Leiden University

ICT in Business and the Public Sector

Influencing Purchase Intention Through Chatbots: The Interaction of Social Influence Tactics and Consumer Personality Traits.

Name: Ioanna Papadaki
Student ID: s3295095

Date: 22/11/2024

Master thesis

1st supervisor: Natalia Amat Lefort

2nd supervisor: Christoph Johann Stettina

Acknowledgment

I want to take a moment to express my deepest gratitude to my thesis supervisor, Natalia Amat Lefort. Your guidance and thoughtful feedback helped me throughout this journey. Thank you for always being there with the right advice and pushing me to see beyond what I thought possible.

To the faculty and staff at Leiden University, thank you for developing an environment where curiosity and learning can succeed. I am especially grateful to Christoph Johann Stettina for his guidance and valuable feedback throughout this project.

To my family, friends, and partner, I owe a huge thank you. Your love, patience, and understanding have kept me grounded through the ups and downs of this process.

Finally, to all the participants who took the time to be part of my study—thank you. Your involvement made this work possible, and I truly appreciate your contribution.

To everyone who supported me in ways big and small, thank you for making this journey unforgettable.

CONTENTS

ABSTRACT

Chatbots have become indispensable tools in e-commerce, particularly in engaging customers and influencing their purchase intentions. The aim of this study is to explore how social influence tactics, including scarcity, authority, and social proof, can influence customer outcomes when employed by chatbots. This exploration is divided into two parts: Study 1, which focuses on the initial assessment of these tactics and their impact on purchase intention and perceived value, and Study 2, which further examines the moderating role of personality traits in these interactions.

Study 1 specifically investigates the mediation effects of social influence tactics—social proof, scarcity, and authority—on purchase intention and perceived value. The study measured whether these tactics positively influenced the customer.

Study 2, on the other hand, explores the moderating effect of two key personality traits: Need to Belong (NTB) and Susceptibility to Informational Influence (SII). This study aimed to determine whether the personality traits of the participants influenced how effectively the social influence tactics shaped their purchase intention and perceived value. For instance, individuals with high NTB might respond more positively to social proof tactics, while those with high SII could react more favorably to authority-based approaches.

Three unique chatbot encounters, each intended to symbolize a different social influence strategy, were designed for the experiment, along with a neutral chatbot for the control group. In the experiment, participants were randomly assigned to interact with one of the four chatbots in a virtual online shopping scenario. Following their interactions with the chatbots, participants' Purchase Intentions (with respect to the products that the chatbot was showing) and Perceived Value (towards the chatbot) were assessed. Additional assessments of personality traits were conducted to determine how these qualities mediate the efficacy of the chatbots' tactics.

The research findings indicate that strategies such as authority tactics, scarcity, and social proof have a significant impact on customer outcomes, with notable differences between Study 1 and Study 2 based on the context and the role of personality traits. Moreover, the effectiveness of these strategies varies based on the personality types of the consumers. Those who are more sensitive to informational influence tend to respond more positively to authority cues, while individuals with a strong need to belong don’t respond positively to social influence tactics. It's worth noting that while scarcity tactics may be effective for some, others perceive them as manipulative, particularly when overused. By testing the efficacy of social influence tactics in chatbot interactions, this study provides valuable theoretical insights. Furthermore, managers in e-commerce and related fields should consider the practical implications of these findings, particularly in the context of chatbot personalization, to enhance sales conversions and improve customer satisfaction.

1 INTRODUCTION

The digital marketplace is undergoing a significant transformation with the emergence of chatbots as virtual shop assistants (Hoyer et al., 2000). Nowadays, conversational agents can offer more than just customer support; they can also actively engage with consumers, providing personalized product recommendations (Jin et al., 2023). Despite their growing role, there is still a significant gap in our understanding of how interactions driven by chatbots influence consumer purchasing decisions. This research explores how chatbots that use social influence tactics—specifically social proof, authority, and scarcity—affect consumer behavior (Cialdini, 2007; Cialdini et al., 2004). Unlike traditional face-to-face interactions or broader digital marketing strategies, the impact of chatbot-mediated influence remains mostly unexamined (e.g., Aral, 2011; Benlian et al., 2012; Roethke et al., 2020), even as this technology rapidly grows in the e-commerce sector.

Addressing this gap is essential because chatbots play a significant role in influencing consumer decision-making (Jin et al., 2023). Without a clear understanding of how social influence tactics operate in this background, businesses risk implementing ineffective chatbot strategies that do not relate to different consumer personalities and behaviors. This could result in missed opportunities and reduced engagement.

To bridge this gap, this thesis systematically investigates the effectiveness of three key social influence tactics employed by chatbots: social proof, authority, and scarcity. Specifically, it explores the moderating role of personality traits such as the Need to Belong (NTB) and Susceptibility to Informational Influence (SII) in these interactions. The research was divided into two studies. Study 1 examined how social influence tactics directly impact consumer outcomes, including purchase intention and perceived value. The focus was on understanding the mediating role of these tactics. On the other hand, Study 2 delved deeper, exploring how the effects of these social influence tactics are moderated by individual personality traits—Need to Belong (NTB) and Susceptibility to Informational Influence (SII). By employing an experimental design, participants were exposed to different chatbot strategies, and data was collected through post-interaction surveys to evaluate their purchasing intentions and perceived values on relevant personality traits. Structural Equation Modeling (SEM) was used to analyze the relationships between chatbot tactics, personality traits, and consumer responses.

This thesis consists of two distinct models evaluated through SEM:

- **Study 1**: Focuses on the mediation role of Need to belong (NTB) and Susceptibility to information (SII) in the relationship between chatbot tactics (social proof, authority, and scarcity) and the dependent variables, Purchase Intention (PI) and Perceived Value (PV).
- **Study 2**: Examines the moderating effect of Need to belong (NTB) and Susceptibility to information (SII) on the relationship between chatbot tactics and the dependent variables, Purchase intention (PI) and Perceived value (PV).

The key findings indicate that chatbot interactions utilizing social proof and authority tactics significantly enhance purchase intentions, while scarcity tactics have a lower impact. Additionally, individual personality traits affect these outcomes; consumers with a higher score on the Need to Belong scale respond negatively to social influence strategies. This suggests that customizing chatbot methods according to consumers' personality traits could greatly improve chatbot effectiveness in e-commerce settings.

This thesis contributes to a deeper understanding of the purpose of social influence tactics in chatbot-based automated settings and highlights the importance of accounting for individual differences. It moves beyond a general approach to chatbot design, emphasizing that consumer responses are influenced by unique psychological characteristics and individual preferences.

This leads us to the guiding questions of this research:

- How do chatbots employing social influence tactics (social proof, authority, and scarcity) influence purchase intentions, compared to a control group (interaction with a chatbot that does not use social influence tactics)?
- Do participant personality traits (need to belong, susceptibility to informational influence) moderate the effectiveness of these social influence tactics?

1.1 OUTLINE

This thesis begins with an **Introduction** that outlines the central theme of the study, specifically focusing on how chatbot strategies influence consumer behavior. It presents the research questions and provides a brief roadmap for the paper. In the **Background and Related Work** section, the historical development and evolution of chatbots in e-commerce are discussed, emphasizing their role in enhancing customer engagement through psychological principles. The section on **Hypothesis development** introduces key social influence tactics such as social proof, authority, and rarity. It also examines the impact of personality traits, particularly the need to belong, on consumers' interactions with chatbots. The **Methodology** outlines the experimental design, chatbot configurations, data collection methods, and tools used, including survey development and measurement techniques. The **Results** section analyzes participants' responses, focusing on the statistical techniques employed, such as Exploratory Factor Analysis (EFA) and Structural Equation Modeling (SEM), to test the hypotheses. Finally, the **Discussion** explores the theoretical and managerial implications of the findings, detailing the contributions to both academic research and practical applications. It concludes with a review of the study's limitations and suggestions for future research. The **Appendix** contains supporting materials, including the questionnaire, the chatbot development process, and additional statistical analysis results.

2 BACKGROUND AND RELATED WORK

This section provides an overview of key concepts and prior research related to the study. It discusses the role of chatbots in e-commerce and the psychological principles influencing consumer interactions with them.

2.1 EVOLUTION OF CHATBOTS IN E-COMMERCE

The invention of artificial intelligence (AI) in the mid-twentieth century opened new possibilities for human-machine interactions. One significant advancement was Joseph Weizenbaum's creation of the first chatbot, ELIZA, at MIT in the 1960s (Wikipedia Contributors, 2019). ELIZA employed pattern-matching algorithms to simulate conversation, highlighting both the capabilities and limitations of intelligent robots. This development was an early milestone in AI, alongside Alan Turing's Turing Test, which established criteria for assessing machine intelligence. These pioneering efforts positioned chatbots as an important tool for communication between people and machines.

In recent decades, chatbots have dramatically evolved, driven by breakthroughs in natural language processing (NLP) and machine learning. Modern chatbots are capable of understanding and responding to human language with much greater accuracy, making them essential in customer service, marketing, and particularly in e-commerce (Misischia et al., 2022). Today's chatbots offer personalized experiences by analyzing browsing history and purchase behavior, improving user engagement, conversion rates, and customer loyalty (Chen, 2021). For instance, Google's BERT (Bidirectional Encoder Representations from Transformers) is a significant advancement in NLP, enabling more contextually nuanced interactions between chatbots and users. (Devlin et al., 2018).

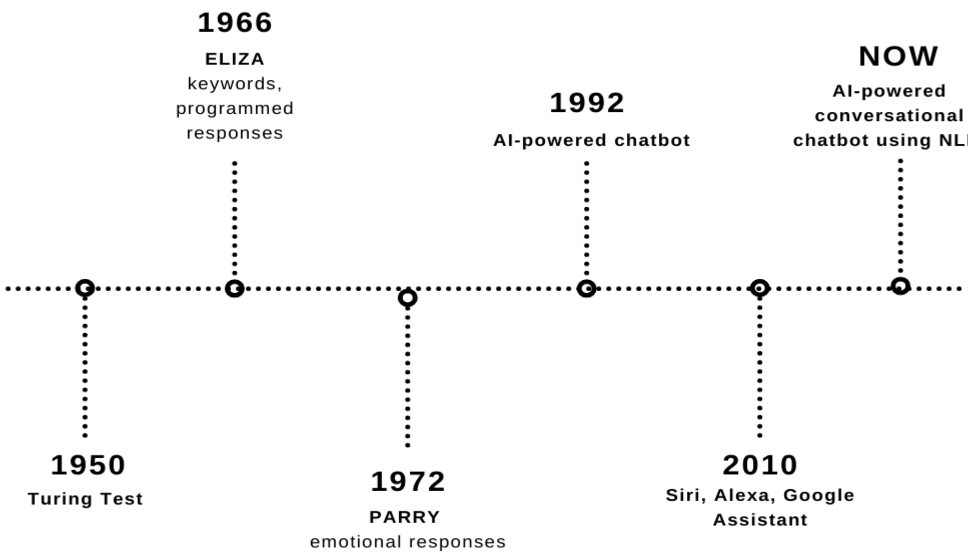


Figure 1 - timeline of chatbot development.

Within e-commerce, chatbots have transformed the online shopping experience by offering 24/7 customer support and handling tasks such as answering frequently asked questions, suggesting products, and generating information. This automation has allowed human agents to focus on more complex tasks, optimizing operational efficiency. According to Ameen et al. (2022), chatbots not only reduce customer wait times but also improve overall satisfaction by providing quick and accurate responses to common inquiries. Studies have shown that chatbots designed with advanced NLP capabilities have a particularly positive impact on customer satisfaction and retention (Chen et al., 2021; Cheng et al., 2022).

As chatbots continue to evolve, their success in e-commerce depends on their ability to provide continuous value to customers. Research by Chung and Joung (2020) suggests that a customer's intention to continue using a chatbot is a key factor in determining its long-term success. Chatbots that offer personalized, responsive, and efficient interactions are likely to become indispensable tools in enhancing customer engagement and improving business operations in the e-commerce landscape.

2.1.1 Consumer Psychology and chatbot usage

Consumer psychology investigates the factors that influence purchasing behavior and decision-making, with a particular emphasis on how people react to marketing and persuasive strategies. Cialdini (2007) identifies six psychological principles: reciprocity, commitment, social evidence, authority, liking, and scarcity. These strategies influence consumer behavior by leveraging natural tendencies and social dynamics, which are essential for effective marketing tactics (Cialdini, 2007). Marketers use social proof, like product reviews or best-seller rankings, to build trust. Scarcity techniques, such as limited-time offers, exploit consumers' fear of missing out, leading to quicker decision-making.

In recent years, the application of these principles has evolved with the integration of artificial intelligence (AI) technologies, such as chatbots. Chatbots are more than just customer support tools; they actively engage consumers by using psychological tactics in real time to influence their purchasing decisions. For instance, a chatbot might create a sense of urgency by informing customers that only a few items remain in stock. Additionally, by analyzing user data, chatbots can personalize their communication, enhancing the shopping experience and tailoring responses to reflect individual consumer behavior. This aligns with Cialdini's principle of liking, where chatbots mirror the customer's language and preferences, fostering a stronger connection (Xu et al., 2021).

Social influence plays a significant role in the consumer decision-making process, as evidenced by studies on online product ratings and reviews. Research has shown that product ratings and reviews, which serve as a form of social proof, affect consumer purchasing choices (Aral, 2011). This influence is especially strong in the digital field, where consumers often depend on the opinions of others when deciding what to buy (Risselada et al., 2014). Chatbots that integrate real-time ratings and social proof mechanisms provide a seamless blend of artificial intelligence and consumer psychology, resulting in more persuasive and impactful interactions.

The integration of emotional design in chatbot communication has been shown to enhance user satisfaction and loyalty. By providing empathetic responses and matching the emotional tone of conversations, chatbots can create a more personal connection with users. This, in turn, significantly improves customer satisfaction and engagement (McLean and Osei-Frimpong, 2019). Establishing this emotional connection is crucial for fostering long-term consumer loyalty, as it builds a deeper bond between the consumer and the brand, leading to repeat interactions and purchases.

Understanding consumer susceptibility to informational influence is crucial for the effectiveness of chatbot interactions. According to Bearden et al. (1989), informational influence occurs when consumers rely on others to guide their decisions, particularly when they lack experience or knowledge about a product. In the context of chatbot interactions, this influence is evident when consumers trust the chatbot's product recommendations or advice. This trust allows the chatbot's social proof and authority strategies to shape the decision-making process. For example, consumers who are highly susceptible to informational influence are more easily persuaded by chatbots that use authority cues, such as expert recommendations (Risselada et al., 2014).

The combination of AI technology and psychological strategies in chatbot design enhances consumer interactions by creating personalized, persuasive, and emotionally engaging experiences. As the role of chatbots in e-commerce and other sectors continues to expand, it is crucial to understand the psychological mechanisms involved in these digital interactions. By strategically incorporating persuasive techniques such as social proof, authority, and scarcity, businesses can engage customers more effectively and increase conversion rates. This intersection of consumer psychology and chatbot usage provides a solid framework for understanding how digital tools influence purchasing decisions in today's marketplace.

2.2 Key Theories

2.2.1 Social influence theory

Social Influence Theory examines how individuals' thoughts, feelings, and behaviors are affected by others. It identifies three processes through which social influence operates: compliance, identification, and internalization. Compliance involves changing behavior to gain approval or avoid disapproval, identification is adopting behaviors to establish a satisfying self-defining relationship with another person or group, and internalization is the acceptance of influence because the induced behavior is congruent with one's value system. These processes are influenced by factors such as the source of influence, the context, and the individual's characteristics (Davlembayeva et al., 2024).

2.2.2 Need to Belong Theory

The Need to Belong Theory suggests that humans have a fundamental drive to form and maintain lasting, positive, and significant personal relationships. This need influences behavior, cognition, and emotion, leading individuals to search for social acceptance and avoid rejection. In consumer behavior, this is exhibited as a preference for products or services that enhance social connections or are supported by one's social group (Baumeister, 2012).

2.2.3 Susceptibility to Informational Influence

Susceptibility to Informational Influence refers to an individual's tendency to accept information from others as evidence about reality. This occurs when individuals are uncertain and look to others for guidance, leading to consistency based on the belief that others possess more accurate information. In the context of consumer behavior, this means that individuals may rely on expert opinions, reviews, or popular trends when making purchasing decisions (Hoffman et al., 2009).

By integrating these theories, the study aims to explore how chatbots employing social influence tactics can affect consumer behavior, considering the moderating roles of individual differences such as the Need to Belong and Susceptibility to Informational Influence.

2.3 Related Work

Several theories and studies have explored how customers interact with chatbots to enhance engagement and effectiveness. A key factor in these interactions is the personality of both the chatbot and the user. According to Ruane et al. (2021), an individual's personality significantly affects how they perceive and engage with a chatbot. In this study, two chatbots with distinct personalities—one extroverted and the other more reserved—were developed using the Microsoft bot platform. The research revealed that through randomized user engagement and post-interaction surveys, consumers could recognize personality differences among chatbots, and these differences influenced their choices. More importantly, users' personalities played a crucial role in shaping their perceptions of the chatbot's personality. This emphasizes the importance of aligning chatbot design with the personality traits of the target audience.

Expanding on this, Go and Sundar (2019) found that the anthropomorphism of chatbots—defined as the extent to which a chatbot seems like a human in its conversational style—significantly affects user engagement and satisfaction. Users tended to respond more positively to chatbots that exhibited more human-like traits, such as empathy and humor. This highlights the importance of precisely designing chatbot personalities to align with user expectations and enhance the overall quality of interactions. Go and Sundar's findings confirm that personality traits, both in users and chatbots, are essential for adopting successful consumer-bot interactions.

Li and Wang (2023) explored how the use of formal and informal language by chatbots affects client reactions toward brands. The study found that chatbots employing informal, conversational language were more effective in boosting customers' willingness to use the chatbot and improving their perceptions of the brand. Interestingly, the research also examined the role of the Personalized System of Instruction (PSI) as a mediator between the chatbot's language style and customer perceptions. The findings suggest that chatbots that adapt their communication style based on user behavior can enhance customer loyalty and long-term engagement.

In a separate study, Xu et al. (2021) explored how personalization affects chatbot communication. Their findings showed that chatbots utilizing real-time user data to tailor conversations significantly enhance consumer engagement. By dynamically implementing persuasion techniques such as scarcity and social proof, these chatbots foster a deeper emotional connection with users. This aligns with the results of Yang X. (2020), which demonstrated that personalized recommendations based on user behavior led to greater satisfaction and loyalty.

The ability of chatbots to establish emotional connections has captured attention. McLean and Osei-Frimpong (2019) showed that chatbots that respond with empathy can enhance user satisfaction and improve brand perception. This emotional bond is crucial for developing long-term customer loyalty, as users feel understood and valued during their interactions with the chatbot.

Despite recent advancements, studies in this field have limitations. For example, research by Li et al., (2023) and Ruane et al., (2021) often utilized pretty small sample sizes and did not involve real-time interactions with chatbots, which restricts the generalizability of their findings. Real-time interaction is a crucial area for further research, as e-commerce chatbots often need to process information and respond to customer inquiries immediately. Future studies should focus on large-scale, real-time interactions to gain deeper insights into how chatbot design affects customer behavior across various industries.

To summarize, combining AI with psychological principles and personalized communication holds exciting potential for enhancing the effectiveness of chatbots. These studies emphasize the need for a thoughtful approach to chatbot design that considers both the language employed and the personality traits of users. This can lead to more engaging and meaningful conversations.

2.4 PROBLEM STATEMENT AND CONTRIBUTION

This study aims to explore how social influence tactics commonly used in human interactions can be effectively integrated into chatbots to enhance customer engagement and increase purchase intentions. As the reliance on AI tools in digital marketing increases, it is crucial to understand the impact of strategies such as authority, scarcity, and social proof in chatbot interactions to maximize their effectiveness. Although these social influence tactics have been extensively studied in traditional marketing contexts (Cialdini, 2007), there is limited empirical evidence on how they translate to digital environments, particularly in e-commerce chatbots. This research seeks to fill this gap by empirically testing the effectiveness of these tactics in a virtual environment, providing valuable insights into their application on digital platforms.

This research explores how personality traits—specifically the need to belong and susceptibility to informational influence—affect consumer interactions with chatbots. Previous studies have emphasized the significance of these traits in consumer decision-making (Bearden et al., 1989; Leary et al., 2013), but there has been limited examination of how they influence interactions with AI systems like chatbots. By analyzing how personality traits shape consumer responses to different chatbot strategies, this study offers a more detailed understanding of the relationship between personality and chatbot engagement. For example, consumers with a strong need to belong may be more leaned by social proof, while those more susceptible to informational influence could respond better to authority-based approaches. This research effectively bridges the gap between psychological theory and practical applications in digital marketing.

One significant contribution of this study is its application of findings to the design and optimization of chatbots for personalized customer experiences. By merging psychological theories with AI, this research provides a framework for customizing chatbot communications to better align with individual consumer profiles. Personalization has become essential for enhancing customer satisfaction and increasing sales conversions in the digital marketplace (Jin et al., 2023). Thus, the insights from this study offer valuable guidance to chatbot developers and marketers on how to tailor interactions to accommodate different personality traits, resulting in more effective chatbot designs.

This study fills an important gap in the current literature by examining the impact of real-time chatbots on consumer behavior in e-commerce environments. While previous research has explored consumer chatbot interactions, many studies have faced limitations due to small sample sizes or hypothetical scenarios. In contrast, this research takes an experimental approach with a larger, real-world sample, providing strong empirical evidence. The findings not only enhance theoretical understanding, but also offer practical recommendations for firms aiming to use AI chatbots to improve customer engagement, satisfaction, and ultimately sales performance.

In summary, this study enhances our academic understanding of social influence tactics in digital marketing while providing practical insights for improving chatbot design and implementation in real-world contexts. By focusing on the interaction between AI, personality traits and consumer behavior, this research aims to provide actionable strategies to increase user satisfaction and optimize e-commerce outcomes.

3 HYPOTHESIS DEVELOPMENT

This section describes the expected relationships among chatbot strategies, personality traits, and customer behavior, building on the theoretical framework discussed in the background.

3.1 SOCIAL INFLUENCE TACTICS

Social influence principles introduced by Cialdini (2007) provide a framework for understanding how chatbots might influence purchase decisions. These theories highlight tactics such as social proof, authority, and scarcity. Studies on human-computer interaction suggest that chatbots can be perceived as social actors (Xu et al., 2022), making social influence tactics potentially applicable.

3.1.1 Social proof

The principle of Social proof states that we use the actions of others as a compass to navigate social situations (Cialdini, 2007). The more we observe others engaging in a particular behavior, the more likely we perceive it as the "correct" course of action. This phenomenon highlights the power of conformity and the desire to belong (Cialdini et al., 1998).

Chatbots can leverage social proof in several ways to influence purchase decisions:

- Highlighting popular choices: Displaying information about products with high purchase rates or positive user reviews can nudge consumers towards those options.
- Showcasing user testimonials: Featuring testimonials from satisfied customers can build trust and credibility for the products and the chatbot recommendations.
- Displaying user-generated content: Incorporating visuals like user photos or videos showcasing the products in use can create a sense of authenticity and social validation.

In the context of chatbot-consumer interaction, we hypothesize that:

H1: Purchase intention will be higher when the chatbot uses social proof tactics (i.e., when social proof cues are present compared to when they are absent).

H1(a): Perceived value will be higher when the chatbot uses social proof tactics (i.e., when social proof cues are present compared to when they are absent).

3.1.2 Authority

Individuals are frequently rewarded for complying with the opinions, recommendations, and instructions of authority figures (Cialdini et al., 2004).

Positioning chatbots as experts or using endorsements could increase their influence on consumer choices:

- Positioning as experts: Chatbots can position themselves as experts (e.g., fashion stylists for clothing recommendations) offering in-depth product information, comparing features with similar products, etc.
- Using expert endorsements: Chatbots can display endorsements from industry professionals or reputable sources to increase their credibility and build trust in their recommendations.

By incorporating these tactics, chatbots can establish themselves as credible sources of information and influence consumer purchase decisions.

Therefore, we hypothesize that:

H2: Purchase intention will be higher when the chatbot uses authority tactics (i.e., when authority cues are present compared to when they are absent).

H2(a): Perceived value will be higher when the chatbot uses authority tactics (i.e., when authority cues are present compared to when they are absent).

3.1.3 Scarcity

The scarcity principle, as described by Cialdini (2007), suggests that the perceived limited availability of a resource (like a product) increases its value and desirability. This phenomenon can be explained by the fear of missing out (FOMO) (Khetarpal et al., 2024) and the psychological tendency to want things that are difficult to obtain.

Chatbots can leverage the scarcity principle in several ways:

- Limited-quantity warnings: Chatbots can inform customers about limited stock availability for a particular product, creating a sense of scarcity and encouraging immediate purchase.
- Exclusive access: Chatbots can offer exclusive product recommendations or deals to a select group of users, making them feel privileged and more likely to take advantage of the offer.

By incorporating these tactics, chatbots can potentially influence consumer behavior by making products seem more valuable and desirable due to their perceived limited availability.

Hence, we hypothesize that:

H3: Purchase intention will be higher when the chatbot uses scarcity tactics (i.e., when scarcity cues are present compared to when they are absent).

H3(a): Perceived value will be higher when the chatbot uses scarcity tactics (i.e., when scarcity cues are present compared to when they are absent).

3.2 INFLUENCE OF PERSONALITY TRAITS ON PERSUASION SUSCEPTIBILITY

Social influence tactics can be highly effective tools for shaping consumer behavior, but their effectiveness can vary depending on individual characteristics. Research suggests that personality traits play a significant role in how people respond to persuasive messages (Hirsh et al., 2012; Janis, 1954). This section explores how specific personality traits can influence susceptibility to social influence tactics, with a focus on the tactics relevant to this study.

3.2.1 Need to belong

The need to belong refers to the motivation to develop and maintain at least a minimum amount of social connections (Baumeister, 2012). According to the need-to-belong theory, the human being is “naturally driven toward establishing and sustaining belongingness” (Baumeister et al., 2017, p. 57). It is considered to be one of the “most powerful, universal, and influential human drives” (Baumeister, 2012). Nevertheless, different people can have different degrees of this need, which can determine their susceptibility to social influence tactics. The following subsections describe the relationship between an individual’s need to belong and different social influence tactics.

3.2.1.1 Social Proof Tactics: Following the crowd

Social proof persuasion tactics leverage the individual’s tendency to rely on the actions and opinions of others to inform their own decisions (Cialdini, 2009). However, individual differences in the need to belong can influence how susceptible someone is to social proof. People with a strong need to belong, measured by instruments like the Need to Belong Scale (Leary et al., 2013), tend to seek many social connections and care deeply about fitting in. On the other hand, individuals with a low need to belong prefer close relationships with a select few (Leary et al., 2009; Leary et al., 2013). Moreover, research shows that people with a high need to belong are more likely to pick up on social cues (Pickett et al., 2004). In the context of online shopping, this suggests that consumers with a high need to belong might be more likely to be influenced by positive reviews and ratings from other users.

Therefore, we hypothesize that consumers with a high need to belong are more susceptible to tactics that rely on social proof (such as positive consumer reviews or high popularity rankings):

H4: The relationship between social proof tactics and purchase intention will be moderated by the need to belong. Specifically, the higher the need to belong, the more positive the effect of social proof tactics on purchase intention

H4(a): The relationship between social proof tactics and perceived value will be moderated by the need to belong. Specifically, the higher the need to belong, the more positive the effect of social proof tactics on perceived value

3.2.1.2 Authority tactics: Social validation through expert endorsements

Research has shown that trusted endorsements significantly impact the credibility of information, even misleading content, on social media (Mena et al., 2020). Perceived message credibility was greater when the content was endorsed by a trustworthy personality. This is because people tend to rely on endorsements from trustworthy figures as a shortcut to judging credibility, especially for online content (Metzger et al., 2013). If something seems to be validated by others (social validation), it is easier to trust it without extensive evaluation (Mena et al., 2020). Similar to trusted endorsements on social media, expert endorsements from chatbots can also be seen as social validation.

In the context of chatbot-consumer interactions, we argue that this social validation can be particularly effective for people with a high need to belong. They might see the chatbot's association with an authority figure as a signal that the recommendations are widely accepted or endorsed by their social group (real or imagined). This validation could then fulfill their need to belong and make them more likely to trust the chatbot recommendations.

Hence, we propose that consumers with a high need to belong are more susceptible to tactics that rely on authority cues (such as expert endorsements):

H5: The relationship between authority tactics and purchase intention will be moderated by the need to belong. Specifically, the higher the need to belong, the more positive the effect of authority tactics on purchase intention.

H5(a): The relationship between authority tactics and perceived value will be moderated by the need to belong. Specifically, the higher the need to belong, the more positive the effect of authority tactics on purchase intention.

3.2.1.3 Scarcity tactics: Fear of exclusion

Scarcity tactics often highlight limited availability or exclusivity, creating a sense of urgency and fear of missing out. This fear is strongly linked to the need to belong (Baumeister et al., 1995; Nadkarni et al., 2012; Przybylski et al., 2013; Seidman, 2013). This connection is further supported by research showing a positive correlation between FOMO scores and the desire for social approval (Lai et al., 2016).

The need-to-belong theory suggests FOMO stems from uncertainty about social acceptance (Dogan, 2019). Hence, this fear can be particularly strong for individuals with a high need to belong. They might be more susceptible to these tactics because they worry about being excluded from a desired product or experience if they do not act quickly. This desire to stay connected to the group could push them towards making a purchase they might not have otherwise considered.

Thus, we posit that consumers with a high need to belong are more susceptible to scarcity tactics (such as limited-time discounts).

H6: The relationship between scarcity tactics and purchase intention will be moderated by the need to belong. Specifically, the higher the need to belong, the more positive the effect of scarcity tactics on purchase intention.

H6(a): The relationship between scarcity tactics and perceived value will be moderated by the need to belong. Specifically, the higher the need to belong, the more positive the effect of scarcity tactics on perceived value.

3.2.1.4 Susceptibility to Informational Influence

Informational influence can be defined as the tendency to accept information from others as evidence about reality (Deutsch et al., 1955). Informational influence relies on the process of internalization, which occurs when “information from others increases the individual's knowledge about some aspect of the environment” (Bearden et al., 1989).

Research has shown that informational influence can impact consumer decision processes in terms of product evaluations (Burnkrant et al., (1975); Cohen et al., (1972); Pincus et al., (1977)) and product/brand selections (Bearden et al., (1982); Park et al., (1977)).

In the context of shop assistant chatbots, susceptibility to informational influence could involve trusting a chatbot's recommendations when making a purchase. We propose that people who are more susceptible to informational influence are more likely to be persuaded by the chatbot's social influence tactics (social proof, authority, scarcity). Therefore, we hypothesize that:

H7: The relationship between social proof tactics and purchase intention will be moderated by the susceptibility to informational influence. Specifically, the higher the susceptibility, the more positive the effect of social proof tactics on purchase intention.

H7(a): The relationship between social proof tactics and perceived value will be moderated by the susceptibility to informational influence. Specifically, the higher the susceptibility, the more positive the effect of social proof tactics on perceived value.

H8: The relationship between authority tactics and purchase intention will be moderated by the susceptibility to informational influence. Specifically, the higher the susceptibility, the more positive the effect of authority tactics on purchase intention.

H8(a): The relationship between authority tactics and perceived value will be moderated by the susceptibility to informational influence. Specifically, the higher the susceptibility, the more positive the effect of authority tactics on perceived value.

H9: The relationship between scarcity tactics and purchase intention will be moderated by the susceptibility to informational influence. Specifically, the higher the susceptibility, the more positive the effect of scarcity tactics on purchase intention.

H9(a): The relationship between scarcity tactics and perceived value will be moderated by the susceptibility to informational influence. Specifically, the higher the susceptibility, the more positive the effect of scarcity tactics on perceived value.

3.3 Research Model and Research Questions

To structure our research, we divided the hypotheses into two studies. Study 1 focuses on the direct effects of social influence tactics on purchase intention and perceived value, while Study 2 examines the moderating role of personality traits, such as Need to Belong and Susceptibility to Informational Influence, on these relationships.

Based on the hypotheses presented in the previous section, we propose the following research models:

3.3.1 Study 1: Mediation analysis

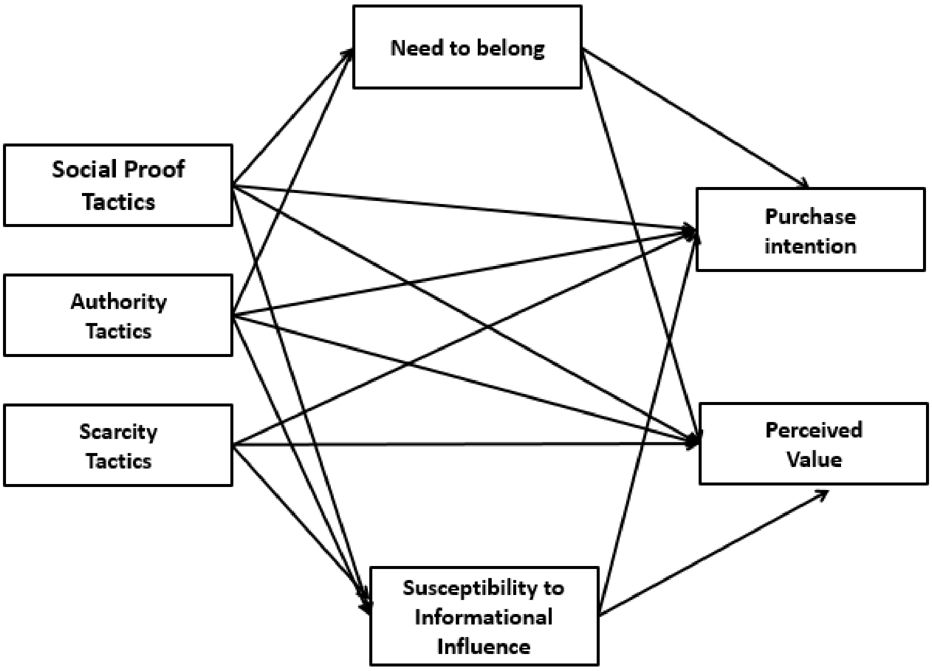


Figure 2 - Mediation analysis.

This model illustrates the relationships between chatbot social influence tactics (social proof, authority, and scarcity), personality traits (Need to Belong and Susceptibility to Informational Influence), and their impact on Purchase Intention and Perceived Value. The lines connecting the variables show how these factors interact. For example, personality traits mediate the effectiveness of social influence tactics, modifying how they affect Purchase Intention and Perceived Value.

3.3.2 Study 2: Moderation analysis

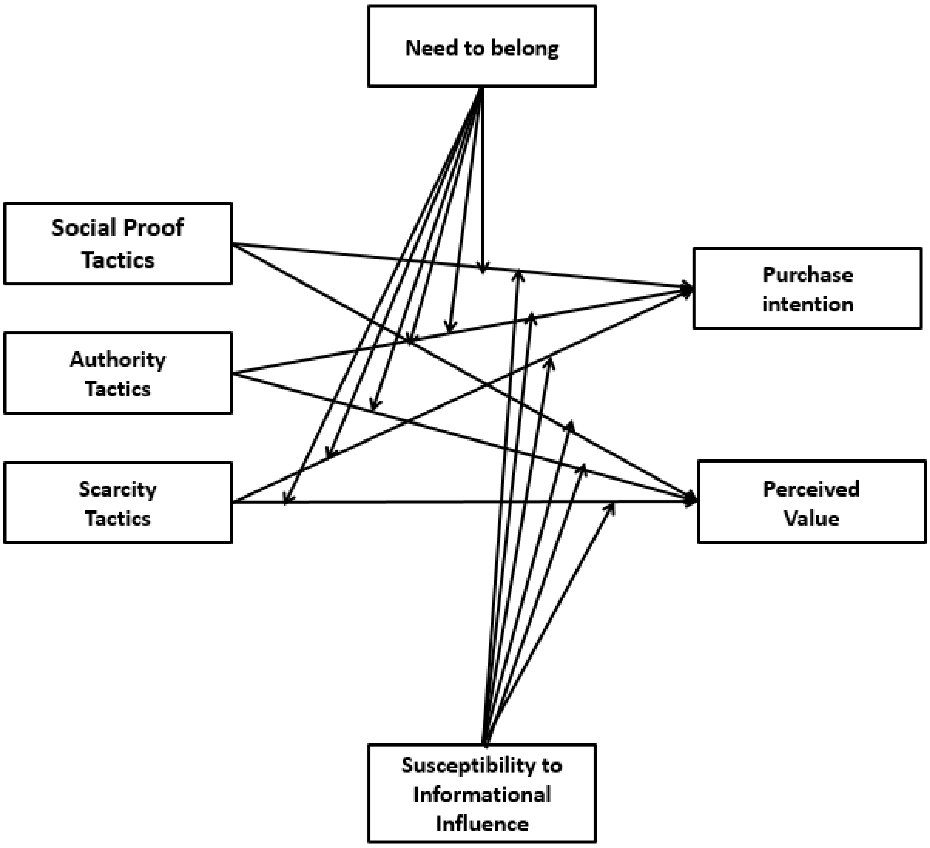


Figure 3 – Moderation analysis.

According to this research model, the dependent variable is Purchase intention and Perceived Value. We hypothesize that different social influence tactics can have an impact on the participants' purchase intention. Moreover, we propose that the Need to Belong and Susceptibility to Informational Influence moderate the relationship between the impact of such tactics on the purchase intention and the perceived value.

3.3.2.1 Hypothesis across studies

This section describes the hypotheses examined in Studies 1 and 2, and how each hypothesis fits within the relevant topic of study. The hypotheses are categorized in the table below to give a clear picture of which studies address each part of the research framework.

Table 1 - Hypothesis testing across studies.

Hypothesis	Study
H1	1,2
H1(a)	1,2
H2	1,2
H2(a)	1,2
H3	1,2
H3(a)	1,2
H4	2
H4(a)	2

H5	2
H5(a)	2
H6	2
H6(a)	2
H7	2
H7(a)	2
H8	2
H8(a)	2
H9	2
H9(a)	2

4 METHODOLOGY

In this section, we introduce the methodology used to implement the experiment. First, explain how the experiment was set up and the development of the chatbots. Then, discuss the data collection procedure and the ethical considerations of the study. Finally, present the data analysis and the specific tools that were used.

4.1 EXPERIMENTAL DESIGN

During the study, four different chatbots were developed that represented each of the social influence tactics, and each participant was randomly assigned to each of these chatbots at a time. These four conditions were:

1. **Social Proof**: The chatbot displayed messages about what other customers were buying or highly rated.
2. **Authority**: The chatbot offered expert recommendations, presenting itself as knowledgeable about the products.
3. **Scarcity**: The chatbot emphasized limited availability, such as highlighting low stock or time-limited offers.
4. **Neutral**: The control chatbot provided standard product information without using any influence tactics.

The random assignment of participants ensured that each group had an equal chance of interacting with any of the four chatbots, which helped to eliminate bias and keep the conditions balanced. The purpose of this design was to compare the effects of various social influence tactics (social proof, authority, and scarcity) on consumer intentions while also investigating how personality traits like Need to Belong and Susceptibility to Informational Influence moderated these effects. We were able to isolate the effect of each approach and draw conclusions about how they affect customer decision-making by keeping the rest of the shopping experience identical, except for the influence methods. This randomized controlled design ensured that the results were trustworthy and that any changes in customer responses could be defined by chatbot interaction type and personality attributes.

The *independent variable* in this study was the type of *chatbot interaction*, meaning that what changed between the groups was the specific social influence tactic used by the chatbot. The *dependent variables* were *perceived value* and *purchase intention*, which were measured after participants completed the chatbot interaction. Additionally, we examined how *personality traits* influenced participants' responses to the chatbots, making the relationship between chatbot interaction and consumer behavior more nuanced. Each participant was guided through a simulated shopping experience using one of the four chatbots. The task was selecting a hiking shoe, with the chatbot providing information based on its assigned influence tactic. After the interaction, participants completed a survey to record their satisfaction with the chatbot and the probability of purchasing the recommended product.

4.2 CHATBOT DEVELOPMENT

The chatbot for this study was developed using a chatbot platform called Voiceflow. The design process started with defining the user interface and interaction flow for each chatbot using Voiceflow' s drag-and-drop interface. This approach allowed for the creation of complex dialogue flows. The general design principles focused on user engagement, easy navigation, and the provision of timely and relevant information.

Voiceflow was selected because of its user-friendly interface and platform integration capabilities. For this experiment, four distinct chatbots were created and embedded into an online Qualtrics survey, which was then distributed to participants.

Each chatbot was equipped with advanced natural language understanding (NLU) capabilities to accurately interpret user inputs and provide relevant responses. Key functionalities included:

- Greeting mechanisms: chatbot greeting the users
- Product handling: the chatbot offered product information and compared products.

4.2.1 Specific chatbot configurations

All four chatbots shared a common goal of assisting customers in purchasing hiking shoes, with consistent initial and final steps to ensure a standardized experience for participants. However, they differed in their interaction styles and the specific social influence tactics employed. The elements of each chatbot in the Voiceflow environment are highlighted in the following figures.

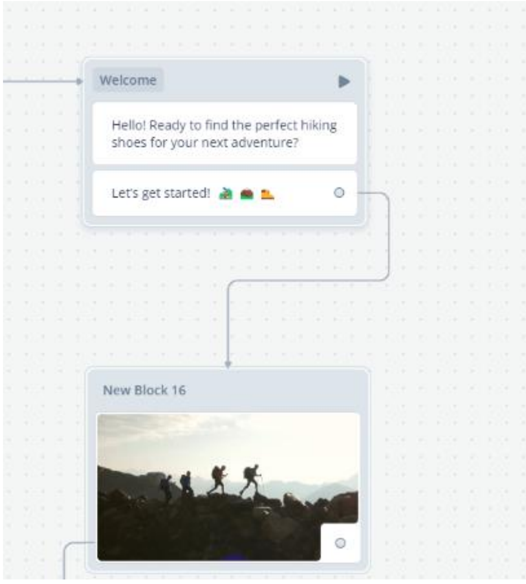


Figure 4 - Welcome message.

All conversations started with a friendly greeting (*"Hello! Are you ready to find the perfect hiking shoes?"*) and a relevant GIF to enhance engagement.

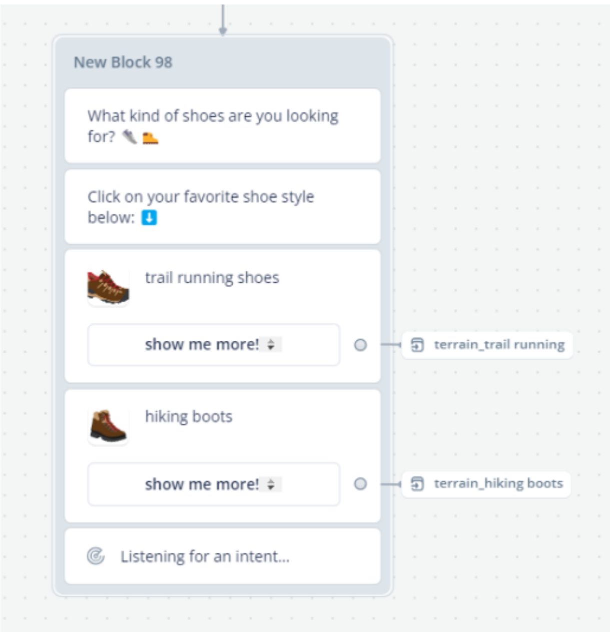


Figure 5 - Shoe selection.

The next step was to ask the customers what kind of shoes they were looking for. Customers were presented with a choice of trail running shoes or hiking boots. After making a choice the customer continues interacting with the chatbot.

Figure 6 – Terrain selection.

Then, the chatbot asked them about the type of terrain expected during their hikes. We have two containers, each with a different color, but both serve the same purpose. The pink container is for running shoes, while the blue one is for boots. Based on the participant's selection of shoe type and terrain, the chatbot recommends the most suitable product. Each chatbot follows a similar procedure, but there are slight variations based on the chatbot's purpose. For example, the language used in a social proof chatbot differs from that in an authority chatbot.

The next step involves the chatbot recommending the shoe that is more suitable based on the previous choice and the terrain. After this, the chatbot uses different tactics to persuade the customer to make the purchase. For example, the scarcity chatbot reminds the customer that only a limited number of items remain in stock and encourages them to make a quick decision.

Following this, the chatbot asks if the customer wants to see any other product with the same characteristics (terrain and type of shoe). If the customer agrees, the chatbot shows a different product; otherwise, it continues to the next step. The chatbot presents the product and utilizes the same tactics to guide the customer through the purchase.

After showing the product, the chatbot asks if the customer wants to compare the two products to make it easier for them to decide which one to buy. It presents a bar chart with specific information about each type of shoe. Finally, the conversation concludes with the chatbot greeting the customer and reminding them to fill in the survey.

Table 2 – Chatbot characteristics.

Characteristic	Social Proof Chatbot	Scarcity Chatbot	Authority Chatbot	Neutral Chatbot
Interaction Style	Emphasizes popular products and user reviews	Highlights limited availability	Uses expert recommendations	Straightforward options
Language Tone	Positive and persuasive, uses phrases like "92% of users prefer this"	Create the sense of urgency, uses phrases like	Confident and informative, e.g., "Recommended by experts"	Neutral without any persuasion

		"Only 5 left in stock!"		
Influence Tactic	Social Proof	Scarcity	Authority	None
Product Recommendation	Suggests based on customer popularity	Suggests based on stock urgency	Suggests based on expert reviews	Presents all options without bias
Customization	Adjusts recommendations based on popularity trends	Adjusts based on availability	Adjusts based on expert opinions	No customization; presents products formally

4.2.2 Types of chatbots

- <u>Neutral chatbot (Control condition):</u> This chatbot serves as a baseline, providing information without employing any social influence techniques. It avoids using persuasive language, emotional appeals, or any other tactics that might influence user behavior. The chatbot's main goal is to deliver clear product details, enabling users to make informed decisions based purely on the facts presented.

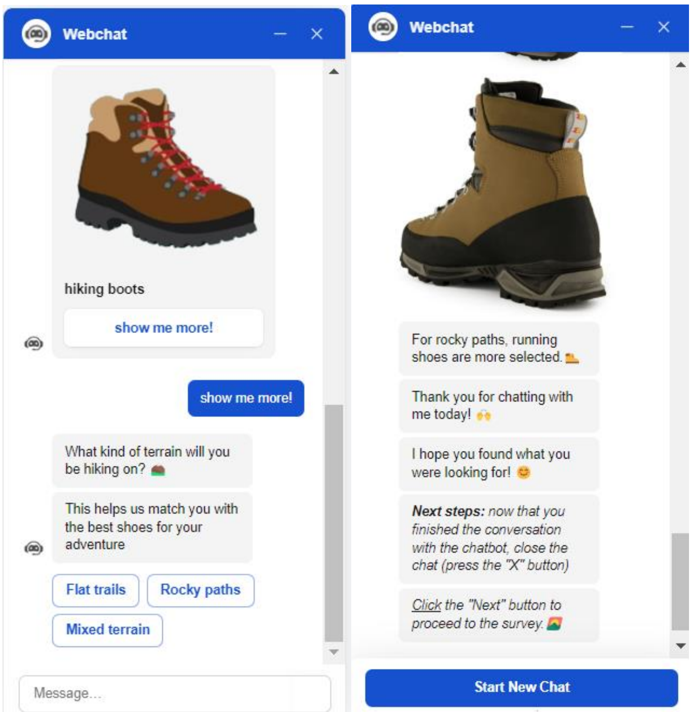


Figure 7 - neutral chatbot

1. Therefore, the chatbot focuses on presenting essential information. When a user interacts with the chatbot, they are first asked if they would like to see more products similar to their initial interest. If they choose to see more, the chatbot straightforwardly displays the next set of options. This direct approach ensures that users are not distracted by persuasive tactics. Afterward, the chatbot asks the user if

they would like to see another pair. If the user says yes, it shows a second option; otherwise, the chatbot concludes the interaction.

- Social Proof chatbot: Social proof chatbot uses social proof tactics by showcasing popular products and featuring user reviews. It effectively uses data and ratings to direct users towards products that are highly preferred by others. The chatbot integrates social proof by dynamically displaying the "most popular" or "highly rated" items within its conversation.

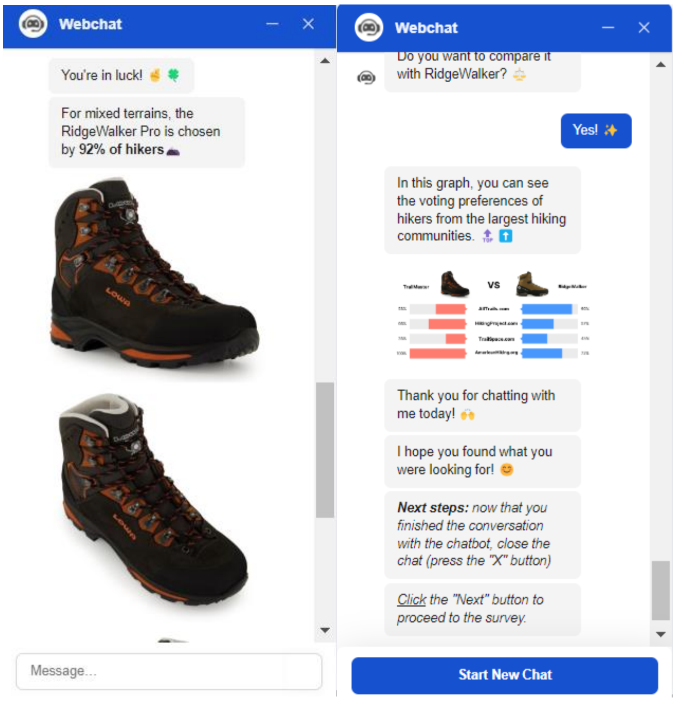


Figure 8 - Social proof chatbot.

For instance, when a user shows interest in a particular type of hiking shoe, the chatbot responds by highlighting a model that has been popular among other shoppers. It displays a message such as *"92% of hikers choose this shoe,"* directly leveraging social proof to engage the user towards a purchase.

The use of statistics on other buyers' choices helps build confidence in the product. In addition, if the user is interested in comparing different shoe models, the chatbot can display a comparison graph. It presents a bar graph showing how the represented shoes compare to each other based on customer reviews and preferences across multiple (fictional) platforms, such as AllTrails.com and HikingProject.com. After guiding the user through this stage, the chatbot ends the conversation with a polite thank you and a gentle reminder to complete the survey.

- Authority chatbot: This chatbot was designed to leverage authority tactics by combining detailed product information and expert reviews, enhancing the credibility of the shopping experience. It acts as a digital expert, guiding users in their purchase decisions with information validated by professionals, which helps to increase user confidence in the suitability of products for their specific needs.

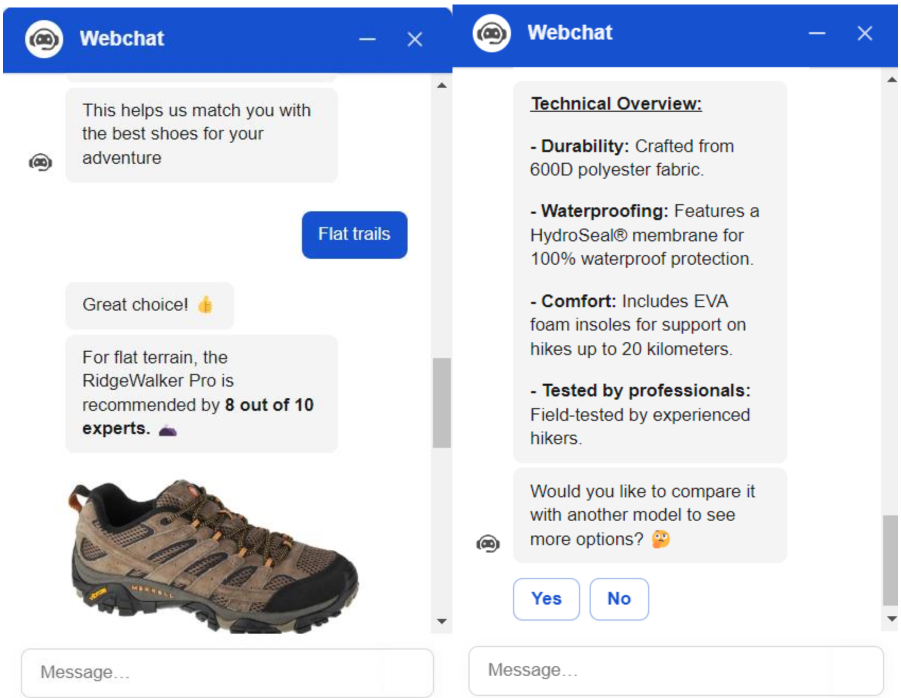


Figure 9 - Authority chatbot.

The authority chatbot provides expert opinions to engage the customer to purchase the items, using prompts such as *"8 out of 10 experts recommend this shoe".* Then a "Technical Overview" provided by the chatbot, listing the key features of the shoe: durability, waterproofing, comfort, and professional testing. The detail within this message further reinforces authority by highlighting that the shoe is made with high-quality materials and has been field-tested by hikers.

- Scarcity chatbot: The system is designed to create a sense of urgency by alerting users to limited availability, to encourage quicker purchasing decisions. The chatbot effectively uses scarcity tactics by continuously notifying users about the limited stock levels.

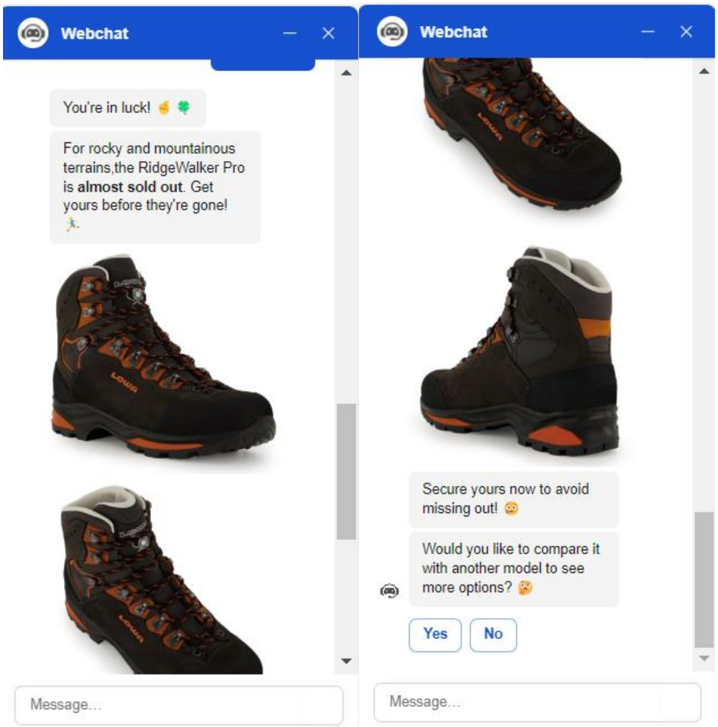


Figure 10 - Scarcity chatbot.

These are images showing a conversation led by the Scarcity Chatbot, pointing out the limited availability of a certain hot-selling hiking boot. The message *"Act fast-Only a couple of pairs are left in stock⏳,"* directly promotes that the customers should make their purchase as soon as possible or else they miss out on them. This is a tactic is meant to result in speedy decision-making, emphasizing how scarce the product is.

4.3 Sample Characteristics

4.3.1 Participants

The majority of participants were recruited through various social media platforms such as LinkedIn, Instagram, and Facebook. Additionally, the survey was frequently shared within participants' own networks, significantly contributing to the collection of responses. Posters were created and displayed in Leiden University buildings, including Gorlaeus and Snellius, as well as university libraries, to attract more university students to the research. No restrictions were placed on age or prior knowledge of chatbot use, given that a wide range of participants was desired.

A total of 200 participants completed the survey, yielding 170 valid responses. The criterion for discarding responses was missing values; participants who did not answer all the questions were eliminated from the final results. Below are the demographic results of the participants.

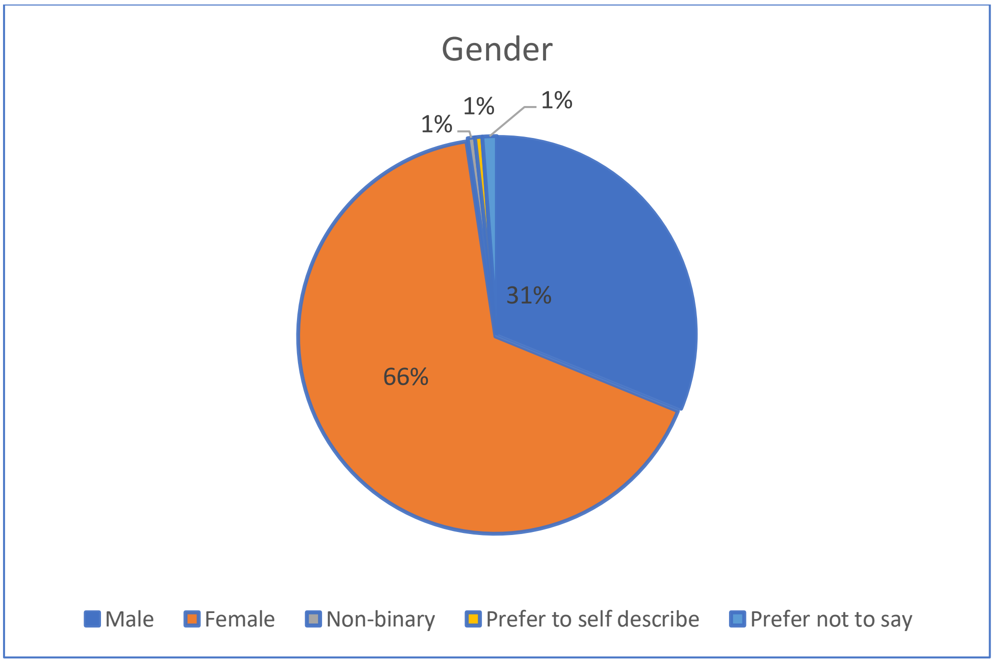


Figure 11 - Gender

The demographic analysis of the participants provides important insights into the composition of the study sample. In terms of gender distribution, the majority of participants were female, making up 66% of the sample, while 31% were male. A small percentage, 1%, identified as non-binary, and another 1% chose not to disclose or self-describe their gender identity.

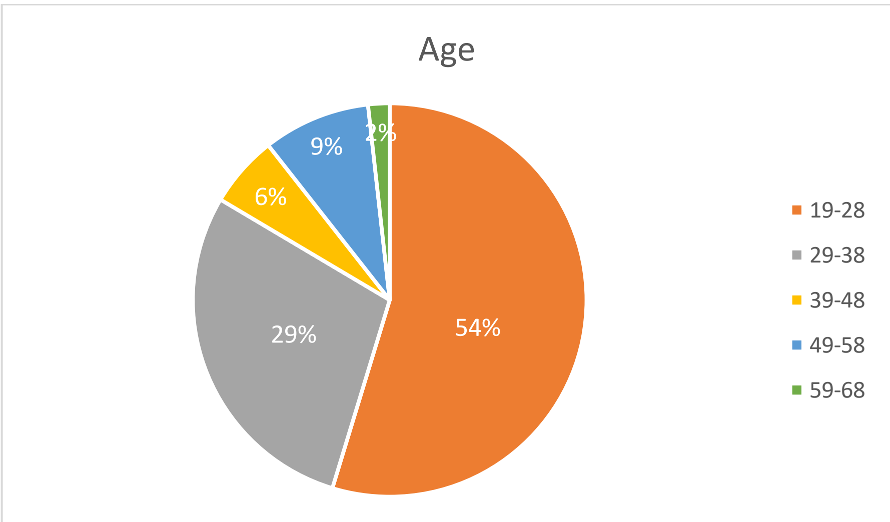


Figure 12 - age range

The largest age group in the sample consisted of individuals aged 19 to 28, representing 54% of the total participants. This was followed by those aged 29 to 38, who included 29% of the sample. Participants aged 39 to 48 accounted for 6%, while those in the 49 to 58 age range contained 9%. Only 2% of respondents were aged 59 to 68. This distribution of age highlights a majority of younger participants, particularly within the 19 to 28 age group.

4.3.2 Software tools

Qualtrics software was used for data collection for this survey. The Qualtrics randomizer allowed for the random assignment of each participant to one of four chatbot conditions, which was essential for the experimental design of the experiment. By ensuring that each chatbot was given identically to each participant, the randomization process removed selection bias and maintained the integrity of the study comparing the different social influence strategies used by the chatbots.

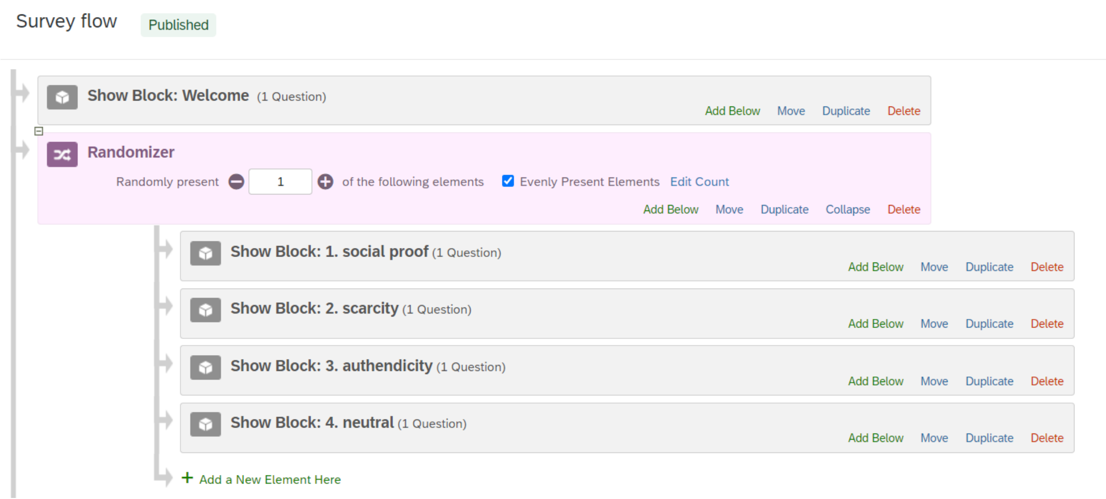
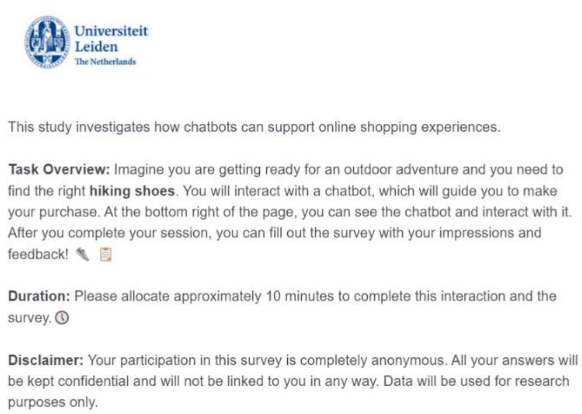


Figure 13 – Qualtrics survey randomizer.

Qualtrics software uses a survey flow where we can implement logic elements. At the beginning of the survey, a randomizer was used to assign each participant to one of the four chatbot conditions. We created a section for each chatbot, and by using the randomizer, we ensured that each participant would be presented with a randomly assigned chatbot type.

4.3.3 Questionnaire development

The questionnaire for this study was designed to gather comprehensive data on participants' experiences, personality traits, and purchase intentions following their interactions with different chatbots. The main aim of the questionnaire was to investigate how various social influence tactics, as adapted by the chatbots, impacted participants' responses. The questionnaire was developed based on established psychological scales and prior research on consumer behavior, ensuring the validity and reliability of the data collected.



Universiteit Leiden
The Netherlands

This study investigates how chatbots can support online shopping experiences.

Task Overview: Imagine you are getting ready for an outdoor adventure and you need to find the right **hiking shoes**. You will interact with a chatbot, which will guide you to make your purchase. At the bottom right of the page, you can see the chatbot and interact with it. After you complete your session, you can fill out the survey with your impressions and feedback!

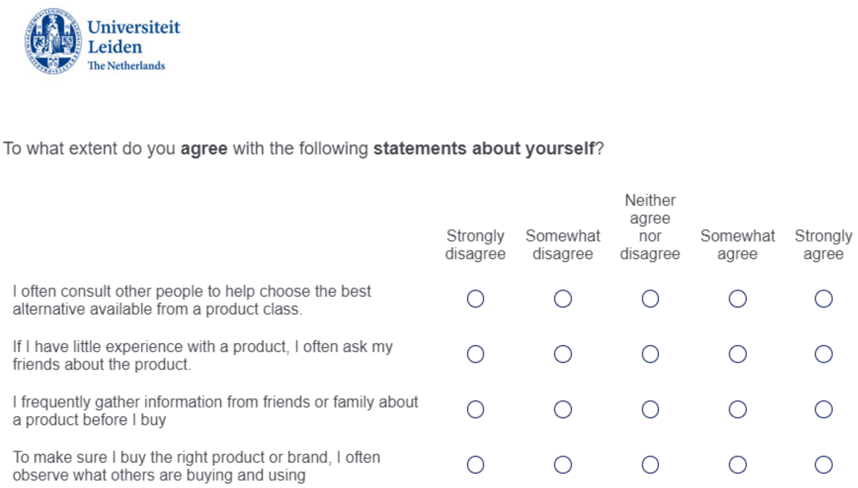
Duration: Please allocate approximately 10 minutes to complete this interaction and the survey.

Disclaimer: Your participation in this survey is completely anonymous. All your answers will be kept confidential and will not be linked to you in any way. Data will be used for research purposes only.

Figure 14 – Survey instructions.

The research begins with an overview of the task, asking participants to imagine that they are preparing for an outdoor adventure and need to choose appropriate hiking shoes. They are instructed to interact with a chatbot designed to guide them in making a purchase. Participants are told that they can find the chatbot at the bottom right of the page to interact with. After completing their session, they are encouraged to complete a survey, providing their impressions and feedback. The task is estimated to take approximately 10 minutes. A disclaimer assures participants that their responses remain anonymous, and that all data is used only for research purposes.

The structure of the questionnaire consisted of several key sections. First, demographic information such as age and gender were collected to provide context for analyzing participants’ responses. Following this, participants were asked to reflect on their experience with the chatbot, specifically addressing their satisfaction with the interaction, purchase intention, and the perceived value of the chatbot in aiding their shopping decisions.


Universiteit Leiden
The Netherlands

To what extent do you **agree** with the following **statements about yourself**?

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I often consult other people to help choose the best alternative available from a product class.	○	○	○	○	○
If I have little experience with a product, I often ask my friends about the product.	○	○	○	○	○
I frequently gather information from friends or family about a product before I buy	○	○	○	○	○
To make sure I buy the right product or brand, I often observe what others are buying and using	○	○	○	○	○

Figure 15 - Survey questions.

In the second part of the study, we measured personality traits using validated psychological scales that were used in existing research. One of the key traits measured was the Need to Belong, a psychological construct that describes an individual's desire for acceptance and fear of rejection (Leary et al., 2013). The Need to Belong is reliable in assessing individuals' sensitivity to social cues and their likelihood of being influenced by social tactics (Leary, et al., 2013). Additionally, we measured participants' Susceptibility to Informational Influence using a scale adapted from Bearden et al. (1989), which evaluates how much individuals rely on social information when making purchase decisions. This scale has been frequently used in consumer research to understand how social cues affect decision-making processes (Bearden et al., 1989).

At the end of the survey, participants were also given a chance to share their feedback about their experience. This open-ended question let them add any thoughts or comments that weren't covered by the survey, giving us extra information that could help improve the study's results.

4.3.4 Measurement

In order to collect data on the participants' experiences, personality traits, and behaviors, we utilized a series of Likert scale questions. This type of question allows participants to express their level of agreement or disagreement with statements on a scale, usually ranging from 1 (strongly disagree) to 5 (strongly agree). The use of Likert scales provided a standardized and clear method to measure subjective responses, simplifying the analysis of participants' attitudes and behaviors.

4.3.4.1 Measurement of Need to Belong

We measured the participant's Need to Belong using the following Likert-scale questionnaire items (Leary et al., 2013)

- *If other people don't seem to accept me, I don't let it bother me. (R)*
- *I try hard not to do things that will make other people avoid or reject me.*
- *I seldom worry about whether other people care about me. (R)*
- *I need to feel that there are people I can turn to in times of need.*
- *I want other people to accept me.*
- *I do not like being alone.*
- *Being apart from my friends for long periods of time does not bother me. (R)*
- *I have a strong "need to belong."*
- *It bothers me a great deal when I am not included in other people's plans.*
- *My feelings are easily hurt when I feel that others do not accept me.*

4.3.4.2 Measurement of Susceptibility to Informational Influence

We measured the participant's Susceptibility to Informational Influence using the following Likert-scale questionnaire items (Bearden et al., 1989):

- To make sure I buy the right product or brand, I often observe what others are buying and using.
- If I have little experience with a product, I often ask my friends about the product.
- I often consult other people to help choose the best alternative available from a product class.
- I frequently gather information from friends or family about a product before I buy.

4.3.4.3 Measurement of perceived value and purchasing intention

Perceived value: Imagine that you were looking to buy hiking shoes. In that scenario, to what extent would you agree with the following statements? (5-point Likert) (Yang, 2020).

- *The chatbot would make my shopping easier.*
- *The chatbot would save me time.*
- *The chatbot would be useful for my shopping.*

Purchase intention: Imagine that you were actually looking to buy hiking shoes. In that scenario, to what extent would you agree with the following statements? (5-point Likert) (Yang, 2020).

- *I would consider buying the products recommended by the chatbot.*
- *I would be likely to buy the products recommended by the chatbot.*
- *I would be willing to buy the products recommended by the chatbot.*

4.4 DATA ANALYSIS

4.4.1 Quantitative Data Analysis

For this study, quantitative data analysis was employed to understand the relationship between the variables of interest, such as personality traits, perceived value, and purchase intention. To perform this analysis, IBM SPSS Statistics and IBM SPSS AMOS were used, given their suitability to conduct statistical analysis and structural equation modeling (SEM).

One of the main reasons for selecting AMOS was its capability to perform moderator analysis, which was essential for this study to examine how different personality traits and chatbot interactions influence outcomes such as purchasing intentions. AMOS offers a rich graphical interface that makes it easier to specify, estimate, and evaluate models using visual path diagrams. This interface simplifies the process of building and testing models, even for complex analyses, such as moderation and mediation effects (Hair et al., 2017). In addition to its ease of use, AMOS provides access to a wide range of advanced statistical techniques. These include mediation, moderation, and multiple group analysis, all of which are critical to understanding how different variables interact. The visual layout provided by AMOS helps researchers track the flow of relationships between observed and latent variables, making it particularly effective for studies like ours that involve examining both direct and indirect effects.

The data analysis process began with data cleaning in SPSS to ensure the dataset was ready for more advanced analysis. This included addressing missing variables and identifying any outliers that could alter the results. Once the data was cleaned and prepared, it was ready for further statistical analysis. Study 1 and Study 2 were conducted after ensuring dataset reliability.

4.4.2 Structural Equation Model (SEM)

Structural Equation Modeling (SEM) was employed to explore and test the hypothesized relationships between latent variables in the study. SEM combines factor analysis and path analysis, making it an effective tool for investigating both direct and indirect relationships between variables (Kline, 2015). Given the complexity of this study's research model, SEM was essential in examining the effects of social influence tactics used by the chatbots on participant satisfaction and purchasing intentions.

The analysis followed a two-step process, starting with Exploratory Factor Analysis (EFA) to identify the underlying structure of the data. The EFA analysis conducted on SPSS to understand which survey questions were most closely related. This step needed to identify the underlying structure of the data, helping to group equivalent items together based on their correlations. By doing this, we were able to determine which questions measured the same latent variables, which prepared the data for the next phase of analysis. The same procedure was followed for both Study 1 and Study 2.

This analysis, performed in AMOS, required the data to be organized based on the results of the EFA. Model fit was assessed using standard indices such as the comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA) (Hu et al., 1999). These measures ensured that the data adequately fit the hypothesized model. The second phase involved evaluating the structural relationships between the variables. This allowed us to assess the direct impact of personality traits on chatbot satisfaction and purchase intentions, as well as any mediating effects of social influence tactics. Hypothesis testing was conducted within the SEM framework by examining the path coefficients and p-values, with significance set at the conventional 0.05 level (Kock, 2016). This enabled us to confirm whether the proposed relationships were supported by the data.

Table 3 - SEM Model Fit Indices

Fit Index	**Abbreviation**	Acceptable Threshold	**Description**
Chi-Square (χ^2)	χ^2	$p > 0.05$	Tests the difference between observed and expected covariance matrices. A non-significant result is desired.
Chi-Square/Degrees of Freedom (χ^2/df)	CMIN/DF	< 3.00	Adjusts chi-square by degrees of freedom. Lower values indicate a better fit.
Comparative Fit Index	CFI	≥ 0.90	Compares the fit of the target model to an independent model. Higher values indicate a better fit.
Tucker-Lewis Index	TLI	≥ 0.90	Similar to CFI, evaluates model fit, penalizing for model complexity. Higher values indicate better fit.
Root Mean Square Error of Approximation	RMSEA	≤ 0.06 to 0.08	Measures model fit per degree of freedom. Lower

			values indicate a better fit.

4.4.3 EFA analysis

To conduct this analysis, the dataset was divided into two parts, with the first part assigned to the exploratory factor analysis (EFA). In SPSS, the "Factor Dimension Reduction" option was selected, and the variables were analyzed iteratively to maximize the percentage of explained variance. Initially, all variables were included, but those with weak relationships were excluded in the following iterations. This procedure was repeated for three iterations until the desired results were achieved. The rotated component matrix was examined, and the variable scores for their component categorization were compared. This process helped to eliminate questions that did not demonstrate a strong correlation with the factors of interest.

The analysis used a principal components matrix with Varimax rotation, a widely used method for Exploratory Factor Analysis (EFA) (Sigudla et al., 2023). Factor loadings below 0.30 were considered insignificant (Kline, 1994) and were excluded from the table. Additionally, only factor loadings of 0.40 and above were considered in assigning items to specific factors (Pett et al., 2003). This approach ensured that only variables with meaningful correlations contributed to the factors, thereby enhancing the reliability of the analysis.

Table 4 – Final rotated component matrix

	1	2	3	4
Nbb8	**,811**	,266	,148	-,010
Nbb10	**,742**	-,024	,346	,001
Nbb9	**,674**	-,171	-,089	,303
Nbb6	**,650**	-,034	-,206	,158
Nbb5	**,634**	,076	,196	,044
Pv3	-,008	**,849**	,310	,101
Pv1	0,91	**,847**	,263	,141
Pv2	-,008	**,828**	,226	,060
Pi1	,001	,248	**,859**	,094
Pi3	,123	,274	**,841**	,061
Pi2	,174	,337	**,818**	,050
Sii4	-,015	-,115	,027	**,864**
Sii2	,238	,271	,009	**,791**
Sii3	,173	,228	,173	**,777**

Table 5 - EFA component analysis

1 Need to belong	
Nbb8	.811
Nbb10	.742
Nbb9	.674
Nbb6	.650
Nbb5	.634

2 Perceived value	
Pv3	.849
Pv1	.847
Pv2	.828

3 Purchase intention	
Pi1	.859
Pi3	.841
Pi2	.818

4 Susceptibility to informational influence	
Sii4	.864
Sii2	.791
Sii3	.777

4.4.4 KMO and Bartlett's test

The Kaiser-Meyer-Olkin (KMO) test reviews the suitability of data for factor analysis by evaluating the strength of its factor structure. KMO values range from 0 to 1, with higher values indicating greater suitability for analysis. A KMO value between 0.8 and 1.0 suggests excellent sampling suitability, while values from 0.7 to 0.79 indicate moderate adequacy. Values between 0.6 and 0.69 are considered average. If the KMO value falls below 0.6, it indicates that the sampling is insufficient for reliable factor analysis (Soroco, 2022).

Another useful analysis for checking the correlation between data is Bartlett's test. This test evaluates whether the correlation matrix resembles an identity matrix, which would suggest that the variables are uncorrelated and not suitable for identifying underlying structures. Essentially, it tests for significant correlations among the variables. If the p-value is less than 0.05, it indicates that factor analysis is appropriate and likely to be meaningful for the dataset (Sigudla et al., 2023).

Table 6 - KMO and Bartlett's test

iteration	1st	2nd	3rd	4th
KMO score	,742	,767	,785	,783
Bartlett's score	0.00	0.00	0.00	0.00

The table shows the results of the KMO (Kaiser-Meyer-Olkin) measure and the Bartlett test for four iterations of the data analysis. The KMO measure, which rates the appropriateness of the factor analysis, shows values increasing from 0.742 in the first iteration to a peak of 0.785 in the third iteration, before decreasing slightly to 0.783 in the fourth iteration. This trend suggests an overall improvement in the suitability of the data for factor analysis.

Furthermore, the Bartlett's test results score consistently 0.00 in all iterations, suggesting strong correlations between the variables. This score confirms the presence of underlying patterns or factors between the variables, indicating that factor analysis is justified and likely provide important insights for this dataset.

4.4.5 Cronbach's alpha validation

A Cronbach's alpha validation test was conducted to address our research's validity and to measure the internal consistency of our data. The survey questions have been tested to see how well they relate to our variables of interest. All our alpha values have been performed higher than the minimum (0.6), indicating a good fit (Sigudla et al., 2023).

The highest reliability was observed in the Perceived Value construct, which demonstrated a very good fit consistency with a Cronbach's alpha of .903. The Purchase Intention construct reported an alpha of .862, indicating good reliability, while the Need to Belong construct recorded slightly lower reliability with an alpha of .802. The Susceptibility to Information construct showed a reliability of .755, which is still above the minimum acceptable value of .6. These alpha values indicate how consistently the survey questions measure the intended constructs, confirming the strength of the study's results.

Table 7 - Cronbach's test

Constructs	Cronbach's Alpha value (α)
Perceived Value	.903
Purchase intention	.862
Need to belong	.802
Susceptibility to information	.755

4.4.6 VIF analysis

Multicollinearity in regression analysis occurs when two or more predictors are closely related, meaning they share a high degree of correlation and do not provide unique or independent information to the model. This can complicate both the fitting and interpretation of the model. Common metrics used to detect and assess the extent of multicollinearity include the Variance Inflation Factor (VIF) and tolerance. In exploratory factor analysis (EFA), it is important to ensure that significant multicollinearity does not exist among the variables (Zach, 2020).

A Variance Inflation Factor (VIF) of 1 indicates that there is no relationship between a predictor variable and the others. A VIF ranging from 1 to 5 suggests a mild relationship, which typically isn't a concern. However, if the VIF exceeds 5, it indicates a strong relationship that can compromise the reliability of your model's results (Potters, 2019). Additionally, Table 8 shows that none of the variables has a score above 5, indicating no multicollinearity issues.

Table 8 - VIF scores

	Purchase intention	Perceived value
NBB	1,041	1,041
SII	1,041	1,041

4.4.7 CFA Model

In this research, we utilize Confirmatory Factor Analysis (CFA) to ensure that our survey questions accurately measure the intended concepts. CFA allows us to verify whether the relationships we anticipate between our questions and the concepts they represent hold true with the collected data. This process is crucial because it confirms that each set of questions effectively corresponds to the specific idea they are meant to measure. To further validate our findings, we present the model fit indices. These indices indicate how well our data aligns with the theoretical model we've proposed.

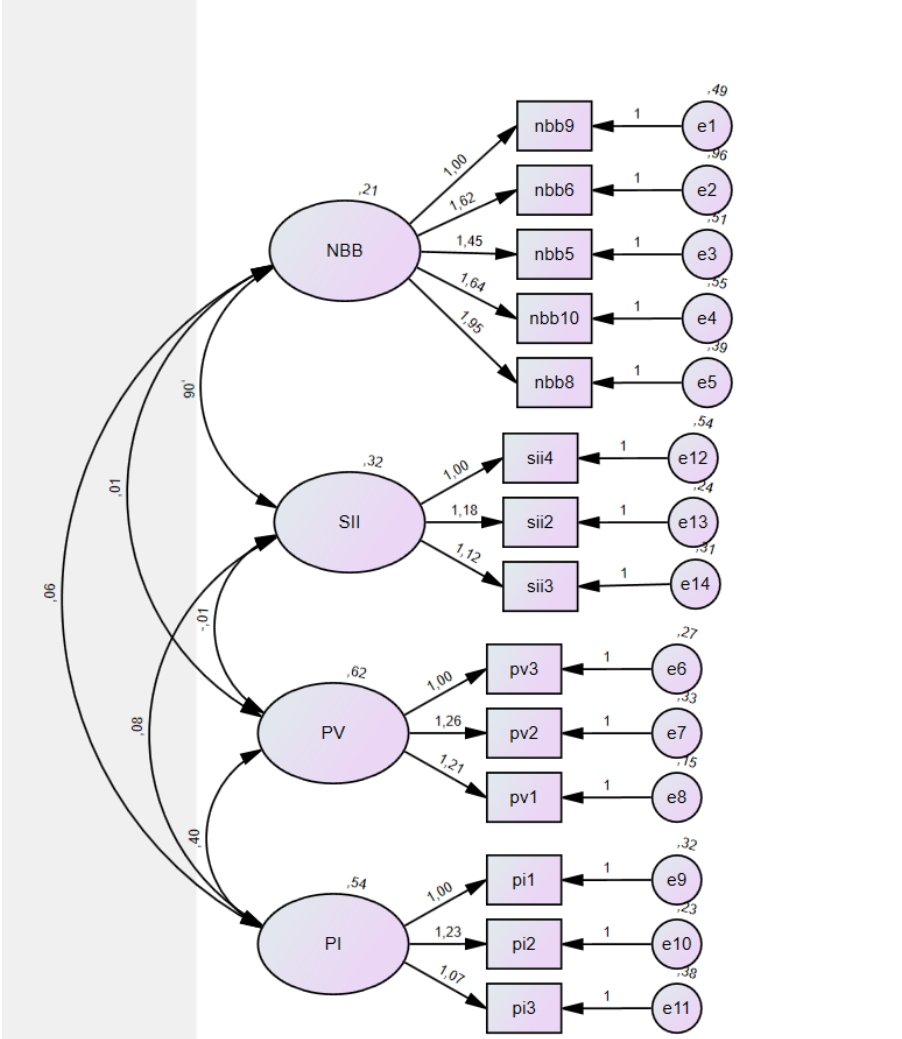


Figure 16 - CFA analysis

The model illustrates four main latent constructs: Need to belong (NBB), Susceptibility to information (SII), Perceived Value (PV), and Purchase intention (PI), each represented by an oval shape. These latent variables are connected to specific observed variables, which are shown as rectangles and represent different questionnaire items detailed in Table 4. Each latent variable is quantified through multiple observed indicators, which exhibit strong connections by their loadings. For instance, NBB shows loadings ranging from 1.45 to 1.82 across its indicators, suggesting a strong measurement of the construct. Similarly, SII's indicators have loadings between 1.12 and 1.18, while PV is measured with loadings from 1.26 to 1.27. The PI construct demonstrates a significant connection to its indicators, with loadings ranging from 1.00 to 1.23. The interconnections between these constructs are illustrated with arrows that show standardized regression weights, indicating the influence one variable has on another. The model also outlines the pathways among the latent variables, highlighting their interconnections. These pathways are likely represented by coefficients that indicate both the strength and direction of the relationships. Additionally, each observed variable contains an error term (e1 to e14), which accounts for measurement error or variance that the latent variables do not capture.

Table 9 - CFA model fit

Index	Acceptable rate for model fit	Our model fit
CMIN/DF	< 3.00	1.102
CFI	≥ 0.90	0.986
TLI	≥ 0.90	0.982
RMSEA	≤ 0.08	0.035
GFI	≥ 0.90	0.88

The table illustrates the model fit indicators from a confirmatory factor analysis (CFA). The Chi-square to degrees of freedom (CMIN/DF) ratio demonstrates excellent fit at 1.102, below the accepted threshold of 3.00. Both the comparative fit index (CFI) and the Tucker-Lewis index (TLI) exceed the minimum standard deviation of 0.90, with values of 0.986 and 0.982, respectively, indicating strong fit. The root mean square error of approximation (RMSEA) is extremely low, 0.035, significantly below the upper bound of 0.08, highlighting the accuracy of the model. However, the goodness of fit (GFI) falls slightly short of the desired benchmark, recorded at 0.88 against a preferred rate ≥ 0.90, suggesting a small scope for improvement in the overall model fit.

5 Results

This section presents the results of our Study 1 and Study 2, including the models developed using SPSS AMOS, followed by hypothesis testing for each study.

5.1 Study 1 – Mediation Analysis

In this section, I present and discuss the results from the structural equation modeling conducted for Study 1, which examined the mediation role of the Need to Belong (NTB) and Susceptibility to Informational Influence (SII) in the relationship between chatbot tactics and the dependent variables: purchase intention (PI) and perceived value (PV). Figure 17 illustrates the connection between the variables of interest. The diagram represents the independent variable – chatbot type, the dependent variables – purchase intention and perceived value, and the mediating variables Need to Belong and Susceptibility to Information. All variables represented in the model are latent constructs derived from selected survey questions identified through exploratory factor analysis (EFA) (Table 4). The model includes 13 error terms (ε), which reflect the measurement error and unexplained variance within the model, highlighting that the paths between these constructs are influenced by factors not explicitly captured in the model.

The neutral chatbot was used as a "control condition" in this study. This means it didn't use any special tactics to influence people's choices. It simply provided information and help, without trying to push people in any direction. The basic chatbot is used as a baseline to compare with other chatbots that use specific strategies like social proof or scarcity. This way, we could see more clearly how those strategies affect what users decide to do.

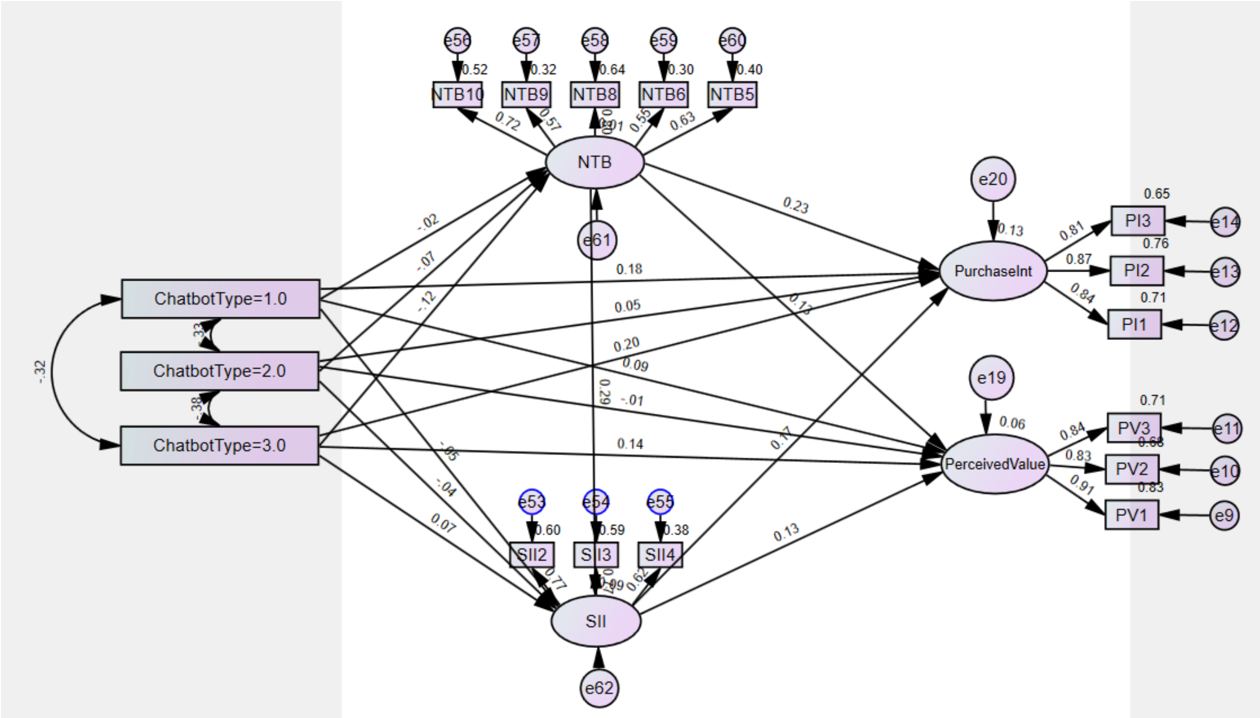


Figure 17 – Study 1, mediation analysis

The model developed in this mediation analysis is based on the relationships identified and outlined in the literature review. Each chatbot type (social proof, scarcity, and authority) is linked to both the Need to Belong (NTB) and Susceptibility to Informational Influence (SII). This indicates an exploration of how different chatbot strategies may impact these personality traits. Additionally, Need to belong (NTB) and Susceptibility to Informational Influence (SII) are connected to Purchase Intention (PI) and Perceived Value (PV), highlighting the investigation into how these traits influence purchasing decisions and the perceived value of customers' intentions. Direct paths from each chatbot type to Purchase Intention and Perceived Value are also illustrated in the diagram. Each dependent variable within the model is also associated with measurement error items (ε), as indicated by lines pointing from constructs to specific measurement variables.

Table 10 - Model fit of Study 1

Index	Acceptable rate for model fit	Our model fit
CMIN/DF	< 3.00	1.729
CFI	≥ 0.90	0.928
TLI	≥ 0.90	0.904
RMSEA	≤ 0.08	0.068
GFI	≥ 0.90	0.873

Table 9 illustrates the model fit from Study 1 we created. It estimates several indices, including the (CMIN/DF) ratio, the (CFI), (TLI), the (RMSEA, and (GFI) index. The CMIN/DF value obtained is 1.729, well below the maximum standard of 3.00, indicating a good model fit. The CFI and TLI scores are 0.928, both above the minimum required level of 0.90, confirming the suitability of the model. In addition, the RMSEA value of 0.068 is below the acceptable threshold of 0.08, indicating a close fit. Lastly, the GFI value is at 0.873, just slightly lower than the desired 0.90. Together, these measures suggest that the model fits the data well, with almost all the indicators meeting the fit criteria.

5.1.1 Test of Hypothesis in Study 1

In Table 10, we can observe the relationships of Study 1 and determine which ones are significant.

Table 11 - Results from Study 1

Effect			Estimate	P-value	Confidence
Need to belong	←	Social proof chatbot	-.041	.840	-
Need to belong	←	Scarcity chatbot	-.117	.544	-
Need to belong	←	Authority chatbot	-.207	.291	-
Susceptibility to information	←	Social proof chatbot	-.086	.615	-
Susceptibility to information	←	Scarcity chatbot	-.063	.698	-
Susceptibility to information	←	Authority chatbot	.104	.529	-
Susceptibility to information	←	Need to belong	.244	.005	-
Purchase Intention	**←**	**Susceptibility to information**	**.204**	***(.089)**	**90%**
Purchase Intention	**←**	**Social proof chatbot**	**.350**	***(.069)**	**90%**
Purchase Intention	←	Scarcity chatbot	.096	.595	-
Perceived Value	←	Need to belong	.148	.178	-
Purchase Intention	**←**	**Authority chatbot**	**.360**	***(.052)**	**90%**

Perceived Value	←	Susceptibility to information	.170	.203	-
Purchase Intention	**←**	**Need to belong**	**.233**	****(.020)**	**95%**
Perceived Value	←	Social proof chatbot	.185	.389	-
Perceived Value	←	Scarcity chatbot	-.015	.940	-
Perceived Value	←	Authority chatbot	.273	.185	-
PV1	←	Perceived Value	1.000		-
PV2	←	Perceived Value	.955	***	-
PV3	←	Perceived Value	.894	***	-
PI1	←	Purchase Intention	1.000		-
PI2	←	Purchase Intention	1.031	***	-
PI3	←	Purchase Intention	.990	***	-
SII2	←	Susceptibility to information	1.000		-
SII3	←	Susceptibility to information	1.025	***	-
SII4	←	Susceptibility to information	.947	***	-
NTB10	←	Need to belong	1.000		-
NTB9	←	Need to belong	.628	***	-
NTB8	←	Need to belong	1.120	***	-

NTB6	←	Need to belong	.877	***	-
NTB5	←	Need to belong	.828	***	-

*Note. **p < 0.05; *p < 0.1;*

The results of Study 1 offer important insights into how different types of chatbots mediate their effectiveness and influence on consumer behavior. This relationship is especially important when considering personality traits such as the Need to Belong (NTB) and Susceptibility to Informational Influence (SII). Additionally, the study examines the outcome variables of Purchase Intention (PI) and Perceived Value (PV).

For Need to belong (NTB), none of the chatbot types had a statistically significant direct effect, as showed by the following estimates: Social proof chatbot (β = -0.041, p = 0.840), Scarcity chatbot (β = -0.117, p = 0.544), and Authority chatbot (β = -0.207, p = 0.291). Since none of these values reached significance, we can conclude that the chatbot types did not have a direct impact on Need to belong in this sample.

When looking at the impact of chatbots on Susceptibility to Informational Influence (SII), we observed similar non-significant results for Social proof chatbot (β = -0.086, p = 0.615), Scarcity chatbot (β = -0.063, p = 0.698), and Authority chatbot (β = 0.104, p = 0.529). However, a significant positive effect was found for the relationship between the Need to belong and the Susceptibility to Informational Influence (β = 0.244, $p < 0.01$), indicating that individuals with a higher Need to Belong are more likely to be influenced by information provided by chatbots.

Turning to Purchase Intention (PI), the results show several significant relationships. Social proof chatbot had a positive and significant effect on Purchase intention (β = 0.350, $p < 0.05$), demonstrating that chatbots using social proof tactics can positively influence consumers' purchase intentions. Similarly, the Authority chatbot also had a significant positive effect on Purchase intention (β = 0.360, $p < 0.05$). In contrast, the Scarcity chatbot did not have a significant impact on Purchase intention (β = 0.096, p = 0.595). Additionally, Susceptibility to Informational Influence had a near-significant impact on Purchase intention (β = 0.204, p = 0.089), and Need to belong positively influenced Purchase intention (β = 0.233, $p < 0.01$).

Regarding Perceived Value (PV), none of the chatbot types had a significant direct effect. The estimates were as follows: Social proof chatbot (β = 0.185, p = 0.389), Scarcity chatbot (β = -0.015, p = 0.940), and Authority chatbot (β = 0.273, p = 0.185). However, Need to belong did not significantly influence Perceived Value (β = 0.148, p = 0.178), nor did Susceptibility to Informational Influence (β = 0.170, p = 0.203).

Table 12 - Summary of hypothesis testing of Study 1

Hypothesis	Relationship	Status	Confidence
H1	Social proof chatbot → Purchase intention	Supported	90%
H2	Authority chatbot → Pur chase intention	Supported	90%
H3	Scarcity chatbot → Purchase intention	Not Supported	-
Exploratory	Need to belong → Purchase intention	Supported	95%
Exploratory	Susceptibility to Informational Influence → Purchase intention	Supported	90%

5.2 Study 2 - Moderation analysis

In the structural equation modeling (SEM) used for this study, moderation analysis plays a crucial role in understanding how variables interact to influence outcomes. Specifically, in Study 2, the moderation process reviews how the relationship between an independent variable (e.g., type of chatbot) and a dependent variable (e.g., perceived value, purchase intention) is affected by a moderator variable (e.g., Need to Belong or Susceptibility to Informational Influence).

To assist this analysis, especially given the latent nature of variables like Need to Belong (NTB), Susceptibility to Informational Influence (SII), Purchase Intention (PI), and Perceived value (PV) composite variables were created to facilitate this analysis. Latent variables, by definition, are not directly observable and are determined from multiple indicators that represent the construct (e.g. survey questions). This requires a methodological approach where composite variables are calculated to represent each latent variable effectively.

Calculation of Composite Variables:

For each latent variable, a composite score was computed by averaging the indicators that conclude the latent construct (Kline, 2015, pp. 71–72). This was done using the following formula:

Equation 1 – the composite variable formula

$$\boldsymbol{Y = (y_1 + \cdots + y_n)/n}$$

For example, the Need to Belong variable was constituted of five items (NTB10, NTB9, NTB8, NTB6, and NTB5). The composite variable was computed by summing the scores for these items (e.g. survey scores) and then dividing by the number of items (e.g. five for NTB), resulting in a median score that effectively represents the latent variable Need to Belong. This same process was applied to the variables Susceptibility to Informational Influence, Purchase Intention and Perceived Value, ensuring that each latent construct had a single, representative score.

To proceed with the moderation analysis, the "interaction term" approach was used, as shown in Table 12. This method involves creating a product term that combines the independent variable and the moderator. The interaction term allows us to assess whether the moderator significantly affects the relationship between the independent variable and the dependent variable.

Table 13 - Product terms

Moderators / Independent variables	Social proof(chatbot=1.0)	Scarcity (chatbot=2.0)	Authority (chatbot=3.0)
Need to belong	SPxNBB	SCxNBB	AUxNBB
Susceptibility to information	SPxSII	SCxSII	AUxSII

A model was developed using the variables from Table 13, which included the three types of chatbots and personality traits to study their interrelationships and effects.

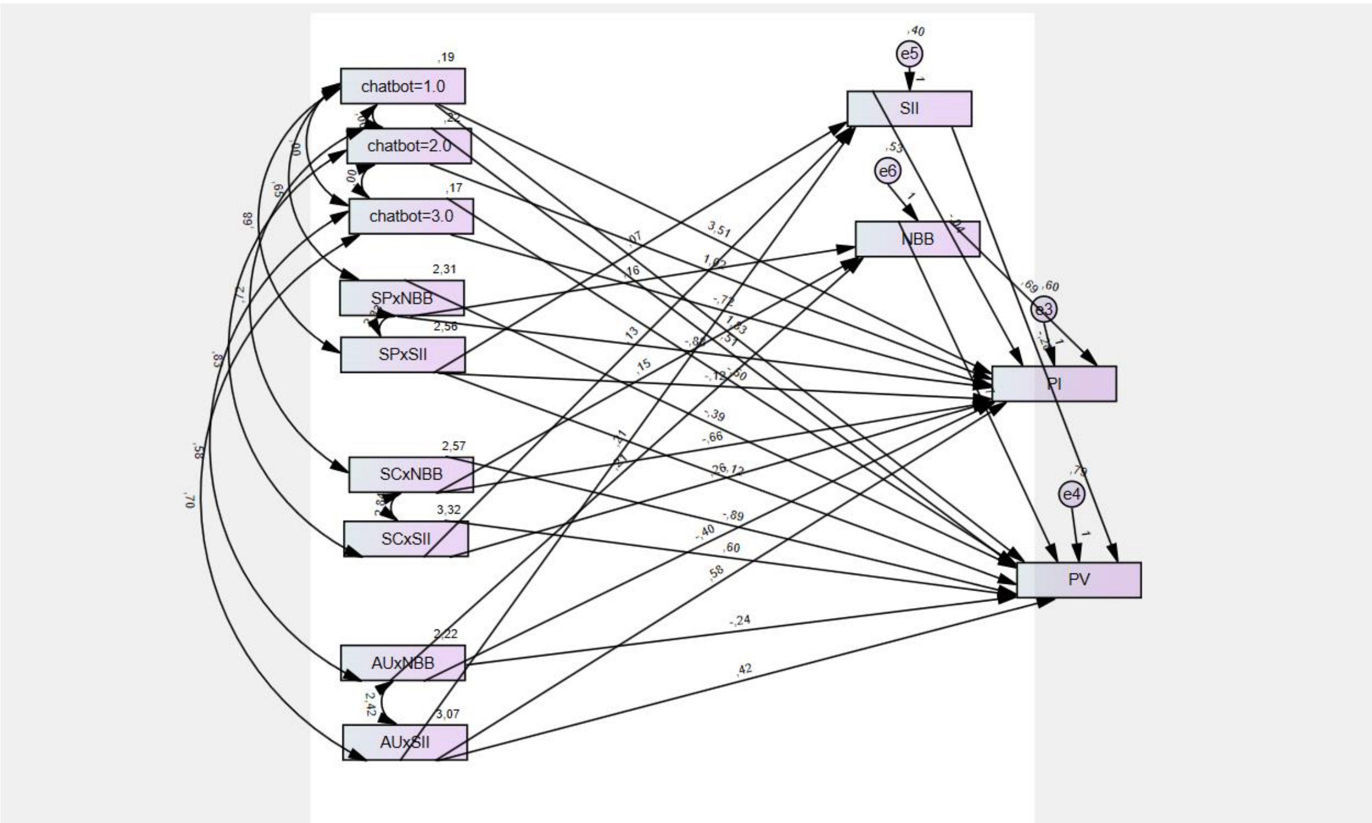


Figure 18 – Study 2, moderation analysis

In Study 2, the structural equation model, various connections are established between different variables, including types of chatbots and personality traits. Each chatbot type (social proof, scarcity, and authority) has a direct impact on both Perceived Value (PV) and Purchase Intention (PI). Further interactions are modeled by including product terms that represent the interaction of social influence tactics with personality traits. These terms—SPxNBB and SPxSII for social proof interactions; SCxNBB and SCxSII for scarcity interactions; and AUxNBB and AUxSII for authority interactions—are directly related to both SII and NBB. Finally, both Susceptibility to informational influence and Need to belong have pathways that lead to Purchase intention and Perceived value, highlighting their influence on these outcome variables.

Table 14 presents the model fit results gained from the developed moderation analysis. It includes several indices such as the Chi-square to degrees of freedom (CMIN/DF) ratio, the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and the goodness of fit (GFI) index.

Table 14 - Model fit of Study 2

Index	Acceptable rate for model fit	Our model fit
CMIN/DF	< 3.00	2.935
CFI	≥ 0.90	0.967
TLI	≥ 0.90	0.919
RMSEA	≤ 0.08	0.152
GFI	≥ 0.90	0.894

The table displays the fit indices from a moderation analysis. The CMIN/DF value of 2.935 indicates a good fit, remaining below the preferred threshold of 3.00. Additionally, the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI) are 0.967 and 0.919, respectively, both suggesting a satisfactory fit since they go above the acceptable criterion of 0.90. However, the Root Mean Square Error of Approximation (RMSEA) is 0.152, which exceeds the desired maximum of 0.08, indicating a poor fit in this area. Finally, the Goodness of Fit Index (GFI) is slightly below the ideal at 0.894, almost reaching the threshold of 0.90.

5.2.1 Testing Hypothesis in Study 2

Study 2 examined how social influence tactics affected customer purchase intentions and explored how personality traits, such as the Need to belong and Susceptibility to informational influence, moderate the relationship between these variables. It was hypothesized that social influence tactics significant impact on purchase intentions (H1, H2, H3), and that certain personality traits also moderate purchase intentions. (H4, H5, H6, H7, H8).

Table 15 – Results from Study 2

Effect			Estimate	P-value	Confidence
Need to belong	←	**SPxNBB**	**,162**	****(,002)**	**95%**
Susceptibility to informational influence	←	SPxSII	,070	,106	-
Need to belong	←	**SCxNBB**	**,153**	****(,002)**	**95%**
Susceptibility to informational influence	←	**SCxSII**	**,128**	*******	**99%**
Need to belong	←	**AUxNBB**	**,212**	*******	**99%**
Susceptibility to informational influence	←	**AUxSII**	**,210**	*******	**99%**

Purchase intention	**←**	**Social proof chatbot**	**3,512**	*******	**99%**
Perceived value	←	Social proof chatbot	1,833	,127	-
Purchase intention	←	Scarcity chatbot	1,018	,322	-
Perceived value	←	Scarcity chatbot	,512	,665	-
Purchase intention	**←**	**SPxNBB**	**-,880**	*******	**99%**
Purchase intention	←	SPxSII	-,120	,625	-
Perceived value	←	SPxNBB	-,393	,138	-
Perceived value	←	SPxSII	-,119	,674	-
Purchase intention	**←**	**SCxNBB**	**-,659**	****(,003)**	**95%**
Perceived value	**←**	**SCxNBB**	**-,890**	*******	**99%**
Purchase intention	←	SCxSII	,258	,374	-
Perceived value	←	SCxSII	,603	,071	-
Purchase intention	**←**	**AUxNBB**	**-,395**	****(,037)**	**95%**
Perceived value	←	AUxNBB	-,243	,266	-
Purchase intention	**←**	**AUxSII**	**,583**	****(,009)**	**95%**
Perceived value	←	AUxSII	,424	,099	-
Purchase intention	**←**	**Need to belong**	**,694**	*******	**99%**
Purchase intention	←	Susceptibility to informational influence	-,044	,741	-
Perceived value	**←**	**Need to belong**	**,472**	*******	**99%**
Perceived value	←	Susceptibility to informational influence	-,276	,070	-
Purchase intention	←	Authority chatbot	-,716	,540	-
Perceived value	←	Authority chatbot	-,501	,709	-

*Note. *p < 0.05; **p < 0.01; ***p < 0.00 1*

Based on the results of the moderation analysis, several relationships between the variables show high confidence levels. For the relationship between Need to Belong (NBB) and the product of Social Proof and Need to Belong (SPxNBB), we observe a positive estimate (β = 0.162) with high significance, confirmed at a 95% confidence level (p = 0.002). Similarly, the Need to belong (NBB) is positively influenced by Scarcity and Need to Belong (SCxNBB), showing an estimate of (β = 0.153) with a 95% confidence level (p = 0.002). Furthermore, the interaction between Authority and Need to Belong (AUxNBB) and Need to belong also demonstrates a significant positive impact (β = 0.212) with 99% confidence (p < 0.001).

Susceptibility to informational influence (SII) is positively affected by the interaction of Authority and Susceptibility to Information (AUxSII), with an estimate of (β = 0.210) at a 99% confidence level (p < 0.001). Additionally, the product of Scarcity and Susceptibility to informational influence (SCxSII) also has a notable positive effect on the moderator (SII) (β = 0.128), supported at a 99% confidence level (p< 0.001).

For the impact on Purchase Intention (PI), the interaction of the Social proof chatbot has a strong positive effect (β = 3.512) with high significance, supported at a 99% confidence level ($p < 0.001$). However, Purchase intention is negatively influenced by the interaction of Social Proof and Need to Belong (SPxNBB) (β = -0.880), which is also highly significant at a 99% confidence level ($p < 0.001$). Additionally, SCxNBB negatively impacts Purchase intention with an estimate of (β = -0.659) at a 95% confidence level ($p = 0.003$).

For Perceived Value (PV), Need to Belong (NBB) positively impacts Perceived value (β = 0.472), with strong confidence at a 99% level ($p < 0.001$). Furthermore, SCxNBB negatively impacts Perceived value (β = -0.890), which is also significant at a 99% confidence level ($p < 0.001$). Finally, Authority and Susceptibility to Information (AUxSII) positively impacts PI (β = 0.583) at a 95% confidence level ($p = 0.009$).

Table 16 - Summary of hypothesis testing of Study 2

Hypothesis	Relationship	Status	Confidence
H1	Social proof chatbot → Purchase intention	Supported	99%
H2	Authority chatbot → Purchase intention	Not Supported	-
H3	Scarcity chatbot → Purchase intention	Not Supported	-
H4	Social proof_chatbot x Need to belong → Purchase intention	Supported	99%
H5	Authority chatbot x Need to belong → Purchase intention	Supported	95%
H6	Scarcity chatbot x Need to belong →Purchase intention	Supported	95%
H7	Social proof_chatbot x Susceptibility to infor. → Purchase intention	Not Supported	-
H8	Authority chatbot x Susceptibility to infor. → Purchase intention	Supported	95%
H9	Scarcity chatbot x Susceptibility to infor. → Purchase intention	Not Supported	-
H6(a)	Scarcity chatbot x Need to belong → Perceived value	Supported	99%

Exploratory	Need to belong → Purchase intention	Supported	99%
Exploratory	Need to belong → Perceived value	Supported	99%

The following table summarizes how different chatbot influence tactics affect Purchase Intention (PI) and Perceived Value (PV). Also, highlights the role of personality traits, as moderating factors. The table illustrates both positive and negative effects, emphasizing the complex responses suggested by various strategies.

Table 17 - effects of chatbot tactics on PI and PV

Chatbot tactic	Personality trait	Purchase intention (PI)	Perceived value (PV)
Social proof		Positive (+)	Not supported
Social proof	Need to belong	Negative (-)	Not supported
Social proof	Susceptibility to inf.	Not supported	Not supported
Scarcity		Not supported	Not supported
Scarcity	Need to belong	Negative (-)	Negative (-)
Scarcity	Susceptibility to inf.	Not supported	Positive (+)
Authority		Positive (+) on Study 1	Not supported
Authority	Need to belong	Negative (-)	Not supported
Authority	Susceptibility to inf.	Positive (+)	Not supported

6 Discussion

6.1 Key findings

6.1.1 Key findings 1: Social proof drives purchase intention.

The study revealed that the social proof tactic effectively affects purchase intentions. Social proof highlights the product's popularity, helping users feel confident in their decisions. These findings suggest that including customer recommendations and focusing on product popularity can enhance purchase intention.

6.1.2 Key findings 2: Scarcity tactics are less effective.

While scarcity tactics are often assumed to create urgency, their effectiveness was inconsistent in this study. For some users, scarcity cues—such as "limited stock available"—felt manipulative or exclusionary. Scarcity-based strategies also presented challenges, as individuals perceived scarcity cues as exclusion rather than attraction. Businesses should use scarcity messaging carefully, focusing on urgency without making customers feel isolated or pressured.

6.1.3 Key findings 3: Authority tactics work selectively.

Authority-based chatbots showed strong results in Study 1 utilizing reliable, evidence-based suggestions to foster trust and increase purchases. However, in Study 2, authority tactics were less effective across the broader audience. This finding suggests that authority messaging needs to be more carefully used and targeted to individuals who are highly influenced by information.

6.1.4 Key findings 4: The negative impact of Need to belong.

The study revealed that personality traits significantly influence how users respond to chatbot tactics. Study 2 showed that the moderating effect of the need to belong between social influence tactics on purchase intention is negative. This means that individuals with a high need to belong are negatively affected when interacting with social influence tactics. This might suggest that customers could feel eliminated due to the messages or their interactions with the chatbot. Messages that trigger feelings of exclusion should be avoided. Moreover, instead of emphasizing only the popularity, focus on why the product is a good fit for the customer. For instance, instead of using the phrase *"This product is recommended by 9 of 10 users."*, this could be adjusted to *"This product is highly recommended by 9 of 10 users, be part of our community!".*

6.1.5 Key findings 5: The role of Susceptibility to informational influence on purchase intention

Individuals with high Susceptibility to informational influence were the only ones who responded positively to authority tactics. To build trust, chatbots should focus on sharing clear and reliable information without overwhelming users. This can be translated that the customers need to know information about the products, but this could be done in a more interactive and engaging, like using pie charts or diagrams and not only plain text. Instead of bombing customers with too much data, the chatbot can keep things simple and easy to follow. A good way to do this is by giving users a choice of the option to select between quick summaries and more detailed ones. By modifying the amount of information to what each user prefers, chatbots can create a better experience and make interactions feel more personal and trustworthy.

6.1.6 Key findings 6: Personalization is crucial.

These results emphasize the need to adapt chatbot strategies to individual user traits, as a one-size-fits-all approach may not effectively engage all consumers. High Need to belong users require messages that emphasize inclusivity and connection, while high Susceptibility to information influences users to prioritize credible and detailed information. By adapting chatbot strategies to individual personality traits, businesses can enhance user engagement and satisfaction. Personalization reduces the risk of isolating users with generic or manipulative messaging. In the future, businesses should focus on developing adaptive chatbots capable of identifying user preferences and dynamically adjusting communication strategies to meet their needs. This approach will create a more meaningful and impactful consumer experience, ultimately driving purchase intentions.

6.2 THEORETICAL IMPLICATIONS

The study provides valuable insights into how chatbots can influence what people purchase, specifically how individual behavior-adapted chatbots make the users likely to buy more.

Social influence strategies are extensively researched in the field of consumer behavior, with Cialdini's (1984) fundamental theories of scarcity, authority, and social proof long being used to explain how marketing tactics can influence customer choices. According to Cialdini's paradigm, consumers tend to imitate the actions of others (social proof), respond to scarcity by placing greater value on limited things, and refer to the judgments of authority figures when making decisions.

Study 1, establishes theories of social influence—such as social proof, scarcity, and authority—in the context of chatbot interactions, providing fresh insights into consumer behavior in digital environments. While social influence strategies have been thoroughly examined in traditional marketing, their use and impact within chatbot interactions remain largely underexplored (Camilleri et al., 2022, Frison et al., 2023, Følstad et al., 2021)**.** By focusing on how these strategies behave in a digital, automated environment, this research fills an important gap, offering a new perspective on how consumers engage with digital agents that replicate social influence.

Our findings reveal that social proof tactics, traditionally used to persuade consumers by emphasizing popularity or widespread acceptance, can significantly enhance purchase intentions when integrated into chatbot interactions. The positive estimates ($\beta = 0.350$, $p = 0.69$; $\beta = 3.51$, $p < 0.001$) of social proof in Studies 1 and Study 2 respectively, suggest that it remains highly effective in chatbot interactions, supporting hypothesis H1. This supports Cialdini's (1984) work but demonstrates its relevance in a digital context, highlighting how automated systems can replicate social influence tactics to shape consumer choices.

When it comes to scarcity tactics—such as indicating that a product is almost sold out or available for a limited time—the effects are not always straightforward. While these strategies typically enhance the perceived value of a product and drive urgency, both Study 1 and Study 2 demonstrated that this was not always the case. In fact, the hypotheses, H2, related to the effectiveness of scarcity were rejected in both studies, suggesting that scarcity cues do not consistently lead to increased purchase intention. This challenges the common belief that scarcity always boosts sales and highlights the potential for some people to feel left out. For digital marketers, this means finding a careful balance to avoid isolating users who prioritize social connection.

On the other hand, authority-based chatbots, which use expert endorsements or credible information, consistently build trust and encourage purchases. While this aligns with classical theories by Milgram (1974) and Cialdini (2009), it introduces a new dimension by showing that automated systems can leverage perceived expertise and authority to influence consumer behavior effectively. In Study 1, authority tactics showed positive estimates ($\beta = .360$, $p = 0.52$), indicating their potential for increasing purchase intention. However, in Study 2, this effect was not supported, leading to a partial acceptance of the hypothesis (H3). Unlike social proof or scarcity, authority cues tend to be accepted across different personality types, making them a steady and effective tool for influencing consumer behavior without causing pushback. This underscores the unique ability of trusted recommendations to engage users in digital spaces.

The data indicate that both social proof and authority-based methods significantly influence purchase intention, while scarcity is less effective. However, perceived value does not appear to have a meaningful connection with these techniques. This suggests that, although social proof and authority cues can affect purchasing decisions, they do not necessarily change customers' perceptions of a product's value.

People with a strong need to belong desire to feel included and accepted by others, which influences their behavior, including their purchasing decisions. According to Leary et al. (2013), those who have a high urge to belong to a group are more likely to make decisions based on social cues, such as other people's opinions. The study indicates that participants with a higher Need to Belong were more likely to desire to buy a product after interacting with chatbots ($\beta = .233$, $p = .020$), indicate results from Study 1. This suggests that when people have a strong need to belong, they are more likely to be influenced by interactions that make them feel connected or part of a community. In addition, Study 1 revealed a positive connection between both personality traits and purchase intention. Moreover, suggested that individuals who are more open to new information showed a significant increase in purchase intention ($\beta = .204$, $p = .089$). This aligns well with established theories for informational influence. For instance, Deutsch and Gerard (1955) and later research by Bearden et al. (1989) both suggest that the source of information plays a crucial role in influencing purchase intention. People are more likely to be influenced by information about products that come from their community circle, which affects their decision-making process. This research also extends this understanding to the impact of chatbot interactions, suggesting that consumers who are more susceptible to information are more likely to follow the recommendations of chatbots, thereby boosting their purchase intention.

Insights from Study 2 reveal the interactions between personality traits and social influence strategies. An interesting result appears when we combine personality traits and social influence. The concept of social proof is questioned by the negative interactions between social proof and the Need to Belong (SPxNBB). The significant relations ($\beta = -.880$, $p<0.001$) for these interactions, support H4, and suggest that individuals with a stronger need for belonging may react negatively to social proof strategies used in chatbot conversations. This adds complexity to the theory and challenges the idea that social proof always increases purchase intention, indicating that personality traits may influence the success of social proof. This finding aligns with the results of Bearden et al. (1989), who observed that the context and the media through which information is accessed can impact an individual's sensitivity to informational effects.

Moreover, the authority chatbot has a smaller negative impact ($\beta = -0.395$ and $\beta = 0.583$, respectively) in its interactions with the Need to Belong (AUxNBB) and Susceptibility to Information (AUxSII), as revealed in Study 2. Both hypotheses H5 and H8 are confirmed. This implies that authority tactics are less likely to push away people with these personality traits than scarcity or social proof. The low negative impact suggests that the authority aspect of the chatbot may cause discomfort for certain individuals, especially those who have a strong urge to belong, which could decrease their likelihood of making a purchase. Customers who are more easily biased by information do not show high resistance to messages that are seen as convincing, particularly if they feel that the marketing is too directive or impersonal.

Similarly, scarcity-based chatbots had an impact on their purchase interactions. Study 2 found a negative relationship between scarcity tactics and the Need to belong (SCxNBB) ($\beta = -0.659$, $p = 0.03$). This suggests that scarcity cues may prompt feelings of exclusion or social discomfort in some users, reducing the likelihood of purchase. However, the interaction between scarcity tactic and information sensitivity (SCxSII) was not validated, suggesting that this method of influence did not consistently affect individuals who were more sensitive to informational cues. Furthermore, scarcity tactics combined with Need to belong (SCxNBB) significantly reduced perceived value ($\beta = -0.890$, $p < 0.001$). This finding suggests that individuals with a strong need to belong may experience feelings of exclusion or discomfort in response to scarcity messages, leading them to assign lower value to the product. This interaction is noteworthy because it is the only significant association found between personality traits and perceived value; all other personality-related interactions did not significantly affect them. These suggest that scarcity, when combined with certain personality traits, uniquely affects how customers perceive their purchase intentions and the value of products. This highlights the importance of careful message design for scarcity, as it can enhance perceived value for some consumers while reducing it for others, particularly those who are sensitive to social inclusion. Therefore, scarcity-based strategies should take into account individual personality profiles to prevent negative effects on customers' perceived value.

By recognizing and addressing individual differences, digital marketing can transform from a simplistic approach into something far more meaningful and impactful. This research deepens our understanding of how social influence functions in virtual environments and establishes a new standard for digital interactions. Imagine a future where chatbots are not only automated agents but empathetic and adaptive guides that learn from every interaction. This evolution paves the way for digital agents that do not just focus on making sales but also truly engage with users, fostering deeper connections and lasting relationships. It aligns with the perception that personalization and empathy-driven influence strategies foster more meaningful engagements, resonating deeply with Cialdini's foundational principles of influence.

These findings emphasize the potential of chatbots as "emotional companions." In addition to answering user queries and promoting products, these chatbots can detect emotional signals—such as hesitation, frustration, or excitement—from users and adapt their responses accordingly. For instance, if a user resists social proof tactics, the chatbot can pivot its approach, either calming the user or providing contextual information. This level of emotional intelligence and adaptability could transform consumer interactions. This line up with findings from Deutsch and Gerard (1955) on informational influence, illustrating how different responses to different cues can better promote trust and engagement.

The personalization in digital influence is essential rather than optional. Traditional marketing often depends on static assumptions about consumer behavior; however, this research emphasizes the need for flexible strategies that take into account each user's unique psychological profile. By customizing tactics like social proof, scarcity, and authority to match individual traits—such as the need to belong or susceptibility to informational influence—chatbots can deliver an experience that feels personalized, respectful, and truly engaging. These features may just be part of the larger psychological environment that influences customer decisions. Other psychological factors, like as openness to experience, conscientiousness, or even risk aversion, could influence how consumers interact with chatbots and react to influencer methods. A more comprehensive approach to consumer profiling, which considers a broader variety of psychological, emotional, and behavioral traits, could result in more accurate and meaningful interactions (Hirsh et al., 2012).

Our research challenges the "one size fits all" approach commonly used in chatbot communication strategies. While social proof, scarcity, and authority are well-known as effective marketing tactics (Cialdini, 2009), our study indicates that their impact is heavily influenced by individual personality traits. These findings contribute to existing theories on social influence by revealing that consumers do not consistently respond to these strategies. Instead, their reactions are shaped by deeper psychological needs and preferences, as highlighted by the contrasting effects of the Need to Belong and Susceptibility to Information. Chatbots, often referred to as "emotional companions," show great potential. Beyond simply answering questions and promoting products, these chatbots can interpret users' emotional signals—such as doubt, impatience, or excitement—and adjust their responses accordingly. For instance, if a user dismisses social proof cues, the chatbot might change its approach by offering a different approach to the issue. This level of emotional adaptability could transform consumer interactions, aligning with the research by Deutsch and Gerard (1955) on how varied responses to cues can enhance trust and engagement.

6.3 MANAGERIAL IMPLICATIONS

This research brings forward essential insights for managers, particularly in e-commerce, who aim to enhance customer interactions with chatbots. By understanding which chatbot strategies work best with different customers, businesses can use their resources more effectively. This helps them focus on strategies that lead to higher customer satisfaction and stronger loyalty.

One of the main findings is the importance of personalization in chatbot interactions. Using AI-driven systems, businesses can adapt chatbot communication to fit individual customer traits, like a high “Need to Belong” or being highly "Susceptible to Information." By tailoring chatbot responses to these traits, companies create more meaningful and engaging customer experiences. Research supports that personalized experiences make customers feel more connected to the brand, ultimately increasing engagement and satisfaction (Smith et al., 2019).

Managers should also recognize that although chatbot strategies such as social proof, authority, and scarcity are generally effective, they work differently depending on the customer segment. For example, some consumers respond positively to social proof tactics, while others might feel pressured or manipulated if these tactics are overused. This makes it crucial for businesses to apply these strategies thoughtfully, ensuring that they don’t overwhelm or alienate their customers. The application of chatbot strategies isn’t limited to e-commerce. These tactics can be used across sectors like banking, travel, and customer service. In banking, for instance, chatbots can offer personalized loan options based on customer preferences, while in travel, scarcity strategies can be used to promote limited-time offers. The flexibility of these strategies allows businesses in various industries to enhance their customer experiences while achieving scalable solutions. Chatbot installations should align with corporate objectives to enhance customer satisfaction, ensuring they are not overly aggressive or impersonal.

Finally, it’s essential for businesses to continuously monitor customer feedback and adjust their chatbot strategies as needed. This ensures that chatbots remain effective tools for increasing engagement without leading to customer dissatisfaction. Ongoing investment in AI improvements allows chatbots to better respond to customer interactions, leading to higher satisfaction rates and improved conversion rates over time. By effectively applying these strategies, businesses can control AI-driven chatbots to enhance customer engagement, satisfaction, and ultimately, long-term loyalty.

6.4 LIMITATIONS

The study provides valuable information, but several constraints must be considered. Firstly, including two different moderators, "Need to Belong" and "Susceptibility to Informational Influence," made the study more complex. Handling both moderators in the same model made it difficult to assess their effects on the connection between chatbots and purchase intention. It might have been easier to develop two independent models, each focusing on one moderator at a time, which could have provided more specific insights.

The SEM analysis was restricted due to the sample size. Even though we received 170 valid replies for the study, SEM generally requires 200 or more responses to ensure accurate results. Some recommendations even suggest 400 responses for a more robust model (Kline, 2015). A larger sample size would have provided greater statistical power. The data analysis process was complex and time-consuming, particularly in understanding and preparing the dataset. Simplifying the data collection method and allocating more time for analysis could have relieved these issues and led to clearer conclusions.

In addition, the experimental setting used a fictional e-commerce environment and a chatbot with a limited set of responses, which may not fully capture the complexity and variability of consumer interactions in the real world. This limitation could affect the external validity and generalizability of the findings. Real-world e-commerce environments, which often present more dynamic and unpredictable interactions, may elicit different consumer behaviors and reactions. In addition, the software used to develop the chatbot limited flexibility and restricted the ability to add features that could improve the user experience. This may have limited participant engagement and interaction with the chatbots, potentially affecting the results of the study.

Despite these challenges, the findings of this study emphasize the importance of carefully planning chatbot interactions and creating tools that improve engagement and accuracy. By addressing these limitations in future research, we can gain a deeper understanding of how chatbots affect consumer intentions and enhance their effectiveness in digital marketing campaigns.

6.5 FUTURE RESEARCH

Future research should focus on increasing the sample size in future studies would provide greater statistical power and more reliable results. Researchers should aim to collect 200 or more responses, with 400 being ideal for robust SEM modeling. This would enhance the accuracy of the model estimates and provide greater confidence in the generalizability of the findings.

To improve data analysis, future research should focus on simplifying data collection methods and allowing more time for the analysis. This would help reduce potential errors, clarify findings, and enhance the overall quality of conclusions.

Future studies should also consider conducting experiments in real-world e-commerce environments rather than relying just on fictional ones. This would provide more realistic insights into how chatbots influence consumer behavior, taking into account dynamic factors such as varying consumer preferences and spontaneous interactions. In addition, using more advanced and flexible chatbot development tools that allow for customization and adaptation could improve user engagement and provide richer interactions, leading to more meaningful results.

Furthermore, this study included a diverse group of participants in terms of age and gender, providing a comprehensive overview of consumer responses to chatbot interactions. However, future research could benefit from a more focused examination of how these demographic factors influence the effectiveness of social influence strategies, as well as the role of personality traits. This demographic perspective may uncover distinct patterns of engagement, enabling more targeted and effective digital marketing initiatives.

To conclude, this study demonstrates that social influence strategies—such as social proof, scarcity, and authority—can impact customer behavior through chatbots. However, their effectiveness is shaped by individual personality traits and the context of the interactions.

Key takeaways include the effectiveness of authority-based chatbots in building trust and increasing perceived value and purchase intentions. This highlights the impact of credible, expertise-driven messaging. Equally, the effects of social proof and scarcity cues were more varying; for instance, purchase intention sometimes decreased when scarcity or social proof triggered resistance in individuals with a high Need to Belong, as they felt isolated or pressured. These findings illustrate that users' ‘’translate’’ interactions with chatbots significantly affect their perceived value and purchase intentions, underscoring the importance of adaptable influencing strategies.

From a practical perspective, these findings offer actionable suggestions for companies aiming to enhance engagement through chatbot conversations. By improving perceived value with targeted messages that align with specific user characteristics, businesses can enhance customer purchase intention. Tailoring chatbots to adapt to users' preferences and psychological needs can create more meaningful experiences for consumers, highlighting the importance of adaptability and empathy in digital interactions.

While the study provides a strong foundation for understanding digital influence, it also highlights areas for further research. Future studies should replicate these findings in real-world settings with larger sample sizes and explore how other personality factors interact with digital influence tactics. By expanding on these findings, researchers can enhance digital marketing strategies and create more effective, empathetic, and responsive consumer experiences.

REFERENCES

Amblee, N., & Bui, T. (2011). Harnessing the influence of social proof in online shopping: The effect of electronic word of mouth on sales of digital microproducts. *International journal of electronic commerce*, *16*(2), 91-114.

Ameen, N., Cheah, J., & Kumar, S. (2022). It’s all part of the customer journey: The impact of augmented reality, chatbots, and social media on the body image and self-esteem of Generation Z female consumers. *Psychology & Marketing*, *39*(11). https://doi.org/10.1002/mar.21715

Aral, S. (2011). Identifying Social Influence: A Comment on Opinion Leadership and Social Contagion in New Product Diffusion. Marketing Science, 30(2), 217–223. https://doi.org/10.1287/mksc.1100.0596

Austin, S. (2024, May 13). *Scarcity Marketing: The Psychology of Using Scarcity in Marketing (10+ Examples & Best Practices) - Marketing Scoop*. Marketing Scoop. https://www.marketingscoop.com/marketing/scarcity-marketing-the-psychology-of-using-scarcity-in-marketing-10-examples-best-practices/

Bartholomew, K., & Horowitz, L. M. (1991). Attachment Styles Among Young Adults: Kim Bartholomew Simon Fraser University Burnaby, British Columbia, Canada A Test of a Four-Category Model. *Journal of Personality and Social Psychology*, *61*, 226–244.

Baumeister, R. F. (2012). Need-to-Belong Theory. Handbook of Theories of Social Psychology, 121–140. https://doi.org/10.4135/9781446249222.n32

Baumeister, R. F. (2012). Need-to-belong theory. *Handbook of theories of social psychology*, *2*, 121-140.

Baumeister, R. F., & Leary, M. R. (2017). The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Interpersonal development*, 57-89.

Bearden, W. O., Netemeyer, R. G., & Teel, J. E. (1989). Measurement of consumer susceptibility to interpersonal influence. *Journal of consumer research*, *15*(4), 473-481.

Benlian, A., Titah, R., & Hess, T. (2012). Differential effects of provider recommendations and consumer reviews in e-commerce transactions: An experimental study. *Journal of Management Information Systems*, *29*(1), 237-272.

Camilleri, M. A., & Troise, C. (2022). Live support by chatbots with artificial intelligence: A future research agenda. *Journal of Service Theory and Practice*. Retrieved from https://link.springer.com/article/10.1007/s11628-022-00513-9

Chen, J., Teng, L., Yu, Y., & Yu, X. (2016). The effect of online information sources on purchase intentions between consumers with high and low susceptibility to informational influence. *Journal of Business Research*, *69*(2), 467–475.

Chen, J.-S., Le, T.-T.-Y., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. International Journal of Retail & Distribution Management, 49(11). https://doi.org/10.1108/ijrdm-08-2020-0312

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and Customer Satisfaction regarding Luxury Brands. *Journal of Business Research*, *117*, 587–595. https://doi.org/10.1016/j.jbusres.2018.10.004

Cialdini, R. B. (2007). Influence: The psychology of persuasion: Robert B. Cialdini. New York, United States: Collins.

Cialdini, R. B., & Goldstein, N. J. (2004). Social influence: Compliance and conformity. Annual Review of Psychology, 55(1), 591–621. https://doi.org/10.1146/annurev.psych.55.090902.142015

Cialdini, R. B., & Trost, M. R. (1998). Social influence: Social norms, conformity and compliance.

Cohen, J. B., & Golden, E. (1972). Informational social influence and product evaluation. *Journal of Applied Psychology*, *56*(1), 54–59.

Davlembayeva, D., & Papagiannidis, S. (2024, March 8). *Social Influence Theory - TheoryHub - Academic theories reviews for research and T&L*. Open.ncl.ac.uk. https://open.ncl.ac.uk/theories/15/social-influence-theory/

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018). BERT: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Dinh,C.-M., & Park, S. (2023). How to increase consumer intention to use chatbots? An empirical analysis of hedonic and utilitarian motivations on social presence and the moderating effects of fear across generations. ElectronicCommerce Research. https://doi.org/10.1007/s10660-022-09662-5

Dogan, V. (2019). Why Do People Experience the Fear of Missing Out (FoMO)? Exposing the Link Between the Self and the FoMO Through Self-Construal. *Journal of Cross-Cultural Psychology*, *50*(4), 524-538.

Følstad, A., et al. (2021). Future directions for chatbot research: An interdisciplinary research agenda. *Software Quality Journal*. Retrieved from https://link.springer.com/article/10.1007/s00607-021-01016-7

Frison, A., & Zerfass, A. (2023). The diffusion of chatbot research across disciplines: A systematic literature review. In *Advances in Artificial Intelligence and Applications* (pp. XX-XX). Springer. Retrieved from https://link.springer.com/chapter/10.1007/978-3-031-58307-0_2

Gallo, K. P., Comer, J. S., Barlow, D. H., Clarke, R. N., & Antony, M. M. (2015). Direct-to-consumer marketing of psychological treatments: A randomized controlled trial. Journal of Consulting and Clinical Psychology, 83(5), 994–998.

Gefen, D., & Straub, D. (2003). *Managing user trust in B2C e-services*. e-service Journal, Vol. 2 No. 2, pp. 7-24.

Go, E., & Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior*, *97*, 304–316. https://doi.org/10.1016/j.chb.2019.01.020

Gretry, A., Horváth, C., Belei, N., van Riel, A.: “Don’t pretend to be my friend!” when an informal brand communication style backfires on social media. J. Bus. Res. 74, 77–89 (2017)

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, Mirror on the Wall: A Comparative Evaluation of Composite-based Structural Equation Modeling Methods. Journal of the Academy of Marketing Science (JAMS), 45(5), 616-632.

Hassanein, K., & Head, M. (2007). Manipulating perceived social presence through the web interface and its impact on attitude towards online shopping. *International Journal of Human-Computer Studies*, *65*(8), 689–708. https://doi.org/10.1016/j.ijhcs.2006.11.018

Hildebrand, C., & Bergner, A. (2020). Conversational robo advisors as surrogates of trust: onboarding experience, firm perception, and consumer financial decision making. *Journal of the Academy of Marketing Science*, *49*(4), 659–676. https://doi.org/10.1007/s11747-020-00753-z

Hirsh, J. B., Kang, S. K., & Bodenhausen, G. V. (2012). Personalized persuasion: Tailoring persuasive appeals to recipients' personality traits. *Psychological science*, *23*(6), 578-581.

Hoffmann, A. O. I., & Broekhuizen, T. L. J. (2009). Susceptibility to and impact of interpersonal influence in an investment context. *Journal of the Academy of Marketing Science*, *37*(4), 488–503. https://doi.org/10.1007/s11747-008-0128-7

Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K., & Shankar, V. (2020). Transforming the customer experience through new technologies. *Journal of interactive marketing*, *51*(1), 57-71.

Hu, L.-t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling, 6(1), 1–55. https://doi.org/10.1080/10705519909540118

Janis, I. L. (1954). Personality correlates of susceptibility to persuasion 1. *Journal of personality*, *22*(4), 504-518.

Jin, E., & Eastin, M. S. (2023). Birds of a feather flock together: matched personality effects of product recommendation chatbots and users. *Journal of Research in Interactive Marketing*, *17*(3), 416-433.

Khetarpal, M., & Singh, S. (2024). "Limited Time Offer": Impact of Time Scarcity Messages on Consumer's Impulse Purchase. *Journal of Promotion Management*, *30*(2), 282-301.

Kline, P. (1994). An Easy Guide to Factor Analysis (1st ed.). Routledge. https://doi.org/10.4324/9781315788135

Kline, R. B. (2015). Principles and Practice of Structural Equation Modeling. Guildford Press.

Kock, N. (2016). Hypothesis Testing with Confidence Intervals and P Values in PLS-SEM. *International Journal of E-Collaboration*, *12*(3), 1–6. https://doi.org/10.4018/ijec.2016070101

Kvale, K., Freddi, E., Hodnebrog, S., Sell, O. A., & Følstad, A. (2021). Understanding the User Experience of Customer Service Chatbots: What Can We Learn from Customer Satisfaction Surveys? *Chatbot Research and Design*, *12604*, 205–218. https://doi.org/10.1007/978-3-030-68288-0_14

Lai, C., Altavilla, D., Ronconi, A., & Aceto, P. (2016). Fear of missing out (FOMO) is associated with activation of the right middle temporal gyrus during inclusion social cue. *Computers in Human Behavior*, *61*, 516-521.

Leary, M. R., Kelly, K. M., Cottrell, C. A., & Schreindorfer, L. S. (2013). Individual differences in the need to belong: Mapping the nomological network. *Journal of Personality*, 81(1), 128-141

Li, M., & Wang, R. (2023). Chatbots in e-commerce: The effect of chatbot language style on customers' continuance usage intention and attitude toward brand. *Journal of Retailing and Consumer Services*, *71*, 103209. https://doi.org/10.1016/j.jretconser.2022.103209

Liaquat, A. (2023, March 24). *Chatbot Marketing: Strategy & Examples for Digital Success*. Aliliaquat.com. https://aliliaquat.com/chatbot-marketing-strategy-and-examples/

Liebrecht, C., Sander, L., van Hooijdonk, C. (2021). Too Informal? How a Chatbot's Communication Style Affects Brand Attitude and Quality of Interaction. In: Følstad, A., *et al.* Chatbot Research and Design. CONVERSATIONS 2020. Lecture Notes in Computer Science (), vol 12604. Springer, Cham. https://doi.org/10.1007/978-3-030-68288-0_2

LLP, S. I. (2024, March 13). *Global Chatbot Market Size To Exceed USD 42.83 Billion By 2033 | CAGR of 23.03%*. GlobeNewswire News Room. https://www.globenewswire.com/news-release/2024/03/13/2845189/0/en/Global-Chatbot-Market-Size-To-Exceed-USD-42-83-Billion-By-2033-CAGR-of-23-03.html

Marimon, F., Mas-Machuca, M., & Akhmedova, A. (2024). Trusting in Generative AI: Catalyst for Employee Performance and Engagement in the Workplace. *International Journal of Human-Computer Interaction*, 1–16. https://doi.org/10.1080/10447318.2024.2388482

McLean, G. and Osei-Frimpong, K. (2019), "Chat now. . . Examining the variables influencing the use of online live chat", Technological Forecasting and Social Change, Vol. 146, pp. 55-67.

McLean, G., & Osei-Frimpong, K. (2019). Examining satisfaction with the experience during a live chat service encounter-implications for website providers. Computers in Human Behavior, 95, 302-315

Mehraban, M. (2023, April 27). *The Power of Scarcity in Marketing: Real-Life Examples and Best Practices - Creativeo*. Www.creativeo.co. https://www.creativeo.co/post/scarcity-examples-marketing

Meichan, L. (2023). Chatbots in e-commerce: The effect of chatbot language style on customers continuance usage intention and attitude toward the brand. *Journal of Retailing and Consumer Services*, *71*(C). https://doi.org/10.1016/j.jretconser.2022.103209

Mena, P., Barbe, D., & Chan-Olmsted, S. (2020). Misinformation on Instagram: The Impact of Trusted Endorsements on Message Credibility. *Social Media + Society*, *6*(2).

Metzger, M. J., & Flanagin, A. J. (2013). Credibility and trust of information in online environments: The use of cognitive heuristics. *Journal of pragmatics*, *59*, 210-220.

Misischia, C. V., Poecze, F., & Strauss, C. (2022). Chatbots in customer service: Their relevance and impact on service quality. *Procedia Computer Science*, *201*(201), 421–428. ScienceDirect. https://doi.org/10.1016/j.procs.2022.03.055

Murtarelli, G., Collina, C., & Romenti, S. (2022). "Hi! How can I help you today?": investigating the quality of chatbots–millennials relationship within the fashion industry. *The TQM Journal*. https://doi.org/10.1108/tqm-01-2022-0010

Nadkarni, A., & Hofmann, S. G. (2012). Why do people use Facebook? *Personality and individual differences*, *52*(3), 243-249.

Pengnate, S.F., & Sarathy, R. (n.d.). *An experimental investigation of the influence of website emotional design features on trust in unfamiliar online vendors*. Computers in Human Behavior. Vol. 67, pp. 49-60.

Perski, O., Crane, D., Beard, E., & Brown, J. (2019). Does the addition of a supportive chatbot promote user engagement with a smoking cessation app? An experimental study. *DIGITAL HEALTH*, *5*, 205520761988067. https://doi.org/10.1177/2055207619880676

Pett, M.A., Lackey, N.R., & Sullivan, J.J. (2003). Making sense of factor analysis: The use of factor analysis for instrument development in health care research. SAGE.

Pickett, C. L., Gardner, W. L., & Knowles, M. (2004). Getting a cue: The need to belong and enhanced sensitivity to social cues. *Personality and social psychology bulletin*, *30*(9), 1095-1107.

Potters, C. (2019). *Variance Inflation Factor Definition*. Investopedia. https://www.investopedia.com/terms/v/variance-inflation-factor.asp

Przybylski, A. K., Murayama, K., DeHaan, C. R., & Gladwell, V. (2013). Motivational, emotional, and behavioral correlates of fear of missing out. *Computers in human behavior*, *29*(4), 1841-1848.

Risselada, H., Verhoef, P. C., & Bijmolt, T. H. A. (2014). Dynamic Effects of Social Influence and Direct Marketing on the Adoption of High-Technology Products on JSTOR. *Journal of Marketing*, *78*(2), 52–68. https://www.jstor.org/stable/26654760

Roethke, K., Klumpe, J., Adam, M., & Benlian, A. (2020). Social influence tactics in e-commerce onboarding: The role of social proof and reciprocity in affecting user registrations. *Decision Support Systems*, *131*.

Ruane, E., Farrell, S., & Ventresque, A. (2021). User Perception of Text-Based Chatbot Personality. *Chatbot Research and Design* , 32–47. https://doi.org/10.1007/978-3-030-68288-0_3

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting Structural Equation Modeling and Confirmatory Factor Analysis Results: A Review. *The Journal of Educational Research*, *99*(6), 323–338. https://doi.org/10.3200/joer.99.6.323-338

Seidman, G. (2013). Self-presentation and belonging on Facebook: How personality influences social media use and motivations. *Personality and individual differences*, *54*(3), 402-407.

Sigudla, J., & Maritz, J. E. (2023). Exploratory factor analysis of constructs used for investigating research uptake for public healthcare practice and policy in a resource-limited setting, South Africa. *BMC Health Services Research*, *23*(1), 1423. https://doi.org/10.1186/s12913-023-10165-8

Sridhar, S., & Srinivasan, R. (2012). Social Influence Effects in Online Product Ratings. *Journal of Marketing*, *76*(5), 70–88. https://doi.org/10.1509/jm.10.0377

Toader, V., De Jong, A., & de Vries, R. (2020). Understanding consumer satisfaction with chatbots: The role of brand equity and usability. *Journal of Retailing and Consumer Services*, 56, 102188.

Van der Heijden, H. (2004). User acceptance of hedonic information systems. *MIS Quarterly*, *28*(4), 695–704.

Wikipedia Contributors. (2019, November 8). *ELIZA*. Wikipedia; Wikimedia Foundation. https://en.wikipedia.org/wiki/ELIZA

Xu, K., Chen, X., & Huang, L. (2022). Deep mind in social responses to technologies: A new approach to explaining the computers is social actors phenomena. *Computers in Human Behavior*, *134*, 107321

Xu, P., Huang, Y., Liao, B., & Lu, K. (2021). Exploring the implementation of artificial intelligence applications among academic libraries in Taiwan. Library Hi Tech.

Xu, Y., Zhang, J., Chi, R., & Deng, G. (2022). Enhancing customer satisfaction with chatbots: the influence of anthropomorphic communication styles and anthropomorphized roles. *Nankai Business Review International*. https://doi.org/10.1108/nbri-06-2021-0041

Yang, X. (2020), "Influence of informational factors on purchase intention in social recommender systems", Online Information Review, Vol. 44 No. 2, pp. 417-431. https://doi.org/10.1108/OIR-12-2016-0360

Zach. (2020). *How to Test for Multicollinearity in SPSS*. Statology. https://www.statology.org/multicollinearity-spss/

APPENDIX

Appendix A: Survey Questionnaire

Task description:
Task This study investigates how chatbots can support online shopping experiences.

Task Overview: Imagine you are getting ready for an outdoor adventure and you need to find the right **hiking shoes**. You will interact with a chatbot, which will guide you to make your purchase. At the bottom right of the page, you can see the chatbot and interact with it. After you complete your session, you can fill out the survey with your impressions and feedback! 👟 📋

Duration: Please allocate approximately 10 minutes to complete this interaction and the survey. 🕔

Disclaimer: Your participation in this survey is completely anonymous. All your answers will be kept confidential and will not be linked to you in any way. Data will be used for research purposes only.

Instructions:
Click on the chatbot icon in the right corner of your screen!
Goal**:** Dive into a conversation with our chatbot and explore your shopping options. Answer a short questionnaire after your interaction with the chatbot.

Thank you!
Your time and input are invaluable to us. 😊

Questions:
Q1 How old are you?

____

Q2 How do you describe yourself?

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary / third gender (3)
- ○ Prefer to self-describe (4) ____
- ○ Prefer not to say (5)

Q28 **Part 1: Chatbot interaction**

In the first section, we will ask you questions about your recent experience with our chatbot.

Q1 Rate your **satisfaction** with the chatbot interaction

- ○ Very Dissatisfied (1)
- ○ Dissatisfied (2)
- ○ Neutral (3)
- ○ Satisfied (4)
- ○ Very Satisfied (5)

Q2 Imagine that you were actually looking to buy hiking shoes 👟. In that scenario, **to what extent** would you **agree** with the following statements?

	Strongly Disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
The chatbot would make my shopping easier. (1)	○	○	○	○	○
The chatbot would save me time. (2)	○	○	○	○	○
The chatbot would be useful for my shopping. (3)	○	○	○	○	○

Q3 Regarding the chatbot's recommendations, **to what extent** would you **agree** with the following statements? (Imagine that you were actually looking to buy hiking shoes 👟)

	Strongly Disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I would consider buying the products recommended by the chatbot. (1)	○	○	○	○	○
I would be likely to buy the products recommended by the chatbot. (2)	○	○	○	○	○
I would be willing to buy the products recommended by the chatbot. (3)	○	○	○	○	○

Part 2: Tell us a bit about yourself

The second section includes some **personal questions** that help us understand our audience better. All your answers will be treated anonymously.

Q48 To what extent do you **agree** with the following **statements about yourself**?

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
To make sure I buy the right product or brand, I often observe what others are buying and using (1)	o	o	o	o	o
If I have little experience with a product, I often ask my friends about the product. (2)	o	o	o	o	o
I often consult other people to help choose the best alternative available from a product class. (3)	o	o	o	o	o
I frequently gather information from friends or family about a product before I buy (4)	o	o	o	o	o

Q44 **You are almost done!**

We just need to ask you some final **personal questions** that help us understand our audience better. All your answers will be treated anonymously.

Q49 To what extent do you **agree** with the following **statements about yourself**?

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
If other people don’t seem to accept me, I don’t let it bother me. (1)	○	○	○	○	○
I try hard not to do things that will make other people avoid or reject me. (2)	○	○	○	○	○
I rarely worry about whether other people care about me. (3)	○	○	○	○	○
I need to feel that there are people I can turn to in times of need. (8)	○	○	○	○	○
I want other people to accept me. (9)	○	○	○	○	○

Q50 To what extent do you **agree** with the following **statements about yourself**?

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I do not like being alone. (1)	○	○	○	○	○
Being apart from my friends for long periods of time does not bother me (2)	○	○	○	○	○
I have a strong “need to belong.” (3)	○	○	○	○	○
It bothers me a great deal when I am not included in other people’s plans. (8)	○	○	○	○	○
My feelings are easily hurt when I feel that others do not accept me. (9)	○	○	○	○	○

Q52 To what extent do you **agree** with the following **statements about yourself**?

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I do not like being alone. (1)	○	○	○	○	○
Being apart from my friends for long periods of time does not bother me (2)	○	○	○	○	○
I have a strong “need to belong.” (3)	○	○	○	○	○
It bothers me a great deal when I am not included in other people’s plans. (8)	○	○	○	○	○
My feelings are easily hurt when I feel that others do not accept me. (9)	○	○	○	○	○

Q51 Feel free to share any other comments you may have.

____

Q47 For a chance to win a €30 Amazon coupon, please enter your email address below:

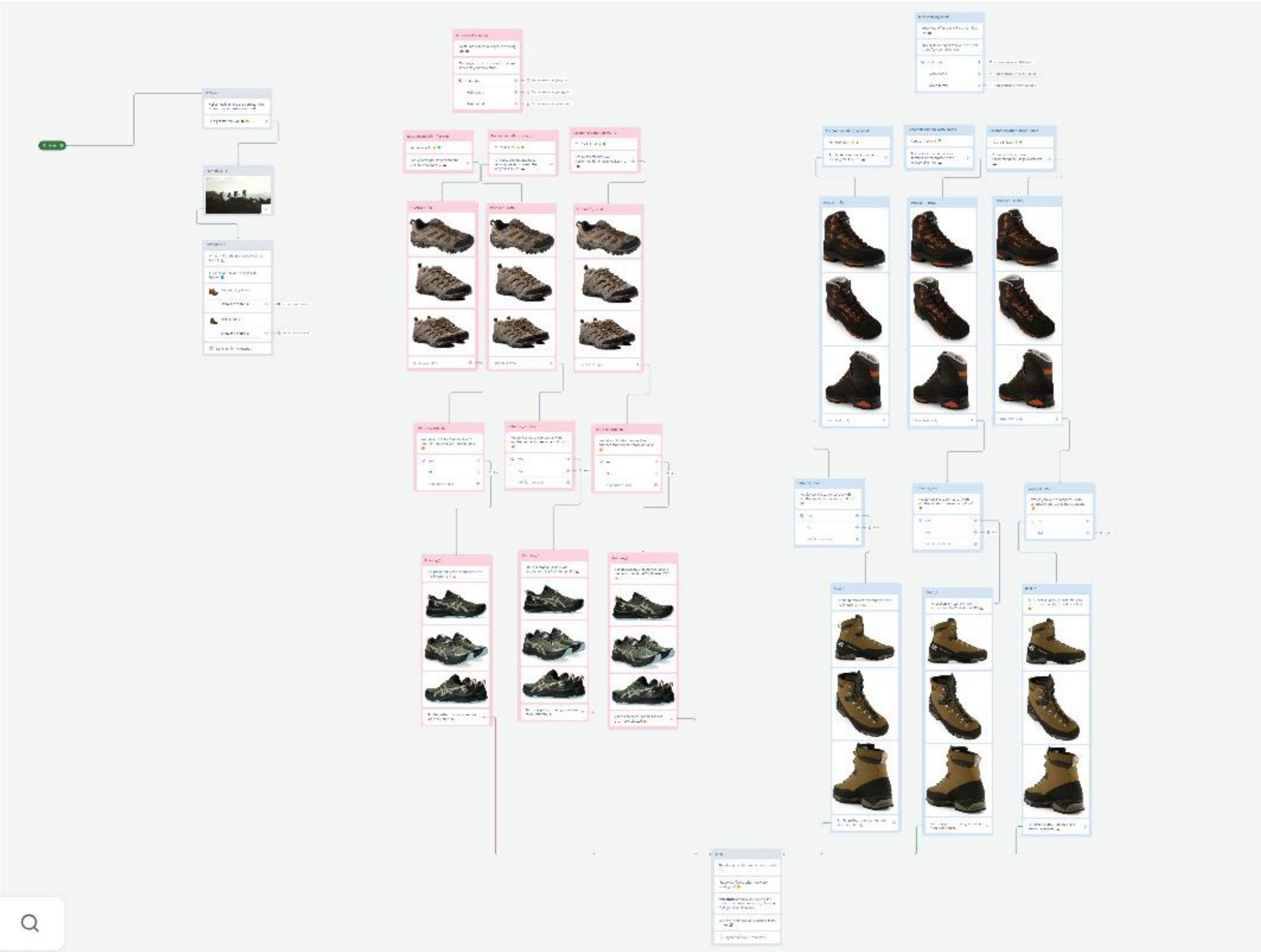
____

Appendix B: Chatbot Development

SOCIAL PROOF CHATBOT

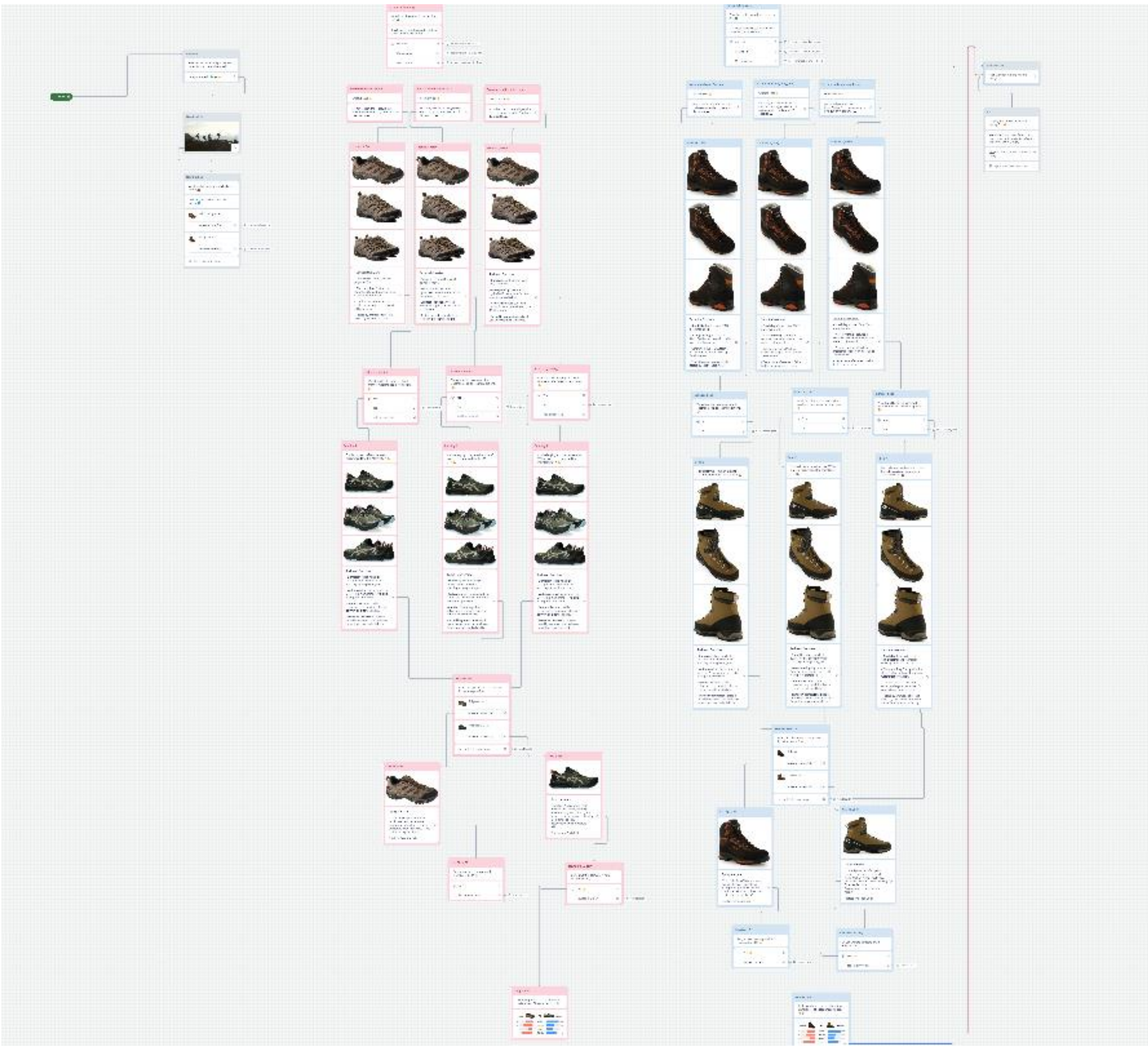
social proof chatbot development

SCARCITY CHATBOT



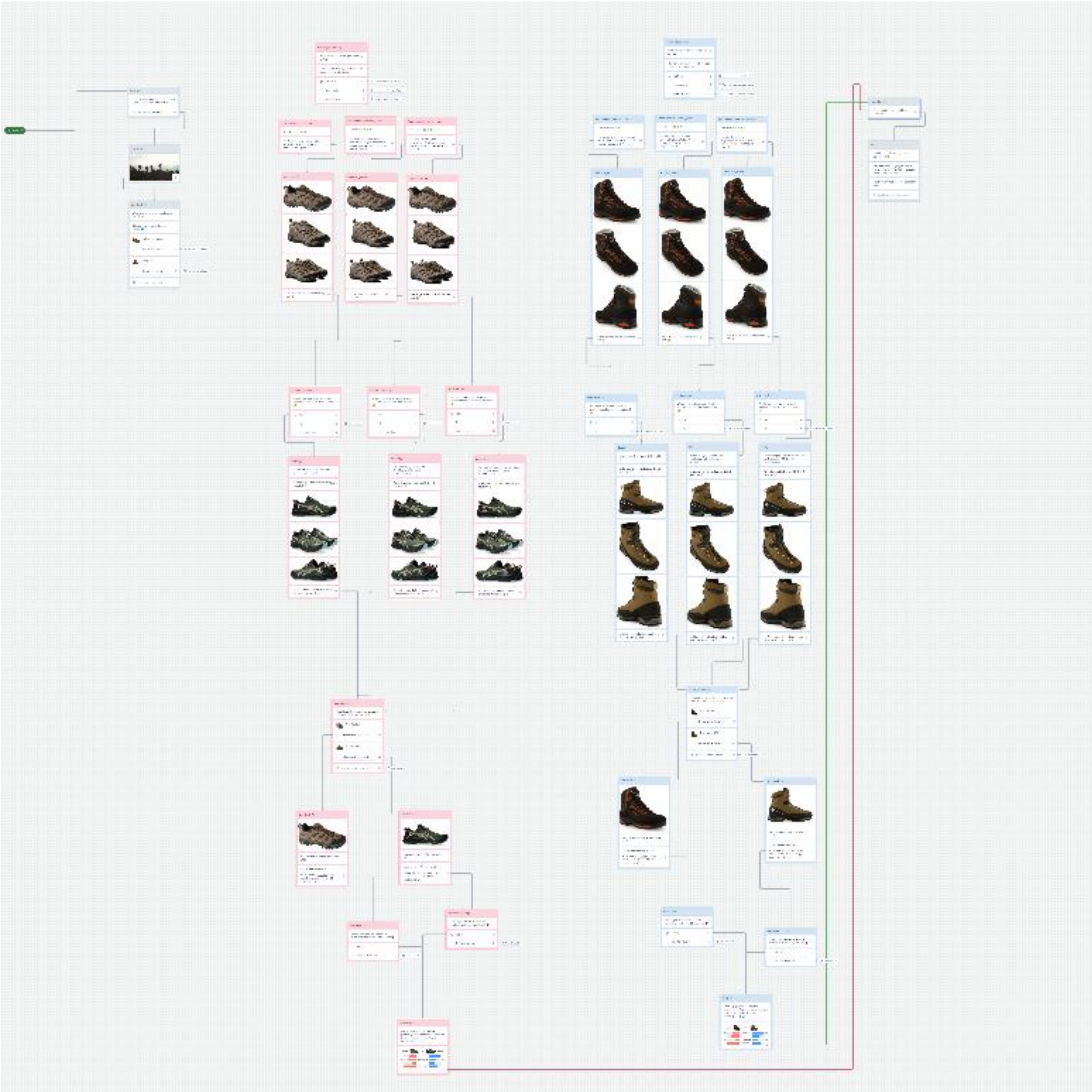
scarcity chatbot development

AUTHORITY CHATBOT



authority chatbot development

NEUTRAL CHATBOT



Neutral chatbot development

Appendix C: Additional Statistical Results

STUDY 1

<u>MODEL FIT SUMMARY</u>

<u>CMIN</u>

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	68	176.362	102	.000	1.729
Saturated model	170	.000	0		
Independence model	34	1165.121	136	.000	8.567

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.849	.798	.930	.904	.928
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.750	.636	.696
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

Model	NCP	LO 90	HI 90
Default model	74.362	41.406	115.186
Saturated model	.000	.000	.000
Independence model	1029.121	923.840	1141.847

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	1.116	.471	.262	.729
Saturated model	.000	.000	.000	.000
Independence model	7.374	6.513	5.847	7.227

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.068	.051	.085	.044
Independence model	.219	.207	.231	.000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	312.362	329.848		
Saturated model	340.000	383.714		

Independence model	1233.121	1241.863		

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	1.977	1.768	2.235	2.088
Saturated model	2.152	2.152	2.152	2.429
Independence model	7.805	7.138	8.518	7.860

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	114	124
Independence model	23	25

EXECUTION TIME SUMMARY

Minimization: .043

Miscellaneous: 1.084

Bootstrap: 63.045

Total: 64.172

REGRESSION WEIGHTS: (GROUP NUMBER 1 - DEFAULT MODEL)

			Estimate	S.E.	C.R.	P	Label
NTB	<---	ChatType_1	-.041	.204	-.202	.840	
NTB	<---	ChatType_2	-.117	.192	-.607	.544	
NTB	<---	ChatType_3	-.207	.196	-1.056	.291	
SII	<---	ChatType_1	-.086	.171	-.503	.615	
SII	<---	ChatType_2	-.063	.161	-.388	.698	
SII	<---	ChatType_3	.104	.165	.629	.529	
SII	<---	NTB	.244	.086	2.822	.005	
PURCHASEINT	<---	SII	.204	.120	1.703	.089	
PURCHASEINT	<---	ChatType_1	.350	.192	1.821	.069	
PURCHASEINT	<---	ChatType_2	.096	.181	.531	.595	
PERCEIVEDVALUE	<---	NTB	.148	.110	1.347	.178	
PURCHASEINT	<---	ChatType_3	.360	.185	1.946	.052	
PERCEIVEDVALUE	<---	SII	.170	.133	1.274	.203	
PURCHASEINT	<---	NTB	.233	.100	2.323	.020	
PERCEIVEDVALUE	<---	ChatType_1	.185	.214	.862	.389	
PERCEIVEDVALUE	<---	ChatType_2	-.015	.202	-.075	.940	
PERCEIVEDVALUE	<---	ChatType_3	.273	.206	1.324	.185	
PV1	<---	PerceivedValue	1.000				
PV2	<---	PerceivedValue	.955	.074	12.881	***	
PV3	<---	PerceivedValue	.894	.068	13.177	***	
PI1	<---	PurchaseInt	1.000				
PI2	<---	PurchaseInt	1.031	.085	12.074	***	
PI3	<---	PurchaseInt	.990	.087	11.355	***	
SII2	<---	SII	1.000				
SII3	<---	SII	1.025	.146	7.038	***	
SII4	<---	SII	.947	.146	6.505	***	

NTB10	<---	NTB	1.000				
NTB9	<---	NTB	.628	.100	6.284	***	
NTB8	<---	NTB	1.120	.136	8.226	***	
NTB6	<---	NTB	.877	.144	6.094	***	
NTB5	<---	NTB	.828	.119	6.976	***	

STUDY 2

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	53	388,362	38	,000	10,220
Saturated model	91	,000	0		
Independence model	13	1934,134	78	,000	24,797

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	,381	,737	,371	,308
Saturated model	,000	1,000		
Independence model	,614	,334	,223	,286

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,799	,588	,815	,613	,811
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,487	,389	,395
Saturated model	,000	,000	,000
Independence model	1,000	,000	,000

NCP

Model	NCP	LO 90	HI 90
Default model	350,362	290,821	417,361
Saturated model	,000	,000	,000
Independence model	1856,134	1716,563	2003,077

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	4,623	4,171	3,462	4,969
Saturated model	,000	,000	,000	,000
Independence model	23,025	22,097	20,435	23,846

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	,331	,302	,362	,000
Independence model	,532	,512	,553	,000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	494,362	515,562	623,822	676,822
Saturated model	182,000	218,400	404,281	495,281
Independence model	1960,134	1965,334	1991,889	2004,889

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	5,885	5,176	6,683	6,138
Saturated model	2,167	2,167	2,167	2,600
Independence model	23,335	21,673	25,084	23,397

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	12	14
Independence model	5	5

Execution time summary

Minimization: ,068

Miscellaneous: ,191

Bootstrap: 4,078

Total: 4,337

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
NBB	<---	SPxNBB	,162	,052	3,094	,002	
SII	<---	SPxSII	,070	,043	1,614	,106	
NBB	<---	SCxNBB	,153	,050	3,079	,002	
SII	<---	SCxSII	,128	,038	3,362	***	
NBB	<---	AUxNBB	,212	,053	3,970	***	
SII	<---	AUxSII	,210	,040	5,296	***	
PI	<---	chatbot_1	3,512	1,045	3,361	***	
PV	<---	chatbot_1	1,833	1,201	1,526	,127	
PI	<---	chatbot_2	1,018	1,029	,990	,322	
PV	<---	chatbot_2	,512	1,182	,433	,665	
PI	<---	SPxNBB	-,880	,231	-3,815	***	
PI	<---	SPxSII	-,120	,246	-,489	,625	
PV	<---	SPxNBB	-,393	,265	-1,481	,138	
PV	<---	SPxSII	-,119	,283	-,421	,674	
PI	<---	SCxNBB	-,659	,225	-2,924	,003	
PV	<---	SCxNBB	-,890	,259	-3,435	***	
PI	<---	SCxSII	,258	,290	,889	,374	
PV	<---	SCxSII	,603	,334	1,807	,071	
PI	<---	AUxNBB	-,395	,190	-2,083	,037	
PV	<---	AUxNBB	-,243	,218	-1,112	,266	

PI	<---	AUxSII	,583	,224	2,605	,009	
PV	<---	AUxSII	,424	,257	1,651	,099	
PI	<---	NBB	,694	,116	5,988	***	
PI	<---	SII	-,044	,133	-,331	,741	
PV	<---	NBB	,472	,133	3,549	***	
PV	<---	SII	-,276	,152	-1,811	,070	
PI	<---	chatbot_3	-,716	1,169	-,612	,540	
PV	<---	chatbot_3	-,501	1,344	-,373	,709	