

Social media marketing: understanding cognitive biases in consumer purchase intentions

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Abstract

Purpose – This study investigates how Confirmation, Halo, Authority and Scarcity biases influence purchase behavior by shaping consumer attitudes and perceptions as mediators. It further examines whether social media usage intensity moderates the relationship between marketing strategies and final purchasing decisions.

Design/methodology/approach – The research collected data from 531 users across three social media platforms: Facebook, Twitter and Instagram. The data analysis was conducted using the structural equation modeling (SEM) approach, with SPSS and AMOS as the primary data processing tools to analyze both inner and outer models.

Findings – The findings of this study disclosed that the hypotheses, such as Security Bias, Authority Bias, Halo effect and Confirmation bias, positively influence customer buying behavior, whereas Usage intensity significantly strengthens the relationship between cognitive biases in SMM and consumer buying behavior.

Originality/value – This research empirically confirms that social media marketing's cognitive biases, notably scarcity and authority, positively influence consumer buying behavior. It uniquely demonstrates how usage intensity significantly moderates this relationship. This provides a new framework for understanding the ethical dimensions of consumer psychology in the digital realm.

Keywords Cognitive biases, Consumer buying behavior, Social media marketing, Theory of reasoned action

Paper type Research article

1. Introduction

Over the past ten years, the use of social media sites like Facebook, Instagram and WhatsApp has increased dramatically (Chen and Qasim, 2021). Interaction and exchange of data have been made possible by real-time messaging. Because of this, businesses view social media platforms as essential resources for thriving in the online market (Ebrahim, 2020). Using social media for promoting events or products to attract potential customers is known as social media marketing or SMM. Since community websites have become so popular, many corporations have begun to figure out how to use them to build strong relationships and interactions with users to facilitate tight and friendly relationships and establish online brand communities (Aljarah and Ibrahim, 2020). Social media marketing enhances idea sharing between marketers and consumers, in addition to making it simpler to recognize brand engagement.

As a result of the internet's continuous development of new tools and apps, people's interactions have changed dramatically and new channels of communication have been established (Tarsakoo and Charoensukmongkol, 2020). Given how common cell phones and the Internet are, and how most people increasingly rely on social media brands. As a result, creating online communities has proven incredibly effective without physically meeting (Yadav and Rahman, 2017). Buyers are interested in establishing deep connections with professionals and other customers in addition to making purchases of goods and services. Customers become more cohesive when they participate in online communities, which affects the market. As a result, it is the responsibility of the businesses to determine the strategies or elements that will motivate consumers to participate in these communities (Ismail *et al.*, 2018).

Numerous studies on brand communities focus on social identification, acknowledging that a person who belongs to a large group is an integral component of that community. Social identity clarifies how an individual uses identity, comparison and classification to increase



self-affirmation and self-esteem (Chen and Lin, 2019). Social networks have had an enormous effect on how people buy things and how online retailing has transformed.

1.1 Research contribution

This research contributes to a deeper understanding of consumer psychology in the digital age by examining how social identity moderates the influence of cognitive biases in social media marketing on purchasing behavior. Social media networks are now a major marketing avenue, giving companies previously unheard-of chances to affect customer behavior. However, cognitive biases and systemic errors in human perception and decision-making frequently influence how effective social media marketing is. These biases, which include social proof, confirmation bias and anchoring, have a significant impact on how customers interpret and react to marketing communications. Even while social media marketing research is expanding, little is known about how cognitive biases explicitly affect customer purchasing decisions. Because of this knowledge gap, marketers find it difficult to create ads that successfully make use of these psychological inclinations without going against moral principles. Furthermore, it is unclear how cognitive biases combine with elements like content format, platform design and user demographics to influence purchasing decisions, given the growing personalization and interaction of social media platforms (Hanaysha, 2022). The originality of the research lies in integrating the under-examined roles of usage intensity and content moderation within the specific cultural and socioeconomic context of India. The study contributes to a more nuanced understanding by testing how consumer susceptibility to cognitive biases shifts based on their engagement level and how platforms might ethically mitigate or unknowingly reinforce these effects.

1.2 Research objectives and questions

The primary goal of the research is to examine the effects of specific cognitive biases of Confirmation Bias, Halo Effect, Authority Bias and Scarcity Bias on consumer purchasing behavior in the context of social media marketing. Furthermore, to investigate whether the degree of social media usage moderates the relationship between social media marketing and consumer purchasing behavior.

- RQ1. What effects do the cognitive biases of confirmation bias, halo effect, authority bias and scarcity bias have on consumer purchasing behavior in social media marketing (SMM)?
- RQ2. Does the degree of usage serve as a moderator between consumer purchasing behavior and social media marketing (SMM)?

The rest of the research is organized as follows: Theories and an overview of earlier studies are presented in [Section 2](#). [Section 3](#) presents our data, descriptive statistics and empirical methodologies. The assessments and empirical findings are shown in [Section 4](#). Discussions, conclusions, limitations and further research for future studies are also covered in [Section 5](#).

2. Literature review

The literature review portion looked at previous investigations to assess how different aspects of cognitive biases in social media marketing impacted consumers' decisions regarding purchases. The theory of reasoned action (TRA) and the expectation confirmation theory paradigm were used to frame these social media marketing elements that affect consumer behavior. [Table 1](#) lists the significant research's focus and findings on the factors influencing SMM and consumer purchasing patterns.

2.1 Related works

[Jameel et al. \(2024\)](#) sought to investigate whether materialism acts as a mediating factor in the relationship between compulsive buying behavior and social media platforms and television

Table 1. Review of related works

Reference	Objective	Keywords	Population	Analysis	Conclusion
Jameel <i>et al.</i> (2024)	To determine whether materialism mediates the association between Saudi Arabian university students' compulsive buying habits and social media and television ads	Internet usage, obsessive behavior, social media, materialism and college students	Data was gathered from 487 Saudi university students	AMOS and the structural equation modeling approach	Both social media use and television ads were positively connected with compulsive buying behavior among college students and materialism functioned as an intermediary variable in this connection
Armutcu <i>et al.</i> (2024)	To explore the connection between green food buying habits and social media	Sustainable marketing, social media, consumer behavior and the green food theory of planned behavior	Information was gathered from the 250 participants using a survey	Smart PLS 4.0	Subjective norms have little influence on consumers' purchasing decisions for green foods
Tanhaei <i>et al.</i> (2024)	To investigate how consumer behavioral intentions are influenced by social media marketing, word-of-mouth and pricing perception	Pricing perception, perceived interaction, consumer behavioral objectives and social media marketing	Three hundred fifty-seven responders were included in the statistical sample	The structural equation modeling approach	Conclusions show the connection between perceived communication and word-of-mouth advertising and social media marketing
Zeqiri <i>et al.</i> (2024)	To assess how social media marketing (SMM) affects purchase intention, brand awareness (BA) and consumer brand engagement (CBE)	Purchase intent, brand awareness and consumer brand engagement	Gather information from 1808 social media users in Albania, Kosovo, Romania, Ukraine and North Macedonia	Partial least squares structural equation modeling	Brand awareness, brand engagement, and purchase intention are all positively impacted by social media marketing. However, the country regulates the relationship between buy intention and brand engagement

(continued)

Table 1. Continued

Reference	Objective	Keywords	Population	Analysis	Conclusion
Wibowo et al. (2020)	Measures of the quality of customer acquaintances, such as purchase intention, loyalty intention and participation intention, can be beneficially affected by social media marketing activity (SMMA) and customer experience (CX)	Social media, customer experience, relationship quality, consumer habits and social media marketing	413 clients who shop online	Smart PLS 3.9 was used to measure and evaluate the online questionnaire surveys	Customer connection quality is greatly impacted by SMMA and CX, which positively impacts consumer behavioral results. Their analysis suggests that SNS marketing material should follow SMMA and CX
Putri et al. (2024)	To investigate how the COVID-19 epidemic impacted Pakistani consumers' online purchasing behaviors, with an emphasis on the role social media played	Brand Image, Purchase Decisions, Social Media Marketing and Brand Awareness	They collected responses from 400 clients in Pakistan	The data were subjected to PLS-SEM analysis	A few particular steps can help online businesses use social media more effectively for marketing and advertising
Palalic et al. (2024)	To look into how Pakistani customers' purchasing habits – whether they be habitual, variety seeking, complex buying or dissonance reducing – are affected by social media	Decisions made by entrepreneurs, social media, consumer purchasing patterns, word-of-mouth, the reliability of content, social network theory and feedback loop theory	396 responders made up the sample size, which was utilized to examine	To determine whether social media and consumer purchasing behavior are related, PLS-SEM is utilized	Social media has a considerable effect on Pakistani consumers' purchasing decisions; the two main determinants of these decisions are word-of-mouth and the reliability of the material
Hanaysha (2022)	To look into the ways that four aspects of social media marketing influence consumers' choices to buy in the fast-food sector	Trust in the brand, Fast-food industry, Purchasing choice, Marketing on social media	Consumers of fast-food cafés in the United Arab Emirates	AMOS 21-structural equation modeling	Brand trust acts as an intermediary in the relationship between just two social media marketing characteristics – interactivity and informativeness – and consumer purchase decisions

(continued)

Table 1. Continued

Reference	Objective	Keywords	Population	Analysis	Conclusion
Sarabi and Jafari (2025)	To examine the behavioral economics applications, particularly cognitive biases, in customer decisions' impact on e-commerce markets	Behavioral Economics, Cognitive Bias, Behavioral Marketing	Data were extracted from the Scopus database and manual searches, which include related articles published between 2019 and 2024	PRISMA model	Cognitive biases play an undeniable role in the sales and pricing process in behavioral marketing and effectively lead to increased marketing efficiency and conversion of potential customers to actual buyers
Bihari et al. (2025)	To investigate the biases in information based on knowledge that affect decisions about investments	Cognitive biases, Knowledge, Information, Investment decision	Data were gathered from 337 retail investors	Multiple linear regression	The investment choice was heavily impacted by regret aversion, followed by loss aversion, overconfidence and the Barnum effect

commercials among Saudi Arabian university students. Data was gathered from 487 Saudi university students. Software packages of SEM and AMOS were used to analyze the data. The study backs up the theory that more materialistic teens are more likely to shop compulsively than less materialistic teens. The results were in line with other studies, indicating that Saudi Arabian culture is no exception. The study found that university students' compulsive purchasing behavior was positively correlated with both television commercials and the use of social media.

[Armutcu et al. \(2024\)](#) investigated the connection between green food buying behavior and social media. SEM was executed using IBM SPSS 26 and Smart PLS 4.0 for examining the data gathered from the participants utilizing the survey approach. Furthermore, it was discovered that digital marketing interactions (DMI) and social media usage (SMU) significantly and favorably influence consumers' decisions to buy green foods. Customers may purchase more green foods if social media platforms provide more information, firsthand accounts, suggestions and opinions on them.

[Tanhaei et al. \(2024\)](#) examined how pricing perception, word-of-mouth and social media marketing affected the behavioral intentions of customers based on perceived interactions. The survey tool and data measurement technique used in this quantitative study are questionnaires. The structural equation methodology relies on the LISREL software, and the random sampling procedure was straightforward. The statistical sample contained 357 respondents, and the findings established a correlation between perceived collaboration and WOM advertising and social media marketing. Additionally, there was a favorable correlation between the customer's behavioral objectives and how they experienced the engagement.

[Zeqiri et al. \(2024\)](#) examined how social media marketing (SMM) affected purchase intention, consumer brand engagement (CBE) and brand awareness (BA) in emerging economies. A self-administered online survey was used to acquire data from 1808 social media users in North Macedonia, Albania, Kosovo, Romania and Ukraine. The theoretical

model has been reviewed using partial least squares structural equation modeling, and the differences across nations were looked at using a multi-group analysis. Brand awareness, brand engagement and purchase intention are all positively affected by social media marketing.

[Wibowo et al. \(2020\)](#) measured the quality of the customer relationship via social media marketing activity (SMMA) and customer experience (CX), which can influence the behavioral outcomes of the consumer, such as the intention to buy, to be loyal or to participate. Smart PLS 3 was used to collect and analyze the 413 online questionnaire surveys. The findings demonstrate that by significantly influencing the caliber of customer connections, SMMA and CX have an advantageous effect on consumer behavioral outcomes.

[Putri et al. \(2024\)](#) examined how the COVID-19 pandemic changed the online buying habits of Pakistani consumers, focusing on the use of social media. The “purposive sampling” method was utilized to get answers from 400 Pakistani clients. Additionally, the data was examined, and the hypothesis was evaluated through PLS-SEM analysis. Online reviews, celebrity endorsements and advertising tools all significantly and significantly influence customers’ online buying decisions, according to a PLS-SEM study done in Pakistan during the COVID-19 pandemic.

[Palalic et al. \(2021\)](#) examined the effects of social media on Pakistani consumers’ purchasing habits, which may manifest as habitual, variety-seeking, complex or dissonance-reducing purchasing. Entrepreneurs must understand the thoughts and feelings of their current and potential clients as well as how they choose which goods and services to buy. To determine if social media and consumer purchasing behavior are related, a sample size of 396 respondents was employed. The two main determinants of these decisions are word-of-mouth and the reliability of the material. Because of their more sophisticated purchasing habits, Pakistani customers under 40 should be taken into account by business owners while developing their future marketing plans.

[Hanaysha \(2018\)](#) examined how four aspects of social media marketing affected consumers’ choices to buy in the fast-food sector. The required data was collected from patrons of different fast-food cafés in the United Arab Emirates using a quantitative online survey. The data was analyzed using AMOS 21, structural equation modeling, after the intended answers were obtained. The findings have highlighted how crucial brand trust is for predicting customer behavior. The results also show that brand trust mediates the association between two social media marketing attributes – interaction and informativeness – and customer purchase decisions.

[Sarabi and Jafari \(2025\)](#) examined the behavioral economics applications, particularly cognitive biases, in customer decisions on e-commerce markets. The information of the research was extracted from the Scopus database and manual searches, including articles in behavioral marketing and pricing published between 2019 and 2024. They analyzed the data using a systematic review and through the PRISMA model. Through the findings, they revealed that cognitive biases play an undeniable role in the sales and pricing process in behavioral marketing and effectively lead to increased marketing efficiency and conversion of potential customers to actual buyers.

[Bihari et al. \(2025\)](#) investigated the biases in information based on knowledge that affect decisions about investments. They collected the data from 337 retail investors. The data of the research were analyzed using multiple linear regression and artificial neural networks. The findings elucidated that the investment choice was heavily impacted by regret aversion, followed by loss aversion, overconfidence and the Barnum effect.

2.2 Research gap

There are several research gaps that exist, such as the need for more in-depth exploration of how specific cognitive biases, like those identified by ([Bihari et al., 2025](#)), are influenced by different types of social media content and marketing activities ([Bihari et al., 2025](#)). There is

also a lack of broad cross-cultural comparative studies, as most research is limited to specific regions, like Saudi Arabia (Jameel *et al.*, 2024), the UAE (Hanaysha, 2018) or emerging economies (Zeqiri *et al.*, 2024). Longitudinal studies tracking the evolution of consumer behavior and social media's long-term impact are missing, with current research often focused on specific periods like the COVID-19 pandemic (Putri *et al.*, 2024). Further research is needed to investigate the integration and interaction of social media with other marketing channels, as well as focused studies on specific product categories and consumer segments (Palalic *et al.*, 2021). A diversification of research methodology to include qualitative approaches is also needed to gain deeper insights (Wibowo *et al.*, 2020; Tanhaei *et al.*, 2024). There is a gap in research exploring the potential negative or unintended consequences of social media marketing beyond the compulsive buying (Jameel *et al.*, 2024). There exists a knowledge gap regarding how the intensity of social media usage specifically moderates the influence of various cognitive biases on consumer purchasing behavior across different cultural and product contexts.

2.3 Theoretical background

This theoretical framework explains how cognitive biases impact customer decisions in the setting of social media marketing by referencing well-established theories from behavioral economics, psychology and consumer behavior. The Theory of Reasoned Action provides the foundational cognitive framework for analyzing the pre-purchase phase, where initial behavioral intentions are shaped by individual attitudes and subjective norms. In this model, TRA-derived attitudes act as the baseline expectations that consumers later evaluate through the post-purchase lens of Expectation Confirmation Theory.

2.3.1 Theory of reasoned action (TRA). One of the most common frameworks for explaining the causal relation between attitudes and behaviors is the Theory of Reasoned Action (TRA). In 1960, Martin Fishbein and Icek Ajzen proposed the TRA, which states that intentions to engage in a particular action can predict that conduct (Hanaysha, 2018). Intentions are determined by action-specific attitudes, such as assessments or appraisals, and subjective standards, such as the felt pressure from significant individuals to engage in a particular conduct. Subjective norms and more positive behavior-specific attitudes lead to greater behavioral intentions. The findings are consistent with the TRA, demonstrating that norms for sunbathing and sun protection, such as friends' sun protection practices, predict intentions to sunbathe and shield from the sun, respectively. The TRA is further supported by further studies that connect intentions to sunbathe or sun protect to actual exposure behavior or protection, respectively.

The TRA is currently regarded as one of the most important theories of human behavior, having undergone many revisions and expansions over time (Ajzen, 1991). Its focus on behavioral goals and inclusion of social norms as important influencing factors set it apart from related cognitive theories (St. Lawrence and Fortenberry, 2007). In this process, attitudes relevant to the behavior under study are crucial; taking into account an individual's opinions in a broader sense is insufficient. The theory further asserts that social pressures or "subjective norms," which originate from an individual's perception of what other people will think of them engaging in the behavior in question, have an impact on an individual's intentions regarding performing that behavior (which ultimately determines whether they will do so) (Vallerand *et al.*, 1992).

2.3.2 Theory of Planned Behavior (TPB). The TPB provides a foundational framework for explaining consumer purchase intentions by positing that intention is shaped by attitude toward the behavior, subjective norms, and perceived behavioral control (Ajzen, 1991). Recent studies of (Le-Hoang and Nguyen, 2025) continue to validate TPB in social media marketing contexts, demonstrating that social media exposure influences purchase intention indirectly by shaping these three determinants rather than exerting a direct effect. For instance, recent empirical research (Zhang *et al.*, 2024) shows that social media content and interactions

significantly enhance consumers' attitudes toward products, strengthen perceived social pressure through peer and influencer endorsement, and increase perceived behavioral control via ease of access and digital purchasing mechanisms, thereby reinforcing intention formation. These findings confirm TPB's relevance for explaining how social media marketing affects consumer decision-making in contemporary digital environments.

However, scholars increasingly argue that TPB alone does not fully capture the cognitive dynamics of social media-driven decision-making, particularly the role of cognitive biases. Recent research highlights that biases such as social proof, confirmation bias and availability heuristics systematically shape how consumers interpret social media cues, thereby influencing attitudes and subjective norms beyond rational evaluation (Wang *et al.*, 2025). In algorithmically mediated platforms, AI-driven personalization further amplifies these biases by repeatedly exposing consumers to preference-congruent content and popularity signals, which can distort perceived norms and control (Sharma, 2024). Accordingly, this study extends TPB by integrating cognitive bias theory to explain how social media marketing affects consumer purchase intentions in AI-driven environments, addressing a key theoretical gap in recent social media and consumer behavior literature.

2.3.3 Expectation confirmation theory. The expectation confirmation theory (ECT) was developed by leveraging the disciplines of consumer research and social psychology. The hypothesis was initially applied in marketing to investigate consumer decision-making and satisfaction (Hair *et al.*, 2014). The term contentment comes from applied psychology research on life and job satisfaction. People have baseline expectations, for example, and any deviation from this affects their level of satisfaction. Customers develop negative attitudes (disconfirmation) and beliefs about the product when it does not live up to their expectations (Yang *et al.*, 2013).

The cognitive dissonance theory, which contends that people undergo psychological conflict when their actions contradict their beliefs and thoughts, is in line with the disconfirmation concept (Harmon-Jones and Mills, 2019). In this case, people's attitudes toward that technology have to change, which leads to disconfirmation. When customers' thoughts and actions align, there is no dissonance and they don't need to change their perspective. ECT demonstrates how the belief – or lack thereof – in the outcomes of comparing performance to expectations drives customer satisfaction.

Likewise, ECT provided information about the post-purchase cognitive effects of attitude and satisfaction. Even relatively low-quality products (like disposable and one-time-use items) can successfully satisfy customers' needs and attain reasonable levels of satisfaction, defying the commonly held belief that higher-quality products result in happier customers. As a result, the premise underlines how expectations both before and after purchases influence consumer satisfaction. Given that maintaining existing clients was far less expensive than recruiting new ones, ECT also sought to provide marketers with advice on how to do so (Anderson and Sullivan, 1993). Figure 1 illustrates the hypothesis framework.

2.4 Hypothetical development

Consumer behavior is greatly affected by cognitive biases, especially whenever it comes to social media marketing. Brands may create more persuasive marketing tactics that relate to the consumers they are targeting by comprehending how these biases shape decision-making processes.

2.4.1 Scarcity bias of social media marketing and consumer buying behavior. According to (Gierl and Huettl, 2010), marketers commonly leverage the scarcity effect, which has a strong social impact, to influence how customers respond to items. High demand and limited supply can result in scarcity. Both forms of scarcity can make people want a commodity more, but they will lead to different conclusions for them. Customers might perceive limited supply scarcity as a status and unique signal, while high demand scarcity could be interpreted as a confirmation of the product's quality. High-scarcity items are more likely to have the value of

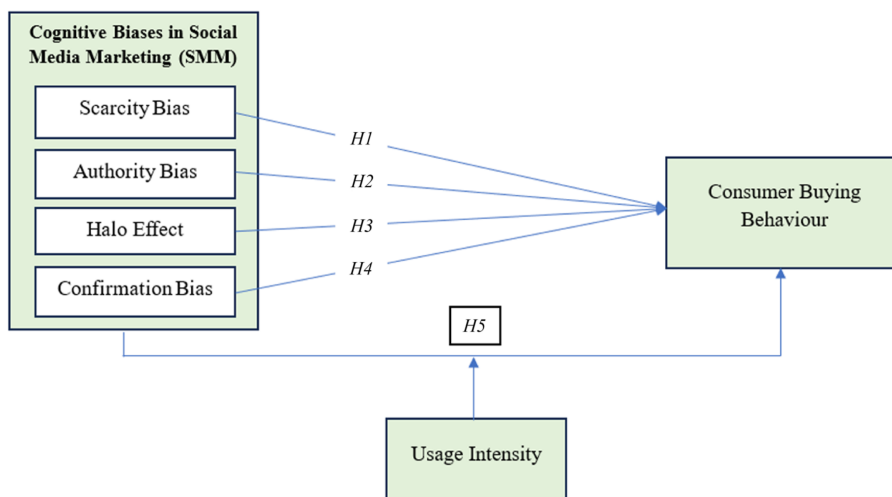


Figure 1. Hypothesis model

identification signals than low-scarcity ones. [Barton et al. \(2022\)](#) stated that people may be envious of and respectful of high-scarcity products. A strong sensation of superiority stems from the earlier belief that the product or opportunity to buy might be difficult to come by. The overt use of things or their visual display in public is known as conspicuous consumption. Giving consumers the impression that a thing is either unavailable or may become unavailable raises the product's perceived value and desirability, as well as their propensity to buy.

According to ([Vennesson, 2017](#)), the scarcity bias increases the perceived worth of products that seem rare, whether due to limited supply or temporary promotions. This appeals to the fundamental survival instinct, which holds that things that are thought to be rare are more desirable. This causes customers to move swiftly to get them. This can significantly affect consumer trust and brand loyalty since a single favorable impression has the capacity to distort how a complete brand or product is perceived. The expectation confirmation theory explains consumer satisfaction and post-purchase behavior. If the product meets or exceeds these expectations, it results in positive confirmation. This leads to customer satisfaction, which ECT posits is a key predictor of repeat purchases and loyalty. It postulates that consumers form initial expectations, then compare the product's actual performance to those expectations ([Bhattacharjee, 2001](#)). The following hypotheses were proposed based on the above discussion:

H1. Scarcity Bias of SMM in cognitive biases has a positive impact on consumer buying behavior

2.4.2 Authority bias of social media marketing and consumer buying behavior. [Herman et al. \(2022\)](#) stated that, in social media marketing, the idea of "authority bias" describes how an authoritative figure – such as a celebrity, influencer or industry expert affects the attitudes, actions and choices of consumers. Customers may be more likely to believe in goods or services that these celebrities recommend, giving them greater legitimacy or significance than they otherwise would. For example, a well-known celebrity endorsing a skincare brand on Instagram could cause followers to regard the brand as more trustworthy, even if their expertise is not pertinent to skincare. This is because, regardless of the product's true advantages, individuals are more likely to believe and heed the advice of persons they perceive to be experts due to authority bias.

Basir *et al.* (2023). When people believe that the opinions of authority figures are more accurate, this is known as authority bias. This bias uses the perceived authority of experts or celebrities to sway customer behavior. Because of this bias, people frequently accept and favor the things that these celebrities recommend, sometimes regardless of their quality. Customers may buy things that don't live up to their expectations or needs as a result of authority bias, which could result in them blindly accepting recommendations or professional opinions. Furthermore, a key component of ethical marketing is maintaining consumer autonomy, which is the guarantee that customers can make decisions on their own based on full and correct information. According to the theory of Reasoned Action, authority bias strategically deployed through SMM effectively manipulates consumer psychology by building trust and reducing perceived risk. It also confirms that authority figures, particularly influencers and verified sources, significantly influence a consumer's attitudes toward a brand. The credibility and authenticity of these figures are powerful predictors of consumer trust, which, in turn, boosts positive purchase intentions (Migkos *et al.*, 2025). The following hypotheses were put up in light of the discussion above:

H2. Authority Bias of SMM in cognitive biases significantly affects the buying behavior of consumers.

2.4.3 *Halo effect of cognitive biases and consumer buying behavior.* Islam *et al.* (2024) argued that the halo effect refers to a distinct cognitive shortcut in which customers extrapolate from a perceived favorable feature, such as the friendliness or attractiveness of a brand ambassador. To more comprehensive assessments of the brand's overall qualities or the efficacy of the product. Azzopardi (2021) stated that the halo effect can persuade customers to believe that a brand's other products are just as reliable since they trust its one product. Apple is a prime example of how high levels of customer satisfaction with a single product, such as an iPhone, improve consumers' perceptions of other items, such as iPads or MacBooks. Marketers must make sure, though, that this trust is not abused but rather applied to enhance the customer experience for all products. Thirdly, creating moral standards is essential to protecting the interests of customers. The ethical application of psychological insights in marketing should be spelt out in these guidelines. A positive halo effect, generated by a brand's social media marketing (SMM) strategy, positively influences a consumer's initial expectations regarding the brand's new product, thereby setting the stage for the disconfirmation and satisfaction phases of the ECT model. In light of the foregoing discussion, the following hypothesis was proposed:

H3. Halo Effect of cognitive biases in SMM affects Consumer buying behavior.

2.4.4 *Confirmation bias and consumer buying behavior.* According to (Joo *et al.*, 2020), the propensity to look for, evaluate, favor, and remember information in a way that supports one's preconceived notions or assumptions is known as confirmation bias. This bias is especially pertinent in marketing because customers choose companies and products that correspond with their values, their viewpoints, and reject data that challenges them. Burr and Leslie (2023) argued that marketers can significantly influence consumer behavior by incorporating these cognitive biases into their marketing techniques. A product's perceived value and appeal can be greatly increased by being aware of and using strategies that take advantage of these biases. However, this strategy presents moral dilemmas regarding influencing customer opinions and decisions, calling for a responsible and balanced use of these insights.

Drawing on the ECT, which posits that consumer satisfaction and repurchase intentions are determined by comparing pre-purchase expectations with post-purchase experiences, confirmation bias significantly influences this process when amplified by Social Media Marketing (Hossain and Quaddus, 2011). During the pre-purchase phase, SMM tactics exploit a consumer's existing beliefs by exposing them to selectively positive, attitude-confirming information, which creates artificially high or biased initial expectations. Following the purchase, confirmation bias continues to operate by causing the consumer to

disproportionately focus on product attributes that meet these skewed expectations, while simultaneously downplaying or ignoring flaws. This biased interpretation of the product's performance leads to a favorable confirmation judgment, resulting in higher post-purchase satisfaction, which, according to ECT, then reinforces brand loyalty and the likelihood of future purchases (Lin *et al.*, 2009). Given the discussion that occurred above, the following hypothesis was put forth:

H4. Confirmation Bias of SMM in cognitive biases influence on consumer buying behavior.

2.4.5 *Usage intensity as a moderator.* The study of social media marketing in consumer behavior was carried out by (Tang and Wu, 2022). Consumer behavior and satisfaction have been the main subjects of social media research for SMM. There is little to no research examining how the intensity of online media affects consumer spending patterns. Credit usage, conspicuous consumption and impulse buying were the three spending habits chosen for this investigation because of the implied connections that have been intermittently made in recent literature without strong empirical support. Because social media is essential for setting standards, monitoring behavior and offering support, encouragement and disincentives, immersion in online social media generates these chances.

According to (Thoumrungroje, 2018), social media offers a wealth of information that could lead to a lack of consensus regarding acceptable conduct. The study by (Croft, 2013) has shown that happiness reduces impulsive behavior. Second, people can become less self-aware by concentrating on the status updates and tales of others while reading social media. Therefore, this weakens self-control and leads to more decadent actions. Lastly, because social media significantly demands cognitive work, excessive use of it might deplete self-control capacity, which is similar to the energy that can be immediately used up and then replenished. Wilcox and Stephen (2013) explained that the intensity of social media encourages conspicuous consumption. Users of social media are receiving an enormous quantity of information about goods and services, which might cause them to have contradictory objectives, lose their sense of self and become more incapable of exercising self-control. These factors can all fail to exercise self-control and increase the risk of engaging in indulgent behaviors. According to ECT, the pre-purchase expectations of the consumer influence post-purchase satisfaction and repurchase intentions. In social media marketing, cognitive biases shape these expectations and higher usage intensity amplifies exposure to marketing cues, thereby strengthening the effect of biases on expectation confirmation and subsequent purchase behavior (Bhattacharjee, 2001). Therefore, usage intensity is expected to moderate the relationship between cognitive biases and consumer behavior through its impact on expectation formation and confirmation. In light of the foregoing discussion, the following hypothesis was proposed:

H5. Usage Intensity acts as a moderator between cognitive biases in SMM and consumer buying behavior.

3. Methodology

3.1 Data collection

This study utilized a purposive sampling method to recruit 597 social media users from India, a fast-expanding BRICS economy. The sample was drawn from individuals who received a survey link and voluntarily opted to participate. To ensure the pertinence of the data for investigating digital engagement, the study focused on seasoned users of specific social media platforms like Facebook and Instagram. Participants, who varied in age, educational background, and professional level, were first asked to select one of four telecom firms they follow on social media, thereby providing insights into modern consumer behavior within India's digital landscape.

3.1.1 Sampling technique. This study used a purposive sampling technique, a nonprobability method where researchers intentionally select participants based on specific characteristics essential to the study's objectives. This approach maximizes the likelihood of collecting rich, in-depth data on specific behaviors and cognitive biases that influence online purchases from a highly relevant group of individuals. The sample is directly relevant to all study variables, which include the cognitive biases, buying behavior and social media usage intensity.

3.1.2 Pilot study. A pilot study with 20 participants was conducted before the main survey. Selection criteria ensured they met the definition of a "seasoned user," with a high frequency of engagement on the target platforms. This mimics the eventual main study and allows for targeted feedback from the intended demographic. The pilot study successfully identified and addressed potential issues, saving time and resources that might have been wasted on a flawed main study. By refining the survey instrument, the researchers enhanced its reliability and validity, increasing confidence that the data collected in the full-scale study would be of high quality and accurately measure the intended variables.

3.1.3 Data screening process. The data screening process began with the 560 responses received from the 597 questionnaires distributed, indicating a preliminary response rate of 93.8%. For quality assurance and validity, all submissions were reviewed for completeness, attention checks and signs of inconsistent responses. This systematic review led to the exclusion of 29 responses, resulting in a final sample of 531 for the analysis.

3.2 Description of sample

The respondent demographics are provided in [Table 2](#), emphasizing important variables including location, income, occupation, education, gender and age. Most participants (62.5%) are male, with a significant proportion in the 18–24 age group (42.6%), followed by those in the 25–34 (23.9%) and 35–44 (23.4%) age groups. Regarding education, the majority of

Table 2. Demographic details

Factors	Categories	Frequency	Percentage
Gender	Male	332	62.5%
	Female	172	32.4%
	Prefer not to say	27	5.1
Age Group	Under 18 years	47	8.9%
	18–24 years	226	42.6%
	25–34 years	127	23.9%
	35–44 years	124	23.4%
	Above 45 years	7	1.3%
Education Level	High School	68	12.8%
	Diploma/Certificate Course	219	41.2%
	Bachelor (BA, BSc, BCom, BTech, etc)	141	26.6%
	Postgraduate (MA, MSc, MCom, MBA, etc.)	88	16.6%
	Doctorate (PhD)	15	2.8%
Occupation	Student	75	14.1%
	Employed (Private Sector)	10	1.9%
	Employed (Government Sector)	52	9.8%
	Self-employed/Business owner	326	61.4%
	Unemployed/Retired	68	12.8%
Monthly Income	Below 20,000	79	14.9%
	20,000–50,000	49	9.2%
	50,000–80,000	216	40.7%
	Above 80,000	187	35.2%
Location	Urban	168	31.6%
	Rural	363	68.4%

respondents (41.2%) have finished their undergraduate studies, followed by those who have earned a diploma or certificate (26.6%) and postgraduate degrees (16.6%). The majority (61.4%) are self-employed or business owners, while students (14.1%) make up a lesser percentage of the workforce. In terms of monthly income, the largest proportion (40.7%) is in the 50,000–80,000 bracket, while a noteworthy 35.2% make over 80,000. In terms of demographics, the sample is more rural (68.4%) than urban (31.6%), which offers important background information for examining how various factors may affect the study's consumer behavior and decision-making.

3.3 Instrument measure

The primary data was collected using a self-administered online questionnaire; each item was developed and adjusted based on the literature research. Social media users' backgrounds and personal information were analyzed in the first section of the questionnaire, while the constructs' aspects were measured in the second section – which is further separated into four subsections – to test the hypotheses. The constructs are presented separately in several parts and are well specified before the measurement items. Before exposing participants to the subsequent question, the software's parameters were changed to remind them of those that remained unanswered. A 5-point Likert scale with the same variables was used for rating each attribute, ranging from (1) strongly disagree to (5) strongly agree.

As displayed in [Table 3](#), the Authority Bias scale has five items adapted from ([Burger et al., 2004](#); [Tormala and Petty, 2004](#)), and the Scarcity Bias variable is measured through five dimensions with their items adapted from ([Lynn, 1991](#); [Verhallen, 1982](#)). A 5-item scale developed by ([Lee et al., 2015](#)) is used to test the Halo Effect of cognitive bias. The five-item scale from Nickerson's study is used to measure confirmation bias ([Nickerson, 1998](#)). Five questions taken from the research of ([Bagozzi et al., 1999](#)) and Sweeney and Swait are used to test the variable of Usage Intensity. Lastly, six items taken from Diallo's study ([Diallo, 2012](#)) are used to measure the variable of consumer purchasing behavior.

4. Data analysis and outputs

Given that the current study involves theory testing, SPSS and AMOS are used to examine the quantitative responses that were collected, performing SEM and confirmatory factor analysis (CFA) ([Anderson and Gerbing, 1988](#)). Before adopting CFA and SEM to improve the authenticity of findings, the validity, reliability and normality of the data are assessed. The measurement model is examined using CFA following the evaluation of the data's appropriateness, discriminant validity, convergent validity and reliability ([Urbach and Ahlemann, 2010](#)). Only 531 of the 597 responses were legitimate and in the right format to be further examined. As a result, 531 replies were used for the current analysis. Since the data for this study were collected from a single source using a self-reported questionnaire, common method bias (CMB) was assessed to ensure that measurement artifacts did not inflate the observed relationships. The study employed Harman's single-factor test, where all items from the constructs were loaded into an exploratory factor analysis without rotation. The results indicated that the first factor accounted for 28.7% of the total variance, which is well below the recommended threshold of 50%, suggesting that a single factor does not dominate the variance.

4.1 Measurement model

The outer model evaluated three basic components: discriminant validity, convergent validity and reliability analysis. Composite reliability values of 0.7 and higher for every construct revealed construct reliability. According to the recommendations of ([Fornell and Larcker, 1981](#)), a construct is considered to have convergent validity if both the AVE and the predictor factor loading are more than 0.5. [Table 4](#) below displays the reliability test results and factor

Table 3. Constructs and items

Constructs	Items	Reference
Scarcity Bias	<p><i>S_Bias1</i>: Labels like “Limited Stock” or “Only a Few Left” make me more likely to buy a product</p> <p><i>S_Bias2</i>: I usually think something is more valuable when it’s rare</p> <p><i>S_Bias3</i>: I tend to believe that investment opportunities that are scarce or hard to get are inherently more valuable than those widely available</p> <p><i>S_Bias4</i>: When I notice an offer that is only valid for a brief time, I am more likely to take immediate action</p> <p><i>S_Bias5</i>: Limited-edition products, in my opinion, are better than ones that are readily accessible</p>	Lynn (1991), Verhallen (1982)
Authority Bias	<p><i>A_Bias1</i>: I’m more inclined to purchase a product endorsed by a well-known authority or celebrity</p> <p><i>A_Bias2</i>: When a product or service is recommended by a higher authority, I feel more comfortable making decisions</p> <p><i>A_Bias3</i>: Product recommendations from reliable sources are more trustworthy to me than those from friends or colleagues</p> <p><i>A_Bias4</i>: I typically purchase products that have been advised by industry experts, even if I don’t conduct a lot of research</p> <p><i>A_Bias5</i>: Expert comments on goods and services are, in my opinion, more reliable than customer feedback</p>	Burger et al. (2004), Tormala and Petty (2004)
Halo Effect	<p><i>H_Bias1</i>: I think that a product works well in other areas as well when it receives positive evaluations in one area, like usability</p> <p><i>H_Bias2</i>: Products from well-known firms are usually of superior quality, in my opinion</p> <p><i>H_Bias3</i>: A positive impression of one feature of a product leads me to form favorable opinions about its other features</p> <p><i>H_Bias4</i>: If a product reminds me of a satisfying experience I had with a prior purchase, I’m more likely to buy it</p> <p><i>H_Bias5</i>: A strong first impression of a product makes me assume it will perform well overall</p>	Lee et al. (2015)
Confirmation Bias	<p><i>C_Bias1</i>: I prefer to pay more attention to product reviews that support my initial assessment of the product</p> <p><i>C_Bias2</i>: I actively look for information to support my preexisting preferences when making purchases</p> <p><i>C_Bias3</i>: I usually focus more on details when assessing a product that supports my original assessment of its quality</p> <p><i>C_Bias4</i>: When I hear information that supports my initial beliefs about a product, I feel more confident in my purchasing decisions</p> <p><i>C_Bias5</i>: I respect the views of people who share my initial assessment of a good or service</p>	Nickerson (1998)

(continued)

Table 3. Continued

Constructs	Items	Reference
Usage Intensity	<i>U_Int1</i> : I actively participate in this product or service each time I use it	Bagozzi et al. (1999) , Sweeney and Swait (2008)
	<i>U_Int2</i> : I use this product/service a lot for my daily needs	
	<i>U_Int3</i> : Compared to other similar products or services, I utilize this one the most	
	<i>U_Int4</i> : This product/service is something I use daily	
	<i>U_Int5</i> : I have used this product/service for a considerable length of time	
Consumer buying behavior	<i>C_BB1</i> : After purchasing items I've wanted for a while, I feel content	Diallo (2012)
	<i>C_BB2</i> : I feel satisfied after buying something I've wanted for a long time.	
	<i>C_BB3</i> : I purchase goods that support the lifestyle or image I want to present	
	<i>C_BB4</i> : If my friends or relatives suggest new products, I'm open to trying them	
	<i>C_BB5</i> : Cultural trends frequently have an impact on my shopping decisions	

Table 4. Assessment of quality of the data

Indicators	Mean value	Std. dev	Skewness	Kurtosis
S_Bias1	3.3070	1.27454	-0.469	-0.870
S_Bias2	3.2316	1.30204	-0.271	-1.030
S_Bias3	3.2072	1.30689	-0.266	-1.090
S_Bias4	3.2580	1.31009	-0.314	-1.040
S_Bias5	3.3107	1.32446	-0.370	-0.997
A_Bias1	3.3315	1.28097	-0.487	-0.868
A_Bias2	3.3051	1.35046	-0.300	-1.138
A_Bias3	3.3409	1.34396	-0.391	-1.047
A_Bias4	3.3220	1.30740	-0.342	-1.003
A_Bias5	3.2900	1.31847	-0.318	-1.042
H_Bias1	3.2806	1.30108	-0.402	-0.960
H_Bias2	3.2655	1.30280	-0.311	-1.051
H_Bias3	3.1921	1.29324	-0.209	-1.090
H_Bias4	3.2392	1.39177	-0.239	-1.249
H_Bias5	3.2053	1.32937	-0.274	-1.056
C_Bias1	3.2674	1.29733	-0.402	-0.974
C_Bias2	3.2542	1.37681	-0.277	-1.173
C_Bias3	3.2486	1.34388	-0.259	-1.169
C_Bias4	3.2731	1.32138	-0.251	-1.090
C_Bias5	3.2900	1.31704	-0.382	-1.016
U_INT1	3.3258	1.28462	-0.417	-0.963
U_INT2	3.3710	1.31027	-0.396	-0.992
U_INT3	3.3559	1.32304	-0.376	-1.067
U_INT4	3.2976	1.33670	-0.275	-1.138
U_INT5	3.2768	1.30912	-0.320	-1.060
C_BB1	2.5292	1.18026	0.583	-0.494
C_BB2	2.5537	1.22645	0.470	-0.748
C_BB3	2.5669	1.26370	0.502	-0.753
C_BB4	2.5311	1.26658	0.554	-0.741
C_BB5	2.5160	1.22291	0.503	-0.748
C_BB6	2.5480	1.22207	0.399	-0.849

loads for each of the several construct elements. Additionally, discriminant validity highlights how distinct construct criteria and measured variables differ from one another.

Each variable suggested a suitable discriminant validity when the factor loadings of each latent item for each assigned construct were greater than those of each other construct (Hair *et al.*, 2021).

Applying the skewness and kurtosis technique, the study applied a normality test to determine whether the data were normal. Kurtosis and skewness must be within the suggested normality ranges for the data to be considered normal. The data are within the appropriate ranges if the skewness and kurtosis vary from ~ 2 to $\beta 2$ and ~ 7 to $\beta 7$, respectively (Byrne and Van de Vijver, 2010). All of the data, illustrated in Table 4, fall inside the threshold, showing a good fit to normality.

To determine whether issues regarding multicollinearity exist among the components in the recommended framework, the Variable Inflation Factor (VIF) was applied in the present study. According to earlier research, this indicator has been widely utilized in quantitative investigations to quantify correlations and multicollinearity between construct measurement scales using the measurement model. According to (Vu *et al.*, 2015), when the VIF values for all items do not exceed 5, the issue with multicollinearity usually does not exist. Table 5 displays that all VIF values for the given measures fall within the range of permitted values (5), proving the authenticity of the collected data for additional investigation.

4.1.1 Convergent validity. According to (Becker *et al.*, 2013), convergent validity looks at how similar two items are to one another within the same construct, as well as how they correlate. According to (Zeqiri *et al.*, 2020), convergent validity is often evaluated by evaluating the loadings, average variance extracted (AVE), and composite reliability.

Scarcity Bias, Authority Bias, Halo Effect, Confirmation Bias, Usage Intensity and Consumer Buying Behavior all have Cronbach's alphas of 0.931, 0.929, 0.940, 0.934, 0.931, and 0.935 for social media marketing, respectively. According to the outcome, all four constructions' reliability coefficients were over the minimum acceptable level of 0.70. According to Fornell and Larcker (1981), convergent validity is achieved if the factor loading is above the 0.7 threshold and the average variance extracted (AVE) surpasses 0.5 (Fornell and Larcker, 1981).

Furthermore, reliability analyses for the constructs were computed. According to (Hair *et al.*, 2021), 0.6 is the threshold point for both Cronbach's Alpha and composite reliability. Reliability assumptions are met since the statistical analysis in Table 6 revealed that all Cronbach's Alpha and composite reliability achieved were higher than 0.60.

4.1.2 Discriminant validity. Discriminant validity explores how items differ quantitatively from other item components, according to (Franke and Sarstedt, 2019). Except for Social MM, Table 7 reflects that the Fornell–Larcker Criterion (FLC) results, where the diagonal elements represent the square roots of the average variance extracted (AVE) for each construct, and off-diagonal elements represent correlations between constructs. For most constructs, the diagonal values exceed the corresponding inter-construct correlations, indicating adequate discriminant validity. Some negative correlations, particularly between Consumer Buying Behavior (C_BB) and bias constructs, reflect theoretically expected inverse relationships and do not indicate measurement errors. The structural view of the measurement model has been developed in Figure 2.

Table 5. Multicollinearity test

Constructs	Tolerance	VIF
Scarcity Bias	0.621	1.611
Authority Bias	0.626	1.597
Halo Effect	0.802	1.247
Confirmation Bias	0.718	1.393

Table 6. Reliability and validity analysis

Variables	Items	CR	Cross loadings	Alpha (α)	AVE
Scarcity Bias	S_Bias1	0.934	0.950	0.931	0.742
	S_Bias2		0.818		
	S_Bias3		0.842		
	S_Bias4		0.847		
	S_Bias5		0.830		
Authority Bias	A_Bias1	0.932	0.944	0.929	0.735
	A_Bias2		0.832		
	A_Bias3		0.852		
	A_Bias4		0.831		
	A_Bias5		0.827		
Halo Effect	H_Bias1	0.940	0.944	0.940	0.770
	H_Bias2		0.843		
	H_Bias3		0.852		
	H_Bias4		0.831		
	H_Bias5		0.861		
Confirmation Bias	C_Bias1	0.936	0.947	0.934	0.748
	C_Bias2		0.842		
	C_Bias3		0.840		
	C_Bias4		0.844		
	C_Bias5		0.850		
Usage Intensity	U_Int1	0.934	0.952	0.740	0.931
	U_Int2		0.850		
	U_Int3		0.848		
	U_Int4		0.838		
	U_Int5		0.827		
Consumer buying behavior	C_BB1	0.939	0.857	0.935	0.720
	C_BB2		0.782		
	C_BB3		0.771		
	C_BB4		0.756		
	C_BB5		0.740		
	C_BB6		0.722		

Table 7. Discriminant validity-FLC

Constructs	S_Bias	A_Bias	H_Bias	C_Bias	U_INT	C_BB
S_Bias	0.862					
A_Bias	0.161***	0.858				
H_Bias	0.231***	0.225***	0.877			
C_Bias	0.129**	0.235***	0.171***	0.865		
U_INT	0.154***	0.216***	0.154***	0.178***	0.860	
C_BB	-0.394***	-0.392***	-0.460***	-0.420***	-0.359***	0.848

To provide a more robust assessment, the heterotrait-monotrait (HTMT) ratio was also calculated (Table 8). HTMT values below the threshold of 0.85 confirm that all constructs are empirically distinct. Using HTMT addresses potential limitations of the Fornell-Larcker criterion in cases of high or negative correlations and strengthens confidence in the measurement model's discriminant validity. Together, these results indicate that the constructs in this study demonstrate satisfactory discriminant validity and are suitable for subsequent structural model analysis.

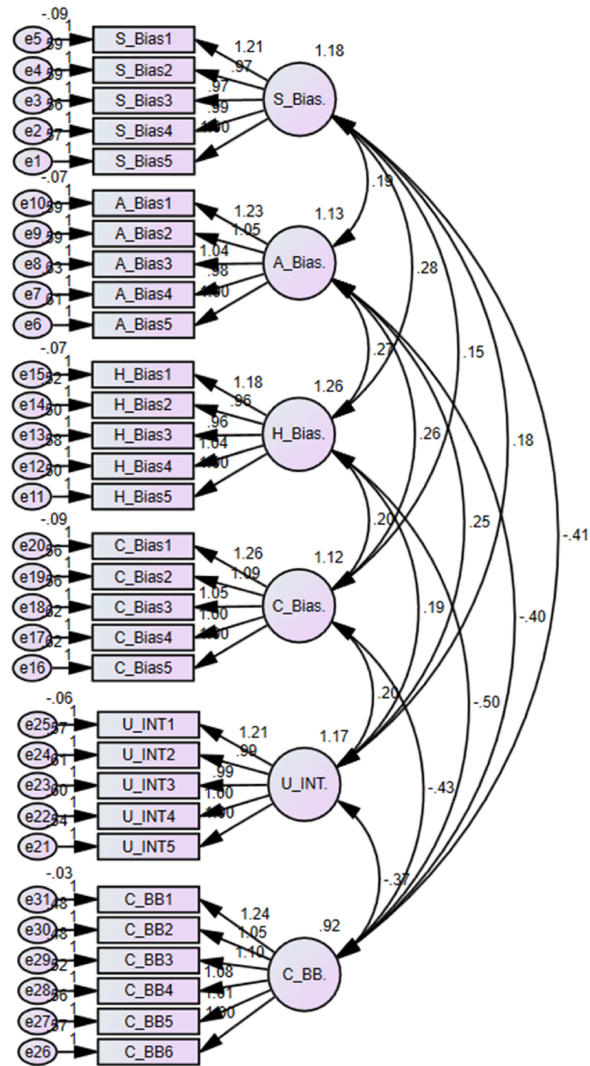


Figure 2. Measurement model

Table 8. Discriminant Validity-HTMT

Constructs	S_Bias	A_Bias	H_Bias	C_Bias	U_INT	C_BB
S_Bias	1					
A_Bias	0.183	1				
H_Bias	0.245	0.231	1			
C_Bias	0.140	0.245	0.185	1		
U_INT	0.160	0.220	0.165	0.180	1	
C_BB	0.390	0.395	0.460	0.420	0.359	1

4.2 Estimation of structural model (inner model) and hypothesis test

SEM can be utilized to confirm the current study’s hypothesis by identifying direct impacts and indirect pathways. The bootstrapping approach in AMOS has been applied to confirm the model’s direct and moderated routes using SEM.

Table 9 presents the fit indices for the confirmatory factor analysis (CFA) of the measurement model. The CMIN/DF value of 1.286 is well below the recommended threshold of 3, indicating a good fit between the proposed model and the observed data. The Goodness-of-Fit Index (GFI = 0.938) and Normed Fit Index (NFI = 0.969) exceed the minimum recommended values of 0.80 and 0.90, respectively, suggesting that the model accounts for a large proportion of the covariance in the data. The Incremental Fit (IF = 0.993), Comparative Fit Index (CFI = 0.993) and Tucker–Lewis Index (TAG = 0.992) are all above 0.90, reflecting excellent relative fit and demonstrating that the proposed model improves substantially over a null or baseline model. Additionally, the Root Mean Square Error of Approximation (RMSEA = 0.023) is far below the acceptable maximum of 0.08, indicating minimal approximation error and confirming a close fit of the model to the population covariance matrix. Overall, these indices collectively indicate that the CFA measurement model fits the data very well.

To assess the explanatory and predictive power of the structural model, study computed the R^2 , f^2 and Q^2 values for all endogenous constructs and is shown in Table 10. The R^2 for Consumer Buying Behavior was 0.52, indicating that 52% of the variance is explained by the cognitive bias and usage intensity constructs, which represents substantial explanatory power. Effect sizes (f^2) for the individual predictors ranged from 0.03 (small) to 0.38 (large), indicating that some constructs have a stronger impact on buying behavior than others. Additionally, Q^2 values for all endogenous constructs were greater than zero, confirming the predictive relevance of the model. These results demonstrate that the proposed model not only fits the data well but also provides meaningful and practically relevant insights into consumer buying behavior.

The significance and relevance of the structural model links are then assessed using a bootstrapping technique with 5,000 samples. The bootstrapping technique is used by (Hair *et al.*, 2021) to obtain the t -value, p -value, critical ratio and standard errors for the connections. Table 11 shows that each of the five hypotheses put forth in this study is validated. The view of the structural model has been developed in Figure 3.

Regarding the correlations between the variables under investigation, the Scarcity Bias of SMM in cognitive biases positively influences customer buying behavior (β value = -0.238, $t = -7.631$, $p < 0.000$); hence, the hypothesis [H1] was accepted. Consumer buying behavior is significantly impacted by the Authority Bias of SMM in cognitive biases (β value = -0.225, $t = -7.337$, $p < 0.000$) built on the result, the hypothesis [H2] was significant and supported, the Halo Effect of cognitive biases in SMM ($\beta = -0.271$, $t = -8.861$, $p < 0.000$) hence

Table 9. Fit indices summary

CFA factors	CMIN/DF	GFI	NFI	IF	CFI	TAG	RMSEA
Threshold Value	≤3	≥0.80	≥0.90	≥0.90	≥0.90	≥0.90	≤0.08
Observed Value	1.286	0.938	0.969	0.993	0.993	0.992	0.023

Table 10. Explanatory and predictive Power of Structural Model

Endogenous construct	R^2	f^2 (S_Bias)	f^2 (A_Bias)	f^2 (H_Bias)	f^2 (C_Bias)	f^2 (U_INT)	Q^2
Consumer Buying Behavior	0.52	0.12	0.15	0.05	0.03	0.38	0.41

Table 11. Summary of hypothesis test

Hypothesis	Path relation	Beta	Standard error	T- value	p- value	Critical ratio	Outcome
[H1]	S_Bias → C_BB	-0.238	0.030	-7.631	0.000	-8.080	Supported
[H2]	A_Bias → C_BB	-0.225	0.029	-7.337	0.000	-7.716	Supported
[H3]	H_Bias → C_BB	-0.271	0.029	-8.861	0.000	-9.455	Supported
[H4]	C_Bias → C_BB	-0.232	0.029	-7.677	0.000	-8.074	Supported

Note(s): **Consumer buying behavior was reverse-coded; therefore, negative β values indicate positive effects

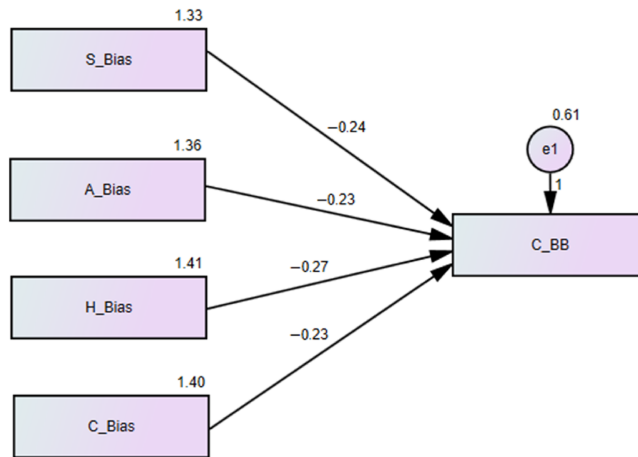


Figure 3. Structural model

hypothesis [H3] was supported, and Confirmation Bias of SMM in cognitive biases ($\beta = -0.232, t = -7.677, p < 0.000$) therefore, the hypothesis [H4] was supported.

The negative signs of the standardized path coefficients in Table 11 arise due to the reverse coding of the consumer buying behavior construct, where higher scores indicate lower buying propensity. Accordingly, the negative coefficients reflect a positive directional influence of cognitive biases on consumer buying behavior. This clarification has now been explicitly incorporated into the Results section to avoid misinterpretation. The hypotheses (H1–H4) remain theoretically and empirically supported.

4.3 Analysis of Moderation Effect

As presented in Table 12 and Figure 4, the hypothesis [H5] examines the moderator of usage intensity in strengthening the relationship between cognitive biases in SMM and consumer buying behavior. Social media marketing has a 0.968 direct effect on customer purchasing behavior, suggesting that it influences consumer purchasing decisions. The direct impact of U_INT on C_BB is 0.481, suggesting that usage intensity positively impacts consumer buying behavior. The interaction effect of SMM_x_U_INT → C_BB provides a positive estimate value of -0.560, proving that the beneficial affiliation between social media marketing and customer purchasing behavior is strengthened with usage intensity.

4.4 Sensitivity analysis by demographics (gender and location)

Sensitivity analysis was performed to evaluate whether the effects of S_Bias, A_Bias, H_Bias, and C_Bias on Consumer Buying Behavior (C_BB) were the same for different genders and

Table 12. Moderation analysis

Variable names	Predictor
Independent variable	SMM
Moderator	U_INT
Dependent variable	C_BB
Regression coefficients	Outcome
SMM → C_BB	0.968
U_INT → C_BB	0.481
SMM_x_U_INT → C_BB	-0.560

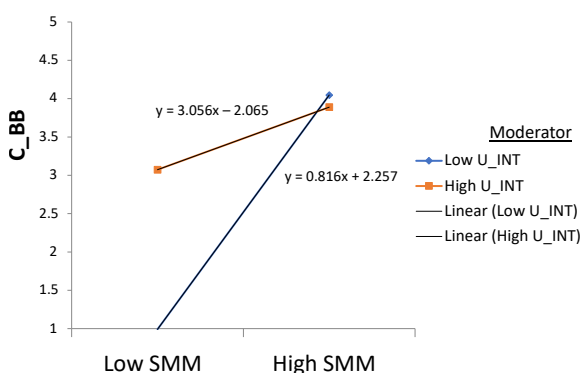


Figure 4. Moderating effect of usage intensity

locations. The results disclosed in Table 13 about regression analysis for male and female respondents and urban and rural participants, showed that the coefficients and significance levels were quite alike for all subgroups. This suggests that the demographic characteristics do not influence the relationships observed, and the model is strong across these groups.

5. Discussion

The findings of the research shows that cognitive biases, such as Halo Effect, Confirmation Bias, Authority Bias and Security Bias, along with social media usage intensity, significantly influence consumer buying behavior, advancing both theory and practice. The study integrates TRA and ECT by aligning them along the consumer decision-making timeline, with TRA

Table 13. Sensitivity analysis by demographics

Variable	DV: C_BB	β (Male)	p (Male)	β (Female)	p (Female)	β (Urban)	p (Urban)	β (Rural)	p (Rural)
S_Bias	C_BB	-0.240	0.000	-0.235	0.000	-0.238	0.000	-0.237	0.000
A_Bias	C_BB	-0.228	0.000	-0.222	0.000	-0.225	0.000	-0.224	0.000
H_Bias	C_BB	-0.273	0.000	-0.268	0.000	-0.271	0.000	-0.270	0.000
C_Bias	C_BB	-0.234	0.000	-0.230	0.000	-0.232	0.000	-0.231	0.000

explaining pre-purchase intentions and behavior, and ECT addressing post-purchase expectation confirmation, satisfaction and repurchase intentions. Cognitive biases and social media marketing cues influence both stages, linking intention formation to expectation confirmation and creating a seamless theoretical flow. TPB is extended by demonstrating that digital engagement amplifies attitudes, subjective norms and perceived control, shaping intentions beyond rational determinants.

According to the findings, the results show that the hypothesis [H1] scarcity bias of SMM in cognitive biases has a positive impact on consumer buying behavior, which was significantly supported. This finding was consistent with the previous studies by (Jameel *et al.*, 2024; Tanhaei *et al.*, 2024; Zeqiri *et al.*, 2024), which demonstrate that the scarcity bias increases the perceived worth of products that seem rare, whether due to limited supply or temporary promotions. This contributes to the scarcity bias, which causes people to act rapidly to acquire things that are more desired when they appear to be less available.

The results of the hypothesis [H2] show that the authority bias of SMM in cognitive biases significantly affects the buying behavior of consumers, which was significantly supported in this research. The findings are in alignment with the previous studies by (Putri *et al.*, 2024; Palalic *et al.*, 2021; Hanaysha, 2022), which elucidate that bias uses the perceived authority of experts or celebrities to sway customer behavior. Because of this prejudice, people frequently accept and favor the things that these celebrities recommend, sometimes regardless of their quality. The findings of hypothesis [H3] disclose that the halo effect of cognitive biases in SMM affects Consumer buying behavior. The results are consistent with the works of (Palalic *et al.*, 2021; Wibowo *et al.*, 2020), which illustrate that allowing one favorable impression to distort how a whole business or product is perceived can significantly affect customer loyalty and trust. Therefore, promoting an atmosphere where customer decisions are well-informed and unaffected by undue influence is necessary for social marketing.

The hypothesis [H4] shows that the confirmation bias of SMM in cognitive biases influences consumer buying behavior. The results are consistent with the findings of articles (Hanaysha, 2022; Tanhaei *et al.*, 2024), which indicate that the ability to look for, assess courtesy, and remember evidence in a way that provisions one's preconceived notions or conventions is known as confirmation bias. The results of the hypothesis [H5] illustrate that usage intensity acts as a moderator between cognitive biases in SMM and consumer buying behavior. They are in alignment with the previous studies of (Armutcu *et al.*, 2024; Zeqiri *et al.*, 2024), which indicates that by affecting the degree to which cognitive biases in SMM influence customer purchasing decisions, usage intensity modifies the association between these biases and consumer behavior.

6. Conclusion

The complex subject of cognitive biases in social media marketing has been examined in this work, emphasizing the psychological insights' dual potential to improve marketing efficacy and present moral dilemmas. One important realization is that using cognitive biases ethically necessitates a thorough comprehension of how they operate and influence consumer choice. Clear criteria that all marketing staff may adhere to are among the practical suggestions for marketers looking to use cognitive biases ethically. These rules ought to stress how crucial it is to avoid deceiving customers about the features or accessibility of products and to make sure that all advertising is clear and accurate. Regulatory agencies can offer a structure and legal support to guarantee that marketing strategies don't go beyond ethical bounds, shielding customers from dishonest marketing tactics. Nonetheless, industry self-regulation is also important since it promotes greater adaptability and speed to new marketing tactics and technologies. To gain the trust and loyalty of customers, businesses should be urged to uphold high ethical standards, which frequently surpass those mandated by law. How marketers might take advantage of cognitive biases will likely change along with technology, according to ethical reflections on the future of marketing practices. But this also makes it more of a duty for

marketers to make sure these tools are used morally. In the future, the marketing sector needs to keep promoting an ethical culture that adapts to new technology while being committed to safeguarding the interests of customers.

6.1 Limitations and future scope

Cognitive biases are intricate and multidimensional; it can be challenging to pinpoint their precise effect on the purchasing behavior of consumers in social media marketing. The use of purposive sampling presents two key limitations for this research. First, the nonrandom, intentional selection of participants, based on the researcher's judgment, introduces a risk of sampling and researcher bias. Future research should employ probability-based sampling or multi-platform recruitment to include more diverse, nonstudent populations and passive users, thereby mitigating engagement bias and enhancing the external validity of findings. Second, because the sample is not representative of the broader population, the findings have limited generalizability and should be interpreted within the specific context of the study. The way several biases interact. Self-reports or surveys are used to collect a large portion of the data in consumer behavior studies, particularly those about social media. Social media companies frequently modify their algorithms, which can have a big impact on how marketing messages are presented. Because of these ongoing changes, it might be difficult to document the long-term impacts of cognitive biases because the way information is presented can alter over time. Beyond cognitive biases, many other factors affect consumer behavior, including personal preferences and external environmental factors like the state of the economy. It can be difficult to separate the impact of cognitive biases while considering these outside factors.

More study could concentrate on the long-term consequences of cognitive biases on consumer behavior, including how biases influence purchase decisions and brand loyalty over time. A fuller comprehension of long-lasting behavioral changes would result from this. Future research should investigate how cognitive biases affect consumer behavior in various ages, showing potential generational disparities in response to marketing, given the rapid changes in social media usage between generations. More research must investigate how newly developed technologies such as artificial intelligence, virtual reality and augmented reality influence cognitive biases in social media marketing and how these technologies can either contribute to or mitigate these biases. Future research should conduct cross-cultural comparative studies to test the generalizability of findings and examine how the effectiveness and biases of AI-driven moderation differ across platforms. Future research should employ longitudinal designs incorporating demographic and behavioral controls, such as digital literacy and brand involvement, to isolate the precise impact of cognitive biases across diverse digital platforms. Future research could examine how cultural variations affect the efficacy of cognitive bias-based marketing methods on social media platforms, given that cognitive biases can differ among cultures. This would make it easier to adapt marketing tactics to a variety of international audiences.

6.2 Implications

6.2.1 Theoretical implications. This study has significant implications by challenging the assumption of perfect rationality in consumer behavior, demonstrating that biases like security bias, authority bias, the halo effect and confirmation bias offer a crucial dynamic extension to existing frameworks like the Theory of Reasoned Action and Expectation Confirmation Theory. It implies that consumer decisions, especially within social media marketing contexts, are not static moments of intention (TRA) but are instead reinforced through repeated exposure and confirmation biases intensified by high usage, leading to a feedback loop where post-purchase behavior and high engagement reinforce the very psychological shortcuts that triggered the initial purchase, thereby shaping and solidifying long-term consumer habits and brand loyalty beyond initial expectations. This theoretical synthesis provides a more realistic and comprehensive model of modern consumer psychology, highlighting how frequent

interaction with digital platforms deepens the effect of cognitive shortcuts, making consumers increasingly susceptible to biased decision-making.

6.2.2 Practical implications. This research offers several practical implications for marketers, consumer protection and consumers. The study's findings reveal how SMM can intensify the power of cognitive biases, raising ethical concerns for policymakers. Digital platforms and marketers should use biases transparently, avoiding deceptive or manipulative practices. Consumers, especially high-intensity social media users, must recognize their susceptibility to these biases. Being aware of what Confirmation Bias can help them actively seek out a diversity of information and challenge their existing beliefs. Instead of blindly trusting a product endorsed by an authority figure or assuming a brand's new product is good based on the Halo Effect, consumers should conduct their own research on specific product attributes. Public institutions and governments can promote digital literacy programs that educate consumers on how cognitive biases function, particularly within social media. This would empower consumers to make more informed decisions.

6.2.3 Managerial implications. This research has several implications, primarily for managers, marketers and consumer advocacy groups, concerning the power of cognitive biases in social media and the amplifying role of usage intensity. Managers must strategically adapt marketing and operational strategies based on the study's findings that cognitive biases influence consumer behavior and that usage intensity on social media amplifies this effect. The primary managerial implications revolve around leveraging these biases ethically, tailoring marketing to user habits, building robust customer trust and implementing internal controls to mitigate potential negative impacts. Managers should train their marketing teams to understand not just the mechanics of cognitive biases but also the ethical boundaries. This training should promote a long-term strategy of building genuine trust and value rather than seeking short-term, manipulative gains.

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