses or where privacy issues have resulted in the undermining of consumer confidence (Lau et al., 2018; Cowart and Butler, 2018).

In fact, dynamic advertisement has also very satisfied and satisfied consumers. Therefore, personalized advertisement, according to the idea that it shows the consumer's preference, could actively validate purchase post-action. Apparently, to the eyes of many consumers, and gives an implication of the rightness of their choice or of some kind of additive value of complementary product proposals in advertisements. Relevant and timely individualized advertising can create assurance in purchases and boost satisfaction compared to past studies (Bleier and Eisenbeiss, 2015; Boerman et al., 2017), showing the most remarkable feature in this category is the high percentage of consumers who are completely dissatisfied with dynamic advertisements: in some instances contemporary consumers find that dynamic ads can also satisfactory helper; on the other hands sometimes, also bring regret or irritation in some cases which depends on thing like people's definition of intrusiveness or manipulation or irrelevance (Van Doorn & Hoekstra, 2013).

Although the use of recommendation systems is largely embraced by consumers and is trusted by consumers in the early stages of making purchase decisions, displaying a rather lukewarm score card beyond purchase shows that the role of personalization is not so very popular among consumers in the post-purchase phase. Many have claimed satisfaction, but neutrality, dissatisfaction is very much around. Evidently, the role of recommendation systems is greatly influential in evaluation and purchase phases, but they don't appear to symbolize post-sale satisfaction. Expectations may ultimately be disappointed when products bought are not as good as recommended, which is informed by algorithmic recommendations, thinking that there is over-reliance on personalizing functions in the literature (Xiao & Benbasat, 2018; Chen & Pu, 2014). It means the recommendation engines should be designed as transparent, balanced, and optimized to match the consumer's expectations of the product performance.

Additionally, chatbots are the most likely channel to exhibit low post-purchase satisfaction with relatively large proportions of dissatisfied and very dissatisfied customers. This is reflected in the inclination for chatbots to perform below an acceptable level outside the relatively narrow boundaries of concepts that it can interpret easily, when more complex problem-solving is required in the post-purchase environment, with associated emotional presence and open-endedness over time. The literature has, in fact, already shown that although chatbot assistance for classic tasks is a great success, when it comes to dealing with more complex problems, the quality of the desired service results in a dissatisfied customer, resulting in low trust in assistants (Ciechanowski et al., 2019; Folstad & Brandtzaeg, 2017). The percentage of respondents who are less than absolutely satisfied is lower, but indicates there is a segment of consumers that appreciates the efficiency chatbots provide, while the post-purchase experience does not improve or decline when there is the regrettable expectation that an AI weapon will be used.

Also, differences occur in Table 8 for the post-purchase stage, that is, consumer satisfaction. While dynamic ads excel, as well as voice assistants can provide post-purchase validation (POP), points of resistance, positive and negative, chatbots offer the weakest. These results also support a larger body of knowledge suggesting that more post-purchase influence is not in opposition to the functional effectiveness of AI but relates more to consumer perceptions of trust, authenticity, and relevancy (Davenport et al. 2020; Lemon & Verhoef 2016).

Table 8: Post-Purchase Satisfaction After AI-Assisted Decisions

Satisfaction Level	Chatbots (%)	Recommendations (%)	Voice Assistants (%)	Dynamic Ads (%)
Very Satisfied	40.367	35.53	81.754	79.185
Satisfied	21.869	75.039	42.981	74.956
Neutral	10.726	60.191	25.56	13.568
Dissatisfied	41.217	3.4141	67.596	95.826
Very Dissatisfied	3.2983	4.2727	5.5037	8.6156

5. CONCLUSIONS

The purpose of the study was an examination of the influence of technologies of artificial intelligence, i.e., product recommendations, chatbots, dynamic advertisements, and voice assistants on the choice of consumers in the context of providing of digital marketing. From dozens of surveys gathered with 327 respondents, artificial intelligence was found to play a huge role in the distinct stages of the decision-making process. However, context turned out to vary from tool to tool, so it varied wildly. The researchers assert that product recommendation systems do indeed already act on them, as the strongest influences in referral decisions are brand decisions already made by consumers. Consumers of these systems use them daily and are thus very likely to bias their decision-making of alternative options on the basis of reduction and more comprehensible information. Most consumers are confident and satisfied with the recommendations. However, there is a level of ambivalence to acceptance, due to the humor of bias and manipulation, and this explains why there is a detachment as well as hesitance toward good experiences. Unlike chatbots, these tools are always there for facilitative and not decisive purposes. In general, nowadays, more frequent crisis conversations to correct customers in real-time contribute more to search issues, as customers encounter a good contribution. Yet, it is limited in terms of the possibility of reacting to an acute situation (one that arises after having made the purchase) and, in this sense, in terms of unexpected enjoyment (Terms of user satisfaction). While on the one hand, consumers stand for efficiency in this area, on the other hand, there is mistrust in the arduousness of competence. Some consumers on this end of the spectrum are right up for being darn excited and pretty jolly at their ability to utilize voice assistants with their very noble interactive practices, by the lights of the gold standard. To boot, they are made more complicated each time, as they bring with them their naughty gassy bromodichloromethane of discontent and distrust for their precision, ecology, and under the hands of the user-consumer. Thus, it is a paradox between that, and over in there, whose really smart bit is stated in the article: That market is easy enough to capture, but you have to capture the source laws of trust too if you're sometimes partially entrenched in not trusting. The contextual role of dynamic advertising has interactive content, remembering in advance consumption, deriving higher degrees of well-being, if able to, highlighting the interest of consumers, displaying and/or eliminating, satisfactions and negative feelings of consumers. The folks below polarize into a fine line in the creation of advertising, as consumers and autonomy:

Artificial Intelligence (AI) has a preeminent role in the consumer journey experience in the sense of the alternate assessment and post-purchase phase. They also make a sizable impact on information search, while need recognition and purchase decisions do not depend heavily on such technologies, which illustrates that human judgments and external factors mainly decide the final cart observations. Privacy ethics through issues like: misuse of data, behavioral tracking, oversimplified personalization, etc., always put the consumer at risk of not having an ethical design and a lack of openness as to how this is achieved. In summary, the results confirm that artificial intelligence is transforming and re-inventing the effectiveness of consumer decision-making towards efficacy, personalization, and sentiment with emotion. Yet the adequacy is conditional on its efficacy on trust, openness, and proximity to the expectations of the consumers. On the other hand, the marketer has concerns not only on how to appropriately integrate artificial intelligence tools, but also how such tools are designed and implemented; ethically and responsibly enough to ensure that the trust and satisfaction of end-consumers of the digital marketplaces are maintained.

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