Algorithmic Brand Discovery on Instagram and Its Effect on Brand Trust and Purchase Intention

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ABSTRACT

Algorithmic recommendations have transformed brand discovery on social media, creating new possibilities to personalize consumer experiences. This study analyses the impact of algorithmically driven recommendations on brand trust and purchase intention.
The research employs a quantitative survey with an experimental between-subjects design. Independent-samples t-tests are used to examine the effectiveness of algorithmic cues, while linear regression and Hayes' PROCESS macro are applied to investigate the mediating role of brand trust and moderating factors like involvement.
The findings indicate that explicit algorithmic attribution does not significantly influence brand trust, suggesting a normalization effect and high baseline awareness among digital natives. Instead, perceived serendipity and objectivity are the main factors enhancing brand trust, which subsequently mediates purchase intention. Furthermore, the findings reveal a backfire effect for users with high privacy concerns and tech savviness. For those consumers, the perception of algorithmic influence triggers reactance rather than trust. Additionally, the results reveal that product involvement may not necessarily moderate the response toward algorithmic cues in fast-moving social media environments.
The research concludes that effective algorithmic brand discovery requires a shift from mere technical precision towards responsible, serendipity- and objectivity-driven curation. These insights carry implications for brand managers, platform developers and policymakers, particularly regarding the need for clearer governance to protect consumers in increasingly automated environments.

Title: Algorithmic Brand Discovery on Instagram and Its Effect on Brand Trust and Purchase Intention

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SUMÁRIO

As recomendações algorítmicas transformaram a descoberta de marcas, criando novas possibilidades de personalização. Este estudo examina o impacto das recomendações algorítmicas na confiança na marca e na intenção de compra.

Utiliza um questionário experimental quantitativo com um desenho entre grupos. Para a análise, são aplicados testes t para amostras independentes, regressão linear e a macro PROCESS de Hayes.

Os resultados indicam que a atribuição algorítmica não influencia significativamente a confiança na marca, sugerindo um efeito de normalização e um elevado nível de conhecimento de base entre os nativos digitais. A descoberta inesperada e a objetividade percebidas emergem como os fatores mais fortes na confiança na marca, o que, por sua vez, medeia a intenção de compra. Os resultados revelam um efeito contrário para utilizadores com elevadas preocupações em matéria de privacidade e literacia tecnológica, desencadeando reatância em vez de confiança. Além disso, os resultados revelam que o envolvimento pode não moderar a resposta a sinais algorítmicos em ambientes de redes sociais.

A investigação conclui que a descoberta algorítmica de marcas requer uma mudança da precisão técnica para uma curadoria responsável, orientada pela serendipidade e pela objetividade. Estas conclusões têm implicações para gestores de marcas, plataformas e r esponsáveis políticos no que diz respeito à necessidade de uma governação mais clara para proteger os consumidores.

Título: Descoberta algorítmica de marcas no Instagram e o seu impacto na confiança na marca e na intenção de compra

Autor: Sabina Schumacher

Palavras-chave: Descoberta algorítmica, sistemas recomendação, confiança na marca, intenção de compra, marketing digital

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ABBREVIATIONS

α	Cronbach's Alpha
AI	Artificial Intelligence
CBBE	Customer-Based Brand Equity
DV	Dependent Variable
FMCG	Fast Moving Consumer Good/s
IV	Independent Variable
KMO	Kaiser-Meyer-Olkin
PKM	Persuasion Knowledge Model
RS	Recommender System/s
SEO	Search Engine Optimization

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1 Introduction and Relevance

“We want to make the most of people’s time and we believe that using technology to personalize everyone’s experience is the best way to do that.” (Mosseri, 2023, para. 3)

The scope and context of brand management have shifted drastically in the past few years due to developments in digital media and changing consumer behavior (Araujo et al., 2020). As Adam Mosseri (2023), head of the social media platform Instagram, recently emphasized in the above citation, the strategic core of modern social media platforms lies in technological personalization of the user experience. This shift is driven by the increasing datafication of brand-consumer interactions, enabling more profound, multidimensional communication and relationships than previously possible (Araujo et al., 2020). Consequently, the way consumers make decisions has fundamentally changed, requiring a deeper understanding of new touchpoints within the digital ecosystem (Araujo et al., 2020). For brands, this means marketers must consider a vast amount of new factors that have changed interactions between themselves and consumers.

1.1 Algorithmic Discovery

A central element of this evolution is the huge amount of input consumers are exposed to in the digital world (Chen & Huang, 2024). Consequently, active search is gradually being replaced by passive discovery, as this extensively lowers search costs for customers (Li & Shi, 2025). This is oftentimes enabled by data, algorithms and artificial intelligence (AI) (Dong et al., 2024). Modern technological enhancements allow for personalized journeys where algorithms influence decision processes, making them more efficient (Hardcastle et al., 2025). Cui and Van Esch (2025) describe this as a transition from a seeker economy to a delegate economy where artificial agents take over the role of discovery, rating and selecting products. This shifts control from brands actively pushing content towards consumers to algorithms that determine which brands gain visibility, thereby fundamentally changing how brands compete for attention. In this context, recommender systems (RS) are gaining importance in e-commerce and social media, where the platforms and their algorithms can be viewed as gatekeepers to discover content (Araujo et al., 2020; Hardcastle et al., 2025; Malthouse et al., 2019). The platforms no longer act as neutral agents but have control to shape visibility and interactions between firms, brands and consumers, redefining brand management (Araujo et al., 2020).

1.2 Relevance of the Topic

The relevance of this research stems from the theoretical research gap, the practical challenges faced by brand managers and the specific characteristics of fast-moving consumer goods (FMCG) in this context.

1.2.1 Theoretical and Practical Contributions

Previous research has investigated AI and consumer behavior in terms of acceptance, trust and the tension between algorithm aversion and appreciation (Voorveld et al., 2024). However, most research has focused on active recommendation-seeking, such as conversational agents and voice assistants (Longoni & Cian, 2022; Puntoni et al., 2021). Furthermore, much research has focused on short-term transactional metrics like click rates and recommendation accuracy (Dong et al., 2024; Meng & Xiao, 2026). Although various product types and levels of involvement have been examined in the literature, there remains a lack of research addressing how these dynamics play out in the context of passive brand discovery in personalized social media feeds (Enes et al., 2024; Hardcastle et al., 2025; Li & Shi, 2025).
This work addresses the gap by examining passive algorithmic discovery and expanding established theories, such as signaling (Erdem & Swait, 2004; Spence, 1973), brand equity (Erdem et al., 1999) and the Persuasion Knowledge Model (PKM) (Friestad & Wright, 1994; Voorveld et al., 2024) to modern algorithmically mediated settings[1]. In this new context, algorithms are viewed as active brand actors and non-human intermediaries, shaping consumers' access to content, brands and products (Cui & Van Esch, 2025).

As consumers increasingly rely on algorithms for discovery and research (Cui & Van Esch, 2025), brand managers need to understand when algorithmic brand discovery builds brand trust and when it causes reactance. This is critical because recommendation channels may generate clicks but not conversion (Dong et al., 2024), meaning reach alone does not translate into purchase intention. This work provides insights into leveraging algorithmic discovery while avoiding privacy-driven backlash.

[1] Throughout this thesis, *algorithmic attribution* refers to the explicit labeling of a recommendation as algorithmically curated; *algorithmic mediation* describes the broader process through which algorithms shape content discovery and *algorithmic perception* denotes the individual's subjective awareness of algorithmic involvement.

1.2.2 FMCG Focus

Finally, the study focuses specifically on the FMCG sector, as consumers' decisions regarding FMCG products are often characterized by lower involvement and strong influence of impulse and heuristics (Drossos et al., 2014; Huang et al., 2025). Algorithmic discovery may be stronger in this context as it increases mental availability bias and significantly accelerates purchasing decisions through unplanned discoveries (Li et al., 2025). This research will analyze a setting in which financial risk is low and consumers bypass deep cognitive evaluation, likely relying on peripheral cues provided by algorithmic attribution.

In conclusion, the goal of this study is to examine the far-reaching implications of algorithmic brand discovery in the digital ecosystem on brand outcomes and purchase intention, especially for FMCG brands in the setting of social media. Therefore, this study addresses the following central research question and corresponding sub-questions:

- Main Research Question: How does algorithmic attribution of recommendations on social media affect consumer brand trust and subsequent purchase intention?
- Sub-Question 1: To what extent does brand trust mediate the relationship between the algorithmic attribution and purchase intention?
- Sub-Question 2: How does the consumer's product category involvement moderate the effect of the algorithmic attribution on brand trust?"

The work will be structured as follows. First, an overview of the existing literature and theories in this context is provided to formulate hypotheses. Second, the research methodology is presented. Next, the results are described, followed by a discussion, implications, limitations, an outlook on future research and a concluding summary.

2 Literature Review and Research Hypotheses

One key element of the new ecosystem are RS, technology that makes use of AI abilities to deliver relevant information to users. Modern RS are designed to serve a dual purpose: while they reduce users' effort in navigating information overload by displaying relevant content, they also enable advertisers to target specific consumer segments more effectively (Ansari et al., 2000; Chen & Huang, 2024; Malthouse et al., 2019). RS therefore function as information filtering tools (Roy & Dutta, 2022) and are broadly categorized into three approaches: content-based filtering, focusing on similarities of product attributes; collaborative filtering, using social validation by matching users with similar interests and hybrid models, combining both (Ansari et al., 2000).

The process by which consumers become aware of brands through this is is called "algorithmic brand discovery" in this work. It describes a process whereby consumers do not actively search for specific brands or products but passively encounter them as recommended content while browsing. Such discoveries can happen in e-commerce settings or on social media where brand messages are integrated into content feeds (Puntoni et al., 2021). Social media is nowadays the primary place for discovery and marketers need to compete for attention long before an actual purchase decision is made (Hudson & Thal, 2013). Algorithms determine the composition and content of the paid, earned and owned media a user sees, therefore they have become new gatekeepers for brand discovery (Araujo et al., 2020; Crawford, 2016).

While these new developments have transformed digital commerce, they do not render classical marketing logic obsolete. On the contrary, well-established marketing and psychological theories provide an analytical frame to interpret the impact of these shifts. In the following, relevant theories will be discussed and applied to the context of algorithmic brand discovery and corresponding consumer behavior.

2.1 Information Processing and the Elaboration Likelihood Model

To understand passive discovery, especially in the FMCG context, the Elaboration Likelihood Model (ELM) (Petty & Cacioppo, 1986) serves as an analytical frame. The model explains how consumers process information and change their attitudes by presenting two different routes of information processing. The central route requires deep, cognitive engagement with presented arguments and features of a product. The peripheral route relies on simple mental shortcuts or heuristics to enable opinion formation with less cognitive effort. Which route is taken depends largely on consumers' motivation and ability to process information, whereby product involvement, defined as the perceived personal relevance of a product category, serves as the primary determinant of motivation (Drossos et al., 2014; Petty & Cacioppo, 1986). FMCG products, like snacks or basic personal care products, are typically considered low-involvement products (Drossos et al., 2014). Since they are generally inexpensive and carry little financial or personal risk, consumers usually have low motivation to rationally analyze complex product information before buying (Drossos et al., 2014). Consequently, peripheral processing dominates FMCG purchasing. As users who passively scroll also do not have an active purchase intention, their motivation for critical information processing is low and they are highly sensitive to external, peripheral cues (Kong & Lou, 2026). Algorithmic attribution can act as such a cue. As Banker and Khetani (2019) argue, low-involvement decisions are exactly those affected most by heavy reliance on algorithmic recommendations, since they are usually fast, with little expertise and high openness to external recommendations. Li and Shi (2025) further support the FMCG focus, demonstrating that under low-involvement conditions, the preference for human over algorithmic recommendations disappears, making algorithmic discovery equally effective across product types. Nevertheless, content type still plays a role in fostering acceptance. Fletcher and Nielsen (2019) show that people agree with algorithmic selection more often for soft content (lifestyle/ entertainment) than for hard facts. This logic arguably extends to hedonic FMCG products, reducing barriers for trust building. Finally, the mechanism of social proof acts as a decisive peripheral cue in this setting. Research shows that in low-involvement contexts, social proof dominates, whereas in high-involvement contexts, risk avoidance is the key driver of purchase intention (Xu et al., 2023). In low-involvement situations, algorithms can serve as shortcuts and cues for collective approval. Overall, these results present evidence that FMCG products might benefit particularly strongly from algorithmic mediation. Chacon et al. (2025), however, identify a lack of research in this low-involvement area, directly legitimizing the focus of this thesis.

In summary, the ELM provides a psychological explanation for the premise of this research. As consumers act cognitively conveniently with FMCG products and avoid the central route, they are heavily dependent on peripheral signals, like algorithmic attribution, during passive brand discovery on social media.

2.2 Signaling, Social Proof and Availability Heuristics

Because consumers in low-involvement settings avoid active cognitive paths, they rely on heuristics during passive discovery. One essential theory here is signaling theory. It states that in markets with asymmetric information, brands serve as signals to convey product positions and reduce consumer uncertainty (Erdem & Swait, 2004; Spence, 1973). Brand credibility is the key characteristic of this signal, consisting of trustworthiness (willingness to deliver) and expertise (ability to deliver) (Erdem & Swait, 2004). This credibility was traditionally built through consistent marketing, however, in modern digital marketing, RS might become a reputational cue themselves. When consumers encounter a brand through RS, the platform's algorithmic credibility can serve as a proxy for the brand's own trustworthiness through a trust transfer process (Beck et al., 2023; Liu et al., 2018). This is especially true under conditions of high uncertainty (Erdem & Swait, 2004), like when discovering new brands. Consumers then usually have limited knowledge and rely on opinions of others to guide their decisions (Beck et al., 2023). A key signal within these systems is social proof, such as likes and comments, that can significantly influence impulse buying and serve as a cue for acceptance (Huang et al., 2025). Crucially, algorithms actively amplify this effect by prioritizing and further distributing content that already shows high engagement, creating a self-reinforcing cycle where social proof signals become increasingly visible (Kong & Lou, 2026). In a broader sense, this has been introduced as the word-of-machine effect in the context of AI recommendations (Longoni & Cian, 2022). On content-driven, interactive platforms, it effectively guides behavior, increases brand trust and enhances engagement (Huang et al., 2025) through peripheral processing and social validation (Kong & Lou, 2026). Moreover, Aral and Walker (2014) argue that algorithmically amplified social proof creates a significantly stronger effect than traditional word-of-mouth, by targeting social structures. The availability bias introduced by Li et al. (2025) further extend this logic, when algorithmically recommended content feels vivid, current and personally relevant, its visibility itself signals social proof through collective acceptance and relevance, functioning as an implicit trustworthiness cue.

2.3 Persuasion Knowledge and Consumer Skepticism

The effectiveness of heuristic cues heavily depends on whether consumers' cognitive defense mechanisms are activated (Hardcastle et al., 2025). The PKM provides the foundational framework for understanding how individuals recognize, evaluate and cope with persuasion attempts (Friestad & Wright, 1994). If consumers interpret a recommendation as a marketing tactic, it often leads to skepticism or resistance. Voorveld et al. (2024) recently extended the PKM to digital personalization by explaining how consumers evaluate and cope with algorithmic recommendations. Key elements are algorithmic awareness, perceived appropriateness and actual coping abilities. According to the PKM, reactions are based on three factors: persuasion knowledge (knowledge of marketing tactics and their effectiveness), agent knowledge (knowledge of the sender's intentions and attributes) and topic knowledge of the product or area of interest (Friestad & Wright, 1994). Voorveld et al. (2024) further demonstrate that factors such as internet literacy and privacy concerns determine group affiliation, which in turn shapes reactions. For example the control paradox group often shows a high acceptance and illusive security leading to easier trust building, the fatigued group are aware of algorithms but feel powerless against them which might erode the basis of trust beforehand, while the group of skilled and critical consumers have high competence and cope with algorithms more skeptically making the formation of long-term brand equity more difficult (Voorveld et al., 2024). This suggests that the positive effects of algorithmic attribution may reverse once consumers' persuasion knowledge is activated.

Nevertheless, the concept of serendipity, defined as feelings resulting from a product encounter that is positive, unexpected and involves some degree of chance, provides a vital counter-mechanism against skepticism. When algorithmic discovery produces such encounters, it can significantly increase satisfaction, enjoyment, purchase intention and brand interest, compared to a personal choice, particularly among consumers who feel insufficiently knowledgeable to decide independently (Kim et al., 2021). Chen and Huang (2024), however, point out the trade-off between diversity and serendipity. Algorithms must balance known preferences and new content to avoid filter bubbles[2] and retain users in the long term. The neutralization of skepticism is further supported by the concept of enchanted determinism (Campolo & Crawford, 2020), which describes how AI systems are perceived as almost magical and beyond human understanding, yet trusted because of their predictive accuracy. This encourages algorithmic appreciation rather than critical questioning, leading consumers to trust outcomes without demanding process transparency. Similarly, Chacon et al. (2025) note that consumers appreciate algorithms because they do not expect emotional warmth from machines. Therefore, highly accurate recommendations feel like a pleasant surprise, evoking algorithm appreciation.

2.4 Brand Trust Formation and Algorithm Appreciation

The central mechanism for long-term impact is how trust in technology and recommendations becomes trust in the brand. This chapter will explain how the interplay of discussed theories may lead to trust formation in the algorithmic brand discovery context.

[2] This concept describes an isolated information environment created through algorithmic personalization, in which users primarily see content that corresponds to their existing preferences and past behavior, thereby severely restricting access to diverse perspectives (Cho et al., 2020; Hardcastle et al., 2025)

Trust transfer theory builds on social psychological association models and organizational trust research and states that trust in a familiar entity can be transferred to a linked but unknown target if there is a perceived relation between them (Stewart, 2003). This occurs through direct communication or cognitive association (Stewart, 2003). In the context of algorithmic discovery, this implies that algorithmic mediation of content featuring a brand may serve as a proxy for a brand's trustworthiness. Recent research extends this by proposing a chain of trust in social commerce, trust in the platform itself serves as a foundational safeguard that facilitates trust in the specific recommendation, which is eventually transferred to the brand (Beck et al., 2023). Furthermore, Liu et al. (2018) have shown that this is significantly enhanced through a communication-based process, facilitated by consumer engagement and interactions.

Depending on context, there might be different underlying mechanisms to this proposed effect:

2.4.1 Objectivity and Neutrality

One strand of research highlights perceived objectivity and neutrality, focusing on system-based trust. A key reason people trust AI over human assistants is the perceived lack of persuasion intent (Lee & Cha, 2025), leading AI to be perceived as more neutral and objective (Chacon et al., 2025), thereby avoiding PKM activation. Algorithms are viewed as unbiased data processors that base decisions on objective mathematical rules and not on subjective influences, directly impacting the promoter score (Chacon et al., 2025).

Aoki and Matsui (2025) compare firms, influencers and algorithms as information sources and similarly demonstrate that algorithms enhance purchase intention, even when trust in the message itself is not high, simply because algorithms are perceived as more objective and less commercial than traditional influencers. They show that purchase intention is driven by the perceived objectivity of the algorithmic source itself, rather than message content. Consequently, the mere presence of an algorithmic recommendation can even substitute influencers. The authors explain this by an increasing influencer overload and skepticism towards advertising, whereas algorithms are perceived as unbiased and non-commercial.

In the context of this research, perceived objectivity might be a lever to mitigate consumers' persuasion knowledge. Because consumers do not attribute conscious manipulative intent to the algorithm, persuasion knowledge is not triggered as much or at all. Consequently, when an unfamiliar product appears in the feed, this is not perceived as intrusive advertising, but rather as an objective, data-driven recommendation. This lack of skepticism breaks down the psychological barrier, enabling a seamless transfer of trust from the supposedly neutral platform to the recommended brand.

2.4.2 Competence and Expertise

Another area of research emphasizes the perceived competence and expertise of such systems. Literature suggests that consumers trust algorithmically discovered brands because they perceive the system and its recommendations as efficient, logic-driven and reliable (Deryl et al., 2023; Lee & Cha, 2025). Deryl et al. (2023) provide an integrated framework based on several theories that consistently shows trust is built through the AI interaction and is then transferred to the brand. Studies on the word-of-machine effect also found that consumers attribute AI systems superior competence in processing complex data (Longoni & Cian, 2022). An algorithm that learns from user behavior is perceived as a highly competent expert, superior to human recommenders (Reich et al., 2023). Other studies further highlight the relevance of the recommendation's accuracy as key to trust building (Almahmood & Tekerek, 2022). Moreover, Banker and Khetani (2019) reveal that when consumers perceive an algorithm as more knowledgeable than themselves, they trust its recommendations more. This can even lead them to select objectively inferior options simply because they were algorithmically recommended. The authors call this algorithm overdependence, referring to situations where consumers overly rely on assistance during decision fatigue and limited attention, when trying to save energy, a state common on social media.

Importantly, research also mentions transparency as a component of competence (Gao & Liu, 2023). Vorm and Combs (2022) demonstrate through their Intelligent Systems Technology Acceptance Model that trust is first developed towards technology and then transferred to the brand. Contrary to the concept of serendipity, this model assumes that when recommendations appear by chance, trust might be lower. Furthermore, Lee and Cha (2025) similarly propose that trust in AI is knowledge-based, where functionality and helpfulness reduce distrust and mistrust, leading to transparency. Complementary Erkan and Evans' (2016) Information Acceptance Model proposes that information adoption depends on source quality, credibility and usefulness. Algorithms fulfill these criteria by presenting highly relevant, personalized content, helping consumers navigate information overload by acting as filters and orientation for trends and products. Furthermore, driven by the word-of-machine effect, AI recommendations are increasingly replacing human sources to function as independent agents of influence (Aoki & Matsui, 2025; Longoni & Cian, 2022). Through algorithmic amplification, these systems can even surpass the impact of conventional word-of-mouth (Aral & Walker, 2014). Moreover, Reich et al. (2023) show that perceiving an algorithm as a learning system directly increases trust and drives choice, suggesting that dynamic recommendations lower the barrier to spontaneous purchase intention.

For this work, especially regarding the low-involvement context, cognitive relief plays a central role. Since consumers do not want to invest time in extensive information search for everyday goods, they unconsciously delegate the decision to the algorithm (Puntoni et al., 2021). Because the platform algorithm is perceived as highly competent and accurate through continuous learning, its recommendation serves as a strong heuristic quality signal. Consumers transfer their trust in the platform's competence directly to the brand, minimizing the perceived risk of a bad purchase and legitimizing impulse purchases of previously unknown FMCG brands.

2.4.3 Personalization and Hyper-Relevance

An additional perspective is the predictive efficacy and ability of such systems to create hyper-relevance through personalization (Darmody & Zwick, 2020). As mentioned in Campolo and Crawford's (2020) enchanted determinism, the predictive accuracy of deep learning systems often creates a magical perception that displaces the need for scientific understanding. This mystification, in turn, leads to high appreciation. Modern systems not only filter content but also create a reality tailored to the individual consumer through algorithmic personalization (Darmody & Zwick, 2020; Gao & Liu, 2023). Studies show that consumers often perceive a high degree of personalization as extremely valuable because it provides adaptive responses to articulated needs (Meng & Xiao, 2026). Furthermore, Cho et al. (2020) explain that algorithms are designed to work with human tendencies, especially the desire for consistency and confirmation, as people feel more comfortable with information that supports their existing opinions. This supports the idea that people are more likely to trust a discovery that fits seamlessly into their existing consumption patterns. Although this deep data collection can theoretically raise privacy concerns, consumers are often willing to overlook them in favor of convenience, quick results and extreme relevance, especially during the first stages of their customer journey (Hardcastle et al., 2025).

In conclusion, this means that in passive brand discovery, perceived hyper-personalization leads to a strong emotional effect (Chacon et al., 2025; Hardcastle et al., 2025; Kim et al., 2021). When a consumer, while passively scrolling, unexpectedly encounters a FMCG product that perfectly matches their lifestyle or needs, this is experienceed as highly rewarding (Chacon et al., 2025). The unexpected relevance strengthens trust in the system. Here trust is transferred because the algorithm seems to understand the user's personal preferences.

Even though the three strands have been presented individually here, the trust-building process is likely an interplay of the different components. Trust transfer in passive discovery functions through perceived neutrality and objectivity in the selection of presented content, while simultaneously demonstrating competence in displaying relevant content to the user and thus creating personal relevance at a hyper-contextual level.

2.4.4 Algorithm Appreciation versus Aversion

Despite the discussed drivers, trust formation is subject to a critical tension. While consumers value efficiency and lower search costs, hyper-personalization, on the other hand, carries significant ethical and psychological risks. Personalization that is too precise or aggressive can be perceived as surveillance, causing psychological reactance. The feeling of being spied on undermines trust when the process is perceived as invasive or non-transparent (Puntoni et al., 2021).

Banker and Khetani (2019) further warn that algorithm appreciation can turn into algorithm overdependence and loss of autonomy, in which consumers blindly and uncritically accept objectively inferior recommendations, simply because they come from the algorithm.

Since algorithms continuously learn based on past behavior, they gradually narrow the consumer's field of vision and reinforce existing patterns, reducing diversity and creating filter bubbles (Airoldi & Rokka, 2022; Hardcastle et al., 2025).

Additionally, the more precise and hyper-relevant the recommendations become, the more privacy concerns emerge. When consumers realize that the supposedly magical fit is based on comprehensive data surveillance, personalization can quickly be perceived as a threat (Chen et al., 2024). Voorveld et al. (2024) identify a growing group of consumers suffering from so-called privacy fatigue in this context. They are highly aware of the massive data collection and algorithmic mediation but feel powerless and exhausted because they see no way to escape it. As consumers become increasingly informed and proactive about their privacy (Necula & Păvăloaia, 2023), trust in an algorithmically discovered brand is not solely based on the algorithm itself, but on its perceived balance between relevance and intrusion.

For passive brand discovery of FMCG products, this section highlights a critical trade-off: the algorithm must appear sufficiently personalized and competent to provide cognitive relief and activate trust transfer. However, if the targeting crosses the threshold of perceived intrusiveness or noticeably pushes the user into filter bubbles, perception shifts to algorithm aversion and privacy fatigue. In this case, trust transfer to the discovered brand is potentially blocked by the consumer's defensive coping behavior. This demonstrates the responsibility of marketing and brand managers when utilizing modern digital opportunities.

2.5 Brand Trust, Brand Equity and Purchase Intention

As shown, algorithmic discovery might build trust via a trust transfer process, but this is only the first step to building persistent competitive advantage. This is where Keller's Customer-Based Brand Equity (CBBE) comes into play. Keller (1993) defines brand equity as the differential effect that brand knowledge has on consumer responses to a brand's marketing. This effect is driven by brand familiarity and favorable, strong, and unique brand associations. Under Keller's (1993) associative network memory model, brand knowledge is composed of brand awareness (recall and recognition) and brand image (the set of associations linked to the brand node). The process of building those associations is now increasingly mediated by algorithms that determine the sets of branded messages presented to consumers (Voorveld et al., 2024). In the context of passive algorithmic discovery, the mere visibility of a product in a customized feed rapidly establishes brand awareness, while the transferred trust, stemming from the algorithm's perceived value, functions as favorable brand association constituting the brand image (Erdem & Swait, 2004; Keller, 1993). Varsha et al. (2021) link AI systems to Keller's model, proposing that they strengthen brand identity by fostering active engagement through new digital interactions. This leads to a shift in brand management from purchasing mere exposure to fostering active engagement (Araujo et al., 2020). Recent research supports this idea, showing that interacting with brands online sparks consumer interest and emotion, quickly building brand trust and a positive attitude, which are the main building blocks of brand equity (Fan et al., 2025). Majeed et al. (2021) further explore the mediating role of brand equity on social media activities and purchase intention and show that information sharing and reward mechanisms positively impact those measures. This reinforces the notion that algorithmic mediation contributes to customer retention and loyalty (Almahmood & Tekerek, 2022).

In summary, these studies demonstrate that brand equity theory remains highly relevant in digital environments, especially on social media and that it has a significant impact on purchase intention in this context (Al-Abdallah et al., 2025; Majeed et al., 2021). While trust has often been considered in relation to the algorithm or technology, this work examines trust-building towards the brand as a representation of long-term brand equity. Brand trust serves as the central mechanism translating algorithm-induced positive affect into purchase intention. For FMCG products, the interplay of perceived objectivity, reduced search costs and social validation ensures that system-based trust transfers directly into behavioral intent, lowering the mental barrier to purchase (Chacon et al., 2025; Erdem & Swait, 2004; Huang et al., 2025). This is supported by Majeed et al. (2021), who demonstrate that algorithmic discovery on social media only converts to purchase when it successfully builds trust in brand quality and strengthens positive brand associations. Consequently, this underscores the importance of examining brand trust as the critical mediator between algorithmic discovery and purchase intention.

2.6 Conceptual Framework and Hypotheses Development

Based on the discussed foundations, this study proposes a conceptual model that explains how algorithmic discovery influences brand perceptions and consumer behavior in the FMCG sector. As the effect of algorithmic attribution on brand trust in this context is a rather novel area of inquiry, a direct effect is tested first, followed by examining brand trust as a mediator, ensuring the foundational relationship is established before investigating deeper mechanisms.

The rise of algorithmic discovery in digital environments has fundamentally altered consumer decision processes, as the underlying algorithmic mediation acts as a powerful quality signal for brands. As established through signaling theory and trust transfer, algorithmic attribution serves as a signal for brands in digital ecosystems. This is because RS are increasingly perceived as objective, data-driven and less commercially biased than traditional advertising or human influencers (Aoki & Matsui, 2025; Chacon et al., 2025). By appearing as neutral gatekeepers that utilize superior computational competence and systematic decision logic to filter relevant information, algorithms reduce the consumer's perceived uncertainty and search costs (Banker & Khetani, 2019). When a brand is discovered through social media feeds, the recommendation's systemic credibility acts as a proxy for the unknown brand's trustworthiness (Beck et al., 2023). Thus, the mere attribution of the algorithmic recommendation based on personal preferences and interests to a brand should enhance its perceived credibility compared to a brand presented without algorithmic attribution. Therefore, it is hypothesized:

> **H1:** Brands presented as algorithmically recommended generate higher brand trust than brands presented without algorithmic attribution.

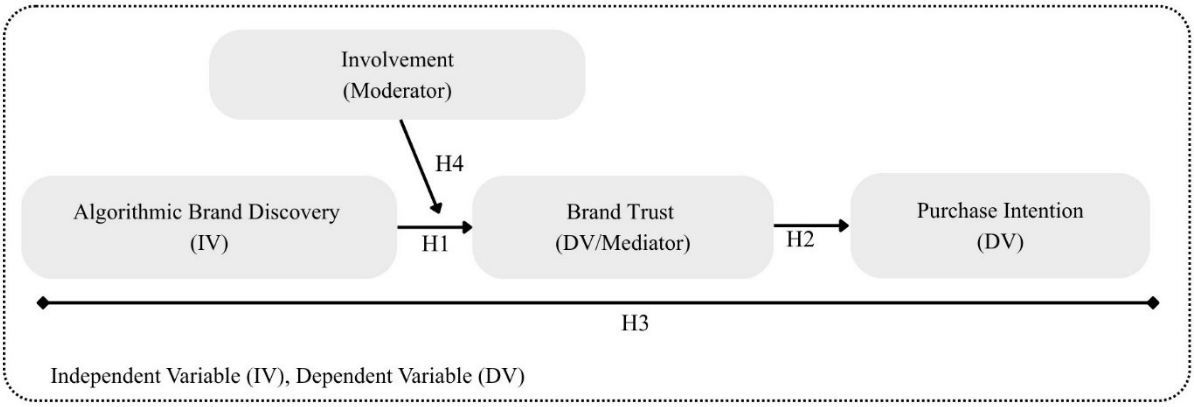
The relationship between consumers' perception and their actual behavior is fundamentally shaped by trust. In marketing literature, brand trust is consistently shown to reduce perceived risk and increase purchase intent, particularly in environments characterized by information overload (Majeed et al., 2021). Brand trust serves as a core component of CBBE, translating favorable associations into behavioral responses (Keller, 1993). In the context of algorithmic discovery, the initial trust formed toward the system and its recommendation is transferred to the brand, which in turn acts as the primary driver for consumers' willingness to buy. Thus, brand trust is expected to be the central mechanism through which algorithmic recommendations exert their influence:

> **H2:** Brand trust positively influences purchase intention.
>
> **H3:** Brand trust mediates the relationship between algorithmic recommendation and purchase intention.

The strength of these effects is likely dependent on the level of consumers' involvement. According to ELM, low-involvement decisions, typical for FMCG, are characterized by limited cognitive effort and a high reliance on peripheral cues and heuristics (Drossos et al., 2014). For low-involvement products, algorithmic recommendations act as cognitive shortcuts, providing a signal without requiring extensive information search. Conversely, high-involvement consumers are more likely to engage in systematic processing, potentially activating higher levels of skepticism or requiring more than a mere algorithmic cue to establish trust. Therefore, the impact of algorithmic mediation should be more pronounced when consumers seek cognitive relief in low-involvement situations:

> **H4:** Category involvement moderates the effect of algorithmic recommendation on brand trust, such that the effect is stronger for low-involvement consumers.

Figure 1: *Conceptual Model*



Source: Own creation

3 Methodology

3.1 Research Approach

Following the experimental approach established in recent algorithmic recommendation research (Chacon et al., 2025; Dong et al., 2024), this study employs a quantitative research design and an online experimental survey to empirically examine the hypotheses. This combines the advantages of causal testing with a broad reach and standardized measurement. The research is deductive and uses a between-subjects design to compare an experimental group with a neutral control group. This allows for a realistic simulation of the social media environment, which increases external validity compared to a laboratory setting.

3.2 Data Collection

3.2.1 Context, Sample and Data

While AI-driven RS have been extensively studied in e-commerce settings, this study focuses on social media, where passive brand discovery is increasingly shaped by algorithmic curation (Beck et al., 2023; Voorveld et al., 2024). Within social media, Instagram was chosen as the specific research context. Instagram is a highly visual platform that relies heavily on algorithmic recommendations (e.g. explore feeds or reels) and is particularly used by younger target groups for discovering lifestyle and products (Geyik & Weijo, 2025; Huang et al., 2025). Furthermore, Instagram's seamless integration of user-generated content, influencer posts and algorithmically curated feeds realistically depicts the phenomenon of passive brand discovery (Geyik & Weijo, 2025). To ensure contextual relevance, participants who reported no Instagram usage were screened out of the study.

The study relied on primary data and followed a scenario-based approach (Chacon et al., 2025; Dong et al., 2024). It was conducted using the platform Qualtrics and data was gathered from March 19 to March 30, 2026. For data collection, non-probability sampling was employed, combining convenience and self-selection sampling (Saunders et al., 2009). This approach is highly efficient for reaching the target group of active social media users. The survey link was distributed through the researcher's professional and social networks, allowing for voluntary participation within an easily accessible sampling frame. Furthermore, this approach aligns with current methodological standards in research on AI-based RS. Recent comprehensive reviews by Masciari et al. (2024) show that surveys and online social networks are the predominant data sources for investigating user responses to algorithmic recommendations. While this sampling strategy allowed for efficient data collection and ensured participants were familiar with the digital environment, it entails certain limitations. Specifically, it limits the generalizability of findings, as the self-selected sample does not represent the full diversity of the total Instagram user base. However, given that a complete sampling frame of all Instagram users is practically unavailable, this method remains a justified choice and widely adopted approach for research (e.g. Dong et al., 2024) for the scope of this research.

3.2.2 Variable Measurement and Operationalization

To quantify the constructs, the survey used 7-point Likert scales (1 = strongly disagree, 7 = strongly agree). Relevant variables such as brand trust, brand equity and purchase intention, as well as exploratory variables like perceived objectivity, perceived competence, perceived personalization and perceived serendipity, algorithm skepticism, privacy concerns, category involvement and product perception, were tested. Moreover, control variables such as category usage and liking, perceived realism, tech savviness and demographics were included. The order of the items within the questions was randomized to avoid order bias.

The measurement of brand trust was adapted from Chaudhuri and Holbrook (2001), which has been validated in digital environments (Liu et al., 2018). The construct consisted of four items adapted to fit this study's setting, including, for example, "I trust this brand" or "This brand seems reliable". This construct is highly reliable, with original studies reporting a Cronbach's Alpha[3] (α) of .81 for their items.

To measure overall brand perception and strength, a 2-item brand equity scale was used. The conceptualization was based on measurements by Yoo and Donthu (2001), capturing the dimensions of perceived quality and brand associations. The scale was reduced to two items to ensure a clear distinction of the brand trust construct and to minimize respondent fatigue. It included, for instance, "This brand has a good reputation". The original measurement demonstrated strong internal consistency, with α = .79-.93 for the constructs.

Purchase intention was measured using a 3-item scale adapted from Drossos et al. (2014), capturing the willingness to try and purchase a specific brand. To ensure the scale fits the digital context, this study's scale was further inspired by the online-shopping framework of Dash et al. (2021) and Xu et al. (2023). The items were slightly adapted, including, for example, "I would consider buying this product". Drossos et al. (2014) reported α = .93, while Dash et al. (2021) demonstrated a similarly strong measure of α = .88.

[3] This is a measure of internal consistency, indicating the degree to which items within a scale measure the same construct. Values range from 0 to 1, with higher values reflecting greater reliability (e.g. Peterson, 1994)

Category Involvement captures the perceived personal relevance of the product category. It was operationalized based on the framework by Zaichkowsky (1994) and its application in digital contexts by Drossos et al. (2014). Items included, for instance, “Products in this category are important to me”. This construct is well-validated and highly reliable, with an original α =.88. The following table summarizes the model’s operationalization. More details on the scales of the additional variables can be found in Appendix 1.

Table 1: *Operational Model Summary*

Role	Variable	Items	Scale	Based on:	Original α[4]
IV	Algorithmic Mediation	na	na	na	na
DV	Purchase Intention	3	7p Likert	Drossos et al. (2014); Dash et al. (2021); Xu et al. (2023)	.93
Mediator	Brand Trust	4	7p Likert	Chaudhuri & Holbrook (2001)	.81
Exploratory	Brand Equity	2	7p Likert	Yoo & Donthu (2001)	.79-.93
Exploratory	Perceived Objectivity	3	7p Likert	Chacon et al. (2025)	-
Exploratory	Perceived Competence	3	7p Likert	Longoni & Cian (2022); Chaiken (1980)	.89
Exploratory	Perceived Personalization	3	7p Likert	Baek & Morimoto (2012)	.89
Exploratory	Perceived Serendipity	2	7p Likert	Kim et al. (2021)	.83
Dispositional	Algorithmic Skepticism	3	7p Likert	Voorveld et al. (2024)	>.80
Dispositional	Privacy Concern	3	7p Likert	Kruikemeier et al. (2020)	.92
Dispositional	Tech Savviness	2	7p Likert	Küper and Krämer (2025)	.81-.85
Moderator	Category Involvement	4	7p Likert	Zaichkowsky (1994); Drossos et al. (2014)	.88

Source: Own creation based on literature

3.3 Stimuli Design and Manipulation

A fictional snack bar was chosen as stimulus for its nature as a classical low-involvement product where consumers rely on peripheral cues rather than in-depth processing, making it ideal for measuring impulsive purchase intentions in digital settings (Drossos et al., 2014; Huang et al., 2025). The stimulus was created using the AI tool Gemini to mimic a realistic Instagram post, presented within a standard mobile interface mockup. Since it was newly designed, any distortion due to prior brand familiarity could be ruled out. The post featured an image suggesting a genuine consumption moment from a fictional user named "alex.meyer". The caption was kept neutral and brief ("needed a small break today") and was consistently presented across all conditions to isolate the effect of the experimental manipulation. To ensure the stimulus was perceived as realistic, three iterative pretests were conducted (n = 5 - 11). The

[4] Original α applies to the full multidimensional scales

pretests confirmed the stimulus was perceived as authentic and realistic while not being seen as overly promotional, distinguishing it from typicali sponsored advertising. Furthermore, a manipulation check was included in the final survey. The experimental manipulation was implemented through the descriptive text introducing the post, defining the source of the recommendation. The study thereby manipulates algorithmic attribution and salience to isolate its signaling effect. For the algorithmic mediated group, the stimulus was presented as " Imagine you're scrolling through your personal Instagram feed. You see the following post, which has been selected for you based on your interests, preferences and past activity" and for the control group as "Imagine you're scrolling through Instagram. You see the following post.".

3.4 Questionnaire Design

Next, the full questionnaire (see Appendices 2 and 3) was tested on a small sample (*n* = 3), to ensure it was understandable and that its length and technical feasibility were optimal. The final survey was designed in a structured block design. First, participants were introduced to the academic purpose of the research and asked for consent. Second, social media usage was tested as screening question. This was followed by the stimulus, where participants were shown the same stimulus and randomly assigned to the algorithm or neutral control group. Next, the manipulation was checked and then the main variables and explorative variables were tested on 7-point Likert scales. Moreover, control variables, such as category usage and tech savviness, as well as demographics, were tested. Furthermore, an attention check was included to ensure data quality.

3.5 Data Analysis

The analysis was conducted using IBM SPSS. For hypothesis testing, the construct scales were tested for internal consistency using α and then combined into mean indices. Hypothesis testing was done using independent-samples t-tests to identify significant differences between the experimental and control group. Regression models, including PROCESS macro, were used to examine mediation and moderation effects.

4 Findings

The analysis followed a structured process, starting with sample description and data cleaning procedures, and subsequently assessing the reliability of the measurement scales. Finally, the results of the hypothesis testing are reported.

4.1 Sample Description and Data Preparation

The final survey yielded a total of $N = 113$ respondents. First, the data was cleaned to ensure quality; all datasets that did not pass the screening and attention check, as well as incomplete datasets, were excluded. Second, respondents who stated to never use the category were excluded to ensure responses did not reflect a general rejection of the category. A cleaned sample of 89 respondents was retained for statistical analysis. The sample consisted of 70% female, 29% male participants and 1% preferred not to indicate their gender. The mean age was $M = 26.47$ years ($SD = 5.84$), ranging from 14 to 57 years. The majority of respondents held a bachelor's (40%) or master's degree (27%) and Instagram usage was mainly daily (85%).

Table 2: *Descriptive Statistics*

		Total Sample		Algorithmic Goup		Control Group	
Characteristic	**Category**	**n**	**%**	**n**	**%**	**n**	**%**
Gender	Female	62	70	27	61	35	78
	Male	26	29	17	39	9	20
	Prefer not to say	1	1	0	0	1	2
Age	Mean (SD)	26.47	(5.84)	26.89	(5.75)	26.07	(5.96)
	Range	14-57	-	15-51	-	14-57	-
Education	High school	9	10	2	5	7	16
	Bachelor	36	40	20	46	16	36
	Masters	24	27	13	30	11	24
	Doctorate	1	1	0	0	1	2
	Other	19	21	9	21	10	22
Instagram Usage	Less than once a month	5	6	2	5	3	7
	A few times a month	2	2	2	5	0	0
	A few times a week	6	7	3	7	3	7
	Daily	76	85	37	84	39	87

Source: Own creation based on survey data

As illustrated in Table 2, a comparison between the experimental groups reveals mostly comparable distributions across demographics, except for gender, where the algorithmic group had a higher proportion of male participants (39 % vs. 20 %). Age and Instagram usage were closely matched across conditions. For detailed descriptive statistics, please see Appendix 4.

4.2 Factor Analysis and Reliability

To assess factorial and discriminant validity of the measurement scales, an exploratory factor analysis with varimax rotation was performed. The prerequisites were met with a Kaiser-Meyer-Olkin (KMO) coefficient of .89 and a significant Bartlett test (p < .001). The analysis yielded five factors explaining 78.33 % of the total variance. While constructs were generally distinct, two cases of conceptual overlap were found. Brand trust and brand equity items loaded on a shared factor, as did personalization and serendipity. Despite this statistical overlap, the constructs were retained as separate constructs, given their theoretical distinctiveness and to allow for a more granular analysis of their effects. Notably, the item "The recommendation seems data-driven" loaded primarily on competence instead of the objectivity factor, suggesting that respondents associate this characteristic with technical performance rather than ethical neutrality. A detailed table of the factor loadings is provided in Appendix 5.

Next, internal consistency of the multi-item scales was evaluated using α, with value above .70 generally considered acceptable (Peterson, 1994). Almost all constructs directly demonstrated high reliability, with coefficients ranging from α = .74 - .93. The only exception was the initial scale for perceived objectivity (α = .61). However, after the exclusion of one inconsistent item, reliability improved to α = .82. This aligns with the results of the factor analysis that revealed this item loaded on competence instead of objectivity.

Table 3: *Reliability Analysis*

Variable	Mean	SD	Min	Max	α (this study)
Brand Trust	4.14	1.39	1.00	7.00	.93
Brand Equity	4.27	1.28	1.00	7.00	.80
Purchase Intention	3.93	1.48	1.00	7.00	.92
Perceived Objectivity	3.58	1.40	1.00	7.00	.82
Perceived Competence	3.46	1.44	1.00	7.00	.89
Perceived Personalization	3.49	1.52	1.00	7.00	.91
Perceived Serendipity	3.04	1.45	1.00	7.00	.74
Algorithmic Skepticism	4.59	1.30	1.00	7.00	.74
Privacy Concern	5.14	1.43	2.00	7.00	.86
Category Involvement	3.55	1.50	1.00	7.00	.88

Source: Own creation based on survey data

The results of the reliability analysis are summarized in Table 3. For more details on the item-total statistics and the exclusion process, please see Appendix 6.

4.3 Manipulation Check

The manipulation check was analyzed using an independent-samples t-test to determine whether respondents in the algorithmic group perceived the seen post as significantly more algorithmically attributed than the neutral condition. The test revealed that the stimulus did not create a significant difference in perceived algorithmic attribution between the two assigned groups ($M_{Algorithmic}$ = 4.70; $M_{Meutral}$ = 4.80, p = .784), indicating that the experimental manipulation was not successful (for more details, please see Appendix 7). To investigate the mechanisms of brand trust despite this result, a post-hoc regrouping based on individual algorithmic perception was conducted.

4.4 Correlation Analysis

A bivariate correlation analysis was conducted to examine general correlations between the variables. The results support the theoretically suggested relationships, indicating that consumers who perceive a recommendation as objective or a pleasant surprise tend to report higher brand trust, which in turn is positively associated with purchase intention. For the full correlation table, please refer to Appendix 8.

Brand trust showed highly significant positive correlations with almost all perception variables ($p < .001$). The highest correlation appeared between brand trust and brand equity ($r = .78$, $p < .001$), followed by serendipity ($r = .55$, $p < .001$), personalization ($r = .50$, $p < .001$), competence ($r = .48$, $p < .001$) and objectivity ($r = .47$, $p < .001$), demonstrating that brand trust is strongly associated with how consumers perceive the quality and relevance of recommendations.

Furthermore, for purchase intention, high, significant correlations were found for the core variables. There was a strong correlation between brand trust and purchase intention ($r = .66$, $p < .001$) and between category involvement and purchase intention ($r = .42$, $p < .001$). These results underscore the relevance of brand trust as a foundation of consumer behavior, as lower levels of trust are associated with lower purchase intention.

Notably, privacy concerns did not show significant correlations with brand trust or purchase intention ($p > .05$), suggesting that data privacy worries alone were not meaningfully associated with algorithmic trust formation in this context. Furthermore, a strong positive association was found between category involvement and perceived personalization ($r = .63$, $p < .001$), indicating that highly involved consumers tend to be more sensitive to the tailored nature of the recommendations. Algorithm skepticism showed significant negative correlations to personalization (r = -.25, p = .017) and serendipity (r = -.23, p = .034), indicating that people with a skeptical attitude towards algorithms tend to perceive personalization more negatively. Furthermore, tech savviness remained largely uncorrelated with the core constructs, suggesting that expertise does not inherently change the general trust-building process.

Importantly, the experimental condition did not have significant correlations to any variables, suggesting there is no linear association between the algorithm cue and the other measures.

4.5 Post-hoc Regrouping

As the manipulation check revealed no significant differences between the experimental conditions in response to the stimulus, the analysis could not be conducted using the randomized groups. To nevertheless investigate the proposed relationships, the analysis followed an exploratory approach regrouping the sample based on the perceived intensity of the algorithmic attribution using a median split on the manipulation check variable. This allows for a more accurate assessment of how the perceived (rather than intended) algorithmic attribution of the post relates to brand trust and other variables. This method yielded a low and a high-perception group and builds the base for further explorative analysis.

4.6 Hypothesis Testing

Following the regrouping, an independent-samples t-test was conducted to examine H1, comparing the new groups on their brand trust evaluations. It revealed no significant differences between respondents with low (M_{low} = 4.30, SD = 1.20) and high algorithm perception (M_{high} = 3.85, SD = 1.45) (p = .153) and thus no support for H1 was found. The mere knowledge or perception of the recommendations algorithmic attribution did not lead to higher brand trust in this setting.

For H2, a linear regression analysis was used to test the effect of brand trust on purchase intention. The analysis revealed supporting evidence for H2 as brand trust was found as strong driver of purchase intention (R^2 = .43, F(1,87) = 66.93, p < .001, β = .66).

Additionally, a two-block hierarchical regression was used to examine if the central path from brand trust to purchase intention remains stable when controlling for involvement, category liking and perceived competence, which showed the highest correlations with purchase intention in the correlation analysis. The baseline model explained 31.8 % of the variance in purchase intention (R^2 = .32, F(3,85) = 13.21, p < .001). When adding brand trust, the model fit improved, explaining an additional 19.6 % of the variance ($\Delta R^2 = .20$, $F(1,84) = 33.89$, $p < .001$), showing that brand trust has incremental explanatory power apart from involvement or liking of the category. Most importantly, brand trust emerged as the strongest predictor in the model ($\beta = .52$, $p < .001$). Notably, perceived competence was significant in model 1 ($p < .001$), but when including brand trust, it lost its significance ($p = .104$), indicating a potential mediating role.

Hypothesis H3 predicted that brand trust would mediate the relationship between the algorithmic attribution and purchase intention. The mediation analysis (PROCESS Model 4) revealed that the indirect effect of the algorithm cue on purchase intention via brand trust was not significant ($ab = -.32$, 95 % BCa CI [-.76, .12]), as the confidence interval includes zero. The direct effect was similarly not significant ($B = .20$, $p = .421$). Therefore, H3 was not supported.

Regarding H4, a regression analysis with interaction terms (PROCESS Model 1) was used to examine if product involvement moderates the relationship between algorithm attribution and brand trust while controlling for algorithm skepticism. Although the overall model was significant ($R^2 = .13$, $F(4, 84) = 3.09$, $p = .020$), the result was based on a direct effect. Involvement acts as a direct predictor of trust ($B = .24$, $SE = .10$, $p = .016$) but does not enhance the effect of algorithm perception. The interaction term was not significant ($p = .702$). Thus, contrary to hypothesized consumers with lower involvement did not react more strongly to algorithmic cues than those with higher involvement. Involvement acts as a driver of brand trust but does not change the effect of the algorithm cue. Consequently, H4 is not supported.
For more details and statistics of all hypothesis testing, please refer to Appendix 9.

Table 4: *Statistical Tests and Results*

Hypothesis	Statistical test	Results
H1: Brands presented as algorithmically recommended generate higher brand trust than brands presented without algorithmic attribution.	Independent-Samples T-Test	Not supported
H2: Brand trust positively influences purchase intention.	Linear Regression	Supported
H3: Brand trust mediates the relationship between algorithmic recommendation and purchase intention.	Hayes' PROCESS macro (Model 4)	Not supported (direct hypothesis), but supported in exploratory path analysis
H4: Category involvement moderates the effect of algorithmic recommendation on brand trust, such that the effect is stronger for low-involvement consumers.	Hayes' PROCESS macro (Model 1)	Not supported

Source: Own creation based on survey data

4.7 Further Exploratory Analyses

To gain further understanding of the mechanisms of algorithmic recommendations, especially in the light of the non-significant hypotheses, analyses beyond the original hypothesis testing were conducted (for details see Appendix 10). These examine the relative strengths of the quality attributes, as well as the mediating and moderating influences of control variables and individual user characteristics.

In a multiple linear regression, all four dimensions of algorithmic quality (objectivity, competence, personalization, serendipity) were included simultaneously as predictors of brand trust ($R^2 = .38$, $F(4,84) = 14.28$, $p < .001$). The results indicated that serendipity ($\beta = .33$, $p = .003$) most strongly predicts of brand trust, with perceived objectivity ($\beta = .21$, $p = .049$)also playing a notable roleu. Competence ($\beta = .12$, $p = .322$) and personalization ($\beta = .15$, $p = .194$) were not significant when all factors were included in a single model. An explorative path analysis (PROCESS Model 4) confirmed these results and extended them. The second step of the model revealed that brand trust in turn drives purchase intention ($\beta = .51$, $p < .001$) and the test for indirect effects confirmed full mediation. The algorithm did not lead to purchase intention solely through its quality dimensions, but only through an increase in brand trust (*ab* = .16, 95 % BCa *CI* [.04, .31]). As the confidence interval does not include zero, this indirect effect is robust.

Additionally, further analysis (PROCESS Model 1) examined how individual factors potentially moderate moderate the effect of perceived algorithmic attribution on brand trust. Regarding general privacy concerns, the analysis showed a marginally significant interaction trend ($\Delta R^2 = .04$, $p = .063$), while the overall model was not significant ($p = .134$). A detailed analysis showed that for respondents with high privacy concerns, a higher algorithmic perception was associated with lower brand trust ($\beta = -1.19$, $p = .019$), while for respondents with low concerns, there was no effect.

A similar analysis for tech savviness revealed a significant interaction ($\Delta R^2 = .06$, $p = .024$). While for low tech savviness the effect of algorithmic perception on brand trust was insignificant, for high tech savviness there was a significant negative effect ($\beta = -1.36$, $p = .008$).

5 Discussion

The findings of this research provide insights into the mechanisms through which algorithmic recommendations on Instagram shape consumer behavior. While the explicit algorithm attribution did not have a direct influence on brand trust, the findings reveal mechanisms driven by perceived quality and individual characteristics. In the following, those aspects will be interpreted and discussed considering current literature.

5.1 The Effect of Algorithmic Attribution on Brand Trust

The manipulation check confirmed that the explicit label did not lead respondents to perceive the post as more algorithmically mediated compared to the control group, resulting in a failed manipulation. Furthermore, even when regrouping participants based on their actual perceived algorithmic attribution, no significant direct effect on brand trust was found, suggesting that algorithmic perception alone is insufficient to drive trust formation. Instead, trust appears to be shaped by the qualitative perception of the recommendation itself, as evidenced by the significant mediating roles of serendipity and objectivity identified in the subsequent exploratory analysis. Regarding the manipulation check, individual characteristics offer a compelling explanation for these results (Barbosa & De Oliveira, 2026; Lee & Cha, 2025). As Lee and Cha (2025) explain, transparency might not always be beneficial for trust building, depending on the cognitive abilities of the user. As this sample consisted mainly of daily users, they likely possess high baseline awareness of algorithmic curation regardless of explicit cues. This is confirmed by the results of the manipulation check question ("The post seemed to be recommended by the platform's algorithm"), where 57.4% of all respondents stated agreement above the neutral point. As highlighted by Kozyreva et al. (2021), nowadays most consumers know what AI is and understand that is is used in digital environments for advertisements and recommendations. Based on this, the signal of the recommendation source used in this study was not sufficient to deliver new information and manipulate users' already high awareness of algorithm mediation further. The authors also suggest that the omnipresence of algorithmic recommendations has led to a saturation effect, where trust might no longer be meaningfully enhanced by algorithmic mediation alone, as it has become an expected rather than exceptional feature of digital environments. This is further reinforced by Balaskas et al. (2025), emphasizing algorithm fatigue, where especially young consumers are overloaded with personalized feeds, therefore they would not cognitively process a label or just not view it as relevant towards building brand trust. Interestingly, this finding contradicts much of the current research.

Literature emphasizes the high importance of transparency as a prerequisite for trust, since a lack of explainability and transparency generates mistrust (Hardcastle et al., 2025; Vorm & Combs, 2022). This study's results however, indicate explicit labels may paradoxically activate persuasion knowledge, heightening consumers' awareness of the post's commercial intent and evoking skepticism rather than trust (Kong & Lou, 2026). It might also trigger more concerns about privacy, diminishing the positive effects of the transparency (Chen et al., 2024). Therefore, the findings position high algorithm literacy as a boundary condition of transparency-based trust literature. Explicit algorithmic attribution and labeling may only be effective in contexts where users lack baseline awareness of algorithmic curation, a condition increasingly unlikely among heavy social media users.

Beyond this activation of persuasion knowledge, Leung et al. (2018) suggest that explicit labeling may trigger resistance if the discovery of a brand is tied to the user's identity motives. In identity-relevant contexts, consumers have a strong desire to attribute successful outcomes, like finding a unique brand, to their own personal taste or effort rather than to an automated process. This process of internal attribution provides diagnostic utility, signaling to the user that they are a person with expertise or good taste. Explicitly labeling a recommendation as algorithmic may therefore hinder this attribution and reduce the self-signaling utility of the experience. For highly engaged users, such as those in this sample, the algorithmically driven discovery might even be perceived as a threat to their autonomy and sense of accomplishment, leading them to discount the recommended brand's trustworthiness.

An additional explanation for the finding may lie in the stimulus design itself and the sample. Participants may not have perceived the distinction between the algorithmic and neutral attribution sufficiently salient, as the visual dominance of the post may have distracted them from the source cue. Aoki and Matsui (2025) encountered comparable issues, noting that the visual layout of a stimulus can be so dominant that information regarding the source origin is overlooked by participants. Moreover, the unequal gender distribution between conditions, with a higher proportion of male participants in the algorithmic group, may have contributed to group differences in algorithmic awareness and critical processing (Gran et al., 2021; Voorveld et al., 2024), representing a minor confound that future research should control for through gender-balanced randomization.

Taken together, these findings suggest that in contexts of high algorithm literacy, the mere salience of algorithmic attribution, whether explicitly labeled or individually perceived, is insufficient to directly shape brand trust. Trust formation in algorithmically driven environments appears to operate through perceptual mechanisms, namely the emotional quality of the discovery experience and the perceived neutrality of the recommendation.

5.2 The Effect of Brand Trust on Purchase Intention

The findings provide strong support for H2, confirming that brand trust is a key driver of purchase intention, aligning with previous literature (Beck et al., 2023; Sufyan Ghaleb & Pardaev, 2025). The result reinforces the idea that in digital environments, trust acts as a necessary psychological bridge before consumers commit to a purchase. Especially on social media platforms like Instagram, where consumers are constantly exposed to new brands and lack physical verifiability, trust serves as the foundational driver and prerequisite of purchase intention (Ranjith et al., 2025). An insight from the additional hierarchical analysis for H2 is the role of perceived competence. While competence initially appeared significant, it lost its predictive power once brand trust was included in the model. This suggests that while the perceived technical ability of an algorithm is a necessary prerequisite, it is not a sufficient condition for purchase. Consumers may acknowledge that an algorithm is competent, but they will only consider buying if they also trust the brand. This aligns with trust transfer theory (Stewart, 2003), which proposes that trust in a system must first be established before it can transfer to the brand and ultimately drive behavior.

5.3 The Effect of Perceived Recommendation Quality on Brand Trust

While H3 was formally rejected, the exploratory analysis revealed a more nuanced reality. The results suggest that the mere algorithmic perception is insufficient to trigger trust, instead, the findings show that once the algorithm is perceived through specific quality dimensions, complete mediation occurs. Thus, algorithmic recommendations do not drive behavior through their mere attribution but through their qualitative perception and the formation of brand trust. Without brand trust, even the most accurate recommendation fails to translate into purchase intention. Interestingly, not technological accuracy or recommendation fit, but serendipity most influenced brand trust among the algorithmic quality measures. This implies that on Instagram, trust is fostered more through emotional impact than through the system's cognitive competence. This finding aligns with literature discussing the risk of boredom when similar content is shown repeatedly (Hardcastle et al., 2025). Due to how algorithms work, such systems restrict exposure, therefore standing out by randomness or chance enhances brand trust. Thus, this research extends the findings of Kim et al. (2021) by showing that serendipitous interactions not only evoke short-term joy or satisfaction but are also relevant to building deeper brand trust. Moreover, perceived objectivity was found as second significant driver of brand trust, suggesting that consumers not only evaluate recommendations based on the affective joy of discovery but also the neutrality of the source, aligning with literature (Aoki & Matsui, 2025; Chacon et al., 2025). Notably, contrary to literature, the factor analysis revealed that objectivity is not based on the data-driven approach of algorithms (Chacon et al., 2025) but the lack of commercial intent and neutrality of the recommendation.

In summary, while H1 and H3 were rejected, the explorative analyses support the idea that the mediating mechanism generally exists but is tied to the subjective indirect perception of the algorithm performance instead of the mere algorithmic presence.

5.4 The Moderating Role of Involvement, Privacy Concerns and Tech Savviness

While literature and theories like ELM suggest involvement does play a role in processing and moderates effects on brand trust, that relationship was not significant in this study. This finding aligns with Xu et al. (2023), where involvement and its interaction with a recommendation label were also not significant, suggesting the effect of algorithmic attribution on brand trust is independent from product involvement in this context.

One approach to explaining this is that in online settings like social media, users are generally in peripheral processing mode (Dong et al., 2024; Erdem et al., 1999). In this low-elaboration environment, the platform's visual and rapid pacing effectively neutralizes the traditional motivating effect of product involvement, causing users to process the experience uniformly regardless of their intrinsic interest in the product category.

Another consideration is that dispositional factors, such as tech savviness or privacy concerns, might outweigh situational factors like involvement in algorithmically driven environments (Vorm & Combs, 2022). The explorative analysis supports exactly this notion, while involvement did not make a difference, tech savviness and privacy concerns emerged as (marginally) significant drivers of reactance[5]. For consumers with high technical expertise or elevated privacy concerns, consciously perceiving the algorithm backfires. Instead of fostering trust, detecting the algorithmic nature of the recommendation triggers a negative evaluation, undermining brand trust. This demonstrates that different consumer groups react differently based on their individual characteristics. The observed effect can be explained by psychological reactance, which gets activated when consumers feel that their autonomy is threatened, leading

[5] Given that the effect for privacy concerns reached only marginal significance, all interpretation regarding this effect are only preliminary and require replication in future research.

to negative evaluations of the source (Puntoni et al., 2021). Highly accurate recommendations may lead to the realization about data gathering, evoking feelings of threat and triggering rejection for expert and generally skeptical consumers (Balaskas et al., 2025). The backfire effect further aligns with the consumer typology of Voorveld et al. (2024), particularly their skilled and critical group. These individuals possess high algorithm awareness, high internet skills and privacy concerns, evaluating the use of algorithms by brands as less appropriate. The authors suggest that this group might take protective measures to experience less personalization. In accordance with that, this research's sample shows a high baseline awareness of algorithms and the exploratory analysis shows that with higher tech savviness and privacy concerns, trust decreases. This reinforces the idea that in algorithmically driven environments, individual dispositional traits might override the impact of involvement, suggesting that the consumer's psychological profile is a more relevant predictor of brand trust than their level of involvement.

5.5 Theoretical and Practical Implications

The findings reveal insightful extensions to previous literature and marketing theories. This study provides an extension to the PKM in the context of social media and algorithms, revealing a conditional effect. The explicit label and increased salience of algorithm influence do not directly influence consumers' reactions on recommendations for digital natives as algorithmic curation has transitioned from a distinct feature to a baseline expectation. However, for consumers with high tech savviness and privacy concerns, the heightened perception of the algorithm triggers psychological reactance, thereby undermining brand trust. Thus, the activation of persuasion knowledge is not a universal response to algorithmic attribution, but rather contingent upon individual dispositional factors.

This study also extends the ELM by demonstrating that on fast-moving visual platforms such as Instagram, users predominantly default to peripheral processing regardless of involvement level. Consequently, this study challenges the traditional role of involvement as a primary moderator in algorithmically driven social media contexts, highlighting that dispositional factors often override situational ones.

Furthermore, the findings expand the understanding of serendipity by showing that it not only increases short-term satisfaction but also strengthens deeper brand measures.

The finding that objectivity is also a driver of brand trust complements trust transfer theory, demonstrating that perceived neutrality of algorithmic recommendations builds trust that transfers to brand perceptions. Moreover, the found backfire effect confirms and expands the understanding of algorithm aversion when certain characteristics are present, identifying individual boundary conditions to trust transfer. For individuals with high tech savviness and privacy concerns, trust transfer from the algorithm to the brand fails and even reverses into a less positive perception.

Finally, the results provide further understanding of users' perception of competence and objectivity as constructs. While users associate a data-driven approach with high algorithmic competence and technical performance, they do not link it to perceived objectivity. This suggests that consumers distinguish between a system's ability to process vast amounts of information and make decisions based on that data and its ability to remain unbiased and neutral. Consequently, emphasizing the data-driven nature of an algorithm may successfully signal expertise, but it remains insufficient for fostering the brand trust necessary for purchase intention.

For brand managers, these findings offer actionable insights on how to position products to derive maximum benefit from algorithmic discovery. Differentiated strategies for algorithmic transparency based on consumer characteristics are required. For most heavy social media users, explicit algorithmic labels add no value, due to their high awareness of algorithmic mediation. Brands should therefore focus less on transparency of the algorithmic origin and more on the perceived quality of the recommendation, specifically fostering serendipity and objectivity as primary trust-building mechanisms.

For tech-savvy consumers and consumers with high privacy concerns, a different approach is needed, as transparency for them leads to skepticism. Explanatory cues that communicate the objectivity and responsible use of data behind a recommendation might help to reduce reactance and overcome the backfire effect. Additionally, offering active consumer control over recommendation settings, such as preference filters or opt-out options, could restore a sense of autonomy and mitigate distrust. These strategies require further investigation in future research. More broadly, brand managers must accept privacy concerns as a structural feature of modern consumer relationships rather than an obstacle to overcome. This requires not only ethical use of algorithmic tools but also clearer governance frameworks that define responsibilities and protect all parties involved (Cui & Van Esch, 2025).

Furthermore, brands and platforms should place less emphasis on technical perfection and overly intrusive hyper-personalization. Instead, they should design recommendations as unexpected yet positive surprises, helping them stand out while reducing consumers' feelings of constant monitoring. This finding is contrary to past literature where accuracy is emphasized as key success factor for building trust (Almahmood & Tekerek, 2022), therefore these findings are of high value for practitioners. Investment in precise algorithmic visibility might be less important than staging serendipity to leverage brand trust. This implies that by framing algorithmic placements as serendipitous and objective, brand trust might be enhanced without expensive advertisements or influencers. The described findings also have practical implications for search engine optimization (SEO) strategies. Traditional SEO provides the technical competence that allows an algorithm to categorize brands correctly (Cui & Van Esch, 2025). Yet, this research shows that while being technically findable is mandatory, it does not trigger the psychological bridge of trust. For brands, this means that SEO ensures visibility, but serendipitous and objective content delivery is the conversion driver. High-quality training data makes a brand visible to the model, but human-resonant quality makes it relevant to the user.

While the findings have shown mechanisms of action regarding consumers and algorithmic recommendations, it is important to note structural risks and ethical considerations as warned by the literature. The black-box nature of algorithms creates power asymmetries where users give their data for personalization, whose internal decision-making criteria remain non-transparent even to experts (Campolo & Crawford, 2020). Algorithm systems are not neutral but based on socio-cultural assumptions and biases within their training data, which may reinforce inequalities technologically (Airoldi & Rokka, 2022). The iterative structure of algorithms further leads to feedback loops that might place users in filter bubbles, limiting the diversity of seen content (Airoldi & Rokka, 2022). Although personalization is often seen as a form of empowerment to the consumer, it also risks restricting the factual autonomy of an individual in its scope for action (Darmody & Zwick, 2020). Furthermore, the approach of seeing algorithms as mere technical objective entities leads to unclear responsibilities and protects creators from accountability. This demonstrates that a responsible approach to algorithmic systems requires a fundamental reorientation of marketing that goes beyond technical optimization and superficial transparency. A clear assignment of legal and operational accountability is needed and marketers must responsibly use algorithms while balancing users' rights and concerns. To achieve this, active steps such as regular audits are essential to mitigate biases and protect vulnerable groups. Crucially, these self-regulatory efforts are no longer optional but are increasingly demanded by external governance (Puntoni et al., 2021). Emerging regulatory frameworks, such as the EU's Digital Services Act (Voorveld et al., 2024), signal a growing institutional recognition of the need for algorithmic accountability.

In summary, if brands want to foster trust and build sustainable relationships in algorithmically driven discovery contexts, they must move beyond mere exploitation of the technology and embrace a governance-first mindset.

5.6 Limitations and Future Research

Despite the findings and implications, this study has methodological and conceptual limitations. First, regarding the sample, the size of the dataset constitutes a limitation. While it was sufficient to detect drivers of brand trust and conditional effects, a larger and more statistically powerful sample might have revealed subtler nuances or stabilized marginally significant effect of privacy concerns. Additionally, the sample consisted mainly of young, heavy Instagram users, limiting generalizability to other user groups like older individuals or less digitally affine users. Moreover, voluntary participation introduced a self-selection bias, as the study likely attracted respondents already engaged with or interested in the topic. Consequently, this may have skewed the baseline levels of the analyzed constructs, restricting the findings' overall representativeness. Finally, all responses were based on self-reporting, introducing potential biases, such as social desirability.

A central methodological limitation is the failed manipulation check regarding the algorithmic label, which necessitated a shift from experimental to an exploratory approach of the analysis. While this allowed for deeper insights, the results must be interpreted with caution and should be validated through dedicated samples.

Furthermore, the conceptual scope of the research design introduces specific limitations. The study utilized a static image as a stimulus, not reflecting the full reality of social media platforms that also feature video formats like reels. Future research should employ more dynamic stimuli to increase ecological validity. Moreover, this study focused exclusively on organic discovery. As consumer skepticism often differs between organic content and paid advertisements, comparing these two contexts could reveal whether the trust-building mechanisms identified here remain stable under the pressure of explicit commercial intent. The scope was further limited to the single product type of a snack bar. While FMCG products are suitable for testing low-involvement decisions, the findings may differ in categories with initial higher involvement, where the trust-building process is potentially more complex. Furthermore, the study was conducted solely focusing on Instagram. Other platforms might yield different results. Regarding the outcome variables, this research measured purchase intent, which does not fully reflect actual purchase behavior. Future longitudinal studies or field experiments with actual sales data would be necessary to confirm the long-term impact on brand performance, especially as technology and RS constantly evolve.

From a statistical perspective a limitation concerns multicollinearity among the perceptual variables. Notably, perceived competence and objectivity showed a strong positive correlation ($r = .59$, $p < .001$). In the regression models, these constructs compete for explanatory power, which may lead to suppressed effects or reduced significance for individual predictors. Future research could benefit from more distinct scale developments to better separate the technical and ethical dimensions of algorithmic perception.

Finally, regarding the literature base, while core theoretical constructs are grounded in established peer-reviewed academic literature, some insights are derived from sources with varying degrees of empirical depth. Consequently, while these insights provide a crucial foundation for understanding current trends, they should be interpreted as preliminary, serving as an exploratory foundation for a rapidly evolving field.

Building upon this basis, several directions for future research emerge to address both the limitations identified and the broader complexities of algorithmic discovery. First, further research should examine a wider scope of stimuli as suggested by Loureiro et al. (2019) to validate findings. Second, it is essential to also investigate the impacts of algorithmic discovery, taking into consideration characteristics of the content itself. Furthermore, other consumer groups, especially older and less heavy users, should be examined to assess the stability of the found effects. Future research could also investigate the relationship between involvement and perceived personalization, as the strong positive association found in this study suggests that involved consumers may be particularly sensitive to recommendation relevance.

Methodically objective behavioral data, instead of self-reporting, should be used to complement and validate effects without desirability bias or other influences. Additionally, longitudinal and larger studies are necessary to validly depict the cumulative and long-term effects, especially on brand equity.

Furthermore, the non-significant manipulation check reveals that further research is needed on specific design and framing of algorithmic labels, exploring how transparency regarding platform logic can be effectively communicated. Going along with this, active control options and their effect on brand trust should be tested to examine how to reduce distrust and reactance.

Finally, future research should focus on the precise operationalization of serendipity and objectivity, examining how brands can intentionally shape and leverage these perceptions to foster trust without activating users' persuasion knowledge

6 Conclusion

In summary, this research reveals a nuanced picture of algorithmic brand discovery on social media and its impact on brand outcomes. While much literature highlights transparency through labeling as a key prerequisite for trust, this study's results demonstrate that explicit algorithmic attribution did not significantly influence brand trust. This is likely due to a high baseline awareness among the sample of heavy Instagram users, where algorithmic mediation is seen as normal. In this context, the label did not offer additional information for users. Thus, success in algorithmic communication depends less on technological processes and more on the emotional and functional quality of the outcomes. Serendipity emerged as the strongest driver of brand trust, complementing the findings of Kim et al. (2021). Experiencing a recommendation as a fortunate surprise can foster trust and reduce cognitive reactance towards algorithms. Perceived objectivity also proved important. The research highlights a data-drivenness paradox: while consumers acknowledge technical competence, trust is only established when the algorithm is perceived as an unbiased, neutral mediator. Technical competence is necessary, but not sufficient for purchase; it requires objectivity to convert into actual consumer behavior. Brand trust acts as the fundamental psychological bridge, without it, even a precise recommendation does not lead to purchase intention. At the same time, there are limiting factors. For tech-savvy consumers and those with high privacy concerns, perceiving algorithmic influence on the recommendation can lead to reactance. For this group, transparency creates a paradox: instead of evoking trust, it causes active devaluation of the brand. In conclusion, successful marketing for FMCG brands on social media requires a shift from mere technical perfection of algorithm precision towards responsible serendipity- and objectivity-driven curation. Only responsible handling of algorithmic power can secure trust in an increasingly automated consumer culture.

Circling back to Mosseri's vision of technology serving the individual, this remains a worthy aspiration. Yet this research demonstrates that truly making the most of people's time requires a fundamental shift in how personalization is designed and communicated. Trust is not built through mere transparency of the algorithm, but through the emotional quality of discovery it enables and only within the boundaries of what consumers accept as appropriate. The future of algorithmic brand discovery therefore, lies not in data and personalization alone, but in more responsibility of platforms, brands and users collectively.

APPENDICES

Appendix 1: Measurement Operationalization Additional Variables

Perceived Objectivity:

Perceived objectivity focuses on how unbiased and neutral the consumers perceive the recommendation. The used 3-item scale was adapted from definitions of Chacon et al. (2025). According to the authors and their literature overview, algorithm objectivity is the ability of systems to use training data and automated formulas to deliver consistent and unbiased results. While their study did not include a scale for this construct, the definitions were used to develop this one.

- PO1: The recommendation seems objective.
- PO2: The recommendation seems unbiased.
- PO3: The recommendation seems data-driven.

Perceived Competence:

Perceived competence evaluates the perceived ability and expertise behind the recommendation. It was measured using two items conceptually adapted from Longoni and Cian (2022), who identify competence perceptions as key mechanisms for brand trust in AI environments. The wordings were adapted from Chaiken (1980), who showed in a factor analysis that the words competence and knowledgeable load on the mutual factor of expertise. The construct of Longoni and Cian (2022) possesses a strong original reliability of $\alpha = .89$.

- PC1: The recommendation seems knowledgeable.
- PC2: The system behind this recommendation seems competent.

Perceived Personalization:

Perceived personalization captures the extent to which consumers feel the content is tailored specifically to them. This 3-item construct was adapted from Voorveld et al. (2024), who developed their scale to depict individual relevance of brand messages in digital contexts. Their scale was adapted to this study's setting and shortened to reduce survey length. The original scale is highly reliable with $\alpha = .89$.

- PP1: The content fits my preferences.
- PP2: The recommendation feels tailored to me.
- PP3: The product seems relevant to me.

Perceived Serendipity:

Perceived serendipity measures the feeling of a positive, unexpected discovery. The scale was directly adapted from Kim et al. (2021), who conceptualized serendipity in algorithmic marketplaces. It was reduced to two items to reduce survey length. This construct demonstrated good reliability in the original study with an α of .83.

- PS1: The recommendation felt like a pleasant surprise.
- PS2: I feel like I found this post by a lucky chance.

Algorithmic Skepticism:

To capture consumers' general defense mechanisms and doubts regarding AI curation, algorithmic skepticism was measured with three items based on the concept of generalized skeptisim by Fletcher & Nielsen (2018). Conceptually, it follows the logic of the consumer skepticism scale by Obermiller and Spangenberg (1998).

- AS1: I am generally skeptical about algorithmic recommendations.
- AS2: I do not fully trust algorithm-based suggestions.
- AS3: Algorithms often misjudge my preferences.

Privacy Concern:

General privacy concerns regarding data usage were measured using a 3-item scale adapted from Voorveld et al. (2024) and shortened. Their scale for online privacy concerns showed internal consistency of α = .92.

- PC1: I am concerned about how companies use my personal data.
- PC2: I feel uncomfortable when platforms use my data for recommendations.
- PC3: Online personalization often feels intrusive.

Tech Savviness:

The scale for tech savviness was adapted from the established dimensions of Küper and Krämer (2025), which correspond to their constructs of control belief and technology affinity. To minimize respondent fatigue the scale was reduced to two items with original constructs reporting internal consistency of α = .81 - .85.

- TS1: I consider myself technologically skilled.
- TS2: I usually understand how digital technologies work.

Appendix 2: Survey Flow

Introduction (1Question)
Screening (1 Question)
Randomizer 1: Evenly Present Elements
Stimulus + Text Group - Algorithmic: Imagine you're scrolling through your personal Instagram feed. You see the following post, which has been selected for you based on your interests, preferences and past activity. Please take a close look at the post before proceeding.
Stimulus + Text Group - Neutral: Imagine you're scrolling through Instagram. You see the following post. Please take a close look at the post before proceeding.
Manipulation Check (1 Question)
Main Constructs: Measurement of Brand Trust, Brand Equity and Purchase Intention (3 Questions)
Exploratory Variables (4 Questions)
Moderator and Control Variables (8 Questions)
Attention Check (1 Question)
Demographics (3 Questions)

Source: Own creation based on survey setup

Appendix 3: Survey Questionnaire

Start of Block: Introduction

This research study is conducted as part of a master's thesis at Católica Lisbon and aims to study consumer behavior in digital environments. There are no right or wrong answers. Your honest opinion is highly appreciated. This survey is expected to take about 5-7 minutes to complete. Your participation is completely voluntary and your responses will be kept strictly confidential. Please click on the "next" button if you agree to continue. Thank you!

- o Next

End of Block: Introduction

Start of Block: Screening

Social media usage - SMU: Thinking about the past 12 months, how often on average did you use Instagram?

- o Never (1)
- o Less than once a month (2)
- o A few times a month (3)
- o A few times a week (4)
- o Daily (5)

End of Block: Screening

Start of Block: Stimulus

Stimulus + Stimulus Text

End of Block: Stimulus

Start of Block: Questions

Manipulation check – MC: Please indicate how much you agree with the following statements regarding the post you have seen. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
The post seemed to be recommended by the platform's algorithm (1)	○	○	○	○	○	○	○
The post seemed tailored to my personal interests (2)	○	○	○	○	○	○	○

Brand trust – BT: Please indicate how much you agree with the following statements regarding the brand shown in the post. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
I trust this brand (1)	○	○	○	○	○	○	○
This brand seems reliable (2)	○	○	○	○	○	○	○
This brand appears honest (3)	○	○	○	○	○	○	○
I feel confident about this brand (4)	○	○	○	○	○	○	○

Brand Equity – BE: Please indicate how much you agree with the following statements regarding the brand shown in the post. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
This brand seems to be of high quality (1)	○	○	○	○	○	○	○
I have a favorable opinion of this brand (2)	○	○	○	○	○	○	○

Page Break

Purchase Intention – PI: Please indicate how much you agree with the following statements regarding the brand shown in the post. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
I would consider buying this product (1)	○	○	○	○	○	○	○
I would likely purchase this brand (2)	○	○	○	○	○	○	○
I would try this product if it was available (3)	○	○	○	○	○	○	○

Perceived Objectivity – PO: Please indicate how much you agree with the following statements regarding the post you have seen. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
The recommendation seems objective (1)	○	○	○	○	○	○	○
The recommendation seems unbiased (2)	○	○	○	○	○	○	○
The recommendation seems data-driven (3)	○	○	○	○	○	○	○

Perceived Competence – PC: Please indicate how much you agree with the following statements regarding the post you have seen. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
The system behind this recommendation seems competent (1)	○	○	○	○	○	○	○
The recommendation seems knowledgeable (2)	○	○	○	○	○	○	○

Page Break

Perceived Personalization – PP: Please indicate how much you agree with the following statements regarding the post you have seen. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
The content fits my preferences (1)	○	○	○	○	○	○	○
The recommendation feels tailored to me (2)	○	○	○	○	○	○	○
The product seems relevant to me (3)	○	○	○	○	○	○	○

Perceived Serendipity – PS: Please indicate how much you agree with the following statements regarding the post you have seen. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
The recommendation felt like a pleasant surprise (1)	○	○	○	○	○	○	○
I feel like I found this post by a lucky chance (2)	○	○	○	○	○	○	○

Algorithm Skepticism – AS: Please indicate how much you agree with the following statements. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
I am generally skeptical about algorithmic recommendations (1)	o	o	o	o	o	o	o
I do not fully trust algorithm-based suggestions (2)	o	o	o	o	o	o	o
Algorithms often misjudge my preferences (3)	o	o	o	o	o	o	o

Page Break

Privacy Concern - Priv.C: Please indicate how much you agree with the following statements. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
I am concerned about how companies use my personal data (1)	o	o	o	o	o	o	o
I feel uncomfortable when platforms use my data for recommendations (2)	o	o	o	o	o	o	o
Online personalization often feels intrusive (3)	o	o	o	o	o	o	o

Involvement – Inv: Please indicate how you generally feel about the product category seen in the post. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
Products in this category are important to me (1)	o	o	o	o	o	o	o
I am interested in this product category (2)	o	o	o	o	o	o	o
I usually invest time when choosing products in this category (3)	o	o	o	o	o	o	o
I feel involved when purchasing products in this category (4)	o	o	o	o	o	o	o

Category Perception – Perc: Please indicate how you generally feel about the product category seen in the post. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
This product mainly serves a practical purpose (e.g., quick energy or convenience) (1)	o	o	o	o	o	o	o

Page Break

Category Usage: How often do you purchase snack bars in your regular daily life?

- o Never (1)
- o Rarely (2)
- o Occasionally (3)
- o Often (4)
- o Very often (5)

Category Liking: Please indicate how you generally feel about the product category seen in the post. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7

In general, I like snack bars (1)	○	○	○	○	○	○	○

Post Realism: Please indicate how you generally feel about the post you have seen. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
It seems realistic that this product would be recommended to me on Instagram (1)	○	○	○	○	○	○	○

Page Break

Technical Savviness – TS: Please indicate how much you agree with the following statements. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
I consider myself technologically skilled (1)	○	○	○	○	○	○	○
I usually understand how digital technologies work (2)	○	○	○	○	○	○	○

Attention check: Please indicate how much you agree with the following statement. 1 = Strongly disagree, 7 = Strongly agree

	1	2	3	4	5	6	7
To ensure data quality, please select 6 for this item (1)	○	○	○	○	○	○	○

Age: Please indicate your age:

____

Gender: Please indicate your gender

- Male (1)
- Female (2)
- Non-binary (3)
- Prefer not to say (4)

Education: Please indicate the highest level of education you have

- High school (1)
- Bachelor (2)
- Masters (3)
- Doctorate (4)
- Other (5)

End of Block: Questions

Thank you for your response!

Appendix 4: Descriptive Statistics

Demographics:

The following tables present the detailed descriptive statistics of the total sample's demographic characteristics, including age, gender, education level and Instagram usage frequency. All tables are based on the survey data and exported as images from SPSS.

Age:

	N	Minimum	Maximum	Mean	Std. Deviation
Age	89	14	57	26,47	5,835
Valid N (listwise)	89				

Gender:

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	26	29,2	29,2	29,2
	Female	62	69,7	69,7	98,9
	Prefer not to say	1	1,1	1,1	100,0
	Total	89	100,0	100,0	

Education:

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	High school	9	10,1	10,1	10,1
	Bachelor	36	40,4	40,4	50,6
	Masters	24	27,0	27,0	77,5
	Doctorate	1	1,1	1,1	78,7
	Other	19	21,3	21,3	100,0
	Total	89	100,0	100,0	

Instagram Usage:

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than once a month	5	5,6	5,6	5,6
	A few times a month	2	2,2	2,2	7,9
	A few times a week	6	6,7	6,7	14,6
	Daily	76	85,4	85,4	100,0
	Total	89	100,0	100,0	

Descriptive Statistics of Additional Constructs:

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
BT_Mean	89	1,00	7,00	4,1433	1,38933
BE_Mean	89	1,00	7,00	4,2697	1,28155
PI_Mean	89	1,00	7,00	3,9326	1,47640
Obj_Mean	89	1,00	7,00	3,5787	1,40190
Comp_Mean	89	1,00	7,00	3,4551	1,44332
Pers_Mean	89	1,00	7,00	3,4906	1,52014
Ser_Mean	89	1,00	7,00	3,0393	1,45427
Scept_Mean	89	1,00	7,00	4,5880	1,30173
PrCon_Mean	89	2,00	7,00	5,1423	1,42656
Inv_Mean	89	1,00	7,00	3,5506	1,50009
TS_Mean	89	2,50	7,00	5,3427	1,22148
Post Realism	89	1	7	4,01	1,818
Category Liking	89	1	7	5,39	1,403
Category Usage	89	2	5	2,67	,703
Category Perception	89	2	7	5,19	1,287
Valid N (listwise)	89				

Appendix 5: Factor Analysis

The following tables present the results of the exploratory factor analysis, including KMO and Bartlett's test, total variance explained, communalities and the rotated component matrix. All tables are based on the survey data and exported as images from SPSS.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,890
Bartlett's Test of Sphericity	Approx. Chi-Square	1319,834
	df	171
	Sig.	<,001

Communalities

	Initial	Extraction
PO_1	1,000	,788
PO_2	1,000	,834
PO_3	1,000	,820
PC_1	1,000	,831
PC_2	1,000	,866
PP_1	1,000	,849
PP_2	1,000	,827
PP_3	1,000	,779
PS_1	1,000	,677
PS_2	1,000	,604
BT_1	1,000	,772
BT_2	1,000	,770
BT_3	1,000	,774
BT_4	1,000	,796
BE_1	1,000	,631
BE_2	1,000	,745
PI_1	1,000	,857
PI_2	1,000	,854
PI_3	1,000	,808

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9,428	49,620	49,620	9,428	49,620	49,620	4,689	24,677	24,677
2	1,879	9,888	59,508	1,879	9,888	59,508	3,304	17,392	42,069
3	1,379	7,256	66,764	1,379	7,256	66,764	2,546	13,399	55,468
4	1,185	6,235	72,999	1,185	6,235	72,999	2,247	11,828	67,296
5	1,013	5,334	78,333	1,013	5,334	78,333	2,097	11,037	78,333
6	,759	3,996	82,330						
7	,557	2,930	85,260						
8	,413	2,171	87,431						
9	,390	2,053	89,485						
10	,362	1,905	91,390						
11	,303	1,596	92,986						
12	,258	1,357	94,343						
13	,232	1,220	95,563						
14	,199	1,049	96,613						
15	,173	,908	97,521						
16	,148	,778	98,299						
17	,127	,669	98,968						
18	,104	,546	99,514						
19	,092	,486	100,000						

Extraction Method: Principal Component Analysis.

Rotated Component Matrix[a]

	Component				
	1	2	3	4	5
PO_1	,289	,222	,064	,092	,802
PO_2	,205	,153	,118	,174	,851
PO_3	,125	,153	,151	,868	-,066
PC_1	,144	,238	,199	,735	,416
PC_2	,273	,286	,111	,723	,418
PP_1	,157	,849	,243	,088	,190
PP_2	,133	,833	,222	,197	,166
PP_3	,201	,770	,206	,142	,288
PS_1	,404	,640	,142	,289	-,006
PS_2	,543	,492	-,161	,199	-,027
BT_1	,777	,198	,236	,182	,202
BT_2	,771	,168	,328	,127	,156
BT_3	,809	,150	,258	,043	,172
BT_4	,803	,231	,276	,100	,109
BE_1	,713	,063	,134	,225	,224
BE_2	,710	,263	,357	,028	,210
PI_1	,337	,167	,812	,203	,122
PI_2	,426	,342	,717	,183	,089
PI_3	,327	,220	,795	,123	,078

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 7 iterations.

Appendix 6: Cronbach's Alpha all Variables

To assess the internal consistency of the constructs, α was calculated. All tables are based on the survey data and exported as images from SPSS:

Brand Trust:

The brand trust scale demonstrated excellent reliability ($\alpha = .93$), exceeding the threshold of .70 (Peterson, 1994). No significant improvement would have been achieved by deleting any item. Consequently, a mean index was created for further hypothesis testing.

Reliability Statistics

Cronbach's Alpha	N of Items
,930	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
BT_1	12,83	17,710	,862	,899
BT_2	12,31	17,377	,832	,909
BT_3	12,03	18,397	,801	,919
BT_4	12,54	17,638	,846	,904

Brand Equity:

The construct of brand equity showed good internal consistency ($\alpha = .80$). Both items contributed significantly to the construct and a mean index was computed for further analysis.

Reliability Statistics

Cronbach's Alpha	N of Items
,798	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
BE_1	3,92	1,869	,665	.
BE_2	4,62	2,080	,665	.

Purchase Intention:

The Purchase Intention scale, consisting of three items, demonstrated excellent reliability (α = .92), exceeding the threshold of $\alpha = .70$ (Peterson, 1994). By deleting any item, the alpha would be reduced. Consequently, a mean index was created for further hypothesis testing.

Reliability Statistics

Cronbach's Alpha	N of Items
,918	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PI_1	7,89	9,510	,825	,889
PI_2	8,22	8,835	,857	,862
PI_3	7,48	8,889	,821	,893

Perceived Objectivity:

The initial reliability analysis for perceived objectivity yielded $\alpha = .61$, which is below the acceptable threshold of .70 (Peterson, 1994). Further inspection of the item-total statistics revealed that PO_3 correlated poorly with the other items ($r = .19$). By excluding PO_3, the internal consistency of the scale improved significantly to $\alpha = .82$. The final mean index was calculated based on the remaining two items.

Reliability Statistics

Cronbach's Alpha	N of Items
,608	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PO_1	7,11	6,033	,571	,283
PO_2	7,21	5,988	,541	,321
PO_3	7,16	7,861	,194	,824

Perceived Competence:

The construct of perceived competence was measured with two items and demonstrated high internal consistency ($\boldsymbol{\alpha}$ = .89). This exceeds the common threshold of α = .70 (Peterson, 1994), confirming the reliability of the scale for further analysis.

Reliability Statistics

Cronbach's Alpha	N of Items
,893	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PC_1	3,19	2,315	,807	.
PC_2	3,72	2,295	,807	.

Perceived Personalization:

Perceived personalization showed excellent internal consistency with α = .91. Despite a minimal potential increase in α if item PP_3 was deleted, all items were retained. The scale already exhibited excellent reliability ($\boldsymbol{\alpha}$ = .91) and PP_3 showed a robust corrected item-total correlation of r = .77.

Reliability Statistics

Cronbach's Alpha	N of Items
,913	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PP_1	6,96	9,384	,876	,832
PP_2	6,97	9,510	,834	,867
PP_3	7,02	10,045	,767	,922

Perceived Serendipity:

The scale for perceived serendipity demonstrated acceptable internal consistency with α = .74. Both items showed a solid corrected item-total correlation, indicating that the items sufficiently represent the underlying construct. Both items were averaged to form a mean index.

Reliability Statistics

Cronbach's Alpha	N of Items
,741	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
PS_1	2,93	2,745	,589	.
PS_2	3,15	2,581	,589	.

Algorithm Skepticism:

Algorithm skepticism achieved a reliable α = .74. Although the exclusion of item AS_3 would have resulted in a slight increase to α = .76, the item was retained to preserve the conceptual breadth of the scale. With a corrected item-total correlation of .48 for the weakest item, all items still met the requirements for internal consistency and were included in the final mean index.

Reliability Statistics

Cronbach's Alpha	N of Items
,744	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
AS_1	9,11	6,896	,598	,630
AS_2	8,36	7,619	,646	,578
AS_3	10,06	8,417	,481	,759

Privacy Concern:

The privacy concern scale exhibited high internal consistency with $\alpha = .86$. While the removal of item Priv.Con_3 could have marginally improved to $\alpha = .88$, it was decided to retain all items to ensure a more robust and content-valid measurement.

Reliability Statistics

Cronbach's Alpha	N of Items
,862	3

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Priv. Con_1	10,28	7,454	,770	,785
Priv. Con_2	10,48	8,048	,814	,732
Priv. Con_3	10,09	10,605	,665	,877

Involvement:

Measurement of product/ category involvement showed excellent reliability with $\alpha = .88$. By deleting any item, the α would be reduced. Consequently, no items were removed and a mean score was calculated for further analysis.

Reliability Statistics

Cronbach's Alpha	N of Items
,881	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Inv_1	10,78	20,972	,777	,833
Inv_2	10,56	21,794	,762	,840
Inv_3	10,62	20,671	,722	,855
Inv_4	10,65	20,798	,712	,859

Tech Savviness:

Tech savviness was measured using a two-item scale, which showed high internal reliability with $\alpha = .89$. The items were highly correlated with a corrected item-total correlation of .80, confirming that they consistently captured the participants' perceived technical expertise. Both items were retained for the mean index.

Reliability Statistics

Cronbach's Alpha	N of Items
,889	2

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
TS_1	5,38	1,671	,800	.
TS_2	5,30	1,646	,800	.

Appendix 7: Manipulation Check

A reliability analysis of the manipulation check items revealed insufficient internal consistency for the construct, therefore only the first item was used as manipulation check measurement. The independent-samples t-test revealed no significant results.

Group Statistics

	Group_numeric	N	Mean	Std. Deviation	Std. Error Mean
MC_1	Algorithmic	44	4,70	1,850	,279
	Neutral	45	4,80	1,392	,207

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
MC_1	Equal variances assumed	5,552	,021	-,275	87	,392	,784	-,095	,346	-,784	,593
	Equal variances not assumed			-,275	79,854	,392	,784	-,095	,348	-,787	,596

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
MC_1	Cohen's d	1,634	-,058	-,474	,357
	Hedges' correction	1,649	-,058	-,470	,354
	Glass's delta	1,392	-,069	-,484	,348

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

One proposed explanation for this result is the high baseline awareness of the sample, which is confirmed in the descriptive statistics of the manipulation check variable. The median of 5 confirms that the sample overall, regardless of assigned experimental condition, perceived high algorithmic influence on the seen post and recommendation.

Statistics

MC_1

N	Valid	89
	Missing	0
Median		5,00

MC_1

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	3	3,4	3,4	3,4
	2	5	5,6	5,6	9,0
	3	12	13,5	13,5	22,5
	4	18	20,2	20,2	42,7
	5	20	22,5	22,5	65,2
	6	15	16,9	16,9	82,0
	7	16	18,0	18,0	100,0
	Total	89	100,0	100,0	

Appendix 8: Correlation Matrix

The following table presents the Pearson correlation coefficients between the most relevant study variables. The table is based on the survey data and exported as image from SPSS. The most relevant correlations are highlighted.

Correlations

		BT_Mean	BE_Mean	PI_Mean	Obj_M	Comp_M	Pers_M	Ser_Mean	Scept_M	PrCon_M	Inv_Mean	TS_Mean	Per_Con
BT_Mean	Pearson Correlation	1	,776**	,659**	,465**	,476**	,499**	,545**	-,195	,011	,276**	,005	-,153
	Sig. (2-tailed)		<,001	<,001	<,001	<,001	<,001	<,001	,067	,921	,009	,962	,153
	N	89	89	89	89	89	89	89	89	89	89	89	89
BE_Mean	Pearson Correlation	,776**	1	,610**	,470**	,480**	,457**	,523**	-,204	,009	,325**	,075	-,062
	Sig. (2-tailed)	<,001		<,001	<,001	<,001	<,001	<,001	,055	,935	,002	,487	,563
	N	89	89	89	89	89	89	89	89	89	89	89	89
PI_Mean	Pearson Correlation	,659**	,610**	1	,384**	,475**	,525**	,491**	-,141	,056	,415**	,016	-,036
	Sig. (2-tailed)	<,001	<,001		<,001	<,001	<,001	<,001	,188	,601	<,001	,881	,737
	N	89	89	89	89	89	89	89	89	89	89	89	89
Obj_M	Pearson Correlation	,465**	,470**	,384**	1	,590**	,447**	,364**	-,065	,170	,341**	,152	-,075
	Sig. (2-tailed)	<,001	<,001	<,001		<,001	<,001	<,001	,545	,110	,001	,156	,484
	N	89	89	89	89	89	89	89	89	89	89	89	89
Comp_M	Pearson Correlation	,476**	,480**	,475**	,590**	1	,551**	,475**	-,075	,191	,324**	,043	-,002
	Sig. (2-tailed)	<,001	<,001	<,001	<,001		<,001	<,001	,482	,073	,002	,691	,987
	N	89	89	89	89	89	89	89	89	89	89	89	89
Pers_M	Pearson Correlation	,499**	,457**	,525**	,447**	,551**	1	,588**	-,253*	,029	,630**	,060	,033
	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001		<,001	,017	,786	<,001	,574	,758
	N	89	89	89	89	89	89	89	89	89	89	89	89
Ser_Mean	Pearson Correlation	,545**	,523**	,491**	,364**	,475**	,588**	1	-,225*	,182	,402**	,074	-,012
	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001	<,001		,034	,088	<,001	,491	,913
	N	89	89	89	89	89	89	89	89	89	89	89	89
Scept_M	Pearson Correlation	-,195	-,204	-,141	-,065	-,075	-,253*	-,225*	1	,302**	-,104	,109	,142
	Sig. (2-tailed)	,067	,055	,188	,545	,482	,017	,034		,004	,331	,310	,186
	N	89	89	89	89	89	89	89	89	89	89	89	89
PrCon_M	Pearson Correlation	,011	,009	,056	,170	,191	,029	,182	,302**	1	,017	,048	,093
	Sig. (2-tailed)	,921	,935	,601	,110	,073	,786	,088	,004		,871	,657	,387
	N	89	89	89	89	89	89	89	89	89	89	89	89
Inv_Mean	Pearson Correlation	,276**	,325**	,415**	,341**	,324**	,630**	,402**	-,104	,017	1	,187	,074
	Sig. (2-tailed)	,009	,002	<,001	,001	,002	<,001	<,001	,331	,871		,080	,491
	N	89	89	89	89	89	89	89	89	89	89	89	89
TS_Mean	Pearson Correlation	,005	,075	,016	,152	,043	,060	,074	,109	,048	,187	1	,192
	Sig. (2-tailed)	,962	,487	,881	,156	,691	,574	,491	,310	,657	,080		,072
	N	89	89	89	89	89	89	89	89	89	89	89	89
Per_Con	Pearson Correlation	-,153	-,062	-,036	-,075	-,002	,033	-,012	,142	,093	,074	,192	1
	Sig. (2-tailed)	,153	,563	,737	,484	,987	,758	,913	,186	,387	,491	,072	
	N	89	89	89	89	89	89	89	89	89	89	89	89

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Appendix 9: Hypothesis Testing

The following tables present the statistical outputs of the hypothesis tests. All tables are based on the survey data and are exported as images from SPSS.

H1:

Hypothesis 1 was tested using an independent-samples t-test on the new groups of low and high algorithmic perception, comparing their brand trust evaluations.

Prior to conducting the test, the statistical assumptions were verified. The dependent variable of brand trust can be treated as continuous[6] and the independent groups are categorical and mutually exclusive. Due to the sample size of $n = 89$, the t-test is robust against minor violations of normality. To account for potential variance heterogeneity, Levene's test was consulted and results were interpreted accordingly. The results show a non-significant Levene's test ($p = .75$), confirming the prerequisite of homogeneity of variances.

Group Statistics

	Perceived_Condition	N	Mean	Std. Deviation	Std. Error Mean
BrandTrust_Mean	1,00	58	4,2974	1,36325	,17900
	2,00	31	3,8548	1,41388	,25394

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
BrandTrust_Mean	Equal variances assumed	,103	,749	1,441	87	,077	,153	,44258	,30723	-,16809	1,05324
	Equal variances not assumed			1,424	59,490	,080	,160	,44258	,31069	-,17901	1,06416

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	95% Confidence Interval Upper
BrandTrust_Mean	Cohen's d	1,38092	,320	-,119	,758
	Hedges' correction	1,39297	,318	-,118	,752
	Glass's delta	1,41388	,313	-,133	,754

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

The difference between the low and high algorithm perception groups is statistically not significant. Notably, the mean of brand trust for the low algorithmic perception group is even slightly higher compared to the high algorithm perception group. This finding indicates that the high perception of the algorithm, contrary to hypothesized, likely evokes persuasion knowledge and thus undermines trust building as respondents reacted with rejection. Following this result, further exploratory analysis was conducted using independent-samples t-tests for the qualitative variables (perceived objectivity, perceived competence, perceived personalization, perceived serendipity) comparing the low and high algorithmic perception groups' evaluations of the

[6] Following established practice in social science research, Likert scale scores were treated as continuous interval-level data to enable the application of parametric statistical methods (Ansari et al., 2000).

respective variables. However, none of these tests revealed significant differences, indicating the algorithm itself is no longer a direct quality signal due to users' high awareness. It is working in the background, delivering recommendations to users, which are in turn evaluated but not influenced by the algorithmic origin alone.

H2:

For H2, a linear regression analysis was used, regarding the effect of brand trust on purchase intention. To assess the model validity, the central assumptions of linear regression were tested. The significant F-test and Pearson correlation confirm a strong linear relationship between the variables. The Durbin-Watson test confirmed independence of residuals, indicating no problematic autocorrelation among residuals. Descriptive statistics of residuals suggested no extreme outliers and indicating sufficient normality and homoscedasticity of the error terms. As this is a simple regression with a single predictor, multicollinearity is mathematically precluded, which is confirmed by tolerance and VIF values of 1000.

The test results reveal that almost half of purchase intention is based on brand trust with an R^2 of .44. The coefficient is strong with a value of β = .66.

Descriptive Statistics

	Mean	Std. Deviation	N
PI_Mean	3,9326	1,47640	89
BT_Mean	4,1433	1,38933	89

Correlations

		PI_Mean	BT_Mean
Pearson Correlation	PI_Mean	1,000	,659
	BT_Mean	,659	1,000
Sig. (1-tailed)	PI_Mean	.	<,001
	BT_Mean	,000	.
N	PI_Mean	89	89
	BT_Mean	89	89

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,659[a]	,435	,428	1,11630	2,130

a. Predictors: (Constant), BT_Mean
b. Dependent Variable: PI_Mean

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	83,405	1	83,405	66,931	<,001[b]
	Residual	108,413	87	1,246		
	Total	191,818	88			

a. Dependent Variable: PI_Mean
b. Predictors: (Constant), BT_Mean

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1,029	,374		2,752	,007		
	BT_Mean	,701	,086	,659	8,181	<,001	1,000	1,000

a. Dependent Variable: PI_Mean

Next, a hierarchical regression was used to test the robustness of the effect when controlling for other variables, confirming the strong role of brand trust for purchase intention:

Descriptive Statistics

	Mean	Std. Deviation	N
PI_Mean	3,9326	1,47640	89
Inv_Mean	3,5506	1,50009	89
Liking_1	5,39	1,403	89
Comp_M	3,4551	1,44332	89
BT_Mean	4,1433	1,38933	89

Correlations

		PI_Mean	Inv_Mean	Liking_1	Comp_M	BT_Mean
Pearson Correlation	PI_Mean	1,000	,415	,207	,475	,659
	Inv_Mean	,415	1,000	,043	,324	,276
	Liking_1	,207	,043	1,000	,180	,216
	Comp_M	,475	,324	,180	1,000	,476
	BT_Mean	,659	,276	,216	,476	1,000
Sig. (1-tailed)	PI_Mean	.	<,001	,026	<,001	<,001
	Inv_Mean	,000	.	,344	,001	,004
	Liking_1	,026	,344	.	,046	,021
	Comp_M	,000	,001	,046	.	,000
	BT_Mean	,000	,004	,021	,000	.
N	PI_Mean	89	89	89	89	89
	Inv_Mean	89	89	89	89	89
	Liking_1	89	89	89	89	89
	Comp_M	89	89	89	89	89
	BT_Mean	89	89	89	89	89

Model Summary[c]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,564[a]	,318	,294	1,24068	,318	13,205	3	85	<,001	
2	,717[b]	,514	,491	1,05349	,196	33,890	1	84	<,001	2,273

a. Predictors: (Constant), Comp_M, Liking_1, Inv_Mean

b. Predictors: (Constant), Comp_M, Liking_1, Inv_Mean, BT_Mean

c. Dependent Variable: PI_Mean

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	60,979	3	20,326	13,205	<,001[b]
	Residual	130,839	85	1,539		
	Total	191,818	88			
2	Regression	98,591	4	24,648	22,209	<,001[c]
	Residual	93,226	84	1,110		
	Total	191,818	88			

a. Dependent Variable: PI_Mean

b. Predictors: (Constant), Comp_M, Liking_1, Inv_Mean

c. Predictors: (Constant), Comp_M, Liking_1, Inv_Mean, BT_Mean

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	,909	,617		1,473	,144		
	Inv_Mean	,289	,093	,294	3,100	,003	,895	1,117
	Liking_1	,137	,096	,130	1,427	,157	,967	1,034
	Comp_M	,365	,098	,356	3,707	<,001	,868	1,153
2	(Constant)	,030	,545		,054	,957		
	Inv_Mean	,219	,080	,222	2,734	,008	,875	1,143
	Liking_1	,063	,082	,060	,763	,448	,944	1,059
	Comp_M	,150	,091	,147	1,643	,104	,726	1,377
	BT_Mean	,548	,094	,515	5,822	<,001	,738	1,354

a. Dependent Variable: PI_Mean

H3:

PROCESS Models[7]:

```
**************** PROCESS Procedure for SPSS Version 5.0 ****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
  Model: 4
      Y: PI_Mean
      X: Per_Con
      M: BT_Mean

Sample
Size:  89

**************************************************************************

OUTCOME VARIABLE:
 BT_Mean

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,1526      ,0233     1,9069     2,0751     1,0000    87,0000      ,1533

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,7400      ,4393    10,7887      ,0000     3,8667     5,6132
Per_Con      -,4426      ,3072    -1,4405      ,1533    -1,0532      ,1681

**************************************************************************

OUTCOME VARIABLE:
 PI_Mean

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6626      ,4391     1,2511    33,6607     2,0000    86,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,7100      ,5441     1,3049      ,1954     -,3717     1,7917
 Per_Con      ,2038      ,2518      ,8095      ,4205     -,2967      ,7044
 BT_Mean      ,7115      ,0868     8,1928      ,0000      ,5388      ,8841


 ***************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

 Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,2038      ,2518      ,8095      ,4205     -,2967      ,7044

 Indirect effect(s) of X on Y:
             Effect     BootSE   BootLLCI   BootULCI
 BT_Mean     -,3149      ,2249     -,7561      ,1182

 ********************** ANALYSIS NOTES AND ERRORS ************************

 Level of confidence for all confidence intervals in output:
   95,0000

 Number of bootstrap samples for percentile bootstrap confidence intervals:
   5000

 ------ END MATRIX -----
```

[7] **Note for all PROCESS analyses:** Copyright 2013-2025 by Andrew F. Hayes. ALL RIGHTS RESERVED. This version of PROCESS requires SPSS version 26 or later. Workshop schedule available at haskayne.ucalgary.ca/CCRAM. In SPSS 29 and later, change default output font to Courier New for tidier output. More information about PROCESS at processmacro.org/faq.html. This beta release has not been completely tested. Use at your own risk.

H4:

```
***************** PROCESS Procedure for SPSS Version 5.0 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
  Model: 1
      Y: BT_Mean
      X: Per_Con
      W: Inv_Mean

Covariates:
 Scept_M

Sample
Size:  89

**************************************************************************

OUTCOME VARIABLE:
 BT_Mean

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3581      ,1282     1,7629     3,0886     4,0000    84,0000      ,0201

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,8422      ,5276     9,1773      ,0000     3,7930     5,8914
Per_Con      -,4450      ,2998    -1,4845      ,1414    -1,0412      ,1511
Inv_Mean      ,2428      ,0982     2,4714      ,0155      ,0474      ,4381
Int_1         ,0727      ,1896      ,3836      ,7022     -,3044      ,4498
Scept_M      -,1532      ,1107    -1,3836      ,1702     -,3733      ,0670

Product terms key:
 Int_1    :        Per_Con  x        Inv_Mean

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0015      ,1471     1,0000    84,0000      ,7022

 ----------
     Focal predict: Per_Con  (X)
           Mod var: Inv_Mean (W)

 Data for visualizing the conditional effect of the focal predictor:
 Paste text below into a SPSS syntax window and execute to produce plot.

 DATA LIST FREE/
    Per_Con    Inv_Mean   BT_Mean    .
 BEGIN DATA.
      -,3483    -1,7006     3,9247
       ,6517    -1,7006     3,3560
      -,3483      ,1994     4,3378
       ,6517      ,1994     3,9073
      -,3483     1,5994     4,6422
       ,6517     1,5994     4,3135
 END DATA.
 GRAPH/SCATTERPLOT=
  Inv_Mean WITH     BT_Mean  BY       Per_Con  .

 ********************** ANALYSIS NOTES AND ERRORS ************************

 Level of confidence for all confidence intervals in output:
   95,0000

 NOTE: The following variables were mean centered prior to analysis:
           Inv_Mean Per_Con

 ------ END MATRIX -----
```

Appendix 10: Exploratory Analyses

Explorative Linear Regression with all Perception Variables:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,636[a]	,405	,376	1,09706

a. Predictors: (Constant), Ser_Mean, Obj_M, Pers_M, Comp_M

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	68,764	4	17,191	14,284	<,001[b]
	Residual	101,097	84	1,204		
	Total	169,861	88			

a. Dependent Variable: BT_Mean

b. Predictors: (Constant), Ser_Mean, Obj_M, Pers_M, Comp_M

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1,589	,368		4,316	<,001					
	Obj_M	,210	,105	,212	1,994	,049	,465	,213	,168	,629	1,589
	Comp_M	,111	,111	,115	,995	,322	,476	,108	,084	,531	1,883
	Pers_M	,136	,104	,149	1,309	,194	,499	,141	,110	,547	1,828
	Ser_Mean	,311	,102	,326	3,047	,003	,545	,315	,256	,620	1,612

a. Dependent Variable: BT_Mean

Exploratory path analysis H3:

```
***************** PROCESS Procedure for SPSS Version 5.0 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
  Model: 4
      Y: PI_Mean
      X: Ser_Mean
      M: BT_Mean

Covariates:
 Obj_M    Comp_M   Pers_M

Sample
Size:  89

**************************************************************************

OUTCOME VARIABLE:
 BT_Mean

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6363      ,4048     1,2035    14,2837     4,0000    84,0000      ,0000
```

Model

	coeff	se	t	p	LLCI	ULCI
constant	1,5893	,3682	4,3162	,0000	,8571	2,3215
Ser_Mean	,3111	,1021	3,0472	,0031	,1081	,5142
Obj_M	,2098	,1052	1,9945	,0493	,0006	,4189
Comp_M	,1107	,1112	,9954	,3224	-,1104	,3318
Pers_M	,1362	,1040	1,3090	,1941	-,0707	,3430

****

OUTCOME VARIABLE:
PI_Mean

Model Summary

R	R-sq	MSE	F	df1	df2	p
,7062	,4987	1,1584	16,5169	5,0000	83,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	,6163	,3993	1,5433	,1266	-,1779	1,4105
Ser_Mean	,0695	,1056	,6579	,5124	-,1405	,2794
BT_Mean	,5096	,1070	4,7603	,0000	,2967	,7225
Obj_M	-,0205	,1056	-,1940	,8467	-,2305	,1895
Comp_M	,1253	,1097	1,1420	,2567	-,0929	,3435
Pers_M	,1817	,1031	1,7629	,0816	-,0233	,3868

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y ******************

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI
,0695	,1056	,6579	,5124	-,1405	,2794

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
BT_Mean	,1585	,0681	,0414	,3062

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
5000

------ END MATRIX -----

Privacy Concern:

```
***************** PROCESS Procedure for SPSS Version 5.0 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
  Model: 1
      Y: BT_Mean
      X: Per_Con
      W: PrCon_M

Sample
Size:  89

**************************************************************************

OUTCOME VARIABLE:
 BT_Mean

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2513      ,0631     1,8722     1,9091     3,0000    85,0000      ,1342

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,1696      ,1457    28,6159      ,0000     3,8799     4,4593
Per_Con      -,4095      ,3065    -1,3362      ,1851    -1,0189      ,1998
PrCon_M       ,0077      ,1031      ,0744      ,9408     -,1973      ,2126
Int_1        -,4193      ,2223    -1,8861      ,0627     -,8614      ,0227

Product terms key:
 Int_1    :        Per_Con  x        PrCon_M

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0392     3,5575     1,0000    85,0000      ,0627
----------
    Focal predict: Per_Con  (X)
          Mod var: PrCon_M  (W)

Conditional effects of the focal predictor at values of the moderator(s):

    PrCon_M     Effect         se          t          p       LLCI       ULCI
    -1,4757      ,2093      ,4641      ,4509      ,6532     -,7135     1,1321
      ,1910     -,4896      ,3065    -1,5975      ,1139    -1,0990      ,1198
     1,8577    -1,1885      ,4971    -2,3910      ,0190    -2,1768     -,2002

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   Per_Con    PrCon_M    BT_Mean    .
BEGIN DATA.
     -,3483    -1,4757     4,0854
      ,6517    -1,4757     4,2947
     -,3483      ,1910     4,3416
      ,6517      ,1910     3,8520
     -,3483     1,8577     4,5978
      ,6517     1,8577     3,4093
END DATA.
GRAPH/SCATTERPLOT=
 PrCon_M  WITH     BT_Mean  BY       Per_Con  .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

NOTE: The following variables were mean centered prior to analysis:
          PrCon_M  Per_Con

------ END MATRIX -----
```

Tech Savviness:

```
***************** PROCESS Procedure for SPSS Version 5.0 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
  Model: 1
      Y: BT_Mean
      X: Per_Con
      W: TS_Mean

Sample
Size:  89

**************************************************************************

OUTCOME VARIABLE:
 BT_Mean

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2851      ,0813     1,8360     2,5059     3,0000    85,0000      ,0645

Model
              coeff         se          t          p       LLCI       ULCI
constant     4,2105      ,1466    28,7219      ,0000     3,9190     4,5020
Per_Con      -,3565      ,3106    -1,1476      ,2543     -,9741      ,2611
TS_Mean       ,0077      ,1213      ,0633      ,9496     -,2336      ,2489
Int_1        -,6059      ,2644    -2,2911      ,0244    -1,1316     -,0801

Product terms key:
 Int_1    :        Per_Con  x        TS_Mean

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,0567     5,2491     1,0000    85,0000      ,0244
----------
    Focal predict: Per_Con  (X)
          Mod var: TS_Mean  (W)

Conditional effects of the focal predictor at values of the moderator(s):

    TS_Mean     Effect         se          t          p       LLCI       ULCI
    -1,3427      ,4570      ,5054      ,9043      ,3684     -,5478     1,4618
      ,1573     -,4518      ,3072    -1,4706      ,1451    -1,0626      ,1590
     1,6573    -1,3606      ,4980    -2,7319      ,0077    -2,3508     -,3703

Data for visualizing the conditional effect of the focal predictor:
Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/
   Per_Con    TS_Mean    BT_Mean    .
BEGIN DATA.
     -,3483    -1,3427     4,0410
      ,6517    -1,3427     4,4980
     -,3483      ,1573     4,3691
      ,6517      ,1573     3,9173
     -,3483     1,6573     4,6971
      ,6517     1,6573     3,3366
END DATA.
GRAPH/SCATTERPLOT=
 TS_Mean  WITH     BT_Mean  BY       Per_Con  .

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

W values in conditional tables are the 16th, 50th, and 84th percentiles.

NOTE: The following variables were mean centered prior to analysis:
          TS_Mean  Per_Con

------ END MATRIX -----
```

REFERENCES

Airoldi, M., & Rokka, J. (2022). Algorithmic consumer culture. *Consumption Markets & Culture*, *25*(5), 411–428. https://doi.org/10.1080/10253866.2022.2084726

Al-Abdallah, G., Barzani, R., Omar Dandis, A.., & Eid, M. A. H. (2025). Social media marketing strategy: The impact of firm generated content on customer based brand equity in retail industry. *Journal of Marketing Communications*, *31*(8), 1025–1054. https://doi.org/10.1080/13527266.2023.2300076

Almahmood, R. J. K., & Tekerek, A. (2022). Issues and Solutions in Deep Learning-Enabled Recommendation Systems within the E-Commerce Field. *Applied Sciences*, *12*(21), 11256. https://doi.org/10.3390/app122111256

Ansari, A., Essegaier, S., & Kohli, R. (2000). Internet Recommendation Systems. *Journal of Marketing Research*, *37*(3), 363–375. https://doi.org/10.1509/jmkr.37.3.363.18779

Aoki, T., & Matsui, A. (2025). Does algorithmic recommendation complement or substitute advertising and influencers? Consumer attitudes toward recommendation information and the formation of purchase intentions. *Computers in Human Behavior*, *172*, 108735. https://doi.org/10.1016/j.chb.2025.108735

Aral, S., & Walker, D. (2014). Tie Strength, Embeddedness and Social Influence: A Large-Scale Networked Experiment. *Management Science*, *60*(6), 1352–1370. https://doi.org/10.1287/mnsc.2014.1936

Araujo, T., Copulsky, J. R., Hayes, J. L., Kim, S. J., & Srivastava, J. (2020). From Purchasing Exposure to Fostering Engagement: Brand–Consumer Experiences in the Emerging Computational Advertising Landscape. *Journal of Advertising*, *49*(4), 428–445. https://doi.org/10.1080/00913367.2020.1795756

Balaskas, S., Konstantakopoulou, M., Yfantidou, I., & Komis, K. (2025). Algorithmic Burnout and Digital Well-Being: Modelling young adults' resistance to Personalized digital Persuasion. *Societies*, *15*(8), 232. https://doi.org/10.3390/soc15080232

Banker, S., & Khetani, S. (2019). Algorithm Overdependence: How the Use of Algorithmic Recommendation Systems Can Increase Risks to Consumer Well-Being. *Journal of Public Policy & Marketing*, *38*(4), 500–515. https://doi.org/10.1177/0743915619858057

Barbosa, I., & Real de Oliveira, E. (2026). Digital well-being and social media usage among Generation Z: A Transformative advertising research perspective. *Journal of Marketing Communications*, 1–21. https://doi.org/10.1080/13527266.2026.2616610

Beck, B., Moore Koskie, M., & Locander, W. (2023). How electronic word of mouth (eWOM) shapes consumer social media shopping. In *Journal of Consumer Marketing*, *40*(7), 1002-1016. https://doi.org/10.1108/JCM-01-2023-5817

Campolo, A., & Crawford, K. (2020). Enchanted Determinism: Power without Responsibility in Artificial Intelligence. *Engaging Science Technology and Society*, *6*, 1–19. https://doi.org/10.17351/ests2020.277

Chacon, A., Martínez-Troncoso, C., & Kausel, E. E. (2025). Customer behavior in the presence of algorithmic marketing agents: The role of hedonic values. *Technological Forecasting and Social Change*, *220*, 124322. https://doi.org/10.1016/j.techfore.2025.124322

Chaiken, S. (1980). Heuristic versus systematic information processing and the use of source versus message cues in persuasion. *Journal of Personality and Social Psychology*, *39*(5), 752–766. https://doi.org/10.1037/0022-3514.39.5.752

Chaudhuri, A., & Holbrook, M. B. (2001). The Chain of Effects from Brand Trust and Brand Affect to Brand Performance: The Role of Brand Loyalty. *Journal of Marketing*, *65*(2), 81–93. https://doi.org/10.1509/jmkg.65.2.81.18255

Chen, L., Sun, R., Yuan, Y., & Zhan, X. (2024). The influence of recommendation algorithm's information flow on targeted advertising audience's coping behavior. *Acta Psychologica*, *243*, 104168. https://doi.org/10.1016/j.actpsy.2024.104168

Chen, Y., & Huang, J. (2024). Effective content recommendation in new media: Leveraging algorithmic approaches. *IEEE Access*, *12*, 90561–90570. https://doi.org/10.1109/access.2024.3421566

Cho, J., Ahmed, S., Hilbert, M., Liu, B., & Luu, J. (2020). Do search algorithms endanger democracy? An Experimental investigation of algorithm Effects on Political Polarization. *Journal of Broadcasting & Electronic Media*, *64*(2), 150–172. https://doi.org/10.1080/08838151.2020.1757365

Crawford, K. (2016). Can an Algorithm be Agonistic? Ten Scenes from Life in Calculated Publics. *Science Technology & Human Values*, *41*(1), 77–92. https://doi.org/10.1177/0162243915589635

Cui, Y. G., & Van Esch, P. (2025). The end of search as we know it: Only those chosen by AI agents will survive in the delegate economy. *Business Horizons*. https://doi.org/10.1016/j.bushor.2025.11.006

Darmody, A., & Zwick, D. (2020). Manipulate to empower: Hyper-relevance and the contradictions of marketing in the age of surveillance capitalism. *Big Data & Society*, *7*(1), 205395172090411. https://doi.org/10.1177/2053951720904112

Dash, G., Kiefer, K., & Paul, J. (2021). Marketing-to-Millennials: Marketing 4.0, customer satisfaction and purchase intention. *Journal of Business Research*, *122*, 608–620. https://doi.org/10.1016/j.jbusres.2020.10.016

Deryl, M. D., Verma, S., & Srivastava, V. (2023). How does AI drive branding? Towards an integrated theoretical framework for AI-driven branding. *International Journal of Information Management Data Insights*, *3*(2), 100205. https://doi.org/10.1016/j.jjimei.2023.100205

Dong, B., Zhuang, M., Fang, E., & Huang, M. (2024). Tales of Two Channels: Digital Advertising Performance Between AI Recommendation and User Subscription Channels. *Journal of Marketing*, *88*(2), 141–162. https://doi.org/10.1177/00222429231190021

Drossos, D. A., Kokkinaki, F., Giaglis, G. M., & Fouskas, K. G. (2014). The effects of product involvement and impulse buying on purchase intentions in mobile text advertising. *Electronic Commerce Research and Applications*, *13*(6), 423–430. https://doi.org/10.1016/j.elerap.2014.08.003

Enes, Y. D. S. O., Demo, G., Porto, R. B., & Zulato, T. S. (2024). What Is Next for Consumer-Based Brand Equity in Digital Brands? Research Itineraries and New Challenges. Sustainability, 16(13), 5412. https://doi.org/10.3390/su16135412

Erdem, T., & Swait, J. (2004). Brand Credibility, Brand Consideration and Choice. *Journal of Consumer Research*, *31*(1), 191–198. https://doi.org/10.1086/383434

Erdem, T., Swait, J., Broniarczyk, S., Chakravarti, D., Kapferer, J.-N., Keane, M., Roberts, J., Steenkamp, J.-B. E. M., & Zettelmeyer, F. (1999). Brand Equity, Consumer Learning and Choice. *Marketing Letters*, 301–318. https://doi.org/10.1023/A:1008135224357

Erkan, I., & Evans, C. (2016). The influence of eWOM in social media on consumers' purchase intentions: An extended approach to information adoption. *Computers in Human Behavior*, *61*, 47–55. https://doi.org/10.1016/j.chb.2016.03.003

Fan, X., Li, H., & Jiang, X. (2025). Owing to interactivity: a meta-analysis on consumer-brand responses in the digital context | Journal of Research in Interactive Marketing | Emerald Publishing. *Journal of Research in Interactive Marketing*, *19*(8), 1165-1183. https://doi.org/10.1108/JRIM-09-2024-0457

Fletcher, R., & Nielsen, R. K. (2019). Generalised scepticism: how people navigate news on social media. *Information Communication & Society*, *22*(12), 1751–1769. https://doi.org/10.1080/1369118x.2018.1450887

Friestad, M., & Wright, P. (1994). The Persuasion Knowledge Model: How People Cope with Persuasion Attempts. *Journal of Consumer Research*, *21*(1), 1–31. https://doi.org/10.1086/209380

Gao, Y., & Liu, H. (2023). Artificial intelligence-enabled personalization in interactive marketing: a customer journey perspective. *Journal of Research in Interactive Marketing*, *17*(5), 663–680. https://doi.org/10.1108/jrim-01-2022-0023

Geyik, P., & Weijo, H. (2025). How consumer market orientations shape algorithmic appreciation and avoidance in fashion. *International Journal of Research in Marketing*, *42*(4), 1187–1202. https://doi.org/10.1016/j.ijresmar.2025.07.007

Gran, A. B., Booth, P., & Bucher, T. (2021). To be or not to be algorithm aware: a question of a new digital divide?. *Information Communication & Society*, *24*(12), 1779–1796. https://doi.org/10.1080/1369118x.2020.1736124

Hardcastle, K., Vorster, L., & Brown, D. M. (2025). Understanding Customer Responses to AI-Driven Personalized Journeys: Impacts on the Customer Experience. *Journal of Advertising*, *54*(2), 176–195. https://doi.org/10.1080/00913367.2025.2460985

Hollebeek, L. D., & Macky, K. (2019). Digital content Marketing's role in fostering consumer engagement, trust and value: framework, fundamental propositions and implications. *Journal of Interactive Marketing*, *45*(1), 27–41. https://doi.org/10.1016/j.intmar.2018.07.003

Huang, W., Wang, X., Zhang, Q., Han, J., & Zhang, R. (2025). Beyond likes and comments: How social proof influences consumer impulse buying on short-form video platforms. *Journal of Retailing and Consumer Services*, *84*, 104199. https://doi.org/10.1016/j.jretconser.2024.104199

Hudson, S., & Thal, K. (2013). The Impact of Social Media on the Consumer Decision Process: Implications for Tourism Marketing. *Journal of Travel & Tourism Marketing*, *30*(1–2), 156–160. https://doi.org/10.1080/10548408.2013.751276

Keller, K. L. (1993). Conceptualizing, Measuring and Managing Customer-Based Brand Equity. *Journal of Marketing*, *57–57*(1), 1–22. https://doi.org/10.1177/002224299305700101

Kim, A., Affonso, F. M., Laran, J., & Durante, K. M. (2021). Serendipity: Chance Encounters in the Marketplace Enhance Consumer Satisfaction. *Journal of Marketing*, *85*(4), 141–157. https://doi.org/10.1177/00222429211000344

Kong, J., & Lou, C. (2026). Beyond persuasion Knowledge: Examining the roles of visual appeal, visual congruence and social proof in influencer advertising. *Journal of Retailing and Consumer Services*, *88*, 104502. https://doi.org/10.1016/j.jretconser.2025.104502

Kozyreva, A., Lorenz-Spreen, P., Hertwig, R., Lewandowsky, S., & Herzog, S. M. (2021). Public attitudes towards algorithmic personalization and use of personal data online: evidence from Germany, Great Britain and the United States. *Humanities and Social Sciences Communications*, *8*(1). https://doi.org/10.1057/s41599-021-00787-w

Küper, A., & Krämer, N. (2025). Psychological Traits and Appropriate Reliance: Factors Shaping Trust in AI. *International Journal of Human-Computer Interaction*, *41*(7), 4115-4131. https://doi.org/10.1080/10447318.2024.2348216

Lee, C., & Cha, K. (2025). Toward the Dynamic Relationship Between AI Transparency and Trust in AI: A Case Study on ChatGPT. *International Journal of Human-Computer Interaction*, *41*(13), 8086–8103. https://doi.org/10.1080/10447318.2024.2405266

Leung, E., Paolacci, G., & Puntoni, S. (2018). Man Versus Machine: Resisting Automation in Identity-Based Consumer Behavior. *Journal of Marketing Research*, *55*(6), 818–831. https://doi.org/10.1177/0022243718818423

Li, X., Zhou, T., Hu, C., & Liu, H. (2025). Availability Bias in AI Recommenders: Impacts on Impulse Buying. *Journal of Computer Information Systems*, 1-13. https://doi.org/10.1080/08874417.2025.2547173

Li, Z., & Shi, Z. (2025). Research on the Interactive Effects of Product Recommendation Approaches and Product Types on Consumers' Purchase Intention–Regulation of Product Involvement. *International Journal of Human-Computer Interaction*, 1–19. https://doi.org/10.1080/10447318.2025.2584725

Liu, L., Lee, M. K., Liu, R., & Chen, J. (2018). Trust transfer in social media brand communities: The role of consumer engagement. *International Journal of Information Management*, *41*, 1–13. https://doi.org/10.1016/j.ijinfomgt.2018.02.006

Longoni, C., & Cian, L. (2022). Artificial Intelligence in Utilitarian vs. Hedonic Contexts: The "Word-of-Machine" Effect. *Journal of Marketing*, *86*(1), 91–108. https://doi.org/10.1177/0022242920957347

Loureiro, S. M. C., Serra, J., & Guerreiro, J. (2019). How fashion Brands Engage on social Media: A Netnography approach. *Journal of Promotion Management*, *25*(3), 367–378. https://doi.org/10.1080/10496491.2019.1557815

Majeed, M., Owusu-Ansah, M., & Ashmond, A. (2021). The influence of social media on purchase intention: The mediating role of brand equity. *Cogent Business & Management*, *8*(1), 1944008. https://doi.org/10.1080/23311975.2021.1944008

Malthouse, E. C., Hessary, Y. K., Vakeel, K. A., Burke, R., & Fudurić, M. (2019). An Algorithm for Allocating Sponsored Recommendations and Content: Unifying Programmatic Advertising and Recommender Systems. *Journal of Advertising*, *48*(4), 366–379. https://doi.org/10.1080/00913367.2019.1652123

Masciari, E., Umair, A., & Ullah, M. H. (2024). A Systematic literature review on AI-Based recommendation Systems and their ethical considerations. *IEEE Access*, *12*, 121223–121241. https://doi.org/10.1109/access.2024.3451054

Meng, K., & Xiao, J. J. (2026). Can ChatGPT relate to you? Exploring consumer satisfaction with AI-generated product advice through the lens of consumption values. *Journal of Retailing and Consumer Services*, *88*, 104496. https://doi.org/10.1016/j.jretconser.2025.104496

Mosseri, A. (2023, May 31). *Instagram Ranking Explained*. Instagram. https://about.instagram.com/blog/announcements/instagram-ranking-explained/

Necula, S. C., & Păvăloaia, V. D. (2023). AI-Driven Recommendations: A Systematic Review of the State of the Art in E-Commerce. *Applied Sciences*, *13*(9), 5531. https://doi.org/10.3390/app13095531

Obermiller, C., & Spangenberg, E. R. (1998). Development of a scale to measure consumer skepticism toward advertising. *Journal of Consumer Psychology*, *7*(2), 159–186. https://doi.org/10.1207/s15327663jcp0702_03

Peterson, R. A. (1994). A Meta-Analysis of Cronbach's coefficient Alpha. *Journal of Consumer Research*, *21*(2), 381-391. https://doi.org/10.1086/209405

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In *Communication and persuasion: Central and peripheral routes to attitude change* (pp. 1–24). Springer. https://doi.org/10.1007/978-1-4612-4964-1_1

Puntoni, S., Reczek, R. W., Giesler, M., & Botti, S. (2021). Consumers and Artificial Intelligence: An Experiential Perspective. *Journal of Marketing*, *85*(1), 131–151. https://doi.org/10.1177/0022242920953847

Ranjith, P., Nisansala, S., Jayasingha, N., Weerasekara, K., Wisenthige, K., & Dayapathirana, N. (2025). Does social media information credibility influence social commerce purchase intention of skincare products? Evidence from Facebook. *PLoS ONE*, *20*(10), e0334126. https://doi.org/10.1371/journal.pone.0334126

Reich, T., Kaju, A., & Maglio, S. J. (2023). How to overcome algorithm aversion: Learning from mistakes. *Journal of Consumer Psychology*, *33*(2), 285–302. https://doi.org/10.1002/jcpy.1313

Roy, D., & Dutta, M. (2022). A systematic review and research perspective on recommender systems. *Journal of Big Data*, *9*(1). https://doi.org/10.1186/s40537-022-00592-5

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students*. Pearson Education.

Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics*, *87*(3), 355. https://doi.org/10.2307/1882010

Stewart, K. J. (2003). Trust Transfer on the World Wide Web. *Organization Science*, *14*(1), 5–17. https://doi.org/10.1287/orsc.14.1.5.12810

Sufyan Ghaleb, M. M., & Pardaev, J. (2025). Effects of Advertisement Language, Communication Style, Information Seeking Behavior and Information Source Credibility on Customers' Intentions towards International Products via Brand Trust.*El Profesional de la Información*, *34*(2). https://doi.org/10.3145/epi.2025.ene.34203

Varsha, P. S. Akter, S., Kumar, A., Gochhait, S., & Patagundi, B. (2021). The Impact of Artificial Intelligence on Branding. *Journal of Global Information Management*, *29*(4), 221–246. https://doi.org/10.4018/jgim.20210701.oa10

Voorveld, H. A., Meppelink, C. S., & Boerman, S. C. (2024). Consumers' persuasion knowledge of algorithms in social media advertising: identifying consumer groups based on awareness, appropriateness and coping ability. *International Journal of Advertising*, *43*(6), 960–986. https://doi.org/10.1080/02650487.2023.2264045

Vorm, E. S., & Combs, D. J. Y. (2022). Integrating Transparency, Trust and Acceptance: The Intelligent Systems Technology Acceptance Model (ISTAM). *International Journal of Human-Computer Interaction*, *38*(18–20), 1828–1845. https://doi.org/10.1080/10447318.2022.2070107

Xu, L., Roy, A., & Niculescu, M. (2023). A Dual Process Model of the Influence of Recommender Systems on Purchase Intentions in Online Shopping Environments. *Journal of Internet Commerce*, *22*(3), 432–453. https://doi.org/10.1080/15332861.2022.2049113

Yoo, B., & Donthu, N. (2001). Developing and validating a multidimensional consumer-based brand equity scale. *Journal of Business Research*, *52*(1), 1–14. https://doi.org/10.1016/s0148-2963(99)00098-3

Zaichkowsky, J. L. (1994). The personal involvement inventory: reduction, revision and application to advertising. *Journal of Advertising*, *23*(4), 59–70. https://doi.org/10.1080/00913367.1943.10673459

AI DECLARATION

I acknowledge the use of generative Al tools during the preparation of this dissertation. The tools were used to improve the quality of some parts of the text, particularly for language refinement, proofreading and to eliminate redundancies. The research concept, theoretical framework, methodology, data collection, analysis, interpretation of results, and conclusions were developed by me. All Al-generated suggestions were critically reviewed, adapted where appropriate, or rejected. Generative Al was not used as a scientific source and all theoretical arguments, empirical findings and external information are based on the cited literature and data sources.