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THE INFLUENCE OF GENERATIVE ARTIFICIAL INTELLIGENCE ON CONSUMPTION PATTERNS: RESULTS OF AN EXPLORATORY STUDY

GABRIEL CUNHA CAMPOS DIEGUEZ

Brasília - DF, 2025

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Orientador
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ABSTRACT

The rise of Generative Artificial Intelligence (Generative AI) represents a significant transformation in digital interactions and consumption patterns. This paper proposes an in-depth analysis of the impact of Generative AI on the formation and modification of consumer behavior on digital platforms, investigating how this technology shapes preferences, purchasing decisions, and trends. Through the identification of the main uses of Generative AI in consumption contexts, the evaluation of its effects on consumer behavior, and the investigation of concrete examples of its influence in creating trends, the study thus seeks to demonstrate how Generative AI redefines consumption dynamics, making it more personalized, but also raising crucial questions about its influence and future implications.

Keywords: Artificial Intelligence, Consumption Patterns, AI-driven Marketing, Consumer Decision-Making, Evolution of recommendation systems.

RESUMO

A ascensão da Inteligência Artificial Generativa (IA Generativa) representa uma transformação significativa nas interações digitais e nos padrões de consumo. Este trabalho propõe uma análise aprofundada do impacto da IA Generativa na formação e modificação do comportamento do consumidor em plataformas digitais, investigando como essa tecnologia molda preferências, decisões de compra e tendências. Através da identificação das principais utilizações da IA Generativa em contextos de consumo, da avaliação dos seus efeitos no comportamento do consumidor, e da investigação de exemplos concretos de sua influência na criação de tendências. O estudo busca, assim, demonstrar como a IA Generativa redefine a dinâmica de consumo, tornando-a mais personalizada, mas também levantando questões cruciais sobre sua influência e implicações futuras.

Palavras-chave: Inteligência artificial, Padrões de consumo, Marketing personalizado por IA, Tomada de decisão do consumidor, Evolução dos algoritimos de recomendação.

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1 INTRODUCTION

In recent years, Artificial Intelligence (AI) has assumed an increasingly prominent position in today's society, affecting crucial areas such as health, education, industry, and, significantly, consumption [1] [2]. In this context, Generative Artificial Intelligence, which encompasses tools like chatbots, image generators, and content recommendations, has stood out for its remarkable ability to instantly generate personalized information and suggestions [3]. These technologies not only react to stimuli but also create new opportunities for interaction and influence over individuals.

The way consumers identify, choose, and use products and services is undergoing a fundamental and profound reconfiguration process. Platforms powered by generative artificial intelligence have the capacity not only to influence preferences but also to offer ultra-personalized recommendations and even predict desires and needs before they are consciously expressed by users [4] [5] [6]. This ability is due to the vast amount of data collection and processing that is intrinsic to the functioning and organization of AI algorithms. Such characteristics allow the identification of emerging patterns and the creation of offers that deeply resonate with the consumer.

In this scenario of profound change, it becomes crucial to explore how this technology plays an active role in the formation and modeling of consumption habits. This analysis is not limited only to its technical processes but also to its ethical, social, and behavioral repercussions. Generative AI, when interacting with consumers on digital platforms, can shape consumption behavior at various stages: from product discovery—creating attractive and informative visual or textual content that directs consumer attention—to evaluation, offering generated comparisons and reviews, or even simulating product usage, up to post-purchase and loyalty-building stages [7] [8].

Considering the issue that consumption patterns are intrinsically linked to human and psychological elements such as culture, income, perceived utility, sense of belonging, and various other subjective components [9], it is proposed that Generative AI, to become an increasingly accepted and effective engine of influence and prediction, must incorporate a growing level of personalization and communication that mimics the complexity of human interaction.

However, the humanization of AI brings with it ethical and social challenges, since feeding these algorithms with user data and preferences can lead to algorithmic confinement, limiting the freedom and truthfulness of information, embedding biases, and sometimes even creating an emotional attachment from users [7], who may no longer have a tool for critical thinking, but rather a replicator of personal preferences and perceptions. In light of this transformation scenario, the following question arises: How does Generative AI influence consumption patterns and customer loyalty on digital platforms?

In this context, the present work has as its central objective to analyze and understand the impact of Generative Artificial Intelligence (AI) on the formation and modification of consumption patterns. To achieve this purpose, the following specific objectives were defined:

- identify the main uses of generative AI in digital consumption contexts;
- examine how generative AI affects consumer behavior; investigating examples in which generative AI played a role in creating or transforming consumption trends;
- apply a structured questionnaire to collect data on the' knowledge, use, and perception of consumers about AI and recommendation algorithms, to understand their experiences and attitudes toward these technologies;
- analyze the collected data through statistical and visual exploration to uncover correlations, trends, and behavioral clusters that reveal how Artificial Intelligence shape consumer decision-making and perception.

The relevance and pressing need for studies in this area are affirmed by data showing an exponential growth of the AI-generated marketing market, valued at USD 20.44 billion in 2024, with projections to reach USD 82.23 billion by 2030 [10]. Such data allows us to conclude that there is great room for growth and evolution on the topic, but also an urgency to understand its implications. This study, in particular, seeks to fill a gap by offering an in-depth analysis of the mechanisms through which Generative AI reshapes consumption patterns, providing critical insights for consumers, companies, and policymakers on how to optimize the use of these algorithms while maintaining an ethical and safe standard.

Given this digital transformation scenario, where Generative Artificial Intelligence positions itself as an active modeler of consumption patterns, it becomes essential to deepen the understanding of its influence not only from a theoretical perspective, but also through empirical analysis. In addition to an in-depth theoretical analysis, this study conducts a computational investigation based on data collected through a structured questionnaire, analyzed with data processing and visualization tools. This dual approach aims to examine how Generative AI not only interacts, but also modifies, facilitates, and refines decisive moments in customer consumption [4] and in the building of loyalty by companies [11].

By analyzing Generative AI through the lenses of human-computer interaction, personalization, and suggestion, this study aims to provide a robust conceptual foundation to understand AI as a behavior-shaping force in consumption, allowing the insights obtained to help understand in what ways the use of these algorithms can be optimized while still maintaining an ethical and safe standard for those who employ them.

To fulfill the requirements defined herein for the proposed course conclusion work, the decision was made to conduct an empirical exploratory study, which, according to the literature, is conducted when there are significant gaps in knowledge regarding a specific phenomenon. Unlike confirmatory research, which starts from well-defined hypotheses and consolidated theories, exploratory studies seek to identify patterns, generate insights, and propose initial relationships between variables [12]. In this context, the following provisional hypotheses will serve as the guide for the collection and analysis of the study data.

Hypotheses proposed for the work:

- H1: The user age group variable is a factor that may impact the perception (positive or negative) regarding the use and trust of recommendation systems utilizing algorithms developed with AI techniques.

- H2: The user monthly income variable is a factor that may impact the perception (positive or negative) regarding the use and trust of recommendation systems utilizing algorithms developed with AI techniques.

- H3: The user education level variable is a factor that may impact the perception (positive or negative) regarding the use and trust of platforms providing AI-based solutions.

2

2

LITERATURE REVIEW

2.1 THEORETICAL FRAMEWORK

For a comprehensive understanding of the proposal, methods, and results of this work, it is first necessary to understand some fundamental concepts that serve as the foundation for the entire study. Thus, this chapter aims to present the theoretical bases that support the development of this project, offering an extensive overview of the central themes.

Delving into Generative AI is essential, given that its ability to produce original content is directly related to the formation and alteration of behaviors and trends. Equally indispensable is the understanding of Consumption Patterns, understood as the observable manifestations of consumers' habits, preferences, and choices, and how these patterns are shaped by external and technological influences. Additionally, it becomes crucial to explore the Impacts of Generative AI on Consumer Behavior, examining how this specific technology influences product discovery, individual preferences, and purchasing decisions, considering the inherent complexity of its analysis in a constantly changing environment.

Beyond the theoretical concepts, this chapter discusses the main applications of Generative AI that will be explored throughout the work, based on specialized literature in Artificial Intelligence, digital marketing, and consumer behavior. It is also fundamental to contextualize consumption trends, their particularities, the challenges faced, and the reasons why their analysis and forecasting are complex in the digital age.

Finally, this section offers a perspective on contemporary consumer behavior, outlining the challenges and opportunities that Generative AI presents for the personalization of experiences and the stimulation of demand. In the following sections, each of these topics will be detailed, providing the necessary foundation to understand the methodological, technical, and analytical choices adopted in this study.

2.1.1 Artificial Intelligence (AI)

Traditional recommendation algorithms serve as the foundational layer of early recommender systems, solidifying in the 1990s and 2000s through approaches such as collaborative filtering, content-based filtering, matrix factorization, and hybrid models

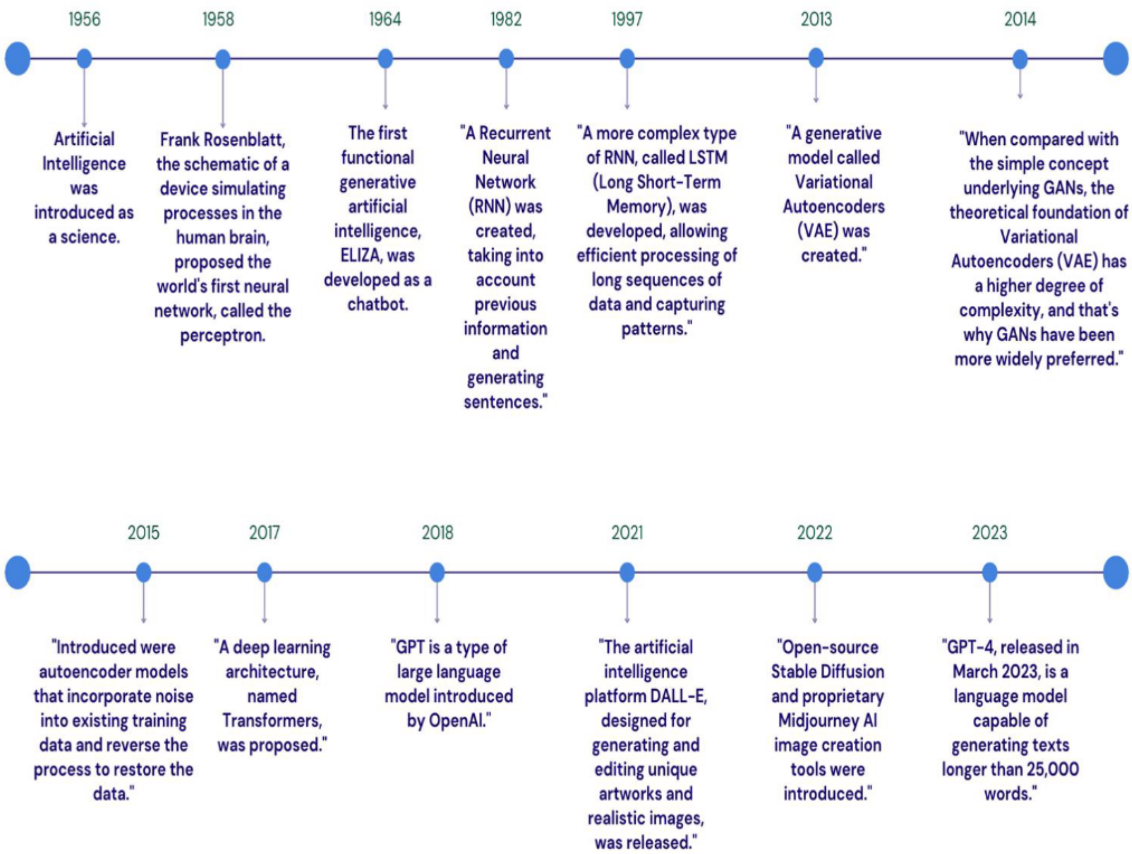
[13] [14]. These systems operated by combining explicit ratings, item attributes, and interaction patterns to estimate preferences, employing similarity metrics and matrix decomposition. While they represented a significant advancement for their time, such methods were heavily reliant on manual structures, attribute engineering, and essentially linear relationships between users and items [15].

As time progressed, these approaches evolved into more efficient and scalable forms, such as optimized neighborhood models and hybrid systems [16], yet they remained constrained in their ability to capture complex patterns, learn dynamic contexts, and generate deep representations of human behavior. Therefore, although they played a crucial role in the establishment of traditional recommendation systems, these methods represent a preliminary stage leading to a greater technological leap: the transition to architectures based on deep learning, large-scale models, and ultimately, Generative Artificial Intelligence, capable of operating adaptively, autonomously, and contextually within digital consumption ecosystems.

The evolution of Artificial Intelligence (AI) over the decades outlines a trajectory that spans from early philosophical and mathematical reflections on the nature of thought to today's technological landscape, dominated by models capable of autonomously generating original content. Broadly defined, AI refers to the intelligence demonstrated by computational systems, as opposed to natural human intelligence, with the goal of replicating cognitive functions such as learning, reasoning, perception, and decision, making. [17]

This historical progression marked by breakthroughs, disruptions, and technological rebirths, is visually summarized in Fig. 1, which presents a timeline consolidating the major milestones from the origins of AI as a scientific discipline to the emergence of modern generative models. The figure reinforces how conceptual shifts and computational advances shaped each stage of AI's evolution, illustrating the transition between paradigms and clarifying the foundations of contemporary Generative AI.

Figure 1: Artificial Intelligence Development Timeline



Source: Generative Artificial Intelligence: A Historical and Future Perspective [18]

The contemporary foundations of AI were established during the period known as the AI Spring (1950–1970). This period was marked by key milestones such as the first questioning of the possibility that machines could think [19] and the primary model of artificial neurons developed, which provided the theoretical basis for neural networks [20].Innovations advancing at an unprecedented pace drew significant attention to this new concept of AI, nevertheless, the early enthusiasm was constrained by hardware limitations and the problem of combinatorial explosion, leading to the first AI Winter [21].

Following this, the Symbolic AI paradigm (1970–1990) emerged, concentrating on the creation of expert systems that explicitly encoded human knowledge through databases of facts and rules [21]. Despite advancements in theory, this approach encountered challenges in knowledge acquisition and maintenance, along with technological limitations, leading to a second period of stagnation. [17]

The revival of AI took place with the establishment of Machine Learning (ML) in the 1990s, which introduced a novel paradigm: rather than programming explicit rules, systems should derive patterns directly from data [22].

The true turning point, however, came with the rise of Deep Learning (DL), a subfield of ML based on deep neural networks capable of extracting complex and hierarchical representations from data [3]. Progress in this area was driven by the availability of large-scale datasets and the growth of computational power, particularly through the use of GPUs [21]. The development of Transformers represented another leap forward, these architectures enabled the parallel processing of large-scale data, ushering in the era of Large Language Models (LLMs) [23] [3].

2.1.2 Generative Artificial Intelligence (Generative AI)

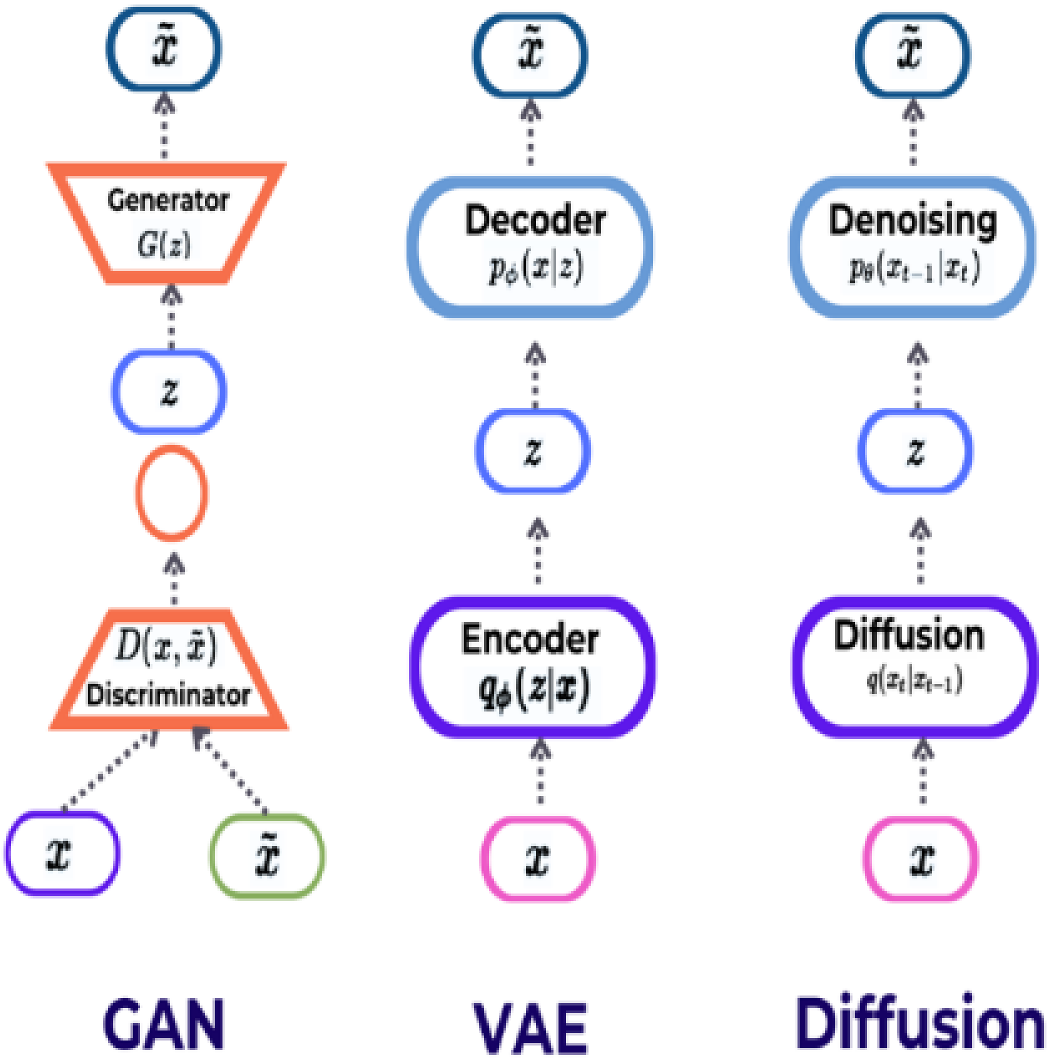
Generative Artificial Intelligence (Generative AI) represents a major advancement in Artificial Intelligence. Unlike traditional AI, which is focused on analyzing or classifying existing data and performing specific tasks, Generative AI creates new and original content. It achieves this by learning from large amounts of unstructured data and adapting to changing data and environments without relying on manual rules [20] [24]. Unlike traditional AI systems, which focus on tasks such as pattern recognition or natural language processing, Generative AI utilizes complex models such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Transformer-based models to learn the structure and patterns of large datasets and, from that, generate new instances that resemble the training data but are unique [23].

Generative Adversarial Networks (GANs) consist of two main components: a generator and a discriminator. The generator aims to create realistic data, while the discriminator's role is to differentiate between authentic and generated data. In contrast, Variational Autoencoders (VAEs) focus on learning a latent representation of the data, which facilitates the generation of new samples from this compressed latent space. In addition, Diffusion Models have emerged as a more contemporary and increasingly significant category of generative models. These models produce new data samples by systematically introducing noise to an initial data point and subsequently removing this noise through a learned denoising process. [18]. In Fig. 2, it is possible to have a better understanding of the different types of the three basic generative models.

Furthermore, Transformer models, such as GPT, stand out for their ability to generate cohesive and contextually relevant text by predicting the next token in a sequence [23]. They represent a distinct category of neural network architecture that utilizes self-attention mechanisms to effectively capture long-range dependencies within the data, rendering them particularly adept for large-scale language modeling endeavors [3].

Generative AI has a vast scope of applications, ranging from the creation of art and visual effects in entertainment to the generation of synthetic data for training other machine learning models, product design optimization, and large-scale personalization [1]. Additionally, AI has been instrumental in fraud detection, inventory management optimization, predictive maintenance, and the automation of repetitive tasks across various industries [3] [25] [26] [27].

Figure 2: Flowchart of generative models



Source: Generative Artificial Intelligence: A Historical and Future Perspective [18]

However, the widespread acceptance and implementation of AI are permeated by significant challenges. Ethical issues, such as algorithmic bias and the lack of transparency in decision-making processes, which can turn systems into ”black boxes”, raise concerns and undermine trust [28]. Data privacy and security are equally critical, requiring robust measures and compliance with regulations [3]. Moreover, the fear of job displacement by autonomous systems, the technical complexity of integrating AI into existing infrastructures, the need for vast computational resources and high-quality data, and the lack of comprehensive regulatory frameworks in the face of rapid technological evolution constitute barriers to full adoption [29].

Nevertheless, it is possible to observe that the widespread, everyday use of generative AI tools and platforms allows for a real and complete user engagement with this type of technology. Understanding AI as a tool capable of enhancing human capabilities rather than fully replacing them is an essential step towards conscious adoption and greater acceptability [30].

As practical experience demonstrates both the added value and the limitations of AI, anxiety and apprehension regarding its use tend to decrease, paving the way for the exploration of its potential in collaboration with human intelligence. Thus, recent studies confirm that consumers use and trust Generative AI as a major indicator, more specialized than humans themselves, when it comes to purchasing material products. However, regarding in-person experiences, human judgment still remains preferred [30].

2.1.3 Consumption Patterns

In the context of the digital age and Artificial Intelligence, consumption patterns refer to the complex web of behaviors, attitudes, and decisions that consumers exhibit when interacting with products and services. This concept goes beyond product acquisition, encompassing all stages of the consumer lifecycle, from need recognition, through the purchase decision process, to post-consumption evaluation and eventual disposal [31]. Understanding these patterns is crucial for companies, as it allows them not only to meet existing demands but also to anticipate trends and shape the market [32].

The growing digitalization and the widespread dissemination of technologies such as Artificial Intelligence have drastically reshaped consumption patterns. Consumers' interactions with online platforms, social media, and smart devices generate a high volume of data, which, when analyzed, reveal valuable insights into their preferences, habits, and motivations [33] [1]. AI, in particular, plays a fundamental role in analyzing this data, enabling companies to identify behavioral patterns that would be imperceptible to human analysis, thereby optimizing marketing strategies and product offerings [6].

Consumption patterns are influenced by a wide range of factors, including socioeconomic, cultural, psychological, and technological aspects. The expansion of digital communities, for example, has led to the formation of consumer groups with similar interests and purchasing behaviors, where the sharing of knowledge and experiences shapes individual decisions [1].

Furthermore, the ability of artificial intelligence to process and analyze data in real time enables a more refined, dynamic, and responsive understanding of consumption behaviors, allowing organizations to adjust their strategies more quickly in response to fluctuations in consumer preferences and transformations in market trends [6] [8].

The concept of consumer behavior, although lacking a single and universally accepted definition, is understood as the particular perceptions of consumers' habits, lifestyles, attitudes, and practices [32]. A widely accepted understanding describes consumer behavior as the process by which individuals evaluate, select, purchase, use, return, or request ideas, products, and services with the goal of meeting their needs and desires, taking into account their attitudes, preferences, actions, and underlying motivations within the market context.

Consumer behavior can be divided into two strands: an attitude, which encompasses the "how" and "why" people consume, acquired attitudes, daily lifestyles, and attitudes, values, and actions manifested from a consumption perspective; and a choice, which encompasses the selection and purchase process, consumption decision-making, and the influence of values that shape purchase and consumption choices, as well as modes of purchase or repurchase based on specific requirements and expectations such as quality, taste, advertising, or price [34].

The evolution of theories on consumer behavior, which originated in Psychology and later gave rise to Social Psychology, began with studies on attitude, communication, and persuasion [35]. Over time, theoretical models have evolved significantly, ranging from theoretical approaches based on pre-existing theories and concepts from economics and psychology, to empirical approaches derived from the observation of behavioral patterns, and eclectic ones, combining the two previous approaches by uniting theoretical concepts with findings from market studies [36].

Initially, the models were predominantly economic in the 19th and early 20th centuries, emphasizing the allocation of limited resources to unlimited needs, but often disregarding psychological factors. From the 1960s onwards, more comprehensive models emerged to explain consumer behavior, combining factors such as information processing, attitudes, intentions, and environmental and personal influences. Subsequently, theories such as Rational Action, Planned Behavior, technology acceptance, and consumption values were developed, along with approaches that analyze psychological impacts and online purchasing behavior [8] [37].

2.1.4 Impacts of Generative AI on Consumer Behavior

The relationship between Generative Artificial Intelligence (Generative AI) and Consumer Decision-Making constitutes a rapidly evolving field of study, characterized by significant opportunities and challenges [2] [38]. Generative AI, with its ability to create original and personalized content, is redefining how consumers interact with brands and products, influencing their purchasing decisions in innovative ways [5].

Traditionally, AI has been used to predict consumer behavior based on historical data. However, Generative AI goes beyond this approach, enabling the creation of dynamic and interactive consumption experiences [8]. For example, it can generate personalized product descriptions, develop tailor-made marketing campaigns, and even simulate product usage scenarios, providing consumers with a more immersive and relevant view before making a purchase decision [39]. This ability to produce on-demand content tailored to individual preferences has the potential to democratize access to information and consumption opportunities, especially for niche markets or marginalized consumers [5].

Nevertheless, the increasing intensity of Generative AI usage in consumer research and behavior raises significant concerns [2]. One of them is the average trap, which refers to the tendency of Generative AI models to predict the most likely behavior, resulting in generic solutions that do not meet the specific needs of less represented consumers. Another challenge is model collapse, which occurs when Generative AI models predominantly learn from their own outputs instead of relying on real-world data. This can lead to homogenization and degradation of accuracy over time, disconnecting findings from actual consumer behavior [5].

To mitigate these challenges, it is important that research and applications of Generative Artificial Intelligence in influencing consumer decision-making prioritize the human perspective. This involves careful attention to specific and marginalized consumer data, engineering responses that incorporate human insights, and integrating human and machine data to realign AI with a human-centered focus [40]. Generative AI holds significant potential to transform consumer decision-making, making it more informed and personalized [41]. However, it is necessary to adopt a careful approach to ensure that the benefits outweigh the risks, preserving consumer autonomy and diversity.

2.2 RELATED WORKS

This section presents and discusses previous studies and experiences that explore Generative Artificial Intelligence and its impacts on consumer behavior, establishing a dialogue with the proposal of this work. The analysis of these related studies allows the research to be contextualized, validates the relevance of the proposed approaches, and provides learning opportunities from successes and challenges faced in similar scenarios of interaction between AI and consumption.

2.2.1 The Role of Artificial Intelligence and Knowledge Sharing in Consumer Behavior

This study [1] establishes a broad conceptual foundation and discusses how the increasing use of digital technologies, with an emphasis on artificial intelligence, has reshaped marketing and consumer behavior, influencing consumer attitudes towards products and services. The authors describe AI as a dynamic tool capable of "learning" and continuously improving based on data generated from consumer interactions, replicating new knowledge to optimize products and services. The work explores how consumer behavior, which encompasses the entirety of purchase, consumption, and disposal decisions, is also a "way of life" that underpins individual decisions.

The study in question [1] also addresses the solution for a deeper understanding of this phenomenon by highlighting AI's capacity to process and analyze vast amounts of information, providing data-driven solutions that benefit both organizations and consumer satisfaction. The study emphasizes that AI significantly advances consumer attitudes and behaviors when knowledge is acquired and that online communities promote curiosity and engagement through experience sharing. Additionally, the article proposes an innovative meta-framework that combines Consumer Behavior (CB), Artificial Intelligence (AI), and Knowledge Sharing (KS), aiming for a more holistic and integrated understanding of consumption dynamics in the digital age.

As a result, the study [1] offers a robust framework for analyzing how AI, including Generative Artificial Intelligence, can influence critical aspects such as price perception, product comparison, and consumer engagement. The research conceptually demonstrates that the strategic integration of AI and knowledge sharing is a catalyst for the evolution of consumption patterns, enabling companies and consumers to navigate more efficiently in this complex and constantly changing scenario.

The relevance of this study [1] to the present work is evident, as it establishes a solid conceptual foundation for research on the impact of Generative AI on consumption patterns. By presenting a meta-framework that connects AI and consumer behavior, the article validates the relevance of investigating how AI technologies, specifically generative ones, influence discovery, preferences, and purchase decisions. This study serves as an essential theoretical pillar, reinforcing the importance of analyzing the complexity and nuances of consumer behavior driven by the evolution of artificial intelligence.

2.2.2 Understanding Purchase Decision-Making with AI Recommendations

This study [4] directly investigates the mechanism by which recommendations driven by Artificial Intelligence—a central and growing capability of Generative AI—influence consumer decision-making. Although the research specifically focuses on the functional food sector, the principles and mechanisms examined have broader applicability.

The authors [4] analyze how the personalization and transparency of AI recommendations, as well as the mediating roles of concepts such as perceived packaging and perceived value, affect purchase intention. The study's methodology employs the Stimulus-Organism-Response (S-O-R) framework, which proves particularly effective in uncovering how external stimuli (such as AI characteristics and product attributes) influence consumers' internal psychological states (their perceptions) and, consequently, their purchase decisions.

The authors address the solution for optimizing consumption decisions by validating that the personalization of AI recommendations significantly increases purchase intention, both directly and indirectly. The research highlights that AI transparency, by building trust and perceived value, illustrates the relevance of interaction quality with AI for consumer acceptance and behavior [4].

The article [4] suggests that AI personalization acts as a direct stimulus for consumer responses, while transparency operates as an indirect facilitator of decision-making. By analyzing how AI, adapting to user behavior and refining suggestions, simplifies decision complexity and strengthens trust in consumer choices, this study offers empirical insights and a detailed theoretical model that clarifies the psychological mechanisms underlying purchase decisions driven by intelligent systems.

As a result, the research demonstrates the power of AI-personalized recommendations in positively influencing purchase intention, emphasizing that transparency and perceived value are determining factors for the effectiveness of these interactions. The applied S-O-R framework provides a valuable lens for breaking down the consumer decision-making process when faced with AI stimuli, highlighting how personalization and clarity in suggestions can optimize the shopping experience and strengthen trust.

The relevance of this study [4] to the present work is undeniable, as it directly investigates the psychological mechanisms through which the core capabilities of Generative AI—such as personalization and transparency in recommendations—impact decision-making and consumption patterns.

2.2.3 The Future of Consumer Research with Generative AI

This study offers a strategic perspective on the future of consumer research in the context of Generative AI [5]. The authors introduce the trajectory of "democratization–average trap–model collapse", an essential framework for understanding the challenges and opportunities that GenAI poses to consumption patterns.

"Democratization" suggests that Generative AI expands access to consumption opportunities, promoting greater participation and data diversity. However, the "average trap" warns of the tendency of Generative Artificial Intelligence models to produce generic results, converging towards the average consumer behavior and often neglecting nuances, especially those of marginalized groups. Finally, "model collapse" points to the risk of Generative AI predominantly learning from its own outputs, which can lead to homogenization and degradation of accuracy, resulting in outputs that lose human sensitivity [5].

The authors [5] address the solution for understanding these phenomena by discussing the evolution from human consumers to hybrids to Generative AI, representing a fundamental shift in consumption patterns. The analysis of machine-to-machine interactions and the potential replacement of human decision-making by Generative AI are crucial aspects for understanding how these new patterns are formed and what their implications are. Discussions on the truthfulness of generated data, inherent algorithmic bias, and the loss of human sensitivities provide an indispensable critical framework for a comprehensive and nuanced evaluation of the impact of Generative AI.

As a result, the study by Huang and Rust [5] not only establishes a conceptual framework for the debate on the future of consumer research but also highlights the urgency and complexity of addressing Generative AI as a transformative agent in consumption.

The research emphasizes the inherent challenges of excessive generalization and the degradation of originality that may arise from the indiscriminate use of Generative AI while also pointing to its democratizing potential.

The relevance of this study to the present work is central, as it directly addresses the evolution of consumption patterns under the influence of Generative AI, providing a framework for analyzing the transformations in consumer behavior. The article offers critical insights into the risks and opportunities associated with Generative AI, making it an essential theoretical pillar for the research by highlighting the urgency and complexity of addressing this technology as a transformative agent in consumption.

2.2.4 Impact of Generative AI-driven Advertising on Generation Z's Consumer Behavior

This article examines the influence mechanism of advertising driven by Generative Artificial Intelligence (AI) on the consumer behavior of Generation Z (Gen Z) in China [2]. The study acknowledges Gen Z as a significant consumer force that exhibits distinct characteristics, such as a quest for uniqueness and personalized psychology. The authors aim to unravel the"intricate black box" of this influence mechanism. The key questions the study seeks to address include: How does emerging AI advertising affect the consumer behavior of Chinese Gen Z youth? What is the influence mechanism? And what problems and challenges does this advertising face?

To achieve its objectives, the study [2] utilized the methodology of programmatic grounded theory, a qualitative method that aims to construct theories from original data. Primary data collection was conducted through in-depth qualitative interviews and semi-structured interviews with 24 Chinese university students belonging to Generation Z. The data analysis involved the three main stages of grounded theory: open coding, axial coding, and selective coding, using the software Nvivo12.0 for processing and establishing category relationships. The research design was based on the paradigm model and referenced the stimulus-response (SOR) theory to systematically analyze the raised issues.

The primary findings reveal the pathways through which four essential cognitive dimensions influence the consumption behavior of Generation Z. These dimensions (Organism factor - O) include corporate cognition, value cognition, emotional cognition, and risk cognition. The complete mechanism is structured by the Stimulus (S), which encompasses the outreach channels and the presentation of AI advertising content, and by the Response (R), which represents consumer behavior. The Response manifests through four consumption intentions: willingness to watch, willingness to buy, willingness to share, and willingness to explore. The results broaden the current research on the influence mechanism on Generation Z's consumer behavior [2].

Other key points revealed include the finding that, in emotional cognition, Generation

Z consumers often display neutral or repulsive emotional responses to AI-generated advertising, which is attributed to a lack of creativity, authenticity, or emotional resonance. In light of these challenges, the study [2] provides practical guidance for the advertising industry, such as the need to optimize the degree of naturalness of the content, enhance data accuracy to avoid the feeling of superficial use of AI, and strengthen the prevention of ethical risks, including privacy protection and the prevention of intellectual property violations.

This article [2] demonstrates its value by employing a procedurally grounded theory methodology. The study not only affirms the significance of the topic but also addresses a clear research gap regarding the impact of AI-generated advertising on young individuals. Its most notable contribution is the expansion of the Stimulus-Organism-Response (SOR) model, identifying four cognitive dimensions (corporate cognition, value cognition, emotional cognition, and risk cognition) that serve as the 'Organism' (O) processing AI advertisements, which in turn stimulate or inhibit consumer behavior. Consequently, the article presents a comprehensive theoretical framework for examining the precise pathways through which AI affects consumer attitudes and intentions related to purchasing, sharing, and exploration, thereby laying a solid foundation for the transformation and application of AI technology in the advertising and consumption sectors.

2.2.5 The Role of Artificial Intelligence in Personalized Marketing

This article explores the ways in which Artificial Intelligence is transforming personalized engagement marketing by altering the methods through which companies generate, convey, and provide tailored value to consumers [8]. The authors contend that the swift advancement of AI, rooted in machine learning, natural language processing, and extensive data analytics, signifies a new phase in the knowledge economy, where the emphasis shifts from information accumulation to information curation as the main catalyst for marketing success. Furthermore, the article presents a significant perspective on the concentration of firms' data on major platforms like Google and Amazon, and discusses how AI can facilitate the restoration of data exchange between customers and firm-owned platforms.

From a methodological standpoint, the research [8] employs a conceptual and theory-building framework that draws upon interdisciplinary literature spanning marketing, consumer behavior, and information systems. The article integrates findings related to personalization, customer engagement, consumer knowledge frameworks, and AI capabilities to develop a multi-wave model of information processing. This model differentiates between traditional human-driven personalization and AI-enhanced curation systems that are capable of continuously learning from consumer interactions.

The framework elucidates the impact of AI on critical phases of consumer decision-making, encompassing information search, choice evaluation, and post-purchase engagement. Moreover, the authors include empirical evidence from industry examples in both developed and developing markets to illustrate how differing levels of data maturity, technological preparedness, and market structure influence the adoption and effectiveness of AI [8].

The primary findings of the study [8] underscore three strategic areas—acquisition, retention, and growth of the customer base—through which AI revolutionizes engagement marketing. In terms of customer acquisition, Artificial Intelligence enhances brand value by tailoring content that is relevant to specific regions and refining targeting accuracy. For retention, human–machine interfaces, including recommendation systems, chatbots, and voice assistants, improve the customer experience by providing adaptive, real-time personalization. Concerning the growth of the customer base, the authors present the notion of customer knowledge value, highlighting how each consumer's interactions aid in the enhancement of machine-learning algorithms, thus improving predictive accuracy and fostering long-term engagement results. In this context, customers contribute not only financial value but also educational value to the organization.

The article [8] further examines the obstacles to AI adoption, especially in emerging markets. Structural challenges such as limited data availability, technological fragmentation, and socioeconomic inequalities may hinder the widespread implementation of AI. Consequently, the authors recommend that companies in developing regions implement incremental and hybrid human–machine approaches, utilizing AI to augment—rather than supplant—human expertise. The study also emphasizes the necessity for management to align AI initiatives with the capabilities of the firm, ensure data maturity, and address risks associated with privacy, trust, and user acceptance.

In summary, this article [8] enhances the existing literature by presenting a thorough theoretical framework that elucidates the ways in which AI modifies the processes of personalization and customer engagement. By conceptualizing AI as both an analytical and curatorial entity, the authors broaden the comprehension of how consumer knowledge is structured, retrieved, and converted into customized experiences. This research offers significant strategic insights for organizations seeking to adapt to the shift towards AI-driven marketing ecosystems and underscores the different trajectories that both developed and developing economies might pursue in this technological advancement.

3

3 METHODOLOGY

This section describes the methodological procedures adopted for the realization of the study, detailing the approaches, techniques, and instruments utilized in data collection and analysis. The definition of methods followed criteria of suitability to the research problem and the proposed objectives, ensuring scientific rigor and reliability of the obtained results. By making the stages of the investigative process explicit, the aim is to ensure transparency, allow for a possible replication of the study developed, as well as offer solid foundations for the interpretation of the conclusions presented in this course conclusion work.

The present study lies at the intersection of Computing and Applied Social Sciences. As emphasized in Wazlawick's work [42], although computing is often categorized within the exact sciences or engineering, several of its sub-areas, especially those focused on the impact of technology on society, require an empirical approach based on observation and data interpretation, and not merely on the creation of artifacts.

In this scenario, the scientific method utilized aims at the practical order, which refers to the generation of knowledge with the objective of understanding a phenomenon more effectively. The research was organized to meet the demand for information regarding a contemporary problem: the influence of algorithms on human decisions. Thus, the study aligns with the category of research directed toward the collection of opinions, intentions of actions, and future consumer decisions [43].

For the execution of the study, the premise was considered that, given the impossibility of analyzing the totality of a population, the use of data samples is essential [44]. The research design opted for Non-Probabilistic Sampling, frequently employed in digital studies due to its accessibility, although its limitations regarding the universal generalization of results are acknowledged.

Data collection was based on a structured survey. To convert the qualitative perceptions of respondents into data that can be analyzed quantitatively, the Likert Scale was utilized. This tool enables the measurement of attitudes and levels of agreement on a gradual scale, allowing data interpretation, considered by Wazlawick [42] as the most relevant aspect of scientific work in computing, to be performed through a reflective and critical discourse, surpassing simple information collection.

The structured methodology utilized makes it possible to classify the research as qualitative-quantitative. The quantitative part is revealed in the statistical measurement of variables through the Likert Scale, while the qualitative approach focuses on the critical analysis of behavior and trust patterns observed in the sample.

To obtain the primary data necessary for analysis, the elaboration of a structured questionnaire hosted on the Google Forms platform was chosen. The collection instrument consisted of twenty questions, organized strategically to cover the various dimensions of the research problem, available in full in the Appendix (Table 2) section of this work. The form structure was divided into five distinct sections:

Table 1: Description of the Questionnaire Sections

Question Section	**Description**
Sociodemographic Profile	To characterize the sample.
Recommendation Algorithms	To evaluate perception and general usage habits.
Artificial Intelligence Platforms	Focused on familiarity and the tools used.
Influence and Trust in Received Information	Intended to measure the impact of suggestions on user behavior.
Reliability in Artificial Intelligence Platforms	Aimed at the perception of security, ethics, and veracity.

Source: Developed by the author.

The formulation and application of the data collection form relied on twenty questions, as previously mentioned. As a response domain for the closed questions, the Likert scale was utilized. The referred scale is a technique widely used to measure attitudes, opinions, and levels of agreement or satisfaction regarding statements; it presents response options on a gradual scale, such as ”strongly disagre” to “strongly agree”, transforming qualitative data into quantitative data for statistical analysis [45].

Before large-scale application, the data collection instrument was submitted to a pre-test (pilot study) with an initial sample of fifteen respondents selected randomly following the same principles as the study’s sampling plan. This stage aimed to validate the semantic clarity of the questions, the fluidity of the questionnaire, and to time the respondents’ average response duration, ensuring the quality and integrity of the final instrument. After this stage was concluded, specific corrections were applied to the questionnaire structure, aiming for better interpretation and quality in obtaining primary data, which were:

- exclusion of the mandatory nature of questions;
- simplification of terms with the goal of increasing question clarity;
- normalization of the response domains of the Likert scale used in the questions;

- calibration of the average response time. Furthermore, the average response time captured was about five minutes, and the test data were excluded from the final work sample with the reset of the form.

For the definitions of sampling and data collection procedures, the research established the participation of individuals under 18 (eighteen) years of age as an exclusion criterion. This decision was made with the intent of reducing ethical and legal implications associated with the use of data from minors, ensuring compliance with academic research guidelines, even under the protection of participant anonymity. Beyond the discretionary nature already cited on the part of the researcher, such a measure aimed at reducing the exploratory time for data acquisition, as well as reducing the research schedule regarding a possible evaluation by a research ethics committee, since the object does not possess any sensitive data and/or questions of a moral, political, ethical, religious, or health nature regarding the interviewees.

Non-probabilistic sampling (NPS) was used as the definition for the participant selection technique, which composes the study's sampling plan. The referred sampling strategy is frequently used in research with online forms due to the ease of distribution and collection, but it possesses limitations in the generalization of results to the entire population, a fact that does not present a limitation to the study's results given its exploratory nature [45].

After validation and the modifications resulting from the pre-test, the questionnaire application strategy adopted a hybrid approach. Digital dissemination was carried out through the social networks WhatsApp and Instagram. Simultaneously, in-person approaches were made, in which access to the form was made available to respondents through the scanning of a QR Code (quick response code). Data collection, therefore, followed a non-probabilistic sampling based on convenience and accessibility.

The collection period was finalized after reaching a critical mass of data considered adequate for the proposed analyses. The form was closed, totaling a final valid sample of 211 respondents, which occurred within 8 days of the research form's opening interval, from its application in the test sample (n = 15) ending at the conclusion of the target of two hundred respondents. It is worth noting that the questionnaire application was carried out during the month of November in the year 2025.

The data treatment and analysis process was performed in an iterative and incremental manner. With an initial sample of 100 (one hundred) responses, data modeling and the creation of the first analytical visuals began using the Microsoft Power BI tool. This preliminary phase enabled the anticipation of database structuring needs.

After the conclusion of collection, the final database (n = 211) was imported in its entirety into Power BI. In this phase, the ETL (Extraction, Transformation, and Load) process was executed, which included validation, cleaning (sanitization), and data grouping. It is important to highlight the treatment performed on multiple-choice questions and open text fields, which were categorized to enable the precise quantification of variables. With the database duly treated and presenting the necessary integrity, the elaboration of charts and visual dashboards began. These visual resources were essential for interpreting consumption patterns and for answering the questions guiding the present work. The data analyses cited herein will be the main focus of the Results and Discussion section of this work.

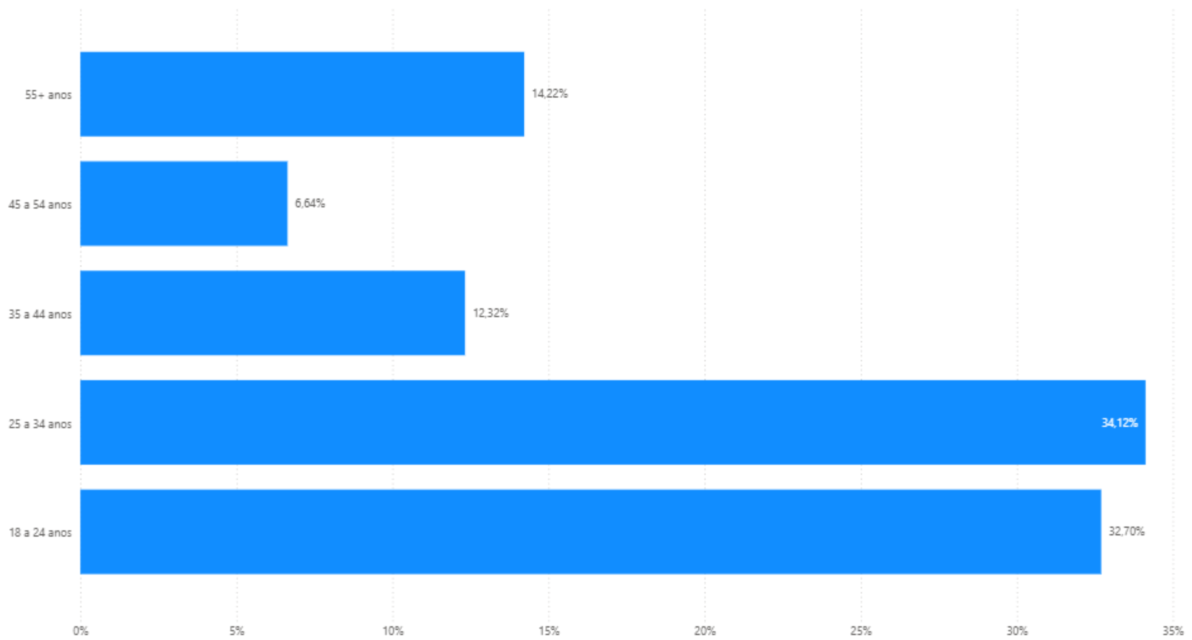
4

4 RESULTS AND DISCUSSION

4.1 CHARACTERIZATION OF THE SOCIODEMOGRAPHIC PROFILE OF THE SAMPLE

As outlined in the preceding section, the data collection process, which utilized non-probabilistic convenience sampling, yielded 211 valid responses. An initial analysis of the sociodemographic variables (age group, education level, and family income) indicates a respondent profile that exhibits both homogeneous and distinct characteristics, which significantly influences the interpretation of consumption habits and the use of Artificial Intelligence discussed in the subsequent sections.

Figure 3: Percentage of Respondents in each Age Group



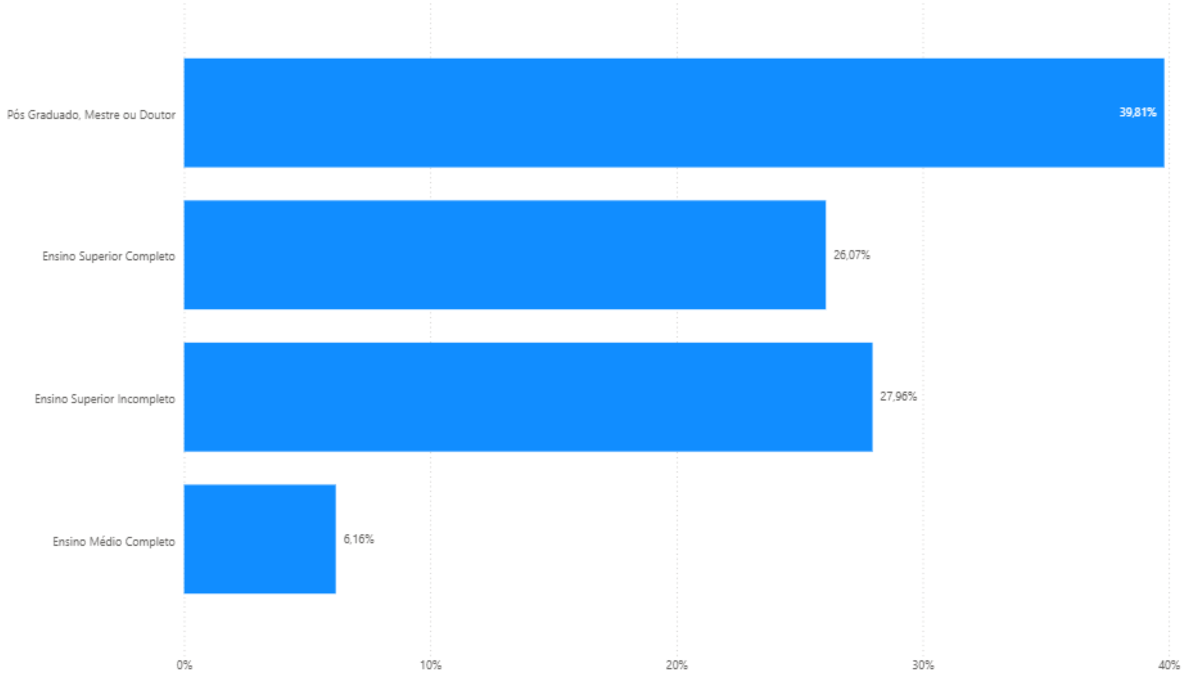
Source: Compiled by the author based on the dataset derived from the exploratory research.

Based on the evidence presented in Fig.3, it is possible to highlight that within the age distribution, there is a significant predominance of young adults. The demographic group comprising individuals aged 18 to 34 years constitutes a substantial majority of the respondents, with a particularly notable concentration in the sub-group of 25 to 34 years. This distribution is not random; rather, it is a direct reflection of the data collection strategies employed. The emphasis on dissemination through digital channels, as mentioned in the previous section, combined with the use of tools such as QR Codes for quick access to the questionnaire, has proven to be highly effective in reaching the population segments classified as"digital natives" and, consequently, the younger demographic. The familiarity and engagement of these groups with digital technologies have facilitated their participation in the study.

In contrast, there is a markedly reduced representation of older age groups, particularly those over 45 years of age. This underrepresentation suggests a lower level of exposure or engagement of these groups with the digital dissemination channels employed, or possibly a lesser familiarity with the digital response collection mechanism, and in addition, a potential lack of time to participate as respondents in an exploratory academic study. Therefore, it is essential to acknowledge that the sample predominantly reflects the perceptions, attitudes, and experiences of younger generations, specifically Millennials and Generation Z. This fact does not technically invalidate the results obtained in the research. This demographic limitation must be taken into account when interpreting the results and extrapolating the findings to the general population, indicating that the study provides an in-depth perspective, albeit generationally more restricted, on the influence of generative artificial intelligence on consumption patterns, a phenomenon under investigation.

Regarding the level of education, there is a significant sampling bias towards high qualifications, as illustrated in graph Fig.4. Collectively, respondents with incomplete or complete higher education, postgraduate studies, master's degrees, or doctorates account for over 93% of the sample, while the participation of individuals with only a high school education is notably limited.

Figure 4: Percentage of Respondents in each Education Group

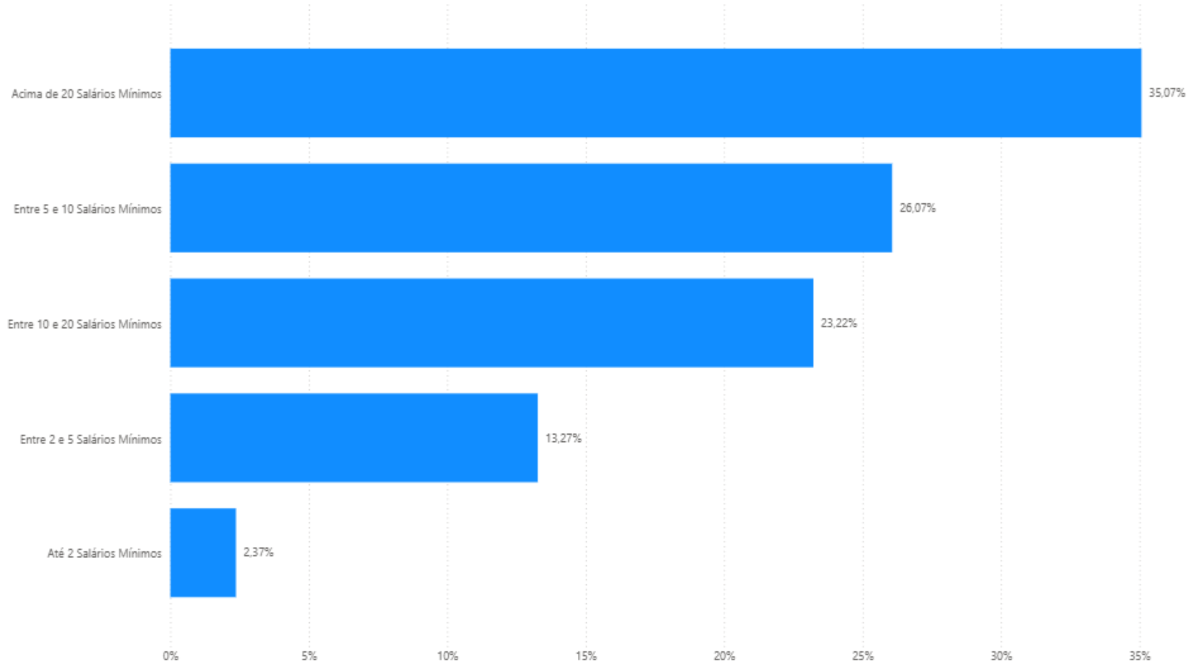


Source: Compiled by the author based on the dataset derived from the exploratory research.

This elevated educational pattern indicates an important characteristic of the participant group: the possession of an advanced level of literacy and, particularly, sharp critical thinking skills. A high educational level is often correlated with an enhanced ability to process complex information, engage in abstract reasoning, and, crucially for this study, a greater competence to interact with, understand, and critically apply sophisticated technological tools such as Generative AI, whose exploration and in-depth analysis are facilitated by users with higher intellectual and educational capital. This characteristic of the sample is a factor to be considered in the interpretation of the results, as the perceptions and uses of Generative AI reported here are likely to reflect the perspective of individuals with greater ease of access, understanding, and engagement with emerging technologies.

Regarding the socioeconomic profile of the sample, as detailed by the analysis of family income and illustrated in Fig.5, there is a significant restriction in the composition of the participants. A notable concentration of income is observed in the higher brackets, with the category “Above 20 Minimum Wages” emerging as the largest isolated group. This category is closely followed by the upper intermediate ranges, particularly those earning between 4 to 10 minimum wages and those earning between 10 to 20 minimum wages. It is particularly noteworthy that the sum of categories declaring a family income exceeding 10 minimum wages encompasses more than 60% of the total respondents.

Figure 5: Percentage of Respondents in each Family Income Group



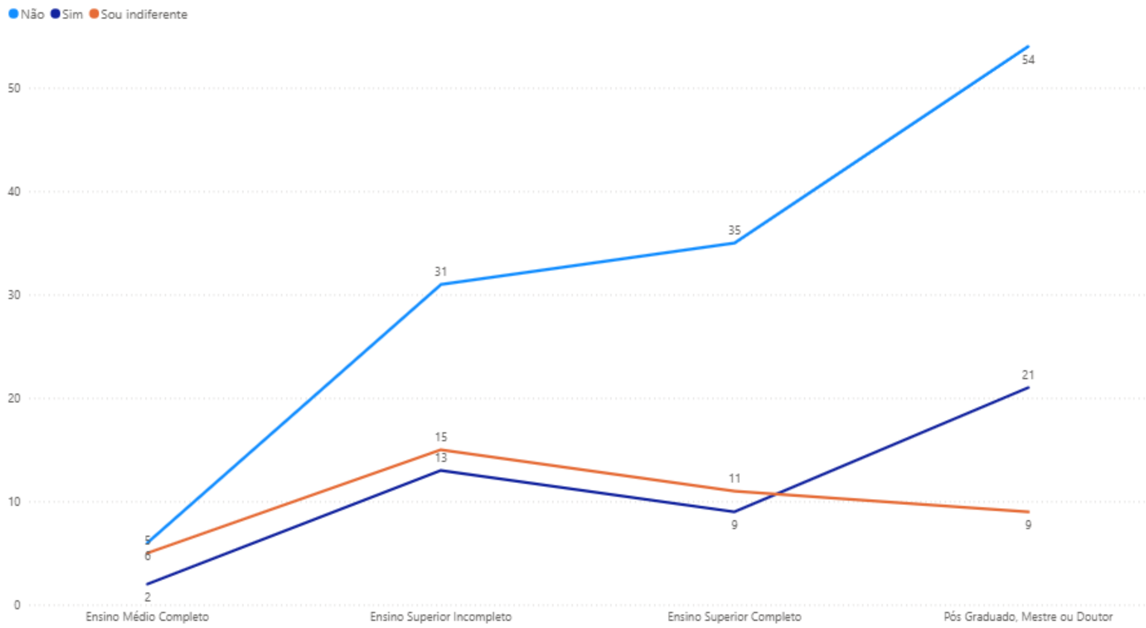
Source: Compiled by the author based on the dataset derived from the exploratory research.

In summary, the “persona” that stands out and predominates in this study can be accurately characterized as a young individual, possessing a high level of academic education (often at the postgraduate level or equivalent) and holding a significant purchasing power, in comparison to the national average in Brazil, which is up to two minimum wages according to recent data from IBGE [46].

4.2 THE INFLUENCE OF EDUCATIONAL LEVEL ON TRUST PERCEPTION AND CONSUMPTION IMPULSE

By integrating data on educational attainment with the level of trust expressed on AI platforms Fig.6, such as Chat GPT, Gemini, Deep Seek, Copilot, and other chatbots, a significant behavioral trend is observed: an increase in formal education appears to be inversely correlated with unconditional trust in the artificial intelligence algorithms developed by these aforementioned platforms.

Figure 6: The Impact of Educational Attainment on Trust in AI Platforms



Source: Compiled by the author based on the dataset derived from the exploratory research.

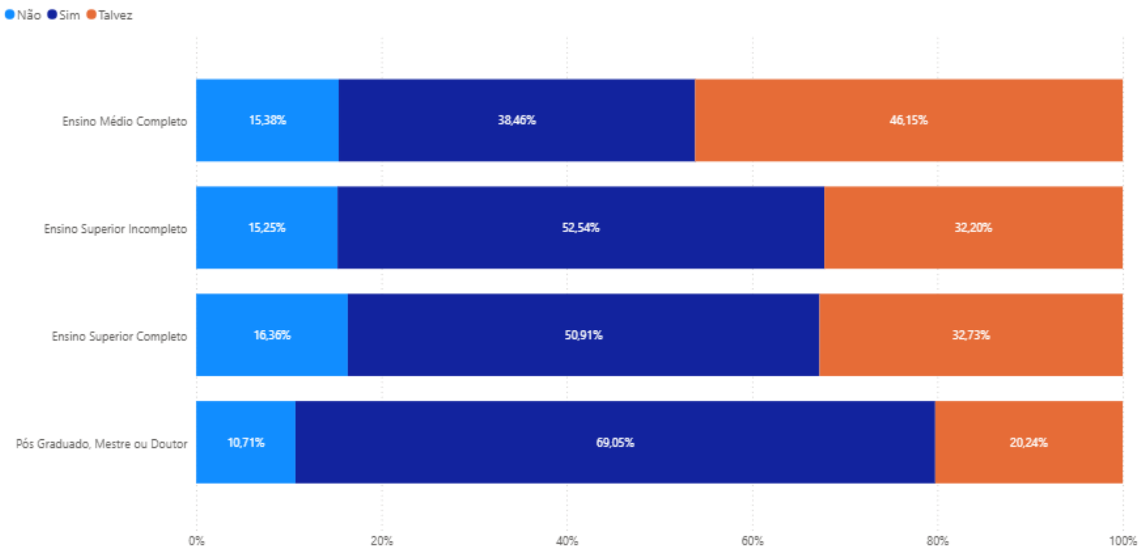
The analysis of the lines indicates that as one progresses through the educational scale, starting from incomplete higher education towards postgraduate studies, master's, and doctoral levels, the negative response to the survey question: "Do you trust artificial intelligence platforms (ChatGPT, Gemini, Deep Seek, Copilot, among others) regarding the security of your data?" tends to intensify or remain at high levels, while trust does not grow at the same pace or shows a proportional decline.

This phenomenon can be examined through the lens of awareness regarding digital privacy and data governance. The audience with a higher educational level, presumably possessing greater digital literacy and understanding of cyber risks, appears to be more cautious about the ability or willingness of these platforms to ensure complete confidentiality of the information provided, especially when it becomes public knowledge, particularly among more educated groups, that much of the data exchanged with chatbots is utilized for their training.

In other words, it is pertinent to assume that this analyzed group tends to question the lack of transparency in the terms of use and the business model of large technology companies, remaining more vigilant about risks such as unauthorized data usage, potential leaks, and the absence of clarity regarding the storage of conversations. Thus, within this sample, academic training serves as a protective factor for privacy, reducing excessive exposure and fostering a more cautious interaction, where the user engages with the tool but refrains from sharing sensitive or confidential data.

Corroborating the hypothesis that academic background promotes a less enamored and more analytical stance regarding technological innovation, the data obtained when investigating the belief that Artificial Intelligence functions as a driver for more immediate and impulsive consumption, whether of material goods or digital content, revealed a significant statistical disparity between the educational extremes (Fig.7).

Figure 7: Impact of Education Level on the Belief in Impulse Buying Influenced by AI



Source: Compiled by the author based on the dataset derived from the exploratory research.

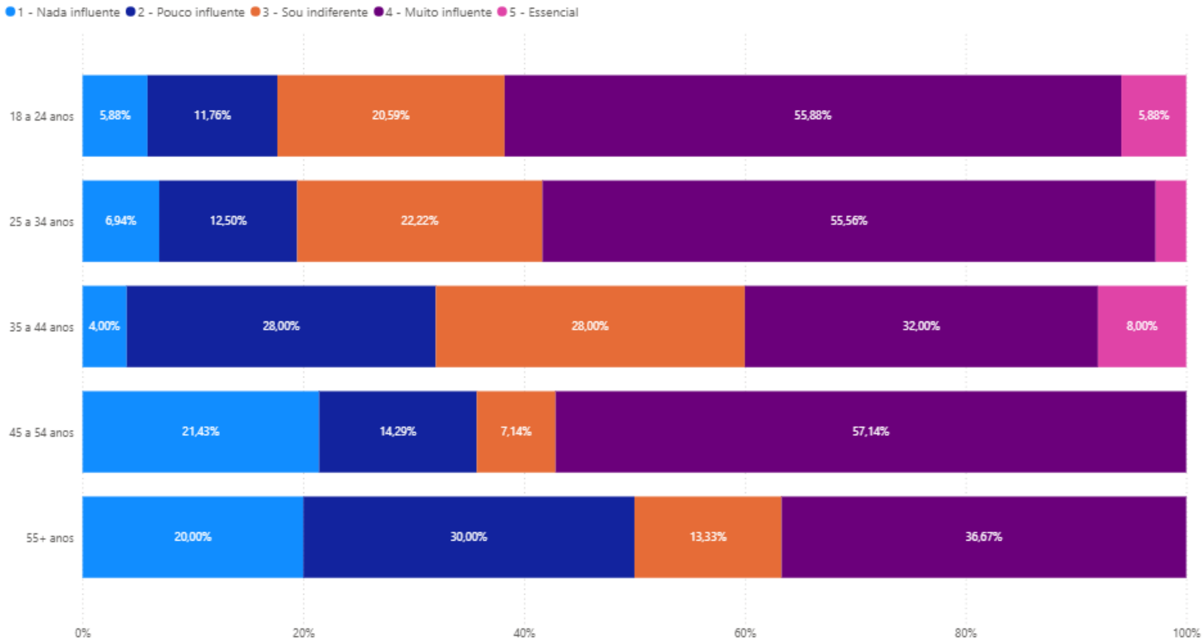
The stratified analysis demonstrates that over 69% of respondents with advanced degrees recognize a direct causal relationship between the use of these technologies and the acceleration of impulse buying. In contrast, this perception of vulnerability to the algorithm decreases drastically to 38% among participants who possess only completed high school education.

This significant percentage differential may indicate that the level of education acts as an instrument to deconstruct the market dynamics embedded within the technology. While the demographic with higher education tends to identify algorithmic persuasion tactics and design aimed at minimizing purchase friction, the demographic with lower formal education seems to naturalize these suggestions, perceiving them less as an external induction and more as a neutral convenience. Therefore, education not only increases distrust regarding data security, but also sharpens critical perception regarding how AI can shape, and at times manipulate, the economic behavior of the user.

4.3 THE INFLUENCE OF AI ON PURCHASE DECISIONS FROM A GENERATIONAL PERSPECTIVE

Upon examining the direct impact of Artificial Intelligence recommendations on the final purchase decision, stratified by age group (Fig.8), a significant inverse correlation is observed between the respondent's age and their receptiveness to algorithmic suggestion.

Figure 8: Influence of AI on Purchase Decisions from a Generational Perspective



Source: Compiled by the author based on the dataset derived from the exploratory research.

The chart illustrates a true "generational gap" in digital consumption behavior. At the top of the pyramid, among respondents from Generation Z (18 to 24 years old), the highest acceptance rate of AI influence is noted. In this group, the sum of responses attributing the degree "Very Influential" or "Essential" to the technology predominates in the distribution, while total resistance is minimal. This datum indicates that, for digital natives, algorithmic curation is not perceived as an intrusion, but rather as an auxiliary tool intrinsic to the purchasing process.

As age progresses, a gradual alteration in stance is observed. The intermediate age group (35 to 44 years) reveals a transitional behavior, where the category "I am indifferent" stands out, suggesting a utilitarian use of the tool, albeit with a reduced perception or acceptance of direct influence.

Furthermore, it is of great importance to highlight an atypical behavior when analyzing the 45 to 54 age group, where the proportion of participants who consider AI as "Very Influential" in their purchasing process is superior to all other age groups. However, as mentioned in Section 4.1, this age group has the lowest number of respondents (n = 14). Thus, we can conclude that the reduced sample of this age group does not reflect the true trend and may indicate a sample bias, a fact that was not the object of investigation given the initial focus of the work.

Finally, the scenario changes drastically in the higher age groups. In the group over 55, the rejection of AI influence becomes the predominant pattern. The categories "Not influential" and "Slightly Influential" account for 50% of the responses from this segment. This phenomenon suggests that, despite this demographic having high education and income, as evidenced in the sample characterization, their purchase decisions continue to be based on analog criteria or active research, evidencing a cultural or trust barrier that prevents AI from functioning as a modeling agent of their consumption.

Thus, we arrive at the conclusion that the efficacy of Generative AI as a marketing and sales instrument is not yet uniform across all ages. This tool is deeply affected by the generational maturity of the target audience, finding a favorable context among the youth and facing considerable challenges in the more mature age group. An analysis that may confirm the lack of Artificial Intelligence literacy among the more mature age groups is the response to the question contained in the research instrument of this study, which evaluates familiarity with the concept of Generative AI.

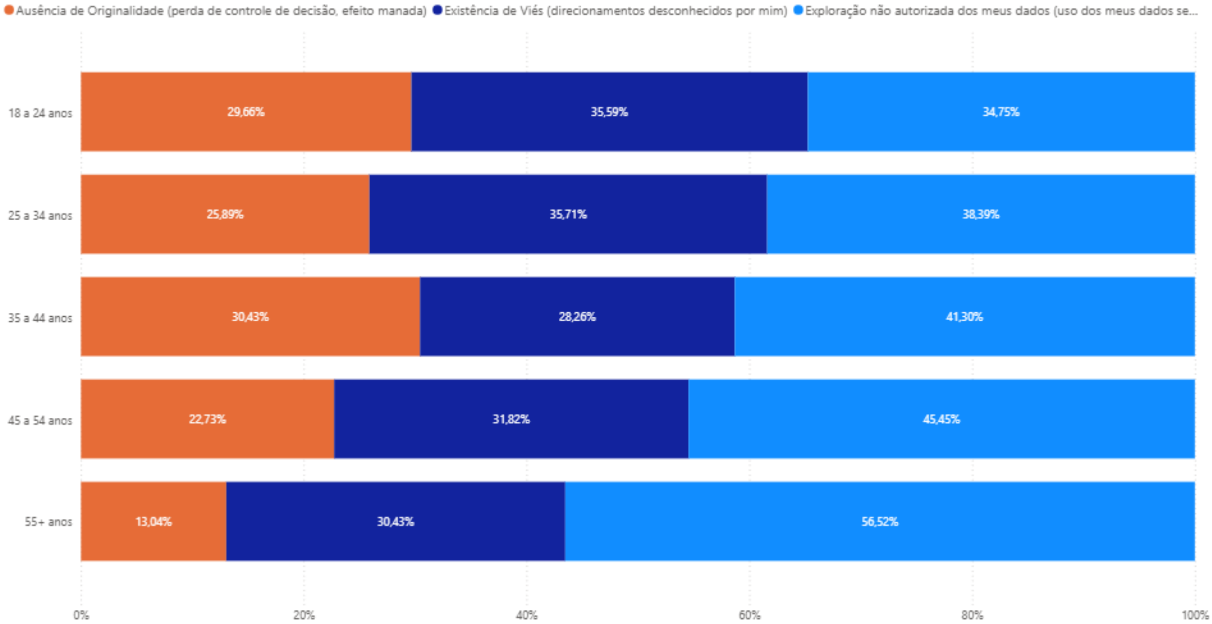
Again, by providing the junction and comparison of data from these two metrics, we observe that in the younger age groups, from 18 to 34 years old, familiarity with AI demonstrates a high level of maturity, with over 30% of participants identifying themselves as "Very familiar" or "Completely familiar". Likewise, in this age group, those who consider themselves not familiar do not exceed 16% among those aged 18 to 24 and 23% among those aged 25 to 34 (Fig.13.

On the other hand, when analyzing the more mature age group, over 86% feel not or slightly familiar, and the option "Completely familiar" did not obtain a single mention in this group. This gap present between age groups evidences that there is indeed a generational and literacy barrier regarding Artificial Intelligence, especially in its Generative form. However, this disparity may be mitigated as algorithms become more accessible and humanized, helping those who are not digital natives in their utilization.

4.4 COMPARISON OF KEY RISK PERCEPTIONS BY AGE GROUP

The analysis of barriers to the adoption of Artificial Intelligence, stratified by age group (Fig.9), reveals a qualitative shift in risk perception as the respondent matures. Although “Unauthorized data exploitation” is the predominant concern across all groups, its intensity varies significantly.

Figure 9: Comparison of Key Risk Perceptions by Age Group



Source: Compiled by the author based on the dataset derived from the exploratory research.

In the younger age brackets (18 to 34 years), a scenario of dispersed concerns is observed. Although they are concerned about privacy, these groups demonstrate an equally high level of unease regarding the “Existence of Bias” and the “Absence of Originality”. This indicates that, for digital natives, algorithmic risks, such as being manipulated or losing creativity, are virtually as severe as security risks.

As age advances, the spectrum of concerns narrows. In the group over 55 years of age, the issue of privacy assumes absolute prominence, accounting for 56.5% of the responses. For this senior demographic, the central fear does not appear to be the sophistication of the algorithm or cognitive bias, but rather the direct violation of privacy and the opaque use of their personal data. In contrast, concern regarding the “Absence of Originality” becomes residual in this group (13%), suggesting that the loss of creative agency to the machine is not viewed as a priority threat. Therefore, it is concluded that the resistance to AI solutions among older individuals, previously cited in the preceding subsection, may be strongly grounded in a fundamental distrust regarding information security, whereas the youth, although heavy users, maintain critical vigilance regarding the quality and neutrality of the generated content.

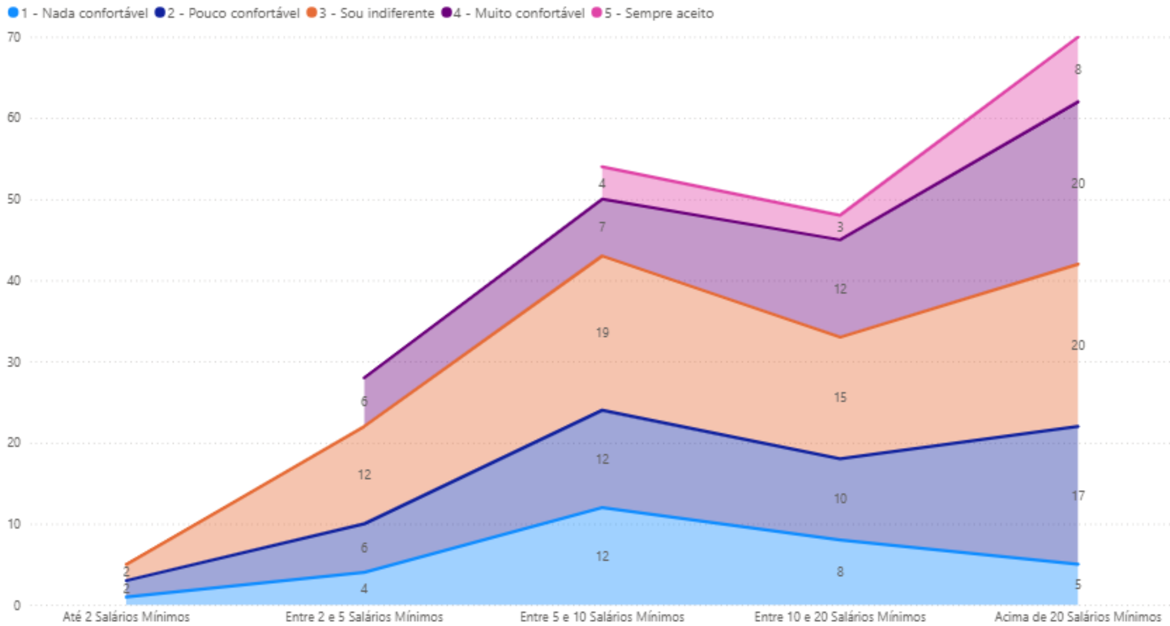
Thus, revisiting the proposition at the end of prior subsection, it can be concluded that mitigating the generational gap requires differentiated strategies. For the more mature audience, the implementation of transparency and algorithmic explainability measures, fostering greater familiarity with the tool and an understanding of data usage, proves to be an essential retention mechanism. By providing greater clarity regarding data processing and decision-making, platforms can lower the barrier of distrust that currently alienates this segment.

Simultaneously, for younger demographics, the approach must focus on the humanization of Generative Artificial Intelligence interfaces. Encouraging fluid and organic interactions strengthens the emotional bond, establishing itself as a strategic vector not only for loyalty, but also for intensifying the continuous use of the technology by this demographic. These measures, when well-structured, are capable of ensuring that Generative AI algorithms do not fall into the Uncanny Valley when attempting to mimic human behavior in a disordered manner.

4.5 THE CORRELATION BETWEEN FAMILY INCOME AND COMFORT IN ALGORITHMIC MEDIATION

The analysis of respondents' willingness to allow the participation of Artificial Intelligence in their purchasing processes, when stratified by family income (Fig.10), reveals distinct behavioral patterns that corroborate the existence of a socioeconomic divide in technological adoption. Data visualization evidences a clear trend: algorithmic acceptance expands proportionally to the increase in purchasing power.

Figure 10: Family Income and Comfort in Algorithmic Mediation



Source: Compiled by the author based on the dataset derived from the exploratory research.

In the lower income brackets (comprising between "Up to 2" and "2 to 5 minimum wages"), it is noted that cautious stances predominate, characterized by the concentration of responses in the categories "I am indifferent" and "Slightly comfortable". This behavior suggests that, for the demographic with greater budgetary constraints, AI has not yet surpassed the barrier of distrust, possibly due to lower digital literacy or a natural defensive stance regarding financial risks.

In contrast, as one advances to the middle and high-income brackets, notably starting from the "5 to 10 minimum wages" bracket, a qualitative shift in value perception is observed. The consistent growth of the categories "Very comfortable" and "Always accept" reaches its peak among respondents with an income "Above 20 minimum wages". This datum indicates that the elite consumer, accustomed to premium digital ecosystems and personalized services, demonstrates superior permeability to technological mediation, viewing it as a convenience rather than a threat.

Therefore, the results reinforce the hypothesis that comfort with AI is, to a large extent, a function of access. Frequent exposure to digital tools and lower technological risk aversion, characteristics of higher-income classes, act as catalysts for the naturalization of Artificial Intelligence as a legitimate and desirable support in consumption decision-making.

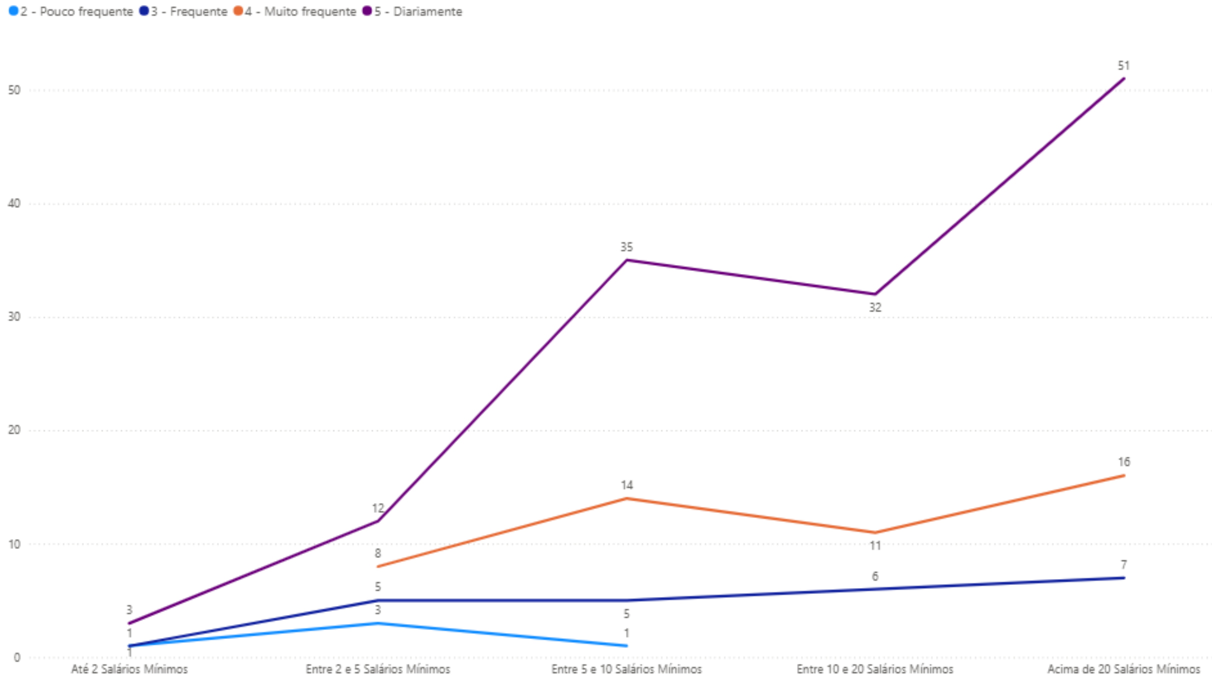
This trend of greater comfort, driven by resource availability and consequent access to cutting-edge technologies, is corroborated by the bivariate analysis between the variables of “Familiarity with Generative AI” and “Income Bracket”(Fig.14. The analysis further reveals that the level of AI literacy does not follow a linear pattern, presenting a qualitative leap as one advances from lower to higher income strata.

Polarization becomes evident when comparing the sample extremes: while approximately 29% of respondents with a family income exceeding 20 minimum wages consider themselves “highly familiar” with the technology, the rate of high proficiency is nonexistent among respondents in the up to two minimum wages bracket, where no participant claimed to have such mastery.

4.6 THE CORRELATION BETWEEN PURCHASING POWER AND ALGORITHMIC TARGETING INTENSITY

The analysis of the frequency distribution with which respondents receive personalized recommendations, stratified by family income (Fig.11), reveals a trend of direct proportionality: exposure to algorithmic curation increases as the income bracket rises.

Figure 11: Purchasing Power and Algorithmic Targeting Intensity



Source: Compiled by the author based on the dataset derived from the exploratory research.

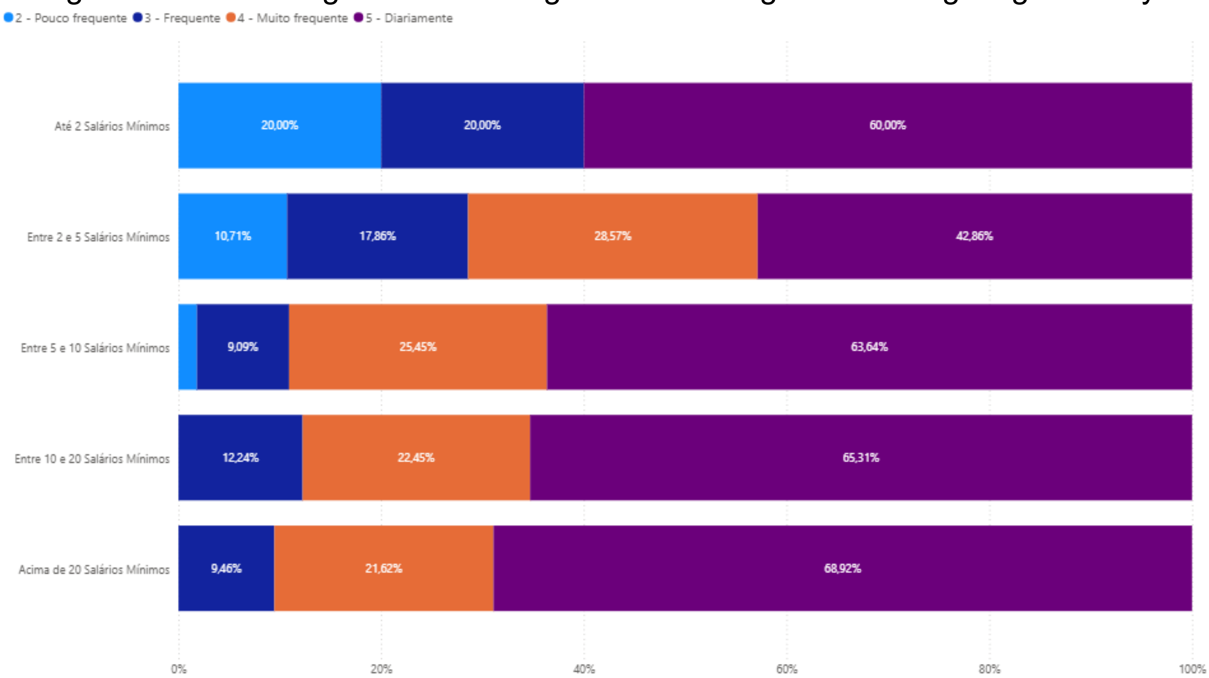
In lower income brackets, the perception of receiving suggestions is more sporadic. However, as one advances to the upper strata, a progressive growth is noted in high-frequency categories, with the predominance of the "Daily" category standing out. In practical terms, the data suggest that the consumer with greater purchasing power is the target of systematically more regular and intense targeting than the one found at the base of the economic pyramid.

This phenomenon is supported by the very operating logic of recommendation systems. High-income consumers tend to have a more significant digital behavior, that is, they tend to perform a greater number of online transactions, utilize a wider variety of digital services, and finally, tend to possess more advanced devices. As a result, they tend to generate a larger volume of data inputs for predictive models, becoming, at the same time, more visible to algorithms and more attractive to advertisers' conversion strategies.

It is crucial, however, to interpret with caution the apparent oscillation or stabilization observed in the income bracket between 10 and 20 minimum wages. It must be taken into account that the absolute number (n) of respondents in this specific group was slightly lower than that recorded in adjacent brackets. This variation in statistical representativeness can create a visual artifact, where the growth trend appears to be interrupted not by actual consumer behavior, but by the lower sample density at that point. Thus, it is likely that the oscillation in the trend curve represents statistical noise resulting from sample fluctuations, and not an indication that this demographic group receives, structurally, fewer recommendations than would be expected by the general trend.

To mitigate this sample representativeness distortion and validate the continuous growth thesis, the decision was made to convert absolute values to a relative frequency analysis, that is, percentage. The result of this normalization is presented in Fig.12. By eliminating the variable of the quantity of respondents, the visual clearly confirms the underlying trend: exposure to algorithmic recommendations maintains its upward and positive trajectory as income increases, dissolving the apparent oscillation identified previously.

Figure 12: Percentage of Purchasing Power and Algorithmic Targeting Intensity



Source: Compiled by the author based on the dataset derived from the exploratory research.

5

5 CONCLUSION

The progress of Generative Artificial Intelligence establishes a crucial milestone at the intersection of technology, society, and consumer behavior. The exploratory research conducted made it possible to observe that the effects of AI do not manifest uniformly among the individuals observed in the sample; on the contrary, they reveal themselves as a multifaceted phenomenon, influenced by variables such as age group (defining the person's generation), income level, education, and digital literacy. Thus, the adoption and influence of generative technologies depend as much on technical familiarity as on the cultural and socioeconomic experiences that shape the way each group interacts with algorithmic tools.

The results obtained point to the need for a strategic and continuous movement to eliminate sociodemographic barriers that still prevent Generative Artificial Intelligence from acting as a widely homogeneous influencer of consumption. Although its impact is already significant among younger, educated segments with higher purchasing power, the challenge presented is to expand this influence to broader social strata, allowing for a more balanced integration of the technology into the daily life of the average consumer.

Even so, the trajectory observed from the data analyses constructed in the work indicates a clear trend: digital natives, already accustomed to algorithm-mediated interactions, demonstrate greater willingness to accept, incorporate, and trust suggestions generated by generative systems. This suggests that, as these generations ascend and come to dominate the economically active population base, the pattern of AI adoption for daily tasks tends to intensify. Consequently, it is projected that the influence of Generative AI on purchase decisions, product exploration, and preference formation will become even more structural in the near future.

The general objective of this course conclusion work, which was defined as "to analyze and understand the impact of Generative Artificial Intelligence on the formation and modification of consumption patterns, with the purpose of anticipating future directions for this technology", was explored and served as the guiding point throughout the work. The research evidenced, through the triangulation between the theoretical framework and empirical data, that AI currently acts as an active modeler of choices, whose effectiveness is directly related to the user's demographic predisposition.

Regarding the specific objectives, these were developed and achieved throughout the sections comprising the referred exploratory research. Initially, the aim was to identify the main uses of Generative Artificial Intelligence in digital consumption contexts, which was addressed in the theoretical foundation section through the literature review, and subsequently validated empirically in the results and discussion section, where the predominance of the use of chatbots and recommendation algorithms in social media, streaming, and e-commerce platforms was confirmed.

Subsequently, how generative AI influences consumer behavior was analyzed. Based on the analyses presented, it became feasible to measure its direct influence on decision-making processes, highlighting relationships between trust levels and the actualization of purchases or contracting of services. Similarly, examples were investigated in which generative AI plays a significant role in creating or transforming consumption trends, which were also discussed theoretically in the theoretical foundation based on the evolution of models and concrete applications.

To substantiate the empirical stage of this work, a structured questionnaire was developed and administered, as described in the Methodology, resulting in two hundred and eleven valid responses that constituted the basis of the empirical evidence study. Finally, data analysis and visualization tools were utilized, especially Microsoft Power BI, allowing for statistical treatment, pattern identification, and the construction of descriptive and bivariate analyses based on the collected and processed data.

Regarding the main conclusions and results of the study conducted, it is important to highlight that data analysis empirically revealed, firstly, the presence of an evident generational gap concerning the use and acceptance of technologies grounded in Artificial Intelligence. Younger age groups, notably Generation Z and Millennials, demonstrated high familiarity with recommendation systems and a greater willingness to follow automated suggestions. In contrast, the senior demographic (55+) presented significant barriers to adoption, largely based on concerns related to privacy and the security of personal data. This behavioral gap emphasizes the need for differentiated digital inclusion and communication strategies targeted at different age groups.

Subsequently, the importance of the economic factor as a determinant of technological adoption was established. The results show that familiarity, trust, and comfort in using AI-based tools increased proportionally to the income level for the individuals in the sample, evidencing that access to financial resources acts as a direct catalyst for digital inclusion. This relationship suggests that AI literacy remains restricted to certain socioeconomic strata, which may widen inequalities in algorithm-mediated consumption and reinforces the importance of educational initiatives that promote access to emerging technologies.

Finally, the research also revealed the possible existence of the phenomenon of "educated skepticism". Paradoxically, individuals with higher levels of education, especially those with postgraduate, master's, and doctoral degrees, although using AI tools frequently, demonstrated greater resistance to acknowledging the power of influence of these tools on their consumption decisions. This behavior indicates that academic background acts as a critical filtering mechanism, diminishing the impact of technological stimuli and reinforcing the capacity for discernment regarding automated recommendations. This finding enriches the understanding of how educational factors influence the relationship between consumers and intelligent systems.

Academically, this research contributes to the broad field of study regarding the impacts of AI usage in daily life by providing updated quantitative data on the Brazilian scenario of Generative Artificial Intelligence adoption, a perspective from the year 2025, a domain whose scientific literature still reveals itself as incipient, fragmented, and subject to rapid transformations, by mapping actual patterns of usage, familiarity, and perception of such technologies. The study also added important empirical evidence to a discussion that, until now, was predominantly theoretical within the national context.

This study makes a significant contribution to the domain of Software Engineering by illustrating how precise problem formulation and thorough systematization of user requirements can steer the development of systems utilizing Generative Artificial Intelligence. By pinpointing deficiencies in perception, trust, and comprehension related to predictive models and recommendation systems, the study has converted these challenges into specific requirements—enhanced transparency, more lucid explanations, and increased user agency. This underscores a fundamental tenet of contemporary engineering: algorithmic tools should be constructed not solely on the basis of technical prowess but also through the accurate modeling of human expectations.

The examination of the gathered data revealed critical engineering skills, such as the organization of information, problem-focused data modeling, and statistical analysis capable of identifying significant patterns. By converting raw feedback into clusters, correlations, and visually interpretable trends, the research demonstrates how methodical engineering processes—from data collection to analysis—yield dependable and reproducible insights. Furthermore, the recognition of biases, generational disparities, and variations in digital literacy underscores the necessity of incorporating sociotechnical awareness into the design of intelligent systems.

The empirical results further indicate that user trust in AI systems is profoundly influenced by the clarity of recommendations, the understanding of data utilization, and the perception of fairness. These findings highlight the critical need to integrate explainability, transparency mechanisms, and ethical considerations into project specifications, system architecture, and algorithmic design. As AI increasingly influences consumption and decision-making, Software Engineering must embrace more comprehensive strategies for Explainable AI and user-centered design, ensuring that algorithmic reasoning is rendered visible, accountable, and in alignment with user expectations.

Ultimately, the project sets itself apart by developing a narrative that prioritizes the user, aligning with the tenets of data storytelling and human-centered design. Instead of merely showcasing numerical results, the research situates these findings within practical, emotional, and social frameworks, illustrating that contemporary Software Engineering demands not just technical expertise but also the capacity to convey insights effectively and foresee real-world consequences. By addressing issues surrounding privacy, bias, and manipulation, this work offers practical recommendations for creating more ethical, adaptable, and responsible AI solutions.

From a professional standpoint, the results offer significant strategic insights for organizations wishing to integrate AI into their consumption journeys. The findings show that the generalist approach, the "one size fits all" model, is inadequate given the diversity of consumer profiles. It became clear that retention and relationship strategies need to be segmented, for example:

- for more mature audiences, priority should be given to transparency, explainability, and the mitigation of perceived risks;
- whereas for younger and technologically fluent consumers, a focus on user experience, personalization, and the naturalness of interaction is recommended.

Therefore, the study not only clarifies important behavioral distinctions, but also suggests practical paths for the development of AI solutions that are more effective, ethical, and aligned with the expectations of different segments of society.

In conclusion, it is essential to emphasize the findings related to the hypotheses presented during the introductory phase of this exploratory research. The empirical results derived from the data analysis reveal that the proposed hypotheses were substantiated; specifically, the suggested bivariate relationship among the identified instrumental variables—age group, monthly income, and education level—exhibited a significant correlation (both direct and indirect) with the items of the data collection instrument employed, thereby supporting the theoretical framework established in the initial phase of the study, which posits that there is evidence of the impact of Generative Artificial Intelligence on contemporary consumption behaviors.

Moreover, it was determined that the age group of users significantly influenced their perception (either positive or negative) regarding the utilization and trust in recommendation systems that employ algorithms developed through AI techniques (Fig.8), as anticipated in hypothesis H1. Additionally, the monthly income variable of the participants in the sample was found to affect their perception (positive or negative) concerning the use and trust in recommendation systems that utilize AI-driven algorithms (Fig.10), thereby validating hypothesis H2 of the research. Lastly, hypothesis H3 was affirmed through the exploratory data analysis, which distinctly demonstrated that the education level variable of the individuals in the sample also served as a significant factor influencing their perception (positive or negative) of the use and trust in platforms offering AI-based solutions (Fig.6).

It is necessary to acknowledge the inherent limitations of the research. The primary one lies in the characteristic of the sample: as it was a non-probabilistic convenience collection, there was a significant socioeconomic and educational bias. The predominance of respondents with higher education and high income limits the generalization of findings to the base of the Brazilian social pyramid. Furthermore, sampling noise was observed in the intermediate income bracket variable, which required caution in the interpretation of linear trends. Moreover, although the hypotheses were confirmed, the conduct of additional studies with larger samples and in different contexts is recommended in order to strengthen the generalization of results, as previously pointed out.

The realization of this work presented significant challenges from personal, technical, and academic standpoints, characteristic of investigations involving exploratory research. One of the main technical difficulties lay in the ETL (Extraction, Transformation, and Load) process, especially in the cleaning of qualitative data originating from open-ended questions, whose lack of standardization demanded intensive manual effort for categorization. Furthermore, the lack of a solid theoretical framework on Generative AI in consumption, due to the novelty of the topic, required additional effort in bibliographic curation.

If the work were started today, under a continuous improvement perspective, the data collection strategy would be restructured, seeking a more diverse sample to mitigate sampling biases, extending the questionnaire application period. In methodological terms, the predominant use of binary or closed multiple-choice questions would be chosen, with the objective of optimizing data treatment and reducing the ambiguity of open-ended responses.

Based on the results of this research, promising opportunities for future investigations arise. It is recommended to conduct studies focusing on the development of evolutionary scenarios for the application of AI in CRM (Customer Relationship Management) strategies, especially regarding customer base maintenance and retention.

Furthermore, it would be of great value to carry out an in-depth qualitative investigation with the elderly demographic, with the objective of developing interfaces that surpass the barrier of distrust and low digital literacy, promoting the complete digital inclusion of this demographic group.

The realization of this research represents the synthesis of a journey of transformation, made possible by an ecosystem of excellence. I express my deep gratitude to the Instituto Brasileiro de Ensino, Desenvolvimento e Pesquisa (IDP), for the infrastructure and educational vision that served as the foundation for this achievement, extending recognition to the Department of Software Engineering and the Course Coordination, whose competent management ensured an academic environment conducive to innovation.

To the professors, with honorable mention to Fabricio, Eduardo, Linik, and Nilson, I thank you for your generosity in transmitting the technical framework, fundamental to the methodological robustness applied here. A special thanks to my advisor, Dr. Bruno Miranda, whose precise mentorship and critical vision were decisive in elevating the quality of this analysis.

To the friends on this journey, thank you for the partnership and mutual support during challenging moments. I close this cycle with the full satisfaction of a duty fulfilled, conscious that the analytical maturation and professional growth achieved transcend the degree, preparing me for future challenges at the intersection of technology and society.

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APPENDICES

Appendix A - Full Questionnaire Used in Data Collection

Table 2 summarizes the relationship between each survey question and the analytical variable it measures. The mapping shows how the instrument was structured to capture key dimensions of interest, including respondents' sociodemographic characteristics, their exposure to and interaction with recommendation systems, their perceptions of influence, trust, bias, and data security in AI-based platforms, as well as their familiarity with generative AI. This organization ensures coherence between the study's objectives and the construction of the questionnaire.

Table 2: Mapping of Survey Questions to Analytical Variables

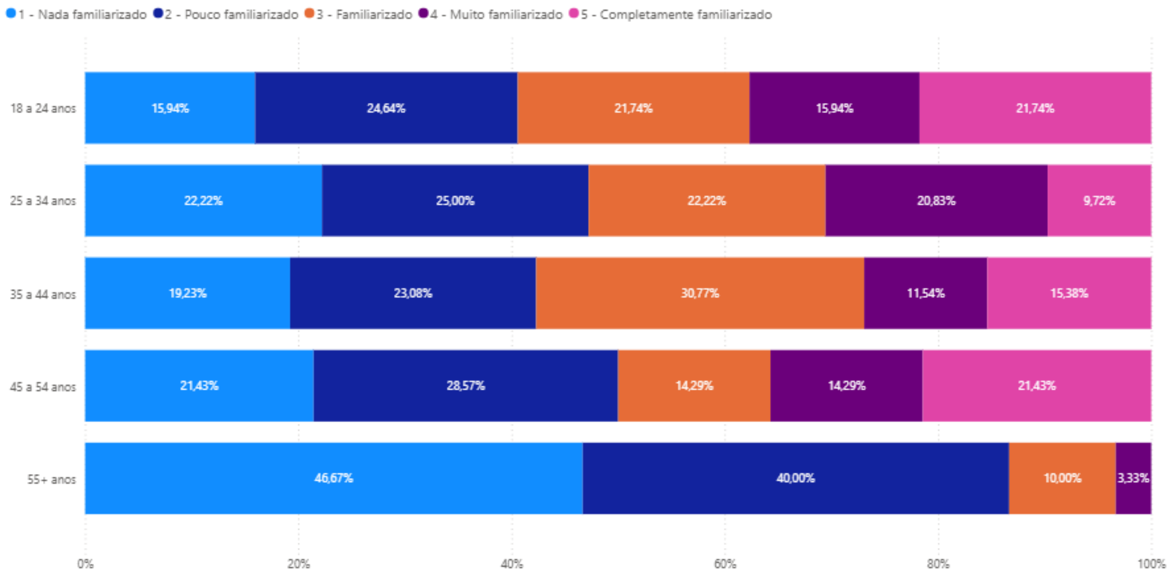
Question	Variable
Are you able to answer this form?	Response Validation
What is your age group?	Social Profile
What is your gender?	Social Profile
What is your educational level?	Social Profile
What is your monthly family income range?	Social Profile
Region	Social Profile
On a scale from 1 to 5, how often do you receive product/service recommendations on digital platforms (e.g., online stores, social media, search engines, apps)?	Recommendation Algorithms
On which types of platforms do you usually receive personalized product or service recommendations?	Exposure Environment
Have you ever purchased a product or hired a service that was directly recommended by a platform?	Recommendation Algorithms
On a scale from 1 to 5, how comfortable do you feel allowing recommendation systems or Artificial Intelligence to participate in your purchase decision process?	Level of Appreciation/Discomfort
Have you ever used any Artificial Intelligence tool (examples included) to research products or services before making a purchase? Which ones?	AI as an Opinion Former
On a scale from 1 to 5, how influential do you consider information obtained through Artificial Intelligence (e.g., advice, summaries, generated recommendations) in your final purchase decision?	AI as an Opinion Former
When seeking product recommendations, which type of source usually influences your decisions the most?	Human–AI Comparison
On a scale from 1 to 5, how much do you trust product and service recommendations made by Artificial Intelligence systems?	Trust Level
What are your biggest concerns when receiving consumption suggestions (material or not) from a platform?	Perception of Bias
Do you believe that the use of Artificial Intelligence to assist in shopping can lead to more impulsive or unnecessary purchases?	Manipulation
On a scale from 1 to 5, how much do you believe that the evolution of Artificial Intelligence is progressing at a safe pace?	Platform Reliability
Do you trust Artificial Intelligence platforms regarding the security of your data?	Platform Reliability
On a scale from 1 to 5, how much do you trust existing regulations regarding Artificial Intelligence tools?	Platform Reliability
On a scale from 1 to 5, how familiar are you with the term ”Generative Artificial Intelligence”?	AI Knowledge

Source: Compiled by the author.

Appendix B - Supplementary Charts and Visual Analyses

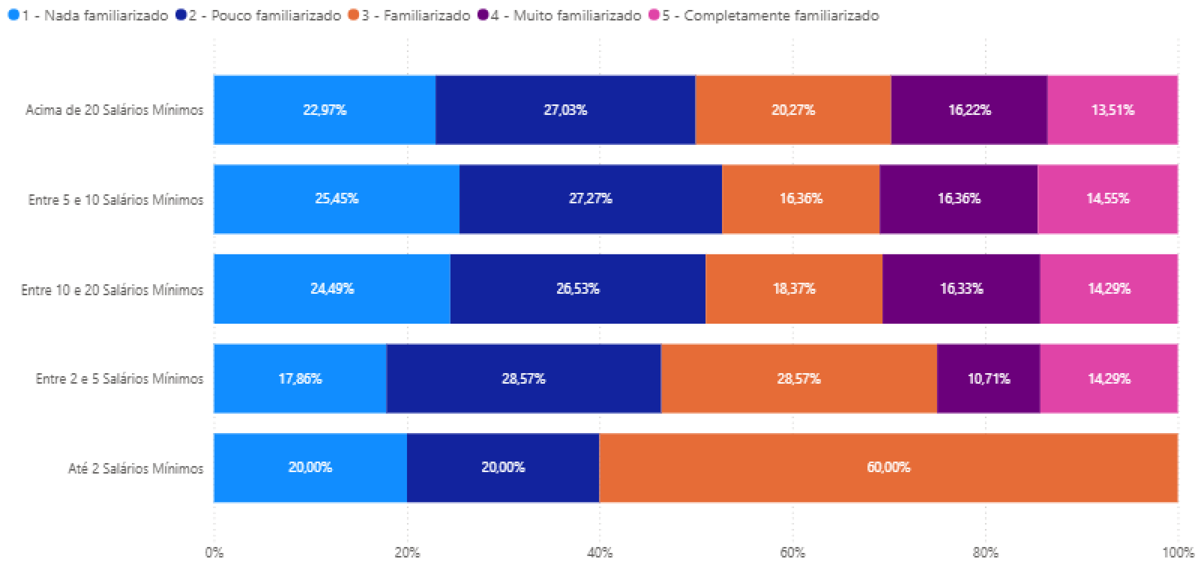
This appendix presents a set of supplementary charts and visual analyses developed to support and expand the findings discussed in the main sections of this study. The visual materials included here provide additional perspectives on consumer behavior patterns, correlations between variables, and exploratory insights derived from the dataset. Although not essential for the core arguments of the research, these visualizations contribute to a more comprehensive interpretation of the results, allowing readers to observe nuances, distributional behaviors, and secondary trends that complement the primary analyses.

Figure 13: Percentage of Familiarity With Gen AI in each Age Group



Source: Compiled by the author based on the dataset derived from the exploratory research.

Figure 14: Percentage of Familiarity With Gen AI in each Familiar Income Group



Source: Compiled by the author based on the dataset derived from the exploratory research.

Appendix C - Databases and Power BI Archive

This appendix provides access to all datasets, processing scripts, and the complete Power BI file used in the analytical procedures described throughout this study. These resources are publicly available in a dedicated GitHub repository to ensure transparency, reproducibility, and the possibility of further exploration by other researchers.

All files used in data preprocessing, visualization design, and statistical analysis can be accessed in this work's GitHub Repository.

The repository includes:

- The original Excel database extracted from Google Forms
- The cleaned and transformed datasets generated during preprocessing
- The *.pbix* Power BI project file
- A full PDF version of the questionnaire applied to collect user responses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Ensino que te conecta