Master Thesis: The Persuasion Knowledge Model as a Determinant of Trust in Chatbot Adoption

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A. Abstract

Chatbots have become increasingly popular in today's era of rapid advances in artificial intelligence and the widespread use of messaging services. However, the widespread use of chatbots is hindered by challenges related to customer trust in chatbots. To address these challenges, it is crucial to understand the factors that influence customer trust in chatbots. This study examines the role of the Persuasion Knowledge Model (PKM) on trust in chatbots and the intention to use chatbots, and whether anthropomorphic chatbot characteristics moderate the relationship between the PKM and trust in chatbots. A quantitative experiment was conducted by distributing an online survey to 134 participants via the crowdsourcing platform Prolific. The analysis reveals no relationship between persuasion knowledge and trust in chatbots, a strong relationship between agent knowledge and trust in chatbots, and a weak relationship between topic knowledge and trust in chatbots. The presence or absence of anthropomorphic chatbot characteristics does not moderate these relationships. These findings contribute to our understanding of customer trust in chatbots and provide insights for organizations to design more effective and trustworthy chatbot interactions.

B. Introduction

In this current era of rapid advances in artificial intelligence, machine learning, and natural language processing techniques, combined with the growth of the mobile device market and the popularity of messaging platforms, chatbots have gained widespread popularity (Mohamad Suhaili et al., 2021). Chatbots are computer programs equipped with natural language processing capabilities (Sheehan et al., 2020) that act as conversational agents and simplify consumers' lives by being user-friendly, time-saving, and accessible 24/7 (Maher et al., 2022). In addition to simplifying consumers' lives, chatbots benefit organizational efficiency by reducing the time and costs spent on customer service tasks (Nicolescu & Tudorache, 2022) and by gathering valuable customer data that can contribute to increasing sales and conversion rates (Hsu & Lin, 2023).

However, the implementation of chatbots also results in difficulties and constraints in terms of customer trust in chatbots, which prevent customers from adopting chatbots, such as risks related to the security of personal and limitations in their ability to understand messages and generate natural language (Nicolescu & Tudorache, 2022). These difficulties and limitations faced by customers also have organizational implications, as customers who do not trust the organization's chatbot are more likely to experience reduced loyalty and decreased purchase intentions toward the organization (Jenneboer et al., 2022).

To address these issues for both customers and organizations, it is important to increase trust in chatbots for both customers and organizations (Jenneboer et al., 2022). However, there exists a gap in understanding the factors that influence customers' trust in chatbots (Følstad et al., 2018). Gaining insights into these influential factors of trust in chatbots will help organizations improve and customize their chatbots to meet customers' expectations and requirements (Nordheim et al., 2019). Prior research has established that perceived trust in chatbots is an essential factor that positively affects the behavioral intention to use chatbots (Mohd Rahim et al., 2022). While some research has been conducted on the factors that influence trust in chatbots, such as credibility, competence, anthropomorphism, social presence, and informativeness (Yen & Chiang, 2021), chatbot-specific and service context factors (Følstad et al., 2018), as well as chatbot-related, environment-related, and user-related factors (Nordheim et al., 2019).

The Persuasion Knowledge Model (PKM) is a model that focuses on how people make use of their understanding of persuasion strategies and goals to interpret, evaluate, and respond to the efforts of marketers (Friestad & Wright, 1994), in this case, chatbots' efforts. The PKM consists of three distinct knowledge structures that shape and determine the outcomes of persuasion attempts: persuasion knowledge, agent knowledge, and topic knowledge (Friestad & Wright, 1994). There remains a research gap in the role of the PKM as an antecedent of trust in chatbots (Kim et al., 2021). Addressing this research gap is important because organizations are increasingly using chatbots for persuasion purposes (Ischen et al., 2020), while no research has been conducted on whether customers' persuasion knowledge influences their trust in and the subsequent intention to use chatbots.

Finding out whether these knowledge structures influence trust in chatbots can help organizations design effective chatbots that are perceived as trustworthy. More specifically, it can help organizations respond to customers' persuasion knowledge when designing chatbots for persuasive purposes. For example, if a customer's persuasion knowledge, agent knowledge, or topic knowledge leads to a decrease in trust in chatbots, organizations might consider creating very transparent chatbots. This will give customers the feeling that they are receiving unbiased and accurate information, which could help to rebuild trust. On the other hand, if a customer's persuasion knowledge, agent knowledge, or topic knowledge, results in an increase in trust in chatbots, organizations can use these insights to further enhance their trust-building strategies by for example emphasizing the expertise and credibility of the chatbot. Organizations can also tailor chatbot interactions and responses based on customers' persuasion knowledge by recognizing the role of the PKM in developing trust in chatbots. For example, if customers have a certain level of persuasion knowledge that leads to a higher level of trust, organizations can modify the chatbot's communication tactics to match the user's level of understanding. This personalization can increase the persuasiveness and trustworthiness of chatbots.

Further, given that many studies on chatbots have recognized the influence of anthropomorphic characteristics of chatbots in the customer adoption process of chatbots (Araujo, 2018; Han, 2021; Schanke et al., 2021), this thesis will also investigate whether chatbot anthropomorphism affects the direction and the strength of the relationship between the PKM and trust in chatbots which will also help organizations design their chatbots effectively. For example, when it turns out that anthropomorphic characteristics positively moderate the relationship between the PKM and trust in chatbots, organizations might consider adding more anthropomorphic characteristics to their chatbots to generate more trust in chatbots when customers have a certain level of persuasion knowledge, agent knowledge, or topic knowledge.

The primary objective of this study is to gain insight into the relationship between customers' persuasion knowledge, agent knowledge, topic knowledge, and trust in chatbots and their subsequent intention to use chatbots. Additionally, this research aims to investigate whether the relationship between these knowledge structures of the PKM and trust in chatbots is influenced by anthropomorphic chatbot characteristics. This leads to the following research question:

RQ: "What is the role and impact of the persuasion knowledge model on trust in chatbots and the subsequent intention to use them?"

This thesis is structured as follows: The thesis begins with a theoretical background on chatbots for customer service, trust in chatbots, the Persuasion Knowledge Model, and anthropomorphism. The third chapter focuses on the data collection process, including sample information and ethical considerations, and the methods used for the data analysis. This is followed by the results chapter, which provides an overview of the findings derived from the analysis. The subsequent chapter brings forth the conclusion, where a clear answer to the research question is provided. In addition, this thesis includes a chapter dedicated to the discussion and theoretical implications of the findings. A separate chapter is devoted to the practical implications, providing suggestions on how organizations can use the findings of this study to improve their practices. Finally, the chapter concerning limitations and suggestions for future research highlights the limitations of the study and potential directions for future research for academics who are interested in the PKM and chatbots.

C. Theoretical background

1. Chatbots for customer service

Organizations have realized that integrating artificial intelligence (AI) technologies into their operations can improve their competitive advantage, innovation processes, and their ability to adapt to changing customer needs (Mariani et al., 2023). AI refers to computer systems that simulate human intelligence and perform humanlike tasks to improve the efficiency of daily tasks (Shi et al., 2021). Organizations are increasingly adopting AI technologies because AI technologies have greater computational information processing capabilities and a greater analytical approach compared to humans (Jarrahi, 2018).

A particularly popular area where organizations are implementing AI technologies is the domain of customer service (Adam et al., 2021). Organizations implement chatbots into their customer service, which are computer programs with natural language processing capabilities that can be programmed to engage in conversations with humans (Sheehan et al., 2020). Users use everyday language to enter requests into chatbots, and the chatbots then use underlying machine learning algorithms to determine the user's intent. The associated response of the chatbot is then triggered by this intent prediction (Zhang et al., 2023). To improve customer service, chatbots are used for various purposes such as customer engagement, sales, and promotions (Ngai et al., 2021).

Such enhanced customer service through chatbots can improve organizational interactions and reinforce favorable organizational attitudes (Zhang et al., 2023). An important reason for implementing chatbots is cost reduction as chatbots can serve as a replacement for employees (Rossmann et al., 2020). Another major benefit of implementing chatbots is their ability to collect valuable customer data. This information helps to gain insights into customer needs and preferences which can lead to increased sales and conversation rates, as well as an improved shopping experience (Hsu & Lin, 2023). For example, Lego introduced a chatbot called Ralph to support its Christmas sales. With his unique personality and engaging demeanor, Ralph drove a remarkable 25% of sales from social media and helped to reduce the costs per conversion by more than 70% (Hsu & Lin, 2023). The benefits of chatbots over human customer service are also being recognized by customers, highlighting a more convenient and unique alternative to long waiting times that offers 24/7 accessibility

(Misischia et al., 2022). Many customers are becoming more comfortable with the idea of algorithms becoming a part of their daily lives. Some even exhibit algorithm appreciation (Schanke et al., 2021), which implies that they prefer algorithm guidance, such as chatbot guidance, above human guidance (Hou & Jung, 2021). This trend serves as an additional incentive for organizations considering the implementation of chatbots in their customer service operations (Schanke et al., 2021). Furthermore, research shows that customers view organizations that use chatbots as more innovative and efficient, indicating a positive attitude toward the implementation of chatbots by an organization (Zhang et al., 2023).

However, customers are not always satisfied with chatbots because they often fail to understand user input (Sheehan et al., 2020). For example, chatbots may respond to customers inappropriately, resulting in a mismatch between customer expectations and system performance, which may then lead to undesirable customer behaviors such as noncompliance (Ngai et al., 2021). Further, it is important to note that chatbots do not have moral reasoning capabilities and cannot act as independent agents with a moral code, leading to ethical challenges in their implementation (Murtarelli et al., 2021). Chatbots may engage in humanlike conversations that are more like data collection exercises than real conversations, raising concerns about privacy and trust. And chatbots may also compromise network security and privacy if they collect and store sensitive data without proper safeguards, which can lead to misunderstanding and potential harm (Murtarelli et al., 2021).

2. Trust in chatbots

Although chatbots offer various benefits, Roy and Naidoo (2021) argue that customers usually prefer to engage with real humans compared to chatbots. For chatbot adoption to be successful, it is crucial that customers trust chatbots (Nordheim et al., 2019). Despite the growing body of research on trust in technologies (Følstad et al., 2018), such as extensions of the Technology Acceptance Model (Pavlou, 2001), extensions of the UTAUT model (Slade et al., 2015), or the Privacy-Trust-Behavioral Intention Model (Liu et al., 2005), there is a lack of research investigating trust in chatbots specifically (Nordheim et al., 2019). It is difficult to find a common definition of trust as the concept of trust is used in different disciplines, such as sociology, psychology, and organization theory (Seitz et al., 2022). Despite the challenge of finding a common definition of trust, the most widely cited definition of trust comes from Mayer et al. (1995). It characterizes trust as the willingness of one party to be open to the actions of another party, based on the expectation that the other party will perform a specific action that is important to the trustor, regardless of the ability to control or manage the other party (Mayer et al., 1995). Mayer et al. (1995) found that benevolence, integrity, and competence are the main indicators of trust. Although their research was on organizational trust, these indicators have also been used in research on trust in technologies (Choung et al., 2022), and even in research on trust in chatbots (Müller et al., 2019).

Given that different technologies, including chatbots, have different unique characters, it is essential to extend research on the concept of trust concerning chatbots. In practical terms, trust plays a crucial role in shaping how people interact with AI technologies. Depending on the specific technology, people may feel anxious or uncertain, and developing trust in these technologies is essential to encourage their adoption (Kim et al., 2021). The adoption intention of a technology, in this case, the intention to use chatbots, has already been measured in several studies, for example by measuring whether individuals intend to use chatbots in the future and whether they believe that more and more people will use chatbots (Rafiq et al., 2022). The relationship between perceived trust in chatbots and the intention to use chatbots has already been investigated by Pillai and Sivathanu (2020), who confirm the expectation that perceived trust in chatbots is positively related to the intention to use chatbots. Based on the already existing results of the relationship between perceived trust in chatbots and the intention to adopt them, the following is predicted:

H1: When customers perceive a high level of trust in chatbots, this will increase their intention to adopt chatbots

Although it is important to understand the role of trust in understanding consumers' decision-making and behavior, and to use it as a critical factor in building business strategies (Kim et al., 2021), there is still considerable discussion about the antecedents of trust due to the different definitions of trust (Elkins et al., 2012). According to the limited research on trust in chatbots, there are also factors other than benevolence, integrity, and competences that explain customer's trust in chatbots for customer service. According to research by Følstad et al. (2018), customer's trust in chatbots for customer service is influenced by various factors including chatbot-specific factors (ability to interpret requests and provide advice, humanlike behavior, its self-presentation, and its professional appearance) and factors concerning the service (the chatbot host's brand, the perceived level of security and privacy of the chatbot, and general risk perceptions related to the topic of the request). Nordheim et al. (2019) categorized factors influencing trust in chatbots into chatbot-related factors (perceived expertise and responsiveness), environment-related factors (risk and brand perceptions), and user-related factors (propensity to trust technology). Additionally, Yen and Chiang (2021) suggest that trust in chatbots is influenced by factors such as credibility, competence, anthropomorphism, social presence, and informativeness. The reason behind the exploration of various factors that influence customer trust is explained by Elkins et al. (2012), who argue that trust is a complex and multifaceted construct that is influenced by many different factors, making it difficult to measure. When implementing chatbots, organizations need to ensure that customers trust their chatbots because if customers do not trust the organization's chatbot, this could have a negative impact on loyalty and purchase intentions towards the organization (Jenneboer et al., 2022).

3. Persuasion Knowledge Model

Studying different antecedents of trust in the context of AI technologies such as chatbots represents a promising field for future research (Kim et al., 2021). As organizations are increasingly using chatbots for persuasive purposes (Ischen et al., 2020), considering the Persuasion Knowledge Model as an antecedent of trust has great potential for future research (Kim et al., 2021). The Persuasion Knowledge Model (PKM) is a model introduced by Friestad and Wright (1994) that examines how people use their understanding of persuasion tactics and motives to understand, evaluate, and respond to attempts by marketers and others. It consists of three distinct knowledge structures of participants that interact with each other to shape and determine the outcomes of these persuasion attempts which are (1) Persuasion knowledge, which refers to individuals' beliefs and knowledge about the persuasive goals of marketers and others (Friestad & Wright, 1994). Persuasion knowledge can be acquired both through exposure to persuasion techniques and through socialization (Ischen et al., 2022); (2) Agent knowledge, individuals' beliefs about the traits, competencies, and objectives of the person attempting to persuade them; and (3) topic knowledge, which refers to the beliefs about the topic of the message being conveyed (Friestad & Wright, 1994). The PKM differs from other persuasion models in that it takes the perspective of the target rather than the persuader (Kirmani & Campbell, 2009). If customers perceive that their interaction with a virtual assistant, such as a chatbot, is to persuade them rather than just being a social interaction, they are more likely to activate persuasion knowledge. This is especially true when the persuasion attempt is embedded in a conversation (Ischen et al., 2022). If the customer acquires a significant amount of persuasion knowledge, the customer is more likely to either ignore or provide counterarguments to best cope with the persuasion attempt (Ham et al., 2015).

The current state of research on the PKM related to trust is limited. There are some notable exceptions such as the work of Ahmad and Guzmán (2020) and Breves et al. (2021). However, both studies focus on the direct effect of persuasion knowledge on the intention to adopt, both in the context of brand evaluation. Previous research has often examined the PKM in the context of advertising and associated fields (Ham et al., 2015). Studying the PKM in the context of chatbots is important as chatbots have the power to influence the way consumers are influenced by them. Chatbots are not just a means of delivering a message but can also be seen as communicators. Therefore, the extent to which people are convinced by suggestions given by a chatbot may depend on their concerns and persuasion knowledge (Voorveld & Araujo, 2020).

Customers become more aware of the capabilities and limitations of persuaders as their persuasion, agent, and topic knowledge increases. As a result of this increased awareness, they can make better decisions and better understand the capabilities of the persuader (Friestad & Wright, 1994), in this case, chatbots. Customers with knowledge of persuasion are more likely to be critical and skeptical about chatbots' attempts at persuasion. They are better able to recognize authentic and reliable interactions thanks to their knowledge of persuasive strategies, which increases their level of trust in chatbots. Similarly, customers who have a high level of agent knowledge and topic knowledge concerning chatbots, have higher expectations for chatbot performance. They can adequately assess the chatbot's capabilities thanks to their in-depth knowledge of its capabilities and expertise in specific areas. As a result, they increase their degree of trust in chatbots based on how knowledgeable they perceive them to be. Therefore, it is expected that users who have a high level of persuasion, agent, and topic knowledge will have a higher level of trust in chatbots. Specifically,

H2: Customers with a high level of persuasion knowledge (H2a), agent knowledge (H2b), and topic knowledge (H2c), will have more trust in chatbots.

4. Anthropomorphism

A current trend in chatbot development is to make chatbots look more humanlike and mimic the conversations between humans (Crolic et al., 2022). Several studies have found that anthropomorphism is an important factor in chatbot literacy (Kühne & Peter, 2023; Misischia et al., 2022; Schanke et al., 2021; Yen & Chiang, 2021). Anthropomorphism refers to the attribution of human characteristics to non-human entities, making it an important factor in chatbot research (Schanke et al., 2021). Humanlike perceptions play a crucial role in chatbot interactions, as human characteristics are often used as guiding principles in chatbot design (Kühne & Peter, 2023). Customers are even more inclined to engage with chatbots when they experience that the chatbot has humanlike characteristics (Schanke et al., 2021), which makes customers' adoption intention dependent on the attitudes and the feelings conveyed by the chatbot (Misischia et al., 2022). It has been shown that enhancing humanlike qualities in technology is beneficial for customer satisfaction and trust in the interface (Schanke et al., 2021). Furthermore, a lack of humanness raises concerns about the interaction capabilities of chatbots. For example, if chatbots fail to meet customer expectations, this could lead to negative customer emotions that may not be properly understood by chatbots (Misischia et al., 2022).

In other cases, the addition of humanlike social cues has led to negative outcomes, such as social anxiety and reduced cooperation (Schanke et al., 2021). More specifically, the adaptive functional capabilities of chatbots, combined with their other visual and interactive humanlike cues, lead users to both perceive chatbots as human and threaten them as such (Sengupta et al., 2021). Schanke et al. (2021) explain that the benefits of incorporating anthropomorphic characteristics into chatbots vary depending on the context. If customers expect to interact with automated customer service agents in any context, their expectations for the interaction may differ significantly from other contexts where they expect to interact with human agents.

Studies use different items to measure the anthropomorphic characteristics of chatbots which may explain different perceptions of them. For example, a recent study by Kühne and Peter (2023) compared several studies on anthropomorphism in chatbot interaction and identified five mental capabilities which are: thinking, feeling, perceiving, desiring, and choosing. This view regarding anthropomorphism is based on the idea that a non-human entity is capable of thinking and feeling like a human (Kühne & Peter, 2023). On the other hand, Crolic et al.

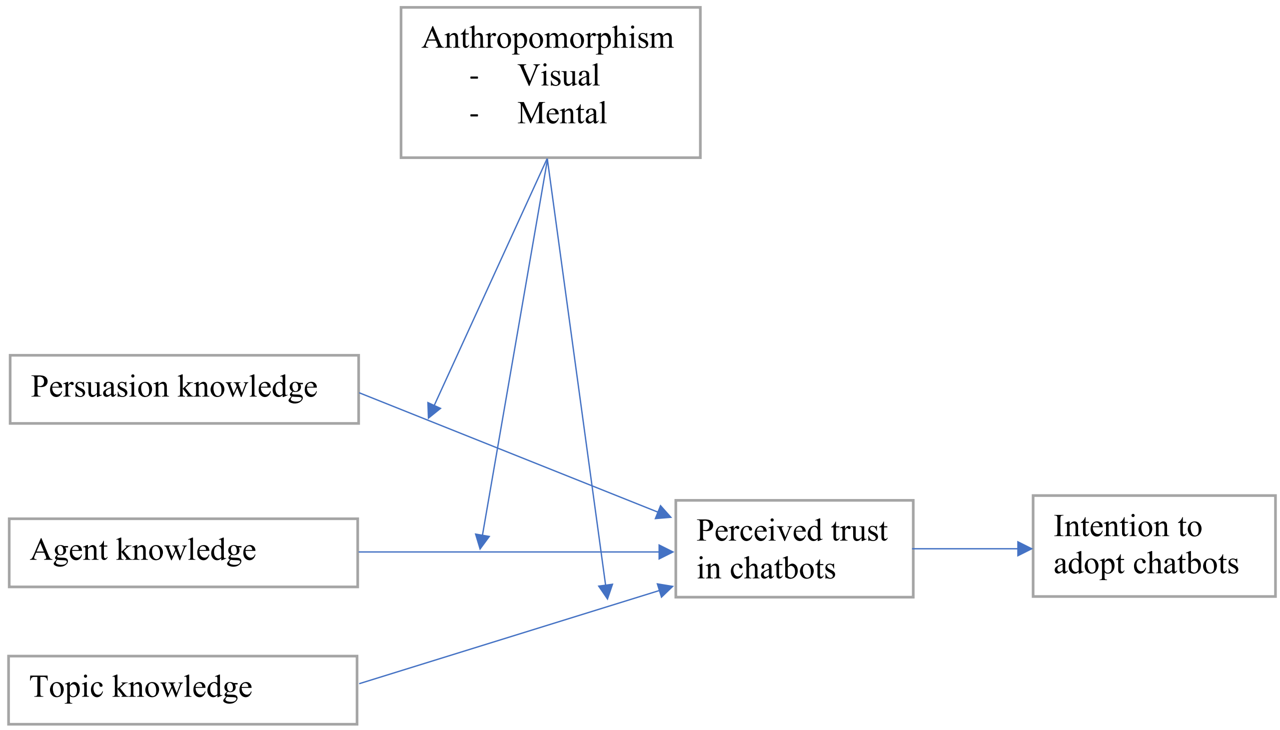
(2022) focused on the visual representation of chatbots, highlighting anthropomorphic characteristics such as a name or an avatar that give chatbots humanlike qualities. This view is based on the idea that a chatbot can be endowed with humanlike qualities (Crolic et al., 2022). Both mental and visual anthropomorphic characteristics are relevant in the context of chatbots. By examining both mental and visual anthropomorphic characteristics, a more complete understanding of how customers perceive and interact with chatbots can be captured.

Anthropomorphism can influence how people evaluate persuasion attempts because these anthropomorphic characteristics make people perceive chatbots as social entities which makes them trust chatbots more. Thus, if a chatbot has high anthropomorphic characteristics, people may be more likely to trust the information it provides (Voorveld & Araujo, 2020). Therefore, depending on the level of anthropomorphism of the chatbot, the effects of persuasion knowledge, agent knowledge, and topic knowledge on trust may vary, making it important to consider the level of anthropomorphism when investigating the relationship between the PKM and perceived trust in chatbots. For these reasons, it is expected that anthropomorphic characteristics will moderate the relationship between persuasion knowledge, agent knowledge, topic knowledge, and perceived trust in chatbots. More specifically, it is expected that the negative effects of increased persuasion knowledge, agent knowledge, and topic knowledge on trust, will be dampened when a chatbot is high on anthropomorphic characteristics.

H3: Chatbot's visual (H3a) and mental (H3b) anthropomorphic characteristics will moderate the relationship between persuasion knowledge (H2a), agent knowledge (H2b), topic knowledge (H2c), and perceived trust in chatbots, such that the negative effects of increased persuasion knowledge, agent knowledge, and topic knowledge, on trust, will be dampened when a chatbot is high on anthropomorphic characteristics.

5. Conceptual model

The conceptual model of this study aims to examine whether there is a relationship between the three structures of the PKM (persuasion knowledge, agent knowledge, and topic knowledge), and the perceived trust in chatbots. Additionally, the model explores how this perceived trust influences the intention to use chatbots. Further, it will be tested whether both visual and mental anthropomorphic chatbot characteristics moderate the relationship between the PKM structures and trust in chatbots.



D. Methodology

1. Data collection

1.1 Experimental design

To investigate the effect of the PKM structures on perceived trust in chatbots, and whether this relationship is moderated by different conditions of anthropomorphic chatbot characteristics, a survey was constructed via Qualtrics, which is a questionnaire software tool. The survey was distributed to participants via Prolific, which is a crowdsourcing platform that allows researchers to acquire respondents from around the world. A survey methodology was chosen for this study as it allows for easy quantification of the variables in the conceptual model and a larger sample size, which allows for greater generalization (Rice et al., 2017). The survey was conducted in English to ensure accessibility to a diverse pool of workers through Prolific, and to facilitate global generalizability. The experiment was sent to four different groups, which allowed the distinction between the anthropomorphic characteristics of the chatbot. According to Sekaran and Bougie (2016), a sample size of at least 30 respondents per group is required to obtain valid results, resulting in a minimum sample size of 4*30=120 respondents.

The survey included a visualization of a chatbot conversation with the customer service of Apple. The respondent acted as a customer who wants to buy a MacBook. However, four different groups saw four different visualizations, which can be found in Appendix 2, consisting of a visualization that is both high in visual and mental anthropomorphic characteristics, a visualization that is high in visual and low in mental anthropomorphic characteristics, a visualization that is low in visual and high in mental anthropomorphic characteristics, and a visualization that is both low in visual and mental anthropomorphic characteristics. These visualizations helped participants answer the questions and to measure whether certain chatbot characteristics lead to a more anthropomorphic view of the chatbot and whether these anthropomorphic chatbot characteristics moderate the relationship between the PKM and trust in chatbots.

The survey is structured as follows: The first part of the survey consists of an introductory section that addresses the aspects of anonymity and confidentiality while also introducing the topic of the study and its purpose. The second part of the survey consists of questions about the intention to use chatbots followed by questions about trust in chatbots. The third part of the survey starts with the visualization followed by questions about the PKM and questions about the anthropomorphic chatbot characteristics. The last part consists of questions about demographics and experience with chatbots. All items, except for the demographic questions, were asked using a 5-point Likert scale, with responses ranging from totally disagree (1) to totally agree (5). A higher score on the scale indicates a higher level of persuasion knowledge, agent knowledge, topic knowledge, trust in chatbots, intention to use chatbots, or perceived chatbot anthropomorphism by the respondent. A more detailed overview of the measurement of the variables related to demographics and familiarity with chatbots can be found in Table 1, and a more detailed overview of the concepts of the conceptual model, their definitions, their possible subdimensions, and their corresponding items and measurements can be found in Table 2.

1.2 Sample

To investigate the effect of the PKM on perceived trust in chatbots, and the moderating effect of anthropomorphic chatbot characteristics on the relationship between the PKM and perceived trust in chatbots, a quantitative experiment is used. An online survey has been created and distributed via Prolific. Prolific offers speed advantages, and it offers access to a large and diverse workforce, which is beyond the scope of personal networks. An advantage of Prolific is that the survey is completed by respondents from all over the world, so the results are not country specific. Compared to other crowdsourcing platforms such as Amazon Mechanical Turk and CrowdFlower, Prolific has the advantage of providing better data quality with more diverse and naive participants at a reasonable response rate (Peer et al., 2017). The limitation of the sample is that anyone can register as a respondent through Prolific, which could have some quality implications, such as a biased sample because participants can choose which studies they participate in and which they do not, potentially resulting in a sample consisting of participants interested in chatbots. However, unlike many other crowdsourcing platforms for acquiring respondents, Prolific offers the option to screen participants. For this study, Prolific has screened participants on being at least 18 years old and fluent in English to ensure respondents understand the questions.

1.3 Ethical considerations

Conducting an online survey can have ethical implications in research concerning privacy, emphasizing the importance of informing participants about the study, and ensuring that their participation is based on informed consent (Ritter & Sue, 2007). Moreover, privacy and confidentiality are protected. To ensure that data is collected and handled ethically, participants are informed about the study, their rights as participants, and how the data will be used. It is emphasized that participation in the research is voluntary. Before taking part in the study, participants were asked to confirm that they understand the information provided about participation and whether they agree to the use of the results they provide for the purposes described. The confidentiality and privacy of participants is protected by the creation of unique pseudonyms for each participant rather than using real names. Data is stored securely so that only approved individuals involved in the thesis, such as supervisors, will have access to the data. Participants are provided with contact details to use if they have any questions or complaints about the research or their participation, or if they wish to withdraw from the research.

2. Data analysis

Once the data has been collected through the survey, the data is analyzed using both SPSS and Adanco. First, descriptive statistics are performed in SPSS to gain more insight into the sample and the distribution of responses. A confirmatory factor analysis is carried out in Adanco by testing the measurement model to ensure that the items represent the concepts. The factor analysis is performed on all multi-item scales in the conceptual model. Adanco also performed a reliability analysis to ensure that the items are internally consistent. To test whether the relationships between the concepts are statistically significant, Adanco has tested the structural model using Partial Least Squares (PLS) regression analysis. This could have been done using regular regression analysis, but PLS regression analysis was chosen over regular regression analysis in SPSS because the relationship between the PKM and trust in chatbots is not yet well understood. PLS makes it possible to explore and uncover potential patterns, dependencies, or non-linear relationships that may exist between these constructs.

The next step was to examine group differences due to different levels of anthropomorphism in the visualization using a 2 (high and low on visual anthropomorphic characteristics) x 2 (high and low on mental anthropomorphic characteristics) between-groups experiment. SPSS was used to examine these differences in the levels of persuasion knowledge, agent knowledge, and topic knowledge between the four groups. The statistical test used for this manipulation test is the one-way ANOVA. This test allows to determine whether the relationship between the PKM and perceived trust in chatbots, is moderated by anthropomorphic chatbot characteristics.

In addition to the ANOVA, a t-test is performed in Excel which also allows to determine whether the relationship between the PKM and perceived trust in chatbots, is moderated by anthropomorphic chatbot characteristics. In contrast to the ANOVA, the t-test examines significant differences between two groups instead of four groups: one consisting of respondents who saw a visualization with high visual anthropomorphism and the other consisting of respondents who saw a visualization with low visual anthropomorphism. This is also done to test for significant differences between the respondents who saw a visualization high in mental anthropomorphism and the respondents who saw a visualization low in mental anthropomorphism.

The reason for using both a t-test and an ANOVA is to allow for a comprehensive investigation by not only investigating whether there are differences between the groups that saw a visualization with high and low levels of anthropomorphism, but also by investigating certain combinations of anthropomorphism. For example, the ANOVA seeks to determine whether combinations such as high visual anthropomorphism and low mental anthropomorphism moderate the relationship between the PKM structures and perceived trust in chatbots.

Although demographics are not included in the conceptual model, a post-hoc control for these variables was conducted to ensure that the observed effects of trust in chatbots were not due to demographics or familiarity with chatbots. Therefore, the study controlled for age, gender, education level, and whether participants were familiar with chatbots using Adanco. These demographics are based on a study by Nordheim et al. (2019) investigating trust in chatbots and are important to control to ensure that the explained variance in trust in chatbots reflects the effects of the variables being studied. For example, by controlling for age, the unique effect of persuasion knowledge on trust in chatbots can be examined without being confounded by the effect of age on trust in chatbots. This will ultimately lead to greater generalizability of the results. A significance level of 0,05 and a confidence interval of 95% are used for all analyses.

Concept	Subdimension	Measurement	Options
Demographics	Age	Fill in question	18-100
	Gender	Categorical options	Male Female Other
	Highest educational level	Categorical options	Primary school Secondary school Vocational/trade school College/University (Bachelor/Master) Doctoral degree or higher
Familiarity with chatbots		1-5 slider	1=not familiar 5=very familiar

Table 1: Measurement demographics & familiarity with chatbots

Concept	Definition	Subdimension	Item	Measurement
Persuasion knowledge	The beliefs and knowledge of individuals about the persuasion goals of marketers and others (Friestad & Wright, 1994).		-I am aware that the chatbot is trying to convince me to purchase the MacBook -I recognize persuasive tactics that the chatbot uses during the conversation about the MacBook -I believe that the chatbot's ultimate goal is to sell me a MacBook	5-Point Likert Scale
Agent knowledge	The beliefs of individuals about the traits, competencies, and objectives of the person attempting to persuade them (Friestad & Wright, 1994).		-The chatbot is able to provide me accurate information -The chatbot has the competences to address my questions and concerns -The chatbot's goals are assisting and selling	5-Point Likert Scale
Topic knowledge	The beliefs about the topic of the message being conveyed (Friestad & Wright, 1994).		-The chatbot is knowledgeable about the features and capabilities of MacBook's -The chatbot has experience with using MacBook's -The chatbot's responses demonstrate an understanding of the MacBook	5-Point Likert Scale
Trust in chatbots	The willingness of a customer to be open to the actions of a chatbot, based on the expectation that the chatbot will carry out a specific action that is important to the customer, regardless of the ability to monitor or manage the chatbot (Mayer et al., 1995)	Benevolence	-Chatbots care about our well-being -Chatbots are sincerely concerned about addressing the problems of human users -Chatbots try to be helpful and do not operate out of selfish interest	5-Point Likert Scale
		Integrity	-Chatbots are truthful in their dealings -Chatbots keep their commitments and deliver on their promises -Chatbots are honest and do not abuse the information and advantage they have over their users	5-Point Likert Scale
		Competence	-Chatbots work well -Chatbots have the features necessary to complete key tasks -Chatbots are reliable -Chatbots are dependable	5-Point Likert Scale
Intention to use chatbots	Individual's intention to use or to not use a particular technology (Davis, 1989), in this case chatbots		-I intend to use chatbots in the future -I will continue using chatbots in the future -When required, I will use chatbots -I think that more and more people will use chatbots	5-Point Likert Scale
Anthropomorphism	The ascription of human characteristics to nonhuman entities (Schanke et al., 2021).	Visual anthropomorphism	-The chatbot has a human name -The chatbot has an avatar -The chatbot appears humanlike	5-Point Likert Scale
		Mental anthropomorphism	-I feel like the chatbot is able to think like a human being -I feel like the chatbot is able to feel like a human being	5-Point Likert Scale

Table 2: Measurement conceptual model

E. Results

1. Univariate and bivariate statistics

134 respondents completed the survey, exceeding the minimum sample size of 120 respondents for a between-groups analysis. For the descriptive overview, the variable age is broken into five different groups: 18-28, 29-38, 39-48, 49-58, and 59-68. Although respondents are anonymous through Prolific, the platform provides insight into the demographics of the respondents. The survey captured responses from a diverse group of people from different countries around the world, representing a variety of ethnicities. There is an appropriate balance of male and female responses. However, it is important to note that the average age of respondents is 28, and the majority (66%) of respondents have a college/university degree as their highest level of education. It may therefore be biased and not fully representative of the general population. There are no missing values as respondents had to answer all questions to continue. The mean scores indicate that overall, respondents have a high intention to use chatbots and a moderate level of trust in chatbots. Participants' persuasion and agent knowledge of chatbots is relatively high, and their topic knowledge is moderate. All means and standard deviations of the descriptive statistics are presented in Table 4 below. The full table of descriptive statistics can be found in Appendix 3.

Dimension	Options	N (%)
Gender	Male	58 (43%)
	Female	75 (55.6%)
	Other	1 (0.7%)
Age	18-28	86 (63.7%)
	29-38	30 (22.2%)
	39-48	11 (8.1%)
	49-58	4 (3%)
	59-68	2 (1.5%)
Education	Primary school	1 (0.7%)
	Secondary school	31 (23%)
	Vocational/trade school	10 (7.4%)
	College/University (Bachelor/Master degree)	89 (65.9%)
	Doctoral degree or higher	3 (2.2%)
Familiarity	1	2 (1.5%)
	2	12 (8.9%)
	3	36 (26.7%)
	4	54 (40%)
	5	30 (22.2%)

Table 3: Sample overview

Item	Mean	Std. Deviation
Use1	3.83	.930

Use2	3.93	.855
Use3	4.28	.698
Use4	4.16	.866
Trust1	2.67	1.095
Trust2	2.87	1.213
Trust3	3.68	1.094
Trust4	3.45	.946
Trust5	3.50	.940
Trust6	3.47	1.001
Trust7	3.66	.885
Trust8	3.66	.894
Trust9	3.47	.939
Trust10	3.39	1.018
Persuasion1	3.69	1.013
Persuasion2	3.39	1.110
Persuasion3	3.57	1.198
Agent1	3.85	.771
Agent2	3.68	.881
Agent3	3.99	.863
Topic1	3.72	1.001
Topic2	2.28	1.271
Topic3	3.27	1.177
VisA1	3.26	1.176
VisA2	3.40	1.176
VisA3	3.16	1.225
MenA1	2.51	1.243
MenA2	1.93	1.193
Age	28.83	9.323
Education	3.46	.898
Familiarity	3.73	.959

Table 4: Descriptive statistics

2. Assessment measurement model

2.1 Initial model

The minimum sample size for PLS is ten times the maximum number of arrowheads pointing to a latent variable. In the model, it is observed that the maximum number of arrowheads pointing to a latent variable is three which results in a minimum sample size of 30. The model fit was then assessed by analyzing whether the model's correlation is sufficiently similar to the empirical correlation matrix. This is done by examining the SRMR of the estimated model, which is found to be 0.0815. Conventionally, the threshold for model fit is an SRMR value below 0.08 (Hair, 2019). However, 0.0815 is still quite close to 0.08 and the higher SRMR can be explained by the relatively small sample size and the low number of items representing the PKM structures (Hair, 2019).

After assessing the model fit, the reliability of the constructs is assessed. The reliability of the constructs can be assessed by looking at Dijkstra-Henseler's rho, Jöreskog's rho, and

Cronbach's Alpha. These values should be above 0.7 to ensure the reliability of the constructs (Gliem & Gliem, 2003). These results show that all constructs except agent knowledge score higher than 0.7 on these three reliability measures. However, agent knowledge still scores above 0.6 on Dijkstra-Henseler's rho, Jöreskog's rho, and Cronbach's Alpha, which makes it still acceptable (Gliem & Gliem, 2003). Given that the agent knowledge construct is only slightly below the threshold of two of the measures, it can still be considered to have a reasonable level of reliability. After assessing the construct reliability, the indicator reliability is assessed. According to Hair (2019), the critical level for indicator reliability is a value above 0.5. Many indicator reliabilities in this study are below this critical value, indicating a low level of common variance with the construct on which they theoretically load (Hair, 2019). The lowest indicator reliability is found for Trust10 with a value of 0.2755 and for Agent3 with a value of 0.2867. To ensure convergent validity, the average variance extracted (AVE) is evaluated. The critical level to assure convergent validity is a value higher than 0.5 for the AVE (Hair, 2019). Unfortunately, trust in chatbots (0.4270) and agent knowledge (0.3837) score below the critical level, indicating that the items of these constructs contain more error than variance shared with the factor on which they load (Hair, 2019). To ensure discriminant validity, HTMT and Fornell-Larcker are evaluated. HTMT shows low values indicating overlap between the constructs and Fornell-Larcker indicates that the items considering agent knowledge load higher on trust in chatbots than on agent knowledge, the items concerning topic knowledge have a high loading on agent knowledge, and the items concerning intention to use chatbots have a high loading on trust in chatbots and on agent knowledge. However, the items related to agent knowledge are the most problematic in this case, as these items load higher on trust in chatbots than on agent knowledge itself.

Finally, when examining the cross-loadings, certain issues are noticed for the items related to trust in chatbots, as they have cross-loadings with agent knowledge, topic knowledge, and the intention to use chatbots. Further, Agent1 cross-loads with trust in chatbots, Agent2 cross-loads with both trust in chatbots and topic knowledge, and cross-loads with agent knowledge. The items Trust10 and Agent3 are the most problematic due to problems with both validity and reliability.

2.2 Model after item deletion

A better model fit would be obtained by deleting Trust10, with an SRMR of 0.0808, which is still very close to the SRMR of 0.0815. All constructs except agent knowledge still score above 0.7 on the three reliability measures, and agent knowledge still scores between 0.6 and 0.7. In addition, the AVE remains essentially unchanged, and cross-loading problems persist. As Trust10 has been a commonly used item in studies measuring trust, and as there has been little to no improvement in terms of validity and reliability, Trust10 will remain in the analysis.

Deleting Agent would also give a better model fit with an SRMR of 0.0766. All constructs, except agent knowledge, still score above 0.7 on the three reliability measures, and agent knowledge scores 0.6709 on all three reliability measures. Trust10 is the only item that still has an indicator reliability below 0.3 with a value of 0.2755. The AVE values have increased. Only trust in chatbots is still below the critical level of 0.5. Unfortunately, discriminant validity issues have not been resolved and the items related to agent knowledge still load higher on trust in chatbots than on agent knowledge, the items related to topic knowledge still have a high loading on agent knowledge, and the items related to intention to use chatbots still have a high loading on trust in chatbots and on agent knowledge. Problems with cross-loading persist but deleting Agent3 results in fewer problems with cross-loadings for Agent1 and Agent2. However, deleting Agent3 may result in limited content coverage. As agent knowledge is only captured by three items, the deletion of an item may reduce the ability of the construct to capture the full range of content it is intended to represent. Despite the reduced ability to capture the full range of content, I decided to delete Agent3 due to the notable improvements in reliability and validity. A full overview including indicator reliability, construct reliability (Cronbach's alpha), and convergent validity (AVE) after deletion of Agent3 can be found in Table 5 and a graphical representation of the model after deleting Agent3 can be found in Figure 1.

Latent variables	**Items**	**Indicator reliability**	**Construct reliability (Cronbach's alpha)**	**Convergent validity (AVE)**
Persuasion knowledge	Persuasion1	0.6272	0.8354	0.6285
	Persuasion2	0.6252		
	Persuasion3	0.6332		
Agent knowledge	Agent1	0.5048	0.6709	0.5048
	Agent2	0.5048		
Topic knowledge	Topic1	0.4528	0.7495	0.5069
	Topic2	0.4686		
	Topic3	0.5991		
Trust in chatbots	Trust1	0.3411	0.8787	0.4270
	Trust2	0.4385		
	Trust3	0.4848		
	Trust 4	0.5150		
	Trust 5	0.5334		

	Trust6	0.5333		
	Trust7	0.3702		
	Trust8	0.3206		
	Trust9	0.4574		
	Trust10	0.2755		
Intention to use chatbots	Use1	0.7305	0.8517	0.6091
	Use2	0.7535		
	Use3	0.4879		
	Use4	0.4643		

Table 5: Reliability and validity

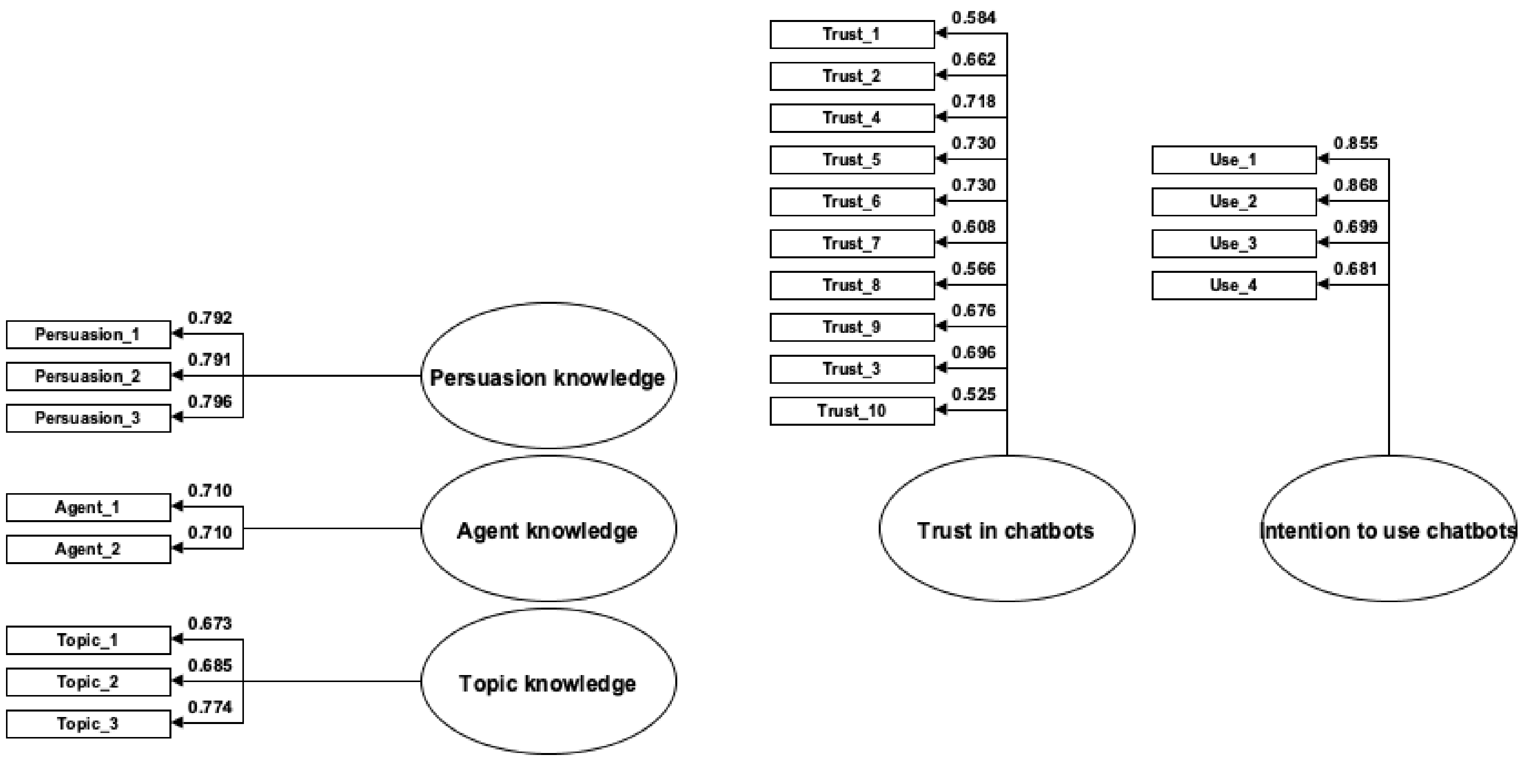


Figure 1: Graphical representation measurement model

3. Assessment structural model

According to the results of the structural model, the adjusted R^2 of trust in chatbots is 0.5861 and the adjusted R^2 of intention to use chatbots is 0.4198. In other words, approximately 58.61% of the variance in trust in chatbots is explained by the PKM and approximately 41.98% of the variance in the intention to use chatbots is explained by the combination of the PKM structures and trust in chatbots.

Cohen's F is used to measure the effect sizes. Cohen's F >0.02 indicates a weak effect, Cohen's F >0.15 indicates a moderate effect, and Cohen's F > 0.35 indicates a strong effect (Hair, 2019). The use of these critical levels reveals no effect (Cohen's F<0.02) between persuasion knowledge and trust in chatbots. A weak positive effect (Cohen's F>0.02) with a beta of 0.2364 is found between topic knowledge and trust in chatbots. A strong positive effect (Cohen's F>0.35) with a beta of 0.6007 is found between agent knowledge and trust in chatbots. Finally, as expected, there is a strong positive effect (Cohen's F>0.35) with a beta of 0.6513 between trust in chatbots and the intention to use chatbots. An overview of the effects can be found in Table 6 and a graphical representation of the model including the structural paths can be found in Figure 2.

Therefore, H1 is accepted, indicating that when customers perceive a high level of trust in chatbots, this will increase their intention to use chatbots. H2 is partly accepted and is revised as follows: Customers with a high level of agent knowledge (H2b) will have a higher level of trust in chatbots, and customers with a high level of topic knowledge (H2c) tend to have a slightly higher level of trust in chatbots, while the level of persuasion knowledge (H2a), does not significantly affect trust in chatbots.

Effect	**Beta**	**Indirect effects**	**Total effect**	**Cohen's f2**
Persuasion knowledge -> Trust in chatbots	-0.0441		-0.0441	0.0047
Persuasion knowledge -> Intention to use chatbots		-0.0287	-0.0287	
Trust in chatbots -> Intention to use chatbots	0.6513		0.6513	0.7365
Agent knowledge -> Trust in chatbots	0.6007		0.6007	0.5135
Agent knowledge -> Intention to use chatbots		0.3912	0.3912	
Topic knowledge -> Trust in chatbots	0.2364		0.2364	0.0804
Topic knowledge -> Intention to use chatbots		0.1539	0.1539	

Table 6: Effect sizes structural model

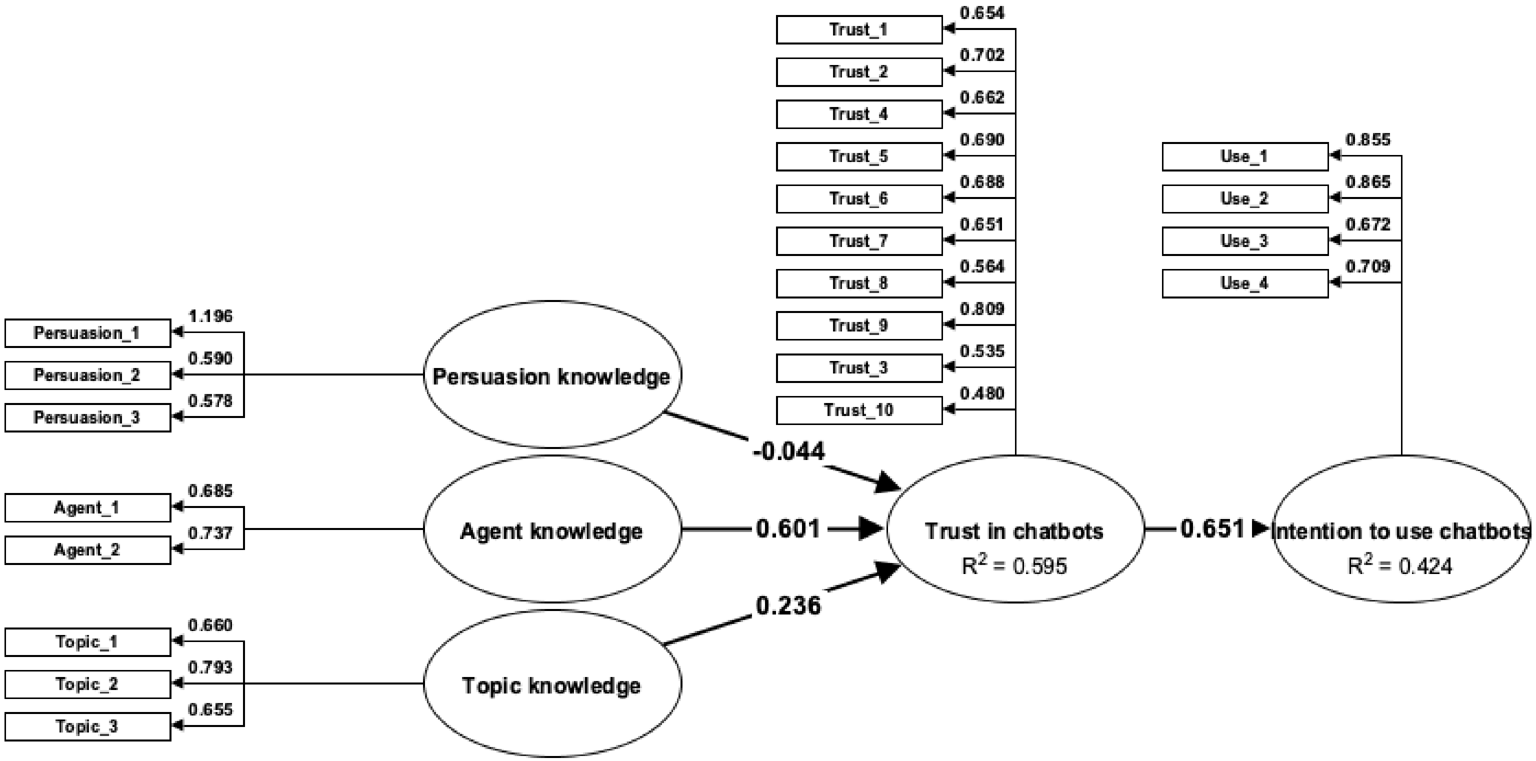


Figure 2: Graphical representation structural model

4. Moderating effect anthropomorphism

4.1 ANOVA

A between-groups analysis is conducted to investigate whether anthropomorphic chatbot characteristics moderate the relationship between the PKM and trust in chatbots. First, it is tested whether the items tested represent a clear distinction between high and low anthropomorphism for both visual and mental anthropomorphism by testing whether there are significant differences between groups for both visual and mental anthropomorphism. The results show that there are significant differences between groups on the questions regarding visual anthropomorphic characteristics. More specifically, groups that saw a visualization that was high in visual anthropomorphic characteristics also scored higher on visual anthropomorphism. However, visual anthropomorphic chatbot characteristics do not moderate the relationship between the PKM and trust in chatbots, as no significant differences are found between groups on the PKM structures. For mental anthropomorphic characteristics, no significant differences between groups are found on the questions regarding mental anthropomorphism, and mental anthropomorphism also does not moderate the relationship between the PKM and trust in chatbots, as no differences between groups are found on the structures of the PKM. Therefore, H3 is rejected and the chatbot's visual (H3a) and mental (H3b) anthropomorphic characteristics do not moderate the relationship between persuasion knowledge (H2a), agent knowledge (H2b), topic knowledge (H2c), and perceived trust in chatbots.

ANOVA						
		Sum of Squares	df	Mean Square	F	Sig.
Persuasion knowledge	Between Groups	5.550	3	1.850	2.052	.110
	Within Groups	117.174	130	.901		
	Total	122.724	133			
Agent knowledge	Between Groups	1.325	3	.442	1.038	.378
	Within Groups	55.323	130	.426		
	Total	56.647	133			
Topic knowledge	Between Groups	3.364	3	1.121	.944	.422
	Within Groups	154.444	130	1.188		
	Total	157.808	133			
Visual Anthropomorphism	Between Groups	39.060	3	13.020	20.289	<.001
	Within Groups	83.422	130	.642		
	Total	122.482	133			
Mental Anthropomorphism	Between Groups	6.610	3	2.203	1.789	.153
	Within Groups	160.145	130	1.232		
	Total	166.756	133			

Table 7: ANOVA

4.2 T-test

A t-test is performed to test whether there are significant differences between the groups that saw a visualization high in visual anthropomorphism and those that saw a visualization low in visual anthropomorphism, and between the groups that saw a visualization high in mental anthropomorphism and those that saw a visualization low in mental anthropomorphism. Due to the directionality of the H3, a one-tailed test is performed. Additionally, given that the means are derived from different groups and homoscedasticity can be assumed, a type 2 t-test is performed. The results show that there are no significant differences in PKM structures between groups that saw a visualization that was high in visual chatbot anthropomorphism and groups that saw a visualization that was low in visual chatbot anthropomorphism. Similarly, no significant differences in PKM structures are found between groups that saw a visualization that was high in mental chatbot anthropomorphism and between groups that saw a visualization that was low in mental chatbot anthropomorphism. Due to the negative variance estimate of the measurement error (Heywood case) of the item persuasion1 in the measurement of visual anthropomorphism and due to the negative variance estimation of the measurement error of both item persuasion1 and persuasion3 in the measurement of mental anthropomorphism, these items are excluded from the analysis. Consequently, since the measurement of persuasion knowledge is based on only three items, the deletion of two items in the measurement of mental anthropomorphism leaves only one item available for the analysis, making it impossible to compare the persuasion knowledge of the groups that saw a visualization high in mental anthropomorphism and the groups that saw a visualization low in mental anthropomorphism. The P-values can be found in Table 8 and the means and mean differences can be found in Appendix 6. These results of the T-test provide further confirmation that H3 can be rejected indicating that chatbot's visual (H3a) and mental (H3b) anthropomorphic characteristics do not moderate the relationship between persuasion knowledge (H2a), agent knowledge (H2b), topic knowledge (H2c), and perceived trust in chatbots.

Concept	**P-value Visual anthropomorphism**	**P-value Mental anthropomorphism**
Persuasion knowledge	0,1378	
Agent knowledge	0,3094	0,4509
Topic knowledge	0,4054	0,3918

Table 8: T-test

5. Control for demographics and familiarity with chatbots

To ensure that the observed effects of the PKM structures on trust in chatbots are not due to demographics or due to familiarity with chatbots, trust in chatbots is controlled for gender, age, education level, and familiarity with chatbots. To account for the complexity of the model and provide a more nuanced estimate of the variance explained, the adjusted R^2 is examined to examine the variance explained of trust in chatbots with and without the control variables. The results show that without controlling for demographics and familiarity with chatbots, the explained variance of trust in chatbots is 0.586 indicating that approximately 58.6% of the variance in trust in chatbots is explained by the PKM. However, when the control variables are added, the adjusted R^2 of trust decreases to 0.577, indicating that the inclusion of control variables slightly reduces the estimated explained variance of trust in chatbots by 0.009. Despite this decrease, the impact of the explained variance is relatively small. These results suggest that the inclusion of the control variables in the model, together with the PKM structures, has reduced the explained variance of trust in chatbots, taking into account the number of variables and degrees of freedom. Therefore, the control variables should not be retained in the model.

F. Conclusion

This study aimed to investigate whether the structures of the PKM influence trust in chatbots and the subsequent intention to use chatbots, and whether anthropomorphic chatbot characteristics moderate the relationship between the structures of the PKM and trust in chatbots. To explore these potential relationships, a quantitative research approach with an experimental research design was used.

The study found a positive relationship between trust in chatbots and the intention to use chatbots, suggesting that if customers feel like they can trust chatbots, they will be more likely to intend to use chatbots. The study found no relationship between persuasion knowledge and trust in chatbots and only a weak effect is found on the relationship between topic knowledge and trust in chatbots. However, a strong relationship is found between agent knowledge and trust in chatbots. This means that the customer's persuasion knowledge about chatbots does not affect the level of trust in chatbots. The topic knowledge that the customer believes the chatbot has only slightly affects the level of trust in chatbots, suggesting that if the customer believes that the chatbot has a high level of understanding and experience with the topic of the message being conveyed, this will result in a slightly higher level of trust in chatbots. The strong relationship between agent knowledge and trust in chatbots indicates that when a customer has a high level of belief in the traits, competencies, and objectives of the chatbot, this results in a higher level of trust in chatbots. Finally, no support is founded for the moderating effect of anthropomorphism, indicating that the chatbot's visual and mental anthropomorphic characteristics do not moderate the relationship between persuasion knowledge, agent knowledge, topic knowledge, and trust in chatbots. In other words, it does not matter whether the chatbot appears human or non-human when it comes to the effect of persuasion knowledge, agent knowledge, and topic knowledge, on trust in chatbots.

G. Discussion and theoretical implications

This thesis contributes to previous research by re-examining the relationship between trust in chatbots and the intention to use chatbots, examining the role of the PKM in relation to trust in chatbots, and investigating whether anthropomorphic chatbot characteristics moderate the relationship between the PKM structures and trust in chatbots. Consistent with previous research by Pillai and Sivathanu (2020) and Mohd Rahim et al. (2022), a positive relationship between trust in chatbots and the intention to use chatbots is found.

By investigating the relationship between the PKM structures and trust in chatbots, a deeper understanding of the complexity of trust in chatbots and the role of the PKM has been developed. Previous research has often treated the PKM as a single concept (Friestad & Wright, 1994), which is understandable considering the overlap between the constructs of the PKM when assessing the measurement model. However, surprisingly, the effects of persuasion knowledge, agent knowledge, and topic knowledge, on trust in chatbots are different. Therefore, this thesis shows that the knowledge structures have different relationships with trust, suggesting that these structures should be considered as different concepts in certain circumstances.

The lack of a moderating effect of anthropomorphic chatbot characteristics between the PKM structures and trust in chatbots is surprisingly given the widely recognized influence of anthropomorphic chatbot characteristics in studies exploring chatbot adoption (Araujo, 2018; Han, 2021; Schanke et al., 2021; Yen & Chiang, 2021). These results challenge the widely recognized influence of anthropomorphic chatbot characteristics in chatbot adoption and can be used by academics to create a better understanding of the boundary conditions that lead to the development of trust in human-chatbot interactions.

Although this study did not find strong effects for all relationships of the PKM structures with trust in chatbots, this thesis makes a valuable contribution to existing research by exploring the concept of the PKM in the context of chatbots. This thesis broadens the scope by applying the PKM specifically to chatbot interactions, whereas other studies have mostly focused on the PKM as a dependent variable or moderating variable in the context of brand evaluation (Ahmad & Guzmán, 2020; Breves et al., 2021). Exploring the concept of the PKM in the context of chatbots provides valuable insights to academics in understanding the unique dynamics of the PKM in different contexts and it offers opportunities for conducting comparative studies to investigate the generalizability of the PKM across different contexts.

H. Practical implications

The study's confirmation that perceived trust in chatbots has a positive effect on customers' behavioral intention to use chatbots, highlights the importance of building trust in chatbot systems to encourage their use. Therefore, creating chatbots that are seen as trustworthy, accurate, and useful sources of information should be a top priority for organizations. This will help build trust in chatbots and increase the intention to use chatbots.

From a PKM perspective, organizations can create this level of trust in chatbots by ensuring that users believe that chatbots have the right traits, competencies, and objectives to foster this trust. Therefore, developing chatbots that can answer users' questions and address their concerns, offer support, and provide reliable information is essential. Organizations can develop these chatbots by enabling user feedback and incorporating user suggestions for improvement. In addition, organizations can communicate to users how the chatbot can help users and highlight the chatbot's qualifications to establish it as knowledgeable and competent.

When customers believe that chatbot has a high level of understanding and expertise in the subject matter of the message being conveyed, this will also result in a slightly higher level of trust. This suggests that organizations need to develop chatbots that excel at understanding and demonstrating expertise in the subject matter, thereby increasing customer trust in the chatbot. Organizations can do this by increasing the knowledge base of chatbots and ensuring that this knowledge base is regularly updated. Therefore, organizations should regularly gather information from reliable sources to ensure that the chatbot is up to date with the latest information. Organizations can also work with experts in the development of the chatbot to ensure that the chatbot's knowledge is in line with expert opinion.

The study finds no evidence to support the claim that chatbots' mental and visual anthropomorphic characteristics moderate the relationship between the PKM structures and trust in chatbots. Therefore, the significant investment organizations make in creating highly anthropomorphic chatbots does not interact with the structures of the PKM to generate higher levels of trust in chatbots. However, it is important to remember that previous research by Yen and Chiang (2021) found that appealing anthropomorphic chatbot characteristics can still increase customer engagement and make a chatbot experience more enjoyable due to the direct positive effect of anthropomorphic chatbot characteristics on trust. Therefore, it is still recommended that organizations invest in integrating anthropomorphic chatbot characteristics into their chatbot systems.

I. Limitations and suggestions for future research

Unfortunately, the results must be interpreted with caution as the sample was rather biased. It seems that the survey is mainly filled in by students, as the average age is 28 and the highest level of education of 66% of the respondents is college/university. Perhaps the results would have been different if there had been more responses from older and lower-educated people. They may have less exposure to chatbot interactions, and less understanding of the persuasion techniques used by chatbots, resulting in a lower level of the knowledge structures of the PKM. This, in turn, could potentially harm their level of trust in chatbots. Therefore, it would be recommended to use a less biased sample by including older and lower-educated people when re-examining the relationship between the PKM structures and trust in chatbots. To achieve a more representative sample, researchers can use multiple channels for participant recruitment. Instead of solely relying on platforms such as Prolific, they can also utilize other channels that target older and less educated people, such as advertisements in newspapers or by reaching out to certain community organizations where these demographics are active.

Further, the relationship between agent knowledge and trust in chatbots should be interpreted with caution. Although a strong relationship is found between agent knowledge and trust in chatbots, agent knowledge has low reliability and discriminant validity, indicating that the items used to measure the construct, may not be accurate or distinct from the other constructs. Furthermore, all constructs of the PKM have problems with discriminant validity, indicating overlap between the constructs. Not only do the constructs overlap, but multiple items also demonstrate cross-loadings with different constructs. Therefore, it would be recommended that future studies in this area consider developing different items for the survey that effectively capture and distinguish the aspects of the knowledge structures to enhance research on the PKM. This process of developing new items can be done by pilot testing and collecting feedback on the items used.

Furthermore, no significant differences in mental anthropomorphism were found between the groups that saw a visualization low in mental anthropomorphic chatbot characteristics and the groups that saw a visualization high in mental anthropomorphic chatbot characteristics. This has posed limitations to the study because without a clear distinction between these groups, it becomes challenging to examine the moderating effect. As SPSS could not find significant differences between these groups, the items did not provide a clear distinction between low and high mental anthropomorphism. Therefore, it is recommended to use different mental anthropomorphism items to ensure that significant differences are found between low and high mental chatbot anthropomorphism. For example, by asking about all mental capabilities identified by Kühne and Peter (2023): thinking, feeling, perceiving, desiring, and choosing.

Although this work has contributed to the study of antecedents of trust in chatbots, the role of the PKM does not fully address the research gap concerning trust in chatbots (Kim et al., 2021). Therefore, it is recommended to investigate other antecedents of trust in chatbots, such as certain personality traits or cultural factors, to identify and examine other variables that may play a role in shaping customers' trust in chatbots. Investigating other antecedents of trust in chatbots can provide a more comprehensive understanding of the trust-building process which can lead to the development of more robust theoretical models that encompass a wider range of factors that influence trust.

Researchers interested in the PKM related to chatbots can conduct qualitative research to further explore the underlying motivations that contribute to the increased trust in chatbots associated with agent knowledge, while persuasion knowledge does not have the same effect. Researchers interested in the PKM can also use this thesis to conduct comparative studies. By examining the similarities and differences between the PKM in relation to chatbots and the PKM in relation to brand evaluation, researchers can gain insights into the unique dynamics of the PKM in different domains. This investigation can clarify whether the cognitive processes underlying the PKM are context specific or whether they are general principles that apply across several contexts.

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K. Appendix

1. Items and associated questions

Item	Question
Use1	I intend to use chatbots in the future
Use2	I will continue using chatbots in the future
Use3	When required, I will use chatbots
Use4	I think that more and more people will use chatbots
Trust1	Chatbots care about our well-being
Trust2	Chatbots are sincerely concerned about addressing the problems of human users
Trust3	Chatbots try to be helpful and do not operate out of selfish interest
Trust4	Chatbots are truthful in their dealings
Trust5	Chatbots keep their commitments and deliver on their promises
Trust6	Chatbots are honest and do not abuse the information and advantage they have over their users
Trust7	Chatbots work well
Trust8	Chatbots have the features necessary to complete key tasks
Trust9	Chatbots are reliable
Trust10	Chatbots are dependable
Persuasion1	I am aware that the chatbot is trying to convince me to purchase the MacBook
Persuasion2	I recognize persuasive tactics that the chatbot uses during the conversation about the MacBook
Persuasion3	I believe that the chatbot's ultimate goal is to sell me a MacBook
Agent1	The chatbot is able to provide me accurate information
Agent2	The chatbot has the competences to address my questions and concerns
Agent3	The chatbot's goals are assisting and selling
Topic1	The chatbot is knowledgeable about the features and capabilities of MacBook's
Topic2	The chatbot has experience with using MacBook's
Topic3	The chatbot's responses demonstrate an understanding of the MacBook
VisA1	The chatbot has a human name
VisA2	The chatbot has an avatar
VisA3	The chatbot appears humanlike
MenA1	I feel like the chatbot is able to think like a human being
MenA2	I feel like the chatbot is able to feel like a human being
Age	What is your age?
Education	What is your highest educational level?
Familiarity	How familiar are you with chatbots?
Gender	What is your gender?

2. Visualizations survey

<table>
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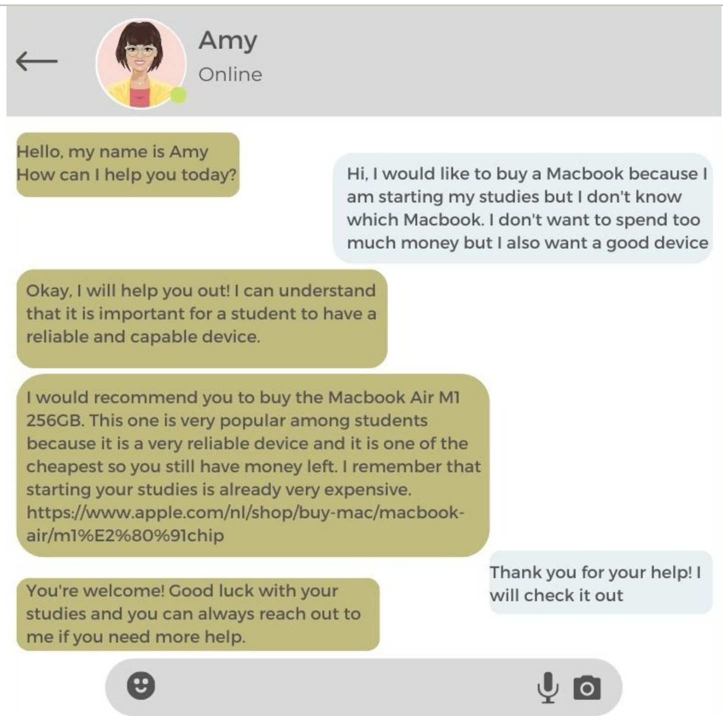
<tr><td>High</td><td>High</td><td>

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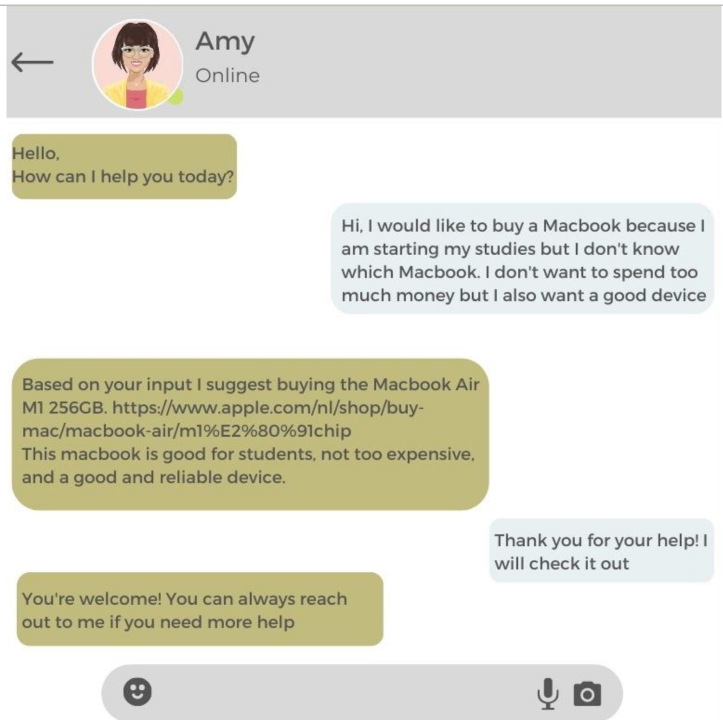
<tr><td>High</td><td>Low</td><td>

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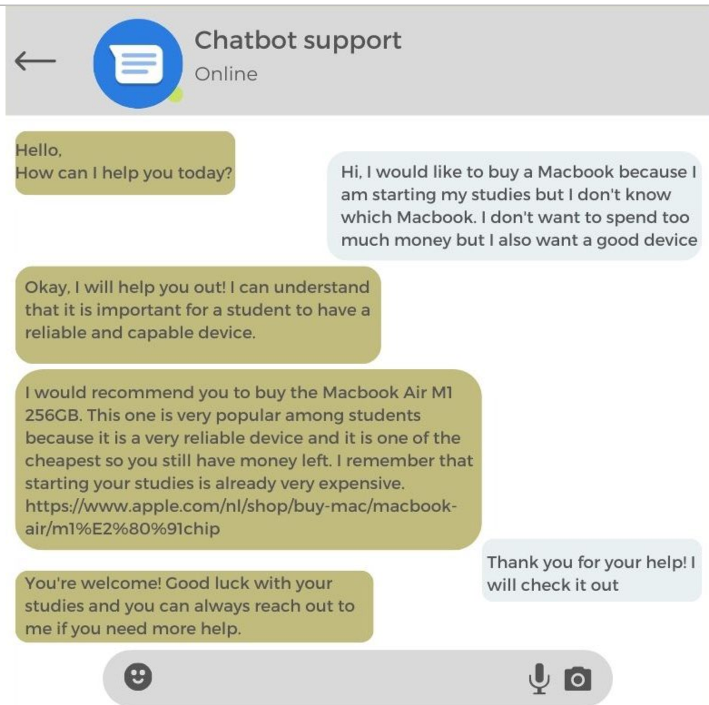
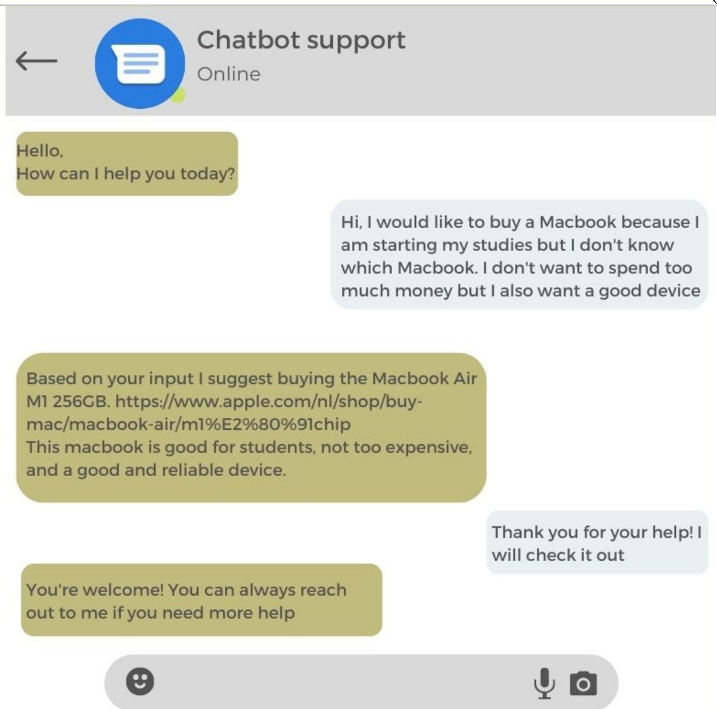
Low	High	 (3)
Low	Low	 (4)

3. Output descriptive statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Use1	134	1	5	3.83	.930	-.845	.209	.730	.416
Use2	134	1	5	3.93	.855	-.808	.209	1.035	.416

Use3	134	1	5	4.28	.698	-1.246	.209	3.624	.416
Use4	134	1	5	4.16	.866	-1.228	.209	1.937	.416
Trust1	134	1	5	2.67	1.095	.127	.209	-.697	.416
Trust2	134	1	5	2.87	1.213	-.021	.209	-.995	.416
Trust3	134	1	5	3.68	1.094	-.765	.209	.163	.416
Trust4	134	1	5	3.45	.946	-.145	.209	.010	.416
Trust5	134	1	5	3.50	.940	-.386	.209	.341	.416
Trust6	134	1	5	3.47	1.001	-.282	.209	-.150	.416
Trust7	134	1	5	3.66	.885	-.586	.209	-.054	.416
Trust8	134	1	5	3.66	.894	-.740	.209	.607	.416
Trust9	134	1	5	3.47	.939	-.354	.209	-.189	.416
Trust10	134	1	5	3.39	1.018	-.234	.209	-.369	.416
Persuasion1	134	1	5	3.69	1.013	-.719	.209	-.294	.416
Persuasion2	134	1	5	3.39	1.110	-.349	.209	-.902	.416
Persuasion3	134	1	5	3.57	1.198	-.520	.209	-.878	.416
Agent1	134	2	5	3.85	.771	-.336	.209	-.142	.416
Agent2	134	2	5	3.68	.881	-.326	.209	-.530	.416
Agent3	134	1	5	3.99	.863	-1.127	.209	1.704	.416
Topic1	134	1	5	3.72	1.001	-.499	.209	-.400	.416
Topic2	134	1	5	2.28	1.271	.670	.209	-.684	.416
Topic3	134	1	5	3.27	1.177	-.370	.209	-.683	.416
VisA1	134	1	5	3.26	1.176	-.270	.209	-.809	.416
VisA2	134	1	5	3.40	1.176	-.420	.209	-.790	.416
VisA3	134	1	5	3.16	1.225	-.305	.209	-.880	.416
MenA1	134	1	5	2.51	1.243	.442	.209	-.856	.416
MenA2	134	1	5	1.93	1.193	1.306	.209	.825	.416
Age	134	18	69	28.83	9.323	1.906	.209	4.085	.416
Education	134	1	5	3.46	.898	-.929	.209	-.613	.416
Familiarity	134	1.00	5.00	3.7313	.95904	-.474	.209	-.210	.416
Gender	133	1	2	1.56	.498	-.261	.210	-1.962	.417
Valid N (listwise)	133								

4. Output assessment measurement model

4.1 Initial model

Goodness of model fit (estimated model)

	Value	HI95	HI99
SRMR	0.0815		
d_{ULS}			
d_G			

Construct Reliability

Construct	Dijkstra-Henseler's rho (ρ_A)	Jöreskog's rho (ρ_c)	Cronbach's alpha(α)
Persuasion knowledge	0.8354	0.8354	0.8354
Trust in chatbots	0.8851	0.8805	0.8787
Agent knowledge	0.6561	0.6492	0.6404
Topic knowledge	0.7583	0.7544	0.7495
Intention to use chatbots	0.8707	0.8603	0.8517

Indicator Reliability

Indicator	Persuasion knowledge	Trust in chatbots	Agent knowledge	Topic knowledge	Intention to use chatbots
Use_1					0.7305
Use_2					0.7535
Use_3					0.4879
Use_4					0.4643
Trust_1		0.3411			
Trust_2		0.4385			
Trust_3		0.4848			
Trust_4		0.5150			
Trust_5		0.5334			
Trust_6		0.5333			
Trust_7		0.3702			
Trust_8		0.3206			
Trust_9		0.4574			
Trust_10		0.2755			
Persuasion_1	0.6272				
Persuasion_2	0.6252				
Persuasion_3	0.6332				
Agent_1			0.4117		
Agent_2			0.4527		
Agnet_3			0.2867		
Topic_1				0.4528	
Topic_2				0.4686	
Topic_3				0.5991	

Convergent Validity

Construct	Average variance extracted (AVE)
Persuasion knowledge	0.6285
Trust in chatbots	0.4270
Agent knowledge	0.3837
Topic knowledge	0.5069
Intention to use chatbots	0.6091

Discriminant Validity: Heterotrait-Monotrait Ratio of Correlations (HTMT)

Construct	Persuasion knowledge	Trust in chatbots	Agent knowledge	Topic knowledge	Intention to use chatbots
Persuasion knowledge					
Trust in chatbots	0.0308				
Agent knowledge	0.2787	0.7214			
Topic knowledge	0.0327	0.6149	0.7242		
Intention to use chatbots	0.0477	0.6538	0.6666	0.5423	

Discriminant Validity: Fornell-Larcker Criterion

Construct	Persuasion knowledge	Trust in chatbots	Agent knowledge	Topic knowledge	Intention to use chatbots
Persuasion knowledge	0.6285				
Trust in chatbots	0.0008	0.4270			
Agent knowledge	0.0656	0.5206	0.3837		
Topic knowledge	0.0011	0.3670	0.5005	0.5069	

Intention to use chatbots	0.0024	0.4132	0.4361	0.2779	

Cross Loadings

Indicator	Persuasion knowledge	Trust in chatbots	Agent knowledge	Topic knowledge	Intention to use chatbots
Use_1	-0.0709	0.5485	0.5246	0.3900	0.8547
Use_2	-0.0328	0.5559	0.6080	0.4687	0.8680
Use_3	-0.0404	0.4365	0.5417	0.4924	0.6985
Use_4	-0.0021	0.4547	0.3733	0.2939	0.6814
Trust_1	0.0042	0.5840	0.4345	0.4816	0.3992
Trust_2	0.0662	0.6622	0.4857	0.5521	0.4162
Trust_3	0.0115	0.6962	0.3047	0.4203	0.3685
Trust_4	-0.0462	0.7176	0.5500	0.3493	0.4132
Trust_5	0.0393	0.7303	0.5251	0.4195	0.4467
Trust_6	0.0035	0.7303	0.5027	0.4030	0.4518
Trust_7	0.1033	0.6085	0.4246	0.3239	0.4592
Trust_8	-0.0868	0.5662	0.4336	0.2826	0.3676
Trust_9	0.0096	0.6763	0.6182	0.4468	0.5492
Trust_10	0.0949	0.5249	0.4309	0.2599	0.3192
Persuasion_1	0.7919	0.0334	0.2390	0.0735	-0.0462
Persuasion_2	0.7907	0.0160	0.1540	-0.0494	-0.0674
Persuasion_3	0.7958	0.0188	0.2160	0.0554	-0.0025
Agent_1	0.0035	0.5029	0.6416	0.3950	0.4664
Agent_2	0.1540	0.5449	0.6728	0.5248	0.4656
Agnet_3	0.3529	0.2639	0.5354	0.3881	0.2757
Topic_1	0.0575	0.4071	0.6783	0.6729	0.4724
Topic_2	-0.0326	0.4870	0.3625	0.6846	0.2965
Topic_3	0.0447	0.4054	0.4795	0.7740	0.3628

4.2 Model after deletion of Agent3

Goodness of model fit (estimated model)

	Value	HI95	HI99
SRMR	0.0766		
d_{ULS}			
d_G			

Construct Reliability

Construct	Dijkstra-Henseler's rho (ρ_A)	Jöreskog's rho (ρ_c)	Cronbach's alpha(α)
Persuasion knowledge	0.8354	0.8354	0.8354
Trust in chatbots	0.8851	0.8805	0.8787
Agent knowledge	0.6709	0.6709	0.6709
Topic knowledge	0.7583	0.7544	0.7495
Intention to use chatbots	0.8707	0.8603	0.8517

Indicator Reliability

Indicator	Persuasion knowledge	Trust in chatbots	Agent knowledge	Topic knowledge	Intention to use chatbots
Use_1					0.7305
Use_2					0.7535
Use_3					0.4879
Use_4					0.4643
Trust_1		0.3411			
Trust_2		0.4385			
Trust_3		0.4848			
Trust_4		0.5150			

Trust_5		0.5334			
Trust_6		0.5333			
Trust_7		0.3702			
Trust_8		0.3206			
Trust_9		0.4574			
Trust_10		0.2755			
Persuasion_1	0.6272				
Persuasion_2	0.6252				
Persuasion_3	0.6332				
Agent_1			0.5048		
Agent_2			0.5048		
Topic_1				0.4528	
Topic_2				0.4686	
Topic_3				0.5991	

Convergent Validity

Construct	Average variance extracted (AVE)
Persuasion knowledge	0.6285
Trust in chatbots	0.4270
Agent knowledge	0.5048
Topic knowledge	0.5069
Intention to use chatbots	0.6091

Discriminant Validity: Heterotrait-Monotrait Ratio of Correlations (HTMT)

Construct	Persuasion knowledge	Trust in chatbots	Agent knowledge	Topic knowledge	Intention to use chatbots
Persuasion knowledge					
Trust in chatbots	0.0308				
Agent knowledge	0.1109	0.7427			
Topic knowledge	0.0327	0.6149	0.6553		
Intention to use chatbots	0.0477	0.6538	0.6581	0.5423	

Discriminant Validity: Fornell-Larcker Criterion

Construct	Persuasion knowledge	Trust in chatbots	Agent knowledge	Topic knowledge	Intention to use chatbots
Persuasion knowledge	0.6285				
Trust in chatbots	0.0008	0.4270			
Agent knowledge	0.0123	0.5437	0.5048		
Topic knowledge	0.0011	0.3670	0.4190	0.5069	
Intention to use chatbots	0.0024	0.4132	0.4302	0.2779	0.6091

Cross Loadings

Indicator	Persuasion knowledge	Trust in chatbots	Agent knowledge	Topic knowledge	Intention to use chatbots
Use_1	-0.0709	0.5485	0.5673	0.3900	0.8547
Use_2	-0.0328	0.5559	0.6097	0.4687	0.8680
Use_3	-0.0404	0.4365	0.5020	0.4924	0.6985
Use_4	-0.0021	0.4547	0.3422	0.2939	0.6814
Trust_1	0.0042	0.5840	0.4416	0.4816	0.3992
Trust_2	0.0662	0.6622	0.4537	0.5521	0.4162
Trust_3	0.0115	0.6962	0.2934	0.4203	0.3685
Trust_4	-0.0462	0.7176	0.5698	0.3493	0.4132
Trust_5	0.0393	0.7303	0.5227	0.4195	0.4467

Trust_6	0.0035	0.7303	0.5268	0.4030	0.4518
Trust_7	0.1033	0.6085	0.5126	0.3239	0.4592
Trust_8	-0.0868	0.5662	0.4789	0.2826	0.3676
Trust_9	0.0096	0.6763	0.6273	0.4468	0.5492
Trust_10	0.0949	0.5249	0.3868	0.2599	0.3192
Persuasion_1	0.7919	0.0334	0.1067	0.0735	-0.0462
Persuasion_2	0.7907	0.0160	0.0857	-0.0494	-0.0674
Persuasion_3	0.7958	0.0188	0.0712	0.0554	-0.0025
Agent_1	0.0035	0.5029	0.7105	0.3950	0.4664
Agent_2	0.1540	0.5449	0.7105	0.5248	0.4656
Topic_1	0.0575	0.4071	0.5910	0.6729	0.4724
Topic_2	-0.0326	0.4870	0.3493	0.6846	0.2965
Topic_3	0.0447	0.4054	0.4489	0.7740	0.3628

5. Output assessment structural model

R-Squared

Construct	Coefficient of determination (R^2)	Adjusted R^2
Trust in chatbots	0.5954	0.5861
Intention to use chatbots	0.4241	0.4198

Effect Overview

Effect	Beta	Indirect effects	Total effect	Cohen's f^2
Persuasion knowledge -> Trust in chatbots	-0.0441		-0.0441	0.0047
Persuasion knowledge -> Intention to use chatbots		-0.0287	-0.0287	
Trust in chatbots -> Intention to use chatbots	0.6513		0.6513	0.7365
Agent knowledge -> Trust in chatbots	0.6007		0.6007	0.5135
Agent knowledge -> Intention to use chatbots		0.3912	0.3912	
Topic knowledge -> Trust in chatbots	0.2364		0.2364	0.0804
Topic knowledge -> Intention to use chatbots		0.1539	0.1539	

6. Output moderation effects

6.1 ANOVA

Descriptives									
		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
Persuasionknowledge	1	33	3.8283	1.05119	.18299	3.4555	4.2010	1.67	5.00

	2	34	3.4216	.92590	.15879	3.0985	3.7446	2.00	5.00
	3	33	3.6566	.89553	.15589	3.3390	3.9741	1.67	5.00
	4	34	3.3039	.91882	.15758	2.9833	3.6245	1.67	5.00
	Total	134	3.5498	.96059	.08298	3.3856	3.7139	1.67	5.00
Agentknowledge	1	33	3.9470	.56857	.09898	3.7454	4.1486	2.50	5.00
	2	34	3.6838	.60399	.10358	3.4731	3.8946	2.50	5.00
	3	33	3.8561	.64053	.11150	3.6289	4.0832	2.50	5.00
	4	34	3.7574	.77481	.13288	3.4870	4.0277	2.00	5.00
	Total	134	3.8097	.65263	.05638	3.6982	3.9212	2.00	5.00
Topicknowledge	1	33	2.9091	1.04174	.18134	2.5397	3.2785	1.00	5.00
	2	34	2.5147	1.01865	.17470	2.1593	2.8701	1.00	5.00
	3	33	2.8939	1.18426	.20615	2.4740	3.3139	1.00	5.00
	4	34	2.7794	1.10913	.19021	2.3924	3.1664	1.00	5.00
	Total	134	2.7724	1.08928	.09410	2.5863	2.9585	1.00	5.00
VisualAnthropomorphism	1	33	4.0000	.69222	.12050	3.7545	4.2455	2.67	5.00
	2	34	3.5784	.77983	.13374	3.3063	3.8505	1.00	5.00
	3	33	2.8485	.96857	.16861	2.5050	3.1919	1.00	5.00
	4	34	2.6667	.73855	.12666	2.4090	2.9244	1.00	4.33
	Total	134	3.2711	.95964	.08290	3.1072	3.4351	1.00	5.00
MentalAnthropomorphism	1	33	2.4091	1.27141	.22132	1.9583	2.8599	1.00	5.00
	2	34	1.9412	.87702	.15041	1.6352	2.2472	1.00	5.00
	3	33	2.4697	1.15879	.20172	2.0588	2.8806	1.00	5.00
	4	34	2.0735	1.10187	.18897	1.6891	2.4580	1.00	5.00
	Total	134	2.2201	1.11973	.09673	2.0288	2.4115	1.00	5.00

Tests of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Persuasionknowledge	Based on Mean	.305	3	130	.821
	Based on Median	.468	3	130	.705
	Based on Median and with adjusted df	.468	3	119.859	.705
	Based on trimmed mean	.266	3	130	.850
Agentknowledge	Based on Mean	1.014	3	130	.389
	Based on Median	1.066	3	130	.366
	Based on Median and with adjusted df	1.066	3	121.777	.366
	Based on trimmed mean	1.023	3	130	.385
Topicknowledge	Based on Mean	.737	3	130	.532
	Based on Median	.292	3	130	.831
	Based on Median and with adjusted df	.292	3	122.641	.831
	Based on trimmed mean	.698	3	130	.555
VisualAnthropomorphism	Based on Mean	1.298	3	130	.278
	Based on Median	1.012	3	130	.390
	Based on Median and with adjusted df	1.012	3	120.856	.390
	Based on trimmed mean	1.312	3	130	.273
MentalAnthropomorphism	Based on Mean	2.581	3	130	.056
	Based on Median	1.613	3	130	.189
	Based on Median and with adjusted df	1.613	3	123.906	.190
	Based on trimmed mean	2.241	3	130	.087

ANOVA

	Sum of Squares	df	Mean Square	F	Sig.

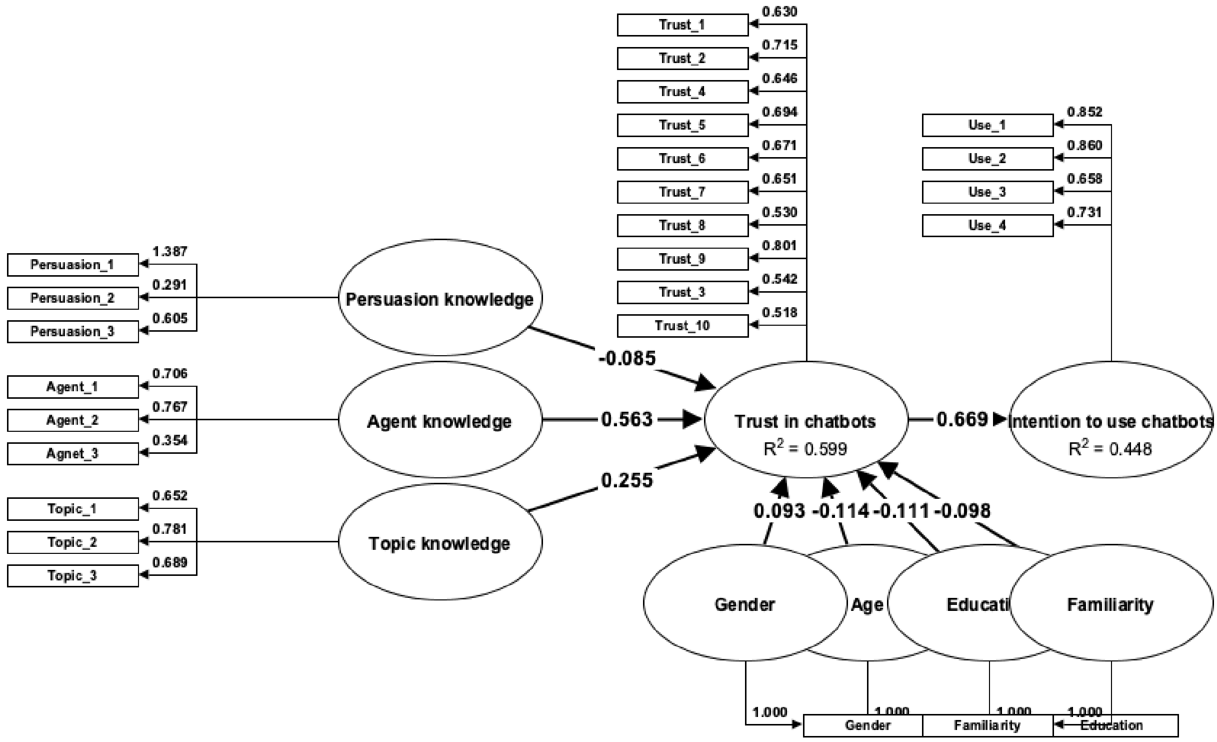
Persuasionknowledge	Between Groups	5.550	3	1.850	2.052	.110
	Within Groups	117.174	130	.901		
	Total	122.724	133			
Agentknowledge	Between Groups	1.325	3	.442	1.038	.378
	Within Groups	55.323	130	.426		
	Total	56.647	133			
Topicknowledge	Between Groups	3.364	3	1.121	.944	.422
	Within Groups	154.444	130	1.188		
	Total	157.808	133			
VisualAnthropomorphism	Between Groups	39.060	3	13.020	20.289	<.001
	Within Groups	83.422	130	.642		
	Total	122.482	133			
MentalAnthropomorphism	Between Groups	6.610	3	2.203	1.789	.153
	Within Groups	160.145	130	1.232		
	Total	166.756	133			

6.2 T-test

Indicator	Mean high visual	Mean low visual	Mean difference
Persuasion_2	3,46	3,31	0,15
Persuasion_3	3,69	3,45	0,24
Agent_1	3,82	3,88	-0,06
Agent_2	3,69	3,67	0,01
Agnet_3	4,13	3,85	0,28
Topic_1	3,61	3,82	-0,21
Topic_2	2,25	2,30	-0,04
Topic_3	3,16	3,37	-0,21

Indicator	Mean high mental	Mean low mental	Mean difference
Persuasion_2	3,15	3,07	0,07
Agent_1	3,74	3,78	-0,04
Agent_2	3,44	3,51	-0,07
Agnet_3	4,21	3,99	0,22
Topic_1	3,35	3,60	-0,25
Topic_2	2,03	2,15	-0,12
Topic_3	3,00	3,15	-0,15

7. Output control demographics and familiarity



Construct	Coefficient of determination (R^2)	Adjusted R^2
Trust in chatbots	0.5990	0.5766
Intention to use chatbots	0.4479	0.4437