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Determinants of trust in voice assistants: the moderating effect of age

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Abstract

This study aims to identify the determinants of trust in voice assistants, as trust is an important factor for their adoption. Based on existing research, emotional state, perceived human-likeness, perceived privacy risk and perceived expertise were identified to potentially influence trust and are therefore examined in this study. Additionally, age was considered as a possible moderator of these factors' effects. Data is collected through an online survey, were respondents had to indicate to what extent they agreed with various items on a 1-7 Likert scale, adapted from existing literature. After data collection, multiple linear regression in SPSS is used to analyze the data and examine the effects of those four factors on trust in voice assistants. Interaction effects are also used to analyze whether age moderates the effect of any of the factors. The results show that perceived expertise has a significant positive effect on trust in voice assistants, indicating that a higher perceived expertise of the voice assistant leads to greater consumer trust. Additionally, it was found that age negatively moderates the effect of emotional state on trust in voice assistants. These findings contribute to existing research by confirming the effect of perceived expertise on trust and identifying the moderating effect between age and emotional state. Additionally, managers and marketers can use these insights to enhance trust by improving the expertise of their voice assistants and using different targeting techniques for different age groups. Future research should consider using random sampling and collecting a larger sample size to achieve better data representativeness. Additionally, the moderation effect between age and emotional state and the potential effect of perceived privacy risk are interesting to further investigate.

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Introduction

The use of Artificial intelligence (AI) has grown rapidly over the last few years. Artificial Intelligence already has a market value of almost 100 billion US dollars, and it is expected that this value will grow to almost 2 trillion US dollars by 2030 (Statista, 2023). Therefore, Artificial Intelligence is becoming increasingly important nowadays. More and more companies are using Artificial Intelligence in their features, such as voice assistants. AI natural language processing technology enables voice assistants to understand human speech and provide responses in a voice that closely resembles a human voice (Wohr, 2023). The use of these voice assistants is growing steadily. In the United States, 42.1% of the population has used a voice assistant in 2022 and it is expected that this percentage will grow to 45.4% in 2026 (Lis, 2022).

Voice assistants, such as Siri and Google, are able to recognize and understand one's voice and therefore customers can make these assistants do certain tasks for them. These tasks can differ from relatively easy tasks, such as setting your alarm, to more sophisticated tasks, such as buying something from Amazon. As voice assistants are fairly new, not much research has been done yet on the important factors of voice assistants that could influence consumers. Further research on this topic would give valuable information for the future, as the implementation of Artificial Intelligence has grown fast over the last few years and the usage of voice assistants is likely to increase in the future (Lis, 2022).

An area within this context that requires more research is the trust of consumers in voice assistants and the factors that influence trust. Although voice assistants are becoming more popular, there are still many people who are not trusting these assistants as this technology is still fairly new to them. People mainly have privacy concerns regarding voice assistants, as these assistants are able to overhear your conversations when you are near the device and some people are not used to using them in their daily lives. A lot of research is already available regarding consumers' trust in technology and their intention to use technology in general. Determinants such as perceived ease of use, perceived usefulness, compatibility and perceived risk are important factors influencing the behavioral intention to use for technology (Wu & Wang, 2005). However, limited research is available regarding the factors that influence consumers' trust in voice assistants specifically, as voice assistants gained popularity only after the introduction of Siri in 2011 (Wohr, 2023). For example, Pitardi and Marriott (2021) found that perceived ease of use, the perceived enjoyment, social presence and social cognition influence trust of consumers in voice assistants. Additional research regarding this topic could explore other determinants that might influence consumers' trust as well.

Research problem & motivation

It is very useful for companies to have more academic research available regarding voice assistants, as Artificial Intelligence is increasingly growing and therefore it could be expected that voice assistants might become more important in the future. Companies could be interested in factors that increase the intention to use voice assistants, as there is currently only a slow steady growth in the market of voice assistants. Trust is a very important factor which positively influences intention to use (Pitardi & Marriott, 2021). Trust can be described as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer, Davis & Schoorman, 1995). It is therefore important for the managers of voice assistant companies to be able to make their potential customers gain more trust in voice assistants in order to increase the intention to use. Hence, it is important to study the factors that could influence consumers' trust in voice assistants.

As mentioned before, much research is already available regarding trust in technology in general, but only limited research is available on voice assistants specifically. However, some studies have already explored important factors regarding voice assistants. The study of Pitardi and Marriott (2021) has shown that perceived ease of use, perceived enjoyment, social presence and social cognition all have a significant effect on the trust of consumers in voice assistants. However, there might be more factors that could influence trust. The study of Fernandes and Oliveira (2021) has also shown that perceived ease of use and social norms influence adoption through perceived usefulness. Additionally, Rapport (for example warmth) and social presence are also crucial factors for consumers regarding the adoption of voice assistants. Furthermore, studies have shown that trust is a really important factor for the adoption of voice assistants by consumers (Fernandes & Oliveira, (2021); Wirtz et al., 2018). Therefore, it is important to focus on the factors that influence trust.

Other factors in literature have also shown to be important for voice assistants. The study of Dunn and Schweitzer (2005) has shown that the emotional state of consumers could influence their trust in general. Emotional state can be described as the current mood of consumers when thinking of voice assistants. Positive emotions such as happiness and gratitude influence their trust in a positive way and negative emotions such as anger and sadness influence their trust in a negative way. Furthermore, Poushneh (2021) has explored the seven most important voice assistant personality traits and questioned participants regarding the personality traits functional intelligence, sincerity and creativity. His study has found that these factors all enhance perceived control, and this significantly increases consumer satisfaction and their willingness to use voice assistants. Additionally, a study that has explored determinants of trust in chatbots has used both a quantitative and a qualitative study to find these determinants (Nordheim, Følstad & Bjørkli, 2019). In the quantitative study, the results have shown that the factors expertise, risk and propensity have a significant effect on trust in chatbots, where human-likeness has a bordered significance. The thematic analysis concludes that expertise is the most crucial factor when looking for trust in chatbots, as this is the most frequently coded category. Additionally, getting fast responses, human-likeness and absence of marketing were three other categories that were important for trust in chatbots. As chatbots are only different from voice assistants in terms of their voice and speaking, these factors might also be important to consider regarding trust of consumers in voice assistants.

As shown above, research has already shown crucial factors for voice assistants, chatbots and technology in general. However, there is still little research available whether these factors might also influence trust in voice assistants specifically. It is important to conduct further research about factors that influence trust as this will add crucial evidence to literature and this will give valuable information to companies that use voice assistants.

Research objectives

As shown above, there are many factors that are important for voice assistants. There also might be a possibility that these factors could influence trust in voice assistants, while there is still little research about these factors regarding trust. This study therefore will try to find other factors which also influence trust of consumers in voice assistants. Therefore, the following research question is formulated:

"What are the determinants of consumers' trust in voice assistants?"

This study aims to explore which factors might have a significant effect on trust and assess whether their influence is positive or negative. This will add additional information on already existing studies on voice assistants by examining additional factors that also might influence trust in voice assistants. Furthermore, the findings will enhance existing knowledge in the field, as companies will be provided with more knowledge about how to improve their voice assistants to foster greater trust among consumers. As shown, trust plays a significant role in the adoption of voice assistants and this information will be particularly useful in the future due to the growing popularity of Artificial Intelligence.

Research methodology

Existing literature is used to explore which factors are important and might also have a possibility to influence trust in voice assistants. These factors are used in this study to find their effect on trust. Items from existing literature are used to measure these factors. Furthermore, while exploring literature more information is gathered regarding trust in voice assistants.

A survey is used to gather data on the factors, to explore whether there might be an effect. This survey is executed with Qualtrics. First, a question is asked whether the person has experience with the voice assistant Siri. Furthermore, participants are asked to answer several questions about each factor extracted from the literature review that could influence trust in voice assistants. Questions will follow regarding their trust in the voice assistant. Here, Siri is used as the voice assistant the participants need to think about while answering these questions, as Siri is currently one of the most used voice assistants. They can answer to what extent they agree or disagree with different items regarding the factors, while keeping Siri in mind. Then, questions are asked about demographics of participants, namely their age, gender and level of education. Furthermore, an attention check question is used to determine whether participants paid attention while filling in the survey. Here, respondents are asked to answer the question with "somewhat agree." Additionally, the order of the questions in the survey is randomized, to avoid possible biases.

The survey is distributed via the social media channels Facebook and Instagram, and via WhatsApp. Furthermore, the websites Survey Swap and Survey Circle are used to optimize the number of participants. A requirement of taking the survey is that the participant needs to already have had experience with the voice assistant Siri, to be able to answer the questions. After collecting the data, the data is converted to Excell to clean the data. Any person who answered the attention check question wrong is excluded, as this shows that the participant did not pay attention and could cause biased results. Furthermore, any participant who answered that they do not have had experience with Siri are also excluded from the data. After cleaning the data, a multiple linear regression is performed in IBM SPSS to analyze the data. Here, trust is the dependent variable and the factors that could influence trust are the independent variables.

Thesis outline

The literature review will follow, where existing knowledge regarding this topic from previous literature is discussed, hypotheses are formulated and the conceptual framework is presented. After formulating the hypotheses, the research methodology follows, where the data collection method, the sampling method and the data analysis method are explained. Furthermore, in the results section both the results and the hypotheses are discussed. In the conclusion, the most important results are summarized and an answer to the main research question is formulated. Furthermore, the implications and limitations of the study and the recommendations for future research are discussed.

Literature review

Existing empirical literature from topics such as technology, voice assistants, AI and marketing is used to find possible determinants of trust in voice assistants. The majority of research used is not older than fifteen years to ensure the information is not outdated.

Trust

Trust is a crucial factor for consumers when deciding to use a certain product or service. As mentioned earlier, trust is “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party” (Mayer, Davis & Schoorman, 1995). When trusting a service or product, consumers expect to be able to rely on this product or service to deliver what is promised (Sirdeshmukh, Singh & Sabol, 2002).

Trust has shown to be one of the most important factors for the adoption of technology (Gefen, Karahanna & Straub, 2003). Therefore, trust has been included in the Technology Acceptance Model (TAM) in several studies. TAM is a model that is used to analyze the determinants of consumers’ acceptance of technology (Marangunić & Granić, 2015). Initially, perceived usefulness, perceived ease of use and attitude towards using technology were the primary factors used in this model. However, modifications in the model were made in other theories to use the model and/or improve predictive validity. Several factors were added, including trust, to improve predictive validity (Gefen, Karahanna & Straub, 2003).

Research conducted by AlHogail (2018) has revealed that improving certain factors affecting trust significantly improves the adoption of technology. The study presents a model wherein trust significantly influences the adoption of technology, and technology adoption is in turn influenced by several factors that influence trust in technology. Therefore, identifying these factors that impact trust provides valuable information. Furthermore, another study has shown that trust is important for the acceptance of service robots in particular (Wirtz et al., 2018). This paper has studied the roles of service robots and the customer perspective on them and included trust as one of the important factors in the service robot acceptance model. Additionally, the study of Fernandes and Oliveira (2021) examined factors that influence the adoption of digital voice assistants. A survey was conducted, and the Partial Least Squares Structural Equation Modelling was used to find relationships between the factors. Functional, social and relational elements were used, and it was found that trust as a relational element is the second most important factor that positively influences the acceptance of voice assistants.

As mentioned above, trust has proven to be of great importance for consumers in the context of the adoption of technology and voice assistants in particular (Gefen, Karahanna & Straub, 2003; Fernandes & Oliveira, 2021). Therefore, it is important to explore the factors associated to trust in voice assistants. This contributes to a deeper understanding and might improve the adoption of voice assistants in the future.

Existing knowledge on important factors

There is already research available regarding some important factors associated with the adoption and trust in technology and voice assistants. Some studies have explored different factors which influence the adoption of technology (AlHogail, 2018; Wu & Wang, 2005). AlHogail (2018) studied factors affecting trust in Internet of Things (IoT) technology which in turn affects the adoption of IoT technology. A survey was used to collect data from four hundred respondents and quantitative analysis was used to analyze the data. The study revealed that product-related factors, social-related factors, and security-related factors all influence trust in IoT technology. Similarly, another study has examined the factors influencing the intention to use technology regarding mobile commerce (Wu & Wang, 2005). Here, a survey was conducted to collect data and interviews were used for feedback. The results show that perceived risk, cost, compatibility and perceived usefulness significantly influence the intention to use technology.

When focusing on voice assistants in particular, Wirtz et al. (2018) examined the factors influencing the acceptance of service robots. Through an examination of various studies on the Technology Acceptance Model (TAM) and service robots, they created a service robot acceptance model. Their results show that functional elements (perceived ease of use, perceived usefulness and subjective social norms), social-emotional elements (perceived humanness, perceived social interactivity and perceived social presence) and relational elements (trust and rapport) are important factors in the service robot acceptance model. Similarly, a study specifically focused on digital voice assistants has applied this model and tested these factors on voice assistants (Fernandes & Oliveira, 2021). A survey was distributed among millennials and Partial Least Squares Structural Equation Modelling was used to analyze the data. Results indicated that perceived social presence, rapport, perceived trust and perceived usefulness have a positive significant effect on the acceptance of digital voice assistants. Additionally, perceived ease of use and subjective social norms, mediated by perceived usefulness, also have a positive significant effect on the acceptance of digital voice assistants.

However, only limited research is available regarding factors that influence trust in voice assistants. The study of Nasirian, Ahmadian and Lee (2017) focused on technology quality factors that may influence trust in voice assistants. Here, only interaction quality is shown to have a significant positive effect on trust. Other studies mainly focused on privacy concerns influencing trust. Pal et al. (2020) has introduced a model including all privacy concerns which can influence trust. However, a more recent study has examined additional factors that might influence trust in voice assistants and in turn the intention to use voice assistants. Pitardi and Marriott (2021) used a survey to collect data and used Structural Equation Modelling to analyze the data. The study found that perceived ease of use, social presence and social cognition significantly influences trust in voice assistants. As not much research has been done on these factors influencing trust in voice assistants, there may be additional variables affecting trust in voice assistants. Therefore, this paper aims to explore these factors and examine their influence on trust, adding valuable insights to already existing research.

Explaining variables and formulating hypotheses

Emotional state

Consumers' emotional state could be an important factor influencing trust in voice assistants. Emotional state can be described as the current mood the consumer describes he or she has. A study conducted by Dunn and Schweitzer (2005) has used five experiments to examine the effects of consumers' emotional state on trust. They manipulated participants' emotional states by letting them think of a certain event that has happened in their lives. The overall results show that positive emotions, such as happiness, positively influences trust and negative emotions, such as anger or sadness, negatively influences trust.

Several studies have examined the effect of consumers' mood on technology adoption (Djamasb, Strong & Dishaw, 2010; Karimi & Liu, 2020). Djamasb, Strong and Dishaw (2010) have studied the role of positive emotions on technology acceptance through a laboratory experiment. Four treatment combinations were used, including a positive mood treatment and a control group, as well as moderate and high task uncertainty treatments. Their findings indicate that a positive mood has a positive impact on technology adoption when uncertainty is moderate, but this influence is not observed when uncertainty is high. Similarly, Karimi and Liu (2020) conducted an experiment involving mood manipulation to investigate the influence of consumer mood on technology adoption, specifically focusing on mobile payment adoption. They found that when consumers are in a positive mood, they are more confident and are more willing to adopt new technologies.

Another study focused on the moderated effects of consumer mood on the ability of the digital assistant (Beeler, Zablah & Rapp, 2022). Consumers tend to give lower ratings to the ability of digital assistants when they are in a positive mood, as they possess greater cognitive recourses in a positive state, and this enables them to offer more critical assessments. Nevertheless, research has shown that cultivating positive moods is crucial for restoring consumer trust, especially after unfavorable situations (Chen, Wu & Chang, 2013). This study used a survey to gather data and used the structural equation modelling to analyze the data. Consequently, a positive mood has the potential to enhance consumer trust. Companies could apply this information by reducing negative perceptions of their products and instead try to enhance a positive mood. Therefore, the following hypothesis is stated:

H1*: Emotional state of consumers has a positive effect on trust in voice assistants.*

Perceived human-likeness

Extensive research has been conducted on the impact of human-likeness on consumers. human-likeness can be described as the perceived anthropomorphic nature of the voice assistant (Ho & MacDorman, 2010). This could be for example using emotional cues and humor in their sentences. Several studies have shown that including human-like features in devices or technology can enhance the relationship between a person and the device or technology (Mourey, Olson & Yoon, 2017; Schweitzer et al., 2019). Consumers describe the voice assistant as a master, a servant, or a partner due to the human-likeness (Schweitzer et al., 2019). Rather than solely focusing on the functionality of voice assistants, consumers frequently evaluate the quality of these devices by considering their good intentions, as they form some sort of relationship with the device. Another study has also shown that products with human-like features are able to satisfy social needs and give social assurance (Mourey, Olson & Yoon, 2017). Furthermore, a study has investigated the experiences of infrequent users (Cowan et al., 2017). Twenty respondents from a university community had to do six tasks using Siri. After every task they had to write down their experience and observations. Several participants see Siri as friendly, and the human-likeness affected their responses in a way that they did not want to hurt Siri. However, a disadvantage of human characteristics is that people expect more from voice assistants than that they are capable of, as they compare the voice assistant with humans.

However, products should not have human characteristics that are too similar, as this could potentially scare consumers away. This phenomenon is associated with the uncanny valley, where people experience discomfort when robots have too many human-like features (Kim, Schmit & Thalmann, 2019). Research conducted by Kim, Schmit and Thalmann (2019) shows that too many human-like features negatively affect consumers' attitude towards robots due to a feeling of uncanniness.

Nevertheless, human-likeness has also shown to increase the trust of consumers. Waytz, Heafner and Epley (2014) have studied the effect of anthropomorphism on trust in technology and applied this on autonomous vehicles. They let three samples use a driving simulator of a normal car, an autonomous car and an autonomous car with human-like features. They used behavioral and psychological measures and let the respondents report their experience. These results show that respondents trusted technology including human-like features the most. Additionally, human-likeness has been identified as one of the primary factors that influences emotional trust in Artificial Intelligence, together with tangibility and immediacy behaviors (Glikson & Woolley, 2020). Furthermore, the study of Pitardi and Marriott (2021) also identified social presence, which is the feeling that another social entity is present, as one of the factors affecting trust in voice assistants by conducting a survey and using the Structural Equation Modelling. As several studies have shown that human-likeness increases the consumer attitude and trust towards technology, it is a possibility that the way consumers perceive human-likeness in voice assistants could increase trust. Therefore, the following hypothesis is formulated:

***H2**: Perceived human-likeness has a positive effect on trust in voice assistants.*

Perceived expertise

Consumers also tend to find expertise very important. Perceived expertise can be described as the perceptions of consumers about the experience, knowledge and competence of the system (Corritore, Kracher & Wiedenbeck, 2003). When a voice assistant successfully answers all questions and performs tasks proficiently, consumers perceive a higher expertise in the voice assistant.

Sekhon et al. (2014) explored the determinants of trustworthiness. They obtained data from a survey conducted by UK consumers, collected in different time periods. A regression was used to analyze the data. The data shows that expertise and competence have a significant positive effect on trustworthiness. This suggests that a higher perceived expertise may lead to increased trust. Similarly, a study focused on chatbots also found that expertise is an important factor for trust (Nordheim, Følstad & Bjørkli, 2019). A survey was used to collect data from chatbot users. Both quantitative and qualitative methods were used to analyze the data, including multiple linear regression and thematic analysis on the open-ended questions. The multiple linear regression shows that expertise of the chatbot is one of the three factors that influence trust. Furthermore, thematic analysis also concludes that expertise is one of the main factors influencing trust. These studies show a significant effect of expertise on trust.

When focusing on voice assistants, several infrequent users have mentioned that voice assistants such as Siri still struggle to understand consumers' questions, particularly in noisy places or with different accents, which they found frustrating (Cowan, 2017). Another study examined factors that influence consumer attitudes (Poushneh, 2021). They let participants interact with a voice assistant before they had to fill in a survey. Results show that the functional intelligence of the voice assistant, which is similar to expertise, significantly increases the sense of control and the satisfaction of consumers. In conclusion, prior studies have demonstrated that expertise can increase trust and the satisfaction of consumers. Therefore, the following hypothesis is formulated:

H3: *Perceived expertise of the voice assistant has a positive effect on trust in voice assistants.*

Perceived privacy risk

Many consumers are concerned about their privacy when trying new technologies. They are for example concerned that their personal information will be sold to third parties without them knowing. While the study of Pitardi and Marriott (2021) did not confirm that privacy concerns have a significant effect on trust in voice assistants, there are still several studies which confirm that privacy risk is a main concern among consumers.

There still have been some privacy issues regarding voice assistants. Personal information could be leaked or stolen, and consumers are afraid that those devices are secretly recording them as they are able to respond to consumers all the time (Hoy, 2018). This have led to major privacy concerns. Hasan, Shams and Rahman (2021) have studied the factors affecting the brand loyalty of voice assistants, applied to Siri. They have conducted a survey to collect data from participants who have experience with Siri. The results show that perceived privacy risk has a negative significant effect on brand loyalty. Furthermore, McLean and Osei-Frimpong (2019) examined the factors influencing the usage of a voice assistant. They gathered data through a survey and used structural equation modelling to analyze the data. Their results indicated a moderating effect of perceived privacy risk, which decreases the positive effects of factors influencing the usage. This suggests that consumers have genuine concerns about privacy risks associated with voice assistants. Another study also concludes that privacy concerns significantly influence the satisfaction of the consumer (Brill, Munoz & Miller, 2022). Results from earlier research show that perceived privacy risk is an important factor for the use and satisfaction of voice assistants. As trust has shown to be an important factor for the adoption and use of voice assistants, perceived privacy risk may have an effect on trust as well. Therefore, the following hypothesis is formulated:

H4: *Perceived privacy risk has a negative effect on trust on voice assistants.*

Moderator: Age

The degree of technology adoption and trust in technology differs across generations. As a result, the age of the consumer may impact how they perceive voice assistants. It has shown that particularly older generations tend to have less trust in new technologies (Knowles & Hanson, 2018). They mainly have concerns regarding privacy, and they have less confidence in using new technologies, as they often do not know how these technologies work. Another study also confirms that older adults have privacy concerns and that this influences the intention to use and trust in technology (Fox & Connolly, 2018).

Another study has examined the adoption of technology applied on mobile payment systems, with age as moderator (Liébana-Cabanillas, Sánchez-Fernánde & Muñoz-Leiva, 2014). They first showed their respondents a video explaining the new mobile payment system. After, they had to fill in a survey. When analyzing the results, they divided the sample in a group below the age of 35 and a group older than 35. The results show that the effect of perceived usefulness on intention to use is higher for older adults. An explanation for this could be that younger adults are more experienced with technology and therefore are better able to understand how to use this.

Furthermore, several studies have examined the responses of older adults to voice assistants (Kowalski et al., 2019; Pradhan, Lazar & Findlater, 2020). Kowalski et al. (2019) used two workshops where older adults interacted with voice assistant Google Home and afterwards group interviews were conducted. Some elderly mentioned that they are uncertain about the expertise and reliability of the voice assistant; whether they are able to really do all the tasks that were demanded, such as turning off the stove. However, they found voice assistants easier in use compared to computers, for example. Additionally, Pradhan, Lazar and

Findlater (2020) implemented Amazon Echo Dot in homes of older adults for a period of three weeks. Usage logs and multiple interviews were collected and these data were analyzed. The older adults mentioned that after a few weeks of use, they are willing to keep using it. However, they were concerned about the expertise skills of the voice assistant, such as not being able to answer some questions or not understanding the question.

There is not much research available regarding the moderating effect of age on the factors affecting trust in voice assistants. However, available research indicates that there is a possibility that age moderates these factors. Studies have shown that when people get older, they tend to have a better regulation of their emotions (Urry & Gross, 2010; Zimmermann & Iwanski, 2014). Younger adults tend to have stronger feelings of sadness, anger and fear compared to older adults as older adults are better able to regulate these emotions (Zimmermann & Iwanski, 2014). Furthermore, older adults generally have a better well-being compared to younger adults due to their emotion regulation (Urry & Gross, 2010). Adults tend to form more effective strategies to control their emotions as they get older. Furthermore, older adults tend to have less effects from specific emotions compared to younger adults when making decisions as older adults are better at regulating their emotions and have more life experience (Peters et al., 2007). As stronger emotions have an effect on trust, for older adults emotional state might be less important for trusting voice assistants compared to younger adults due to their enhanced regulation of emotions when making decisions. Therefore, the following hypothesis can be formulated:

H5a: *Age negatively moderates the effect of emotional state on trust in voice assistants.*

Additionally, older adults tend to be more socially isolated compared to younger adults, while they still have their social needs (Iwamura et al., 2011). It has shown that devices with anthropomorphic features tend to decrease this feeling of social exclusion and are able to partially satisfy social needs, as they are able to have emotional conversations (Mourey, Olson & Yoon, 2017). Furthermore, as people get older, their preferences for emotional connections instead of informational conversations increases, as their life expectancy decreases (Carstensen, 1995). This increases the importance of emotional conversations. However, older adults tend to have greater trust for devises with human-like features, as this is more familiar to them compared to devices with robotic features (Tu, Chien & Yeh, 2020). Conversations with human-like assistants are namely more comparable to conversations with humans. Another study shows that elderly prefer robots with more human-like features and are more willing to use these robots compared to robots with less human-like features (Esposito, 2020). This study also concludes that elderly are more likely to trust robots with human-like features. In conclusion, perceived human-likeness could have a greater importance for trusting a voice assistant for older adults. Therefore, the following hypothesis is formulated:

H5b: *Age positively moderates the effect of perceived human-likeness on trust in voice assistants.*

Furthermore, the study of Liébana-Cabanillas, Sánchez-Fernánde and Muñoz-Leiva (2014) used age as a moderator and the results show that as age increases, the effect of perceived usefulness on the intention to use technology is stronger. Older people tend to have more difficulty in learning new technologies and have less confidence in using new technologies (Barnard et al., 2013; Knowles & Hanson, 2018). Due to the difficulty in learning, older people tend to place more importance on the benefits of using new technologies and trusting the devices to do what is asked when deciding to learn how to use those (Melenhorst, Rogers & Bouwhuis, 2006). Therefore, older people may find it more important that voice assistants more easily understand and complete the tasks given by older adults, in order to trust the voice assistants to successfully complete their tasks and give the right answers (Kowalski et al., 2019). Therefore, the following hypothesis is formulated:

H5c: *Age positively moderates the effect of perceived expertise on trust in voice assistants.*

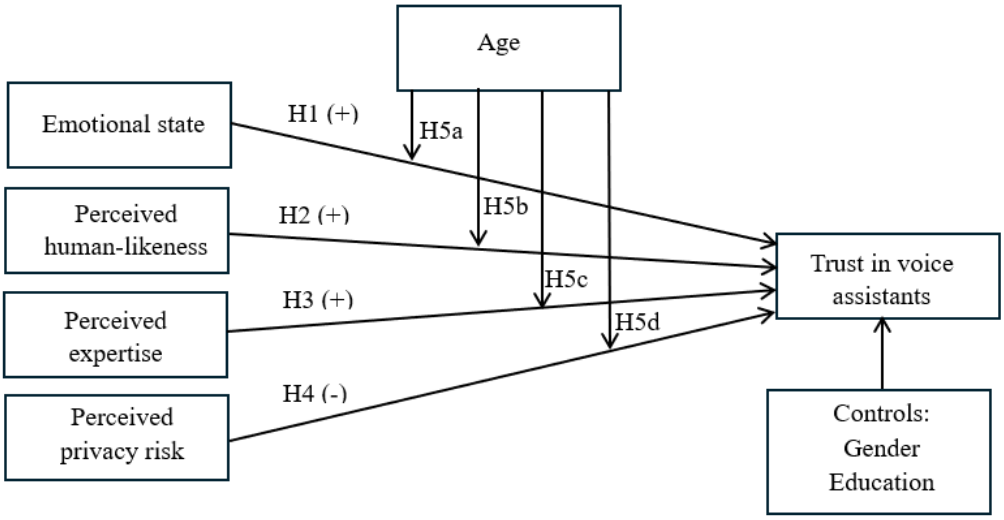
Lastly, some studies have already shown a moderating effect of age on privacy concerns. The study of Aboobucker and Bao (2018) examined the factors that influence the adoption of technology in the context of internet banking. The moderators age and gender were used, and the results show that the effect of risk and security and privacy are moderated by age. The older age group shows to have a stronger effect of risk and security and privacy on technology adoption. When people get older, they tend to be more likely to avoid uncertainty in situations with risk (Mather et al., 2012). They prefer choosing the safer option and avoid situations where risk is involved and where they are more likely to lose, as they are loss avers. In a situation with privacy risk, older people may find trusting a voice assistant riskier and therefore find perceived privacy risk of great importance in whether to trust a voice assistant. The study of Hoofnagle et all. (2010) shows that adults older than 65 significantly show more privacy concerns than adults between 25 and 34 years old. In contrast, younger individuals tend to have more positive attitudes towards management of their data, as they have more knowledge on how this works and therefore perceived privacy concern may be a less important factor for trust for younger consumers (Miltgen & Peyrat-Guillard, 2014). In conclusion, perceived privacy risk may have a stronger effect on trust for older consumers compared to younger consumers. Therefore, the following hypothesis is formulated:

H5d: *Age positively moderates the effect of perceived privacy risk on trust in voice assistants.*

Conceptual framework

Figure 1

Conceptual framework voice assistants



Overview hypotheses

Table 1

Hypotheses

Hypothesis	Description
H1	Emotional state of consumers has a positive effect on trust in voice assistants.
H2	Perceived human-likeness has a positive effect on trust in voice assistants.
H3	Perceived expertise of the voice assistant has a positive effect on trust in voice assistants.
H4	Perceived privacy risk has a negative effect on trust on voice assistants.
H5a	Age negatively moderates the effect of emotional state on trust in voice assistants.
H5b	Age positively moderates the effect of perceived human-likeness on trust in voice assistants.
H5c	Age positively moderates the effect of perceived expertise on trust in voice assistants.
H5d	Age positively moderates the effect of perceived privacy risk on trust in voice assistants.

Research methodology

Research design

This study aims to search for factors that are significantly influencing the trust in voice assistants, and whether age might moderate these effects. Therefore, a quantitative approach is used for several reasons. First, a quantitative approach allows to find significant effects on the dependent variable trust. Additionally, this approach allows to discover whether the effects of the independent variables on the dependent variable are positive or negative. Lastly, the influence of age as moderator can be determined with a quantitative approach.

A survey design is used for this study, as these designs are typically used when examining behaviours, opinions or attitudes. With the survey design, data can be collected from consumers across different age groups regarding their emotional state, perceived human-likeness, perceived expertise and perceived privacy risk and the trust in voice assistants. This information enables to answer the research question, including the effects of differences in age. As there is no need for manipulation of variables, an experimental design is not necessary. Furthermore, as existing studies which studied the factors influencing trust in voice assistant also used survey designs, it proves to be a suitable approach for this subject (Pitardi & Marriott, 2021; Pal et al., 2020; Nasirian, Ahmadian, & Lee, 2017). With this design a large and diverse group of consumers can be reached which allows for more representative findings.

Sampling method

This study focuses on voice assistants, where Siri is used in the survey as this is one of the most used voice assistants. Therefore, the target population consists of people who have had experience with the voice assistant Siri to be able to answer the survey questions. Participants who still fill in the survey while not having experience with Siri are excluded from the data, as their answers would bias the results due to not having knowledge about the subject.

Two types of non-probability sampling techniques are used in this study to collect participants. Convenience sampling is used, as this technique allows to select participants who are easily reachable such as friends, relatives and other students. Due to the time constraint of writing the thesis, this sampling technique is a suitable technique to reach enough participants for this study (Taherdoost, 2016). Furthermore, snowball sampling is used to collect more participants. Here, participants are asked to send the survey to other friends or relatives. This is another way to quickly collect more participants in a cost-effective way, as only your social network is needed (Taherdoost, 2016). However, as these are non-probability sampling techniques, the sample may not be representative of the population (Sharma, 2017). Nevertheless, only participants who have experience with voice assistants will be used and these sampling techniques make it possible to reach many participants with different ages. The survey was distributed on Instagram, Facebook and WhatsApp. Participants are kindly asked to send the survey to their friends and relatives who have experience with Siri. Furthermore, the platforms Survey Swap and Survey Circle are used to reach more participants who are willing to fill in surveys.

There are several rules of thumb for the desired sample size. One of them is that for every independent variable, a minimum of ten participants is needed to examine relationships. However, it would be more optimal to reach thirty participants per independent variable, as the power would increase (VanVoorhis & Morgan, 2007). In total, two control variables and age, four independent variables and four moderations are used to regress on trust in voice assistants. Therefore, this rule of thumb concludes that the sample size should be between 110 and 330 participants. However, another rule of thumb states that when you want to test the relationship of every predictor individually, the sample size should be bigger than 104 + m, where m stands for the number of independent variables (Green, 1991). This rule of thumb concludes that the sample size should be bigger than 115. When considering the rule of thumbs while keeping in mind the time constraints for this study, this study requires a minimum sample size of 120 participants.

Data collection methods and measurements

The data is collected through an online survey which is created with the software program Qualtrics. An advantage of an online survey is that it can be easily distributed online to a large number of potential participants. Furthermore, an online survey ensures anonymity, as participants do not have to show up in person to conduct the survey. Different measures with multiple items for the variables from existing research are used in the survey, to ensure reliability and validity. All items which are used in the survey to measure the variables are shown in table 2.

Trust

Trust is the dependent variable in this study. Trust can be defined as “the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer, Davis & Schoorman, 1995). The study of Pitardi and Marriott (2021) have also examined the factors influencing trust in voice assistants. Their study uses four items with a 7-point Likert scale in their survey, with 1= strongly disagree and 7=strongly agree. These four items are used in this study to measure trust with the same Likert scale.

Emotional state

Emotional state refers to the current mood of the participant. As previously mentioned in the literature review, positive emotions may positively influence trust in voice assistants, while negative emotions may negatively influence trust. Therefore, a measurement is used to measure whether the participant is in a positive or negative emotional state. The study of Djamasbi, Strong and Dishaw (2010) asked participants how much they related to three different moods, namely "happy", "glad" and "pleased" with a 7-point Likert scale. Here, "strongly agree" (7) is associated with a positive emotional state and "strongly disagree" (1) is associated with a negative emotional state. These three items are used in this study with a 7-point Likert scale to measure emotional state.

Perceived human-likeness

Perceived human-likeness refers to the perceived anthropomorphic nature of the voice assistant (Ho & MacDorman, 2010). The study of Li and Sung (2021) measured perceived anthropomorphism of AI assistants, which is similar to perceived human-likeness. Here, the items from the study of Waytz, Cacioppo and Epley (2010) were used to measure perceived anthropomorphism. These five items are also measured on a 7-point Likert scale with 1= strongly disagree and 7=strongly agree. These items are used in this study to measure perceived human-likeness and the items are rephrased to voice assistants.

Perceived expertise

Perceived expertise can be described as the perceptions of consumers about the experience, knowledge and competence of the system (Corritore, Kracher & Wiedenbeck, 2003). The study of Sekhon et al. (2014) used four items to measure perceived expertise and competence. These four items are used in this study to measure the perceived expertise of the voice assistant. These items are rephrased to items about voice assistants. A 7-point Likert scale is used, where 1= strongly disagree and 7=strongly agree.

Perceived privacy risk

Perceived privacy risk refers to the concern of consumers that their personal information might be leaked or stolen through voice assistants. The study of McLean and Osei-Frimpong (2019) examined the effect of perceived privacy risk on the intention to use voice assistants. Here, four items were used to measure perceived privacy risk. A 7-point Likert scale is used, where 1= strongly disagree and 7=strongly agree. As this study has a similar subject, these four items are used to measure the perceived privacy risk of participants.

Moderator and control variables

The moderator age is measured as the current age of the participant. Here, the participant is only able to numerically fill in their age, to avoid confusion. Furthermore, gender and level of education are used as control variables. People are asked to select if they are male or female. Gender is coded as a dummy variable, where male is used as the reference category. Furthermore, the different levels of education are shown where participants are able to select their highest completed level of education. These are also coded as dummy variables, where the lowest level of education will be used as the reference category. Gender and level of education belong to the most used control variables in research (Shavitt, Lowrey & Haefner, 1998). Control variables are variables where the researcher is not particularly interested in but could still have influence on the dependent variable. Differences may occur between males and females in the trust in- and preferences for voice assistants (Moradbakhti, Schreibelmayr & Mara, 2022). Furthermore, level of education may influence trust in voice assistants, as people differ in knowledge about how voice assistants work.

Table 2

Overview of items used to measure variables

Variables	Items	Adopted from
Trust	I feel that voice assistant Siri makes truthful claims.	Pitardi &
	I feel that voice assistant Siri is trustworthy.	Marriott (2021)
	I believe what voice assistant Siri tells me.	
	I feel that voice assistant Siri is honest.	
Emotional state	Right now, I feel happy.	Djamasbi,
	Right now, I feel glad.	Strong &
	Right now, I feel pleased.	Dishaw (2010)

Perceived human-likeness	I feel like the voice assistant Siri has intentions.	Li & Sung (2021)
	I feel like the voice assistant Siri has free will.	
	I feel like the voice assistant Siri can experience emotions.	
	I feel like the voice assistant Siri has consciousness.	
	I feel like the voice assistant Siri has a mind of its own.	
Perceived expertise	Voice assistant Siri has the information it needs to conduct its tasks.	Sekhon et al., (2014)
	Voice assistant Siri competently handles all my requests.	
	Voice assistant Siri is efficient.	
	Voice assistant Siri is knowledgeable.	
Perceived privacy risk	I have my doubts over the confidentiality of my interactions with voice assistant Siri.	McLean & Osei-Frimpong (2019)
	I am concerned to perform a financial transaction via the voice assistant Siri.	
	I am concerned that my personal details stored with voice assistant Siri could be stolen.	
	I am concerned that voice assistant Siri collects too much information about me.	

Survey design

The online survey shown in Appendix A consists of a few parts. In the introduction, participants are assured that their answers will stay confidential and their anonymity will be assured. Furthermore, information is given about the subject of the study. It will be explained that the questions in the survey are about Siri and that participants must have experience with this voice assistant to be able to answer the questions. Therefore, at the beginning of the survey a question is asked whether the respondent has experience with Siri. Respondents who will answer no are removed from the data. The voice assistant Siri is chosen, as this is one of the most known voice assistants. It has shown that 98% of all iPhone users has used the voice assistant Siri at least once (Cowan et al., 2017). Additionally, voice assistants only became popular after Siri was introduced in 2011 (Wohr, 2023). Right now, Siri is one of the most used voice assistants (Wardini, 2024). Using Siri ensures that enough respondents of different ages can be reached who have had experience with Siri. Furthermore, using one particular voice assistant enables participants to imagine their experience with voice assistant Siri when answering the questions. Participants will also be made aware of the existence of an attention check question in the survey, so they will pay more attention when answering the questions.

After the introduction, respondents had to answer to what extent they agree with statements regarding their emotional state, perceived human-likeness of Siri, perceived expertise of Siri and perceived privacy risk when using Siri. The items from table 2 are used in this survey, with a 7-point Likert scale with 1= strongly disagree and 7= strongly agree. Qualtrics enables to place the questions in random order, to avoid potential order effects. Furthermore, an attention check question is used in the survey. Here, respondents are asked to select the answer “somewhat agree”. An attention check question allows to check whether respondents are not randomly selecting answers when conducting the survey. Respondents who wrongly answer this question are removed from the data to avoid biases. Lastly, demographic questions are asked regarding age, gender and level of education. The survey ends by thanking the respondents for their time and effort.

Data analysis

When a sufficient number of respondents is collected, the survey data can be converted from Qualtrics to excel. These data were first cleaned before any analyses are made. Data are removed from respondents who mentioned that they have never used Siri, respondents who wrongly answered the attention check question and respondents who did not complete the survey. Additionally, any unrealistic outliers, for example an age above 100, are also removed from the data. After cleaning the data, the data can be converted to SPSS.

First, the descriptive statistics of the sample are examined. Furthermore, the data is tested on validity and reliability by conducting a factor analysis and Cronbach’s alpha on the items. First, factor analysis is conducted to check for validity. Items who do not meet the requirements are excluded from the data. Additionally, Cronbach’s Alpha is used to ensure reliability of the data. After these checks, the average from the items can be computed to create one measure for each variable. Before analysing these data in a linear regression, the assumptions for linear regression are tested. After this, a multiple linear regression is used to analyse the possible relationships between the dependent variable and independent variables and moderations. A multiple linear regression allows to find significant effects and whether the correlations are positive or negative. The first regression only includes the four variables emotional state, perceived human-likeness, perceived expertise and perceived privacy risk. Second, the interaction terms are stepwise included in the next four models. Then, the sixth regression model includes all interaction terms. These interaction terms are made by multiplying the moderator age with the four independent variables. Here, the hypotheses H5a, H5b, H5c and H5d are tested. Furthermore, the hypotheses H1, H2, H3 and H4 are tested. Finally, the last multiple regression also includes the control variables. Here, the possible influences of the control variables can be examined. The final linear regression can be described as follows:

$$Trust = \beta_0 + \beta_1 * female + \beta_2 * lower/intermediate\ secondary\ education + \beta_3 * higher\ secondary\ education + \beta_4 * pre - university\ secondary\ education + \beta_5 * higher\ professional\ education + \beta_6 * university + \beta_7 * PhD + \beta_8 * age + \beta_9 * emotional\ state + \beta_{10} * perceived\ human - likeness + \beta_{11} * perceived\ expertise + \beta_{12} * perceived\ privacy\ risk + \beta_{13} * age \times emotional\ state + \beta_{14} * age \times perceived\ human - likeness + \beta_{15} * age \times perceived\ expertise + \beta_{16} * age \times perceived\ privacy\ risk + \varepsilon$$

Results

In this chapter, the results from the data gathered through Qualtrics were analysed. First, the dataset preparation and the sample demographics are described. Second, the data was checked for validity and reliability. Furthermore, the four assumptions of multiple linear regression were checked. After the validation of the assumptions, the multiple linear regression was run, and the hypotheses are analysed.

Dataset preparation

In total, 164 respondents filled out the survey created by Qualtrics. While all respondents fully completed the survey, some responses still needed to be deleted. From the 164 responses, nineteen respondents indicated that they have never used Siri before. As the respondents needed to have had experience with Siri to be able to answer the survey questions, these nineteen responses had to be deleted. Furthermore, six responses were deleted, as they did not correctly answer the attention check question. This could indicate that they did not pay enough attention while filling out the survey. Lastly, the total duration time of each response was checked. It is not desirable to have responses who quickly clicked through the survey without paying attention to the questions asked, because this could bias the results. The average duration time of completing the survey was 157 seconds, where most responses had a duration time between 120 and 240 seconds. Therefore, responses with a duration time lower than 60 seconds were deleted from the data, as this differs significantly from the average duration time. In total, eleven respondents with a duration time below 60 seconds were deleted from the dataset. After the preparation, the sample size consisted of 128 responses, which is in line with the minimum desired sample size of 120 responses discussed earlier.

Sample demographics

The demographics gender and education are shown in table 3. Of all 128 respondents, 27.3% identified themselves as male and 72.7% identified themselves as female. Furthermore, the majority of respondents, namely 46.1%, completed university. Secondly, 25.8% completed higher professional education. Additionally, 12.5% completed pre-university secondary education and 7.0% completed higher secondary education. Lastly, 7.8% completed lower or intermediate secondary education, followed by 0.8% who completed primary school. However, no one indicated that they have completed a PhD. Therefore, this category is not used in the results. Furthermore, it was decided that lower/intermediate secondary education was used as a reference category instead of primary school for the education level dummy variables, as only one respondent indicated that they completed primary school as their highest form of education. Lastly, the average age of the sample is 28 with a standard deviation of 11.4. The age distribution of the sample is shown in figure 2. Here, the youngest respondent is 15 and the oldest respondent is 75. The majority of respondents is between 15 and 25 years old, followed by the 25-35 age group. The output of the demographics is shown in Appendix B.

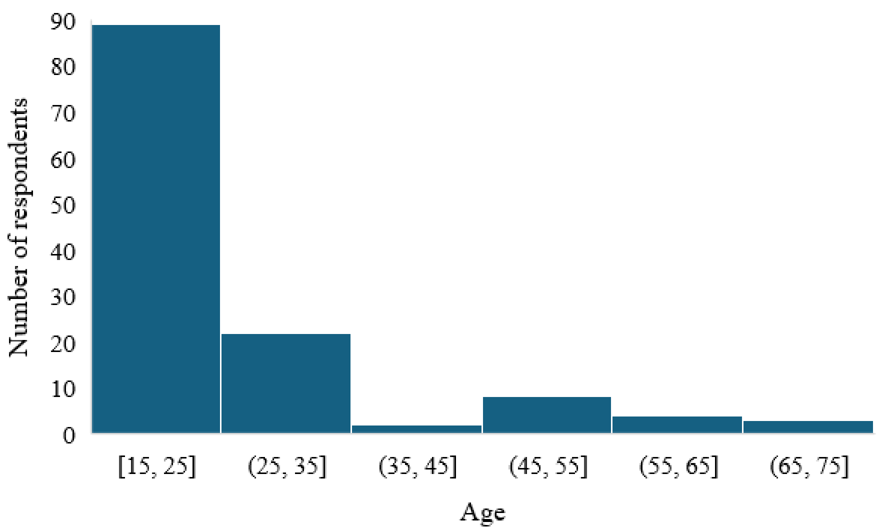
Table 3

Demographics gender and education

Demographic	Category	Frequency	Percentage
Gender	Male	35	27.3%
	Female	93	72.7%
Education	Primary school	1	0.8%
	Lower or intermediate secondary education	10	7.8%
	Higher secondary education	9	7.0%
	Pre-university secondary education	16	12.5%
	Higher professional education	33	25.8%
	University	59	46.1%
	PhD	0	0.0%

Figure 2

Distribution of age respondents



Validity- and reliability analysis

Factor analysis

Multiple items are used to measure emotional state, perceived human-likeness, perceived expertise, perceived privacy risk and trust. To test the validity of these items and to compute the variables, an exploratory factor analysis was conducted in SPSS. First, the Pearson bivariate correlation matrix was used to check for potential high correlations between the items. Here, a correlation of >0.8 was found within the three items of emotional state. Item 3 of emotional state showed a correlation of 0.836 with item 1 and a correlation of 0.815 with item 2. Furthermore, the determinant of the matrix was 0.00000962, which is lower than the minimum desired score of 0.00001. Field (2013) recommends eliminating one item from the pair of items when a bivariate correlation score exceeds 0.8, to avoid the existence of intercorrelation in the data. Therefore, it was decided to remove item 3 of emotional state, namely “Right now, I feel pleased”.

After removing item 3, the Pearson bivariate correlation matrix had a determinant of 0.0000523>0.00001 and showed no more correlations greater than 0.8. Therefore, the exploratory factor analysis could be run in SPSS, using the Principal Axis Factoring technique with a Varimax rotation. In total, five factors were generated with an eigenvalue greater than one. Furthermore, a KMO of 0.739 was found and the Bartlett’s test of sphericity was significant with $p<0.001$. However, item 2 of perceived privacy risk showed a low communality of 0.211, which is somewhat above the minimum advised communality of 0.2 but is still much lower compared to the communalities of the other items. Additionally, this item had a factor loading of 0.436, which is lower than the preferred minimum loading of 0.512 for a sample size of around one hundred respondents (Stevens, 2012). Due to the low communality score and low factor loading compared to the other items, it was decided to remove item 2 of perceived privacy risk, namely “I am concerned to perform a financial transaction via the voice assistant Siri”. This item could have a low factor loading because this item is about financial transactions, whereas the other items do not address this specifically. After the removal of item 2 of perceived privacy risk, the exploratory factor analysis was run again. Here, still five factors were found with an eigenvalue greater than one. Additionally, the KMO was 0.744 and the Bartlett’s test of sphericity was again significant with $p<0.001$. Furthermore, the five factors with the remaining items explain 73.1% of the variance, with a lowest factor loading of 0.686. The factor loadings are shown in table 4. The output of the factor analysis is shown in Appendix C.

Table 4

Factor loadings exploratory factor analysis

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Perceived human-likeness1	**0.705**	0.026	-0.004	0.068	0.026
Perceived human-likeness2	**0.781**	0.056	-0.035	0.064	0.072
Perceived human-likeness3	**0.686**	-0.060	-0.049	0.014	0.022
Perceived human-likeness4	**0.831**	0.091	0.078	0.065	-0.032
Perceived human-likeness5	**0.798**	0.079	-0.016	0.033	0.160
Perceived expertise1	-0.039	**0.712**	0.242	0.028	-0.058
Perceived expertise2	0.139	**0.742**	0.142	-0.039	0.057
Perceived expertise3	0.018	**0.810**	0.192	0.058	-0.004
Perceived expertise4	0.045	**0.778**	0.128	-0.010	0.035
Trust1	-0.019	0.127	**0.708**	-0.009	-0.068
Trust2	-0.032	0.167	**0.789**	-0.130	0.054
Trust3	0.038	0.222	**0.781**	-0.007	0.006
Trust4	-0.022	0.174	**0.720**	-0.127	0.069
Perceived privacy risk1	-0.016	-0.048	-0.107	**0.729**	-0.066
Perceived privacy risk3	0.141	-0.008	-0.018	**0.885**	0.068
Perceived privacy risk4	0.095	0.087	-0.093	**0.761**	-0.030
Emotional state1	0.005	0.027	-0.030	-0.037	**0.927**
Emotional state2	0.192	0.001	0.071	-0.003	**0.835**

Note: An exploratory factor analysis is conducted with Varimax rotation. The rotated factor loadings are used in this table. The KMO shows a score of 0.744 and the Bartlett's test of sphericity is significant with $p<0.001$.

Reliability analysis

After running the factor analysis, Cronbach's Alpha was run in SPSS to check the reliability of the data. The output of Cronbach's Alpha is shown in Appendix C. A minimum score of 0.7 is needed to ensure reliability of the data. As shown in table 5, all scores are above 0.7, with a minimum score of 0.835 and a maximum score of 0.874. This implies that the data is reliable and that the variables can be computed from their items to be used for further analysis. Each variable was computed by adding up the items belonging to the variable and dividing this number by the number of items.

Table 5

Cronbach's Alpha

Factor	Number of items	Cronbach's Alpha
Emotional state	2	0.872
Perceived human-likeness	5	0.874
Perceived expertise	4	0.859
Perceived privacy risk	3	0.835
Trust	4	0.853

Assumptions multiple linear regression

Several assumptions needed to be tested before multiple linear regression could be used to analyse the data and test the hypotheses. The output of the tests is shown in Appendix D. First, the data was checked for outliers by looking at the standard residuals and Cook's Distance. Here, the minimum standard residual had a value of -2.742 and the maximum standard residual had a value of 2.426. this shows no large outliers as the standard residuals lie between the range of -3 and 3. However, Cook's Distance showed a maximum value of 1.166 >1, which indicates that there is a potential outlier. In total, only one datapoint showed a value greater than one. To ensure that this potential outlier would not influence the results, this datapoint was removed from the data.

Secondly, the variables used in the multiple linear regression should not show any signs of multicollinearity. This was tested by analysing the Pearson's Bivariate Correlation matrix and by calculating the Tolerance statistic and the Variance Inflation Factor (VIF) for each independent variable in SPSS. To satisfy this assumption, the Tolerance statistic must be greater than 0.1 and the VIF must be lower than 10. However, the inclusion of interaction terms in the model might increase the chance of multicollinearity. Therefore, the variables were first centred before computing the interaction terms which decreases the chance of multicollinearity, without influencing the results. The Pearson's Bivariate Correlation matrix showed no correlations greater than 0.8. Furthermore, the lowest value for the Tolerance statistic is 0.131 and the highest value of the VIF is 7.621. This indicated that the data showed no high concern of multicollinearity, and the assumption was met.

Additionally, the assumption of no autocorrelation was analysed. The Durbin-Watson test was used to test for autocorrelation in the data. Here, a value between 1.5 and 2.5 indicates that there is no high concern for the existence of autocorrelation. The Durbin-Watson test showed a value of 1.889, which indicates that there is no sign of autocorrelation. Therefore, this assumption was also met.

Thirdly, the histogram and the Q-Q plot were used to test the assumption of multivariate normality. The histogram of the standardised residuals showed an approximate normal distribution of the data errors. Additionally, the normal Q-Q plot of the dependent variable trust showed that the datapoints are mainly closely following the line. These criteria indicated that the variables are multivariate normal and therefore this assumption was met.

Lastly, the assumptions of linearity and the presence of homoscedasticity were checked by analysing the scatterplot of the standardized residuals. The scatterplot of the standardized residuals showed that the standardized residuals are approximately equally scattered around zero, which indicates no concern for heteroscedasticity. Furthermore, all datapoints in the scatterplot were randomly scattered between -3 and 3, which indicates that the data is linear. Therefore, the assumptions of homoscedasticity and linearity were also met.

Hypotheses testing

After testing the data for validity and reliability and meeting the assumptions of multiple linear regression, it was possible to test the hypotheses with multiple linear regression analysis. In total, seven models were analysed. In model I only the main variables were included. Additionally, in models II, III, IV and V the interaction effects were included in a stepwise manner. Furthermore, in model VI all interaction effects were added. These models were used to analyse whether age moderates the relationship between the main effects and trust. Lastly, model VII represents the whole model including the main effects, the interaction effects and the control variables. The control variables were added to control for possible confounding effects and to analyse whether demographics influence trust in voice assistants as well.

All linear regression models were tested for significance of the models. Model I was found significant ($F(4, 122) = 5.980$, $p < 0.010$) with an adjusted R-square of 0.137. Furthermore, models II ($F(6, 120) = 4.565$, $p < 0.010$), III ($F(6, 120) = 3.972$, $p < 0.010$), IV ($F(6, 120) = 4.191$, $p < 0.010$) and V($F(6, 120) = 4.061$, $p < 0.010$) were also found significant with adjusted R squares of 0.145, 0.124, 0.132 and 0.127. Additionally, model VI was found significant ($F(9, 117) = 3.246$, $p < 0.010$) with an adjusted R square of 0.138. Lastly, model VII was also found significant ($F(15, 111) = 2.327$, $p < 0.010$) with an adjusted R square of 0.136. This indicates that all models can be used to test the hypotheses. A significance level of 5% is used to test the hypotheses. The coefficients of the seven models are shown in Table 6.

Table 6

Multiple linear regression models

Variables	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**
Constant	3.504***	3.521***	3.474***	3.425***	3.472***	3.685***	3.572***
Emotional state	0.010	-0.034	0.006	0.005	0.004	-0.046	-0.158
Perceived human-likeness	-0.025	-0.035	-0.040	-0.047	-0.043	-0.043	-0.046
Perceived expertise	0.350***	0.354***	0.351***	0.370***	0.354***	0.366***	0.399***
Perceived privacy risk	-0.114*	-0.121*	-0.115*	-0.117*	-0.122*	-0.126*	-0.156**
Age	-	0.011	0.004	0.003	0.005	0.006	0.019
Age x Emotional state	-	-0.014*	-	-	-	-0.017*	-0.032**
Age x Perceived human-likeness	-	-	0.001	-	-	0.006	0.011
Age x Perceived expertise	-	-	-	0.010	-	0.008	0.009
Age x Perceived privacy risk	-	-	-	-	-0.005	-0.005	-0.008
Female	-	-	-	-	-	-	-0.093
Primary school	-	-	-	-	-	-	-2.516*
Higher secondary education	-	-	-	-	-	-	0.542
Pre-university secondary education	-	-	-	-	-	-	0.511
Higher professional education	-	-	-	-	-	-	0.454
University	-	-	-	-	-	-	0.463
Adjusted R square	0.137	0.145	0.124	0.132	0.127	0.138	0.136
N	127	127	127	127	127	127	127

Note: *** = p<0.01, ** = p<0.05 and * = p<0.10. For the interaction terms, the variables were centred to reduce the chance of multicollinearity. "Female" is a dummy variable with "male" as a reference category. Furthermore, the levels of education are also created as dummy variables, with "lower/intermediate secondary education" as reference category.

Main effects

First, the results for the main effects were analysed. Hypothesis 1 states that emotional state of a consumer has a positive effect on trust in voice assistants. Studies have shown that a positive emotional state of consumers positively influence their trust in voice assistants and the adoption of technology (Chen, Wu & Chang, 2013; Karimi & Liu, 2020). However, in all models the effect of emotional state on trust is not significant and the coefficients are really small. Therefore, there is no evidence that emotional state has a significant effect on trust in voice assistants and hypothesis 1 is rejected.

Furthermore, hypothesis 2 states that perceived human-likeness has a positive effect on trust in voice assistants. Studies have shown that human-likeness of the voice assistant is an important factor for trust in voice assistants (Glikson & Woolley, 2020; Pitardi and Marriott, 2021). However, none of the models show a significant effect of perceived human-likeness on trust. Therefore, hypothesis 2 is also rejected, as the models show no evidence for a significant effect of perceived human-likeness on trust in voice assistants.

Regarding perceived expertise, hypothesis 3 states that perceived expertise of the voice assistant has a positive effect on trust in voice assistants. Studies have indicated that consumers are more likely to trust voice assistants to accurately complete tasks when they perceive the assistants to have higher expertise (Poushneh, 2021; Cowan, 2017). All models show a significant effect of perceived expertise on a one percent significance level ($p<0.001$) and all coefficients are positive. Therefore, hypothesis 3 is supported. Model II is used to describe the effect, as this model has the highest adjusted R square and therefore explains the most variance of the dependent variable. Regarding model II, the trust of the sample in voice assistants increases with 0.354 out of 7 when perceived expertise increases with 1 out of 7.

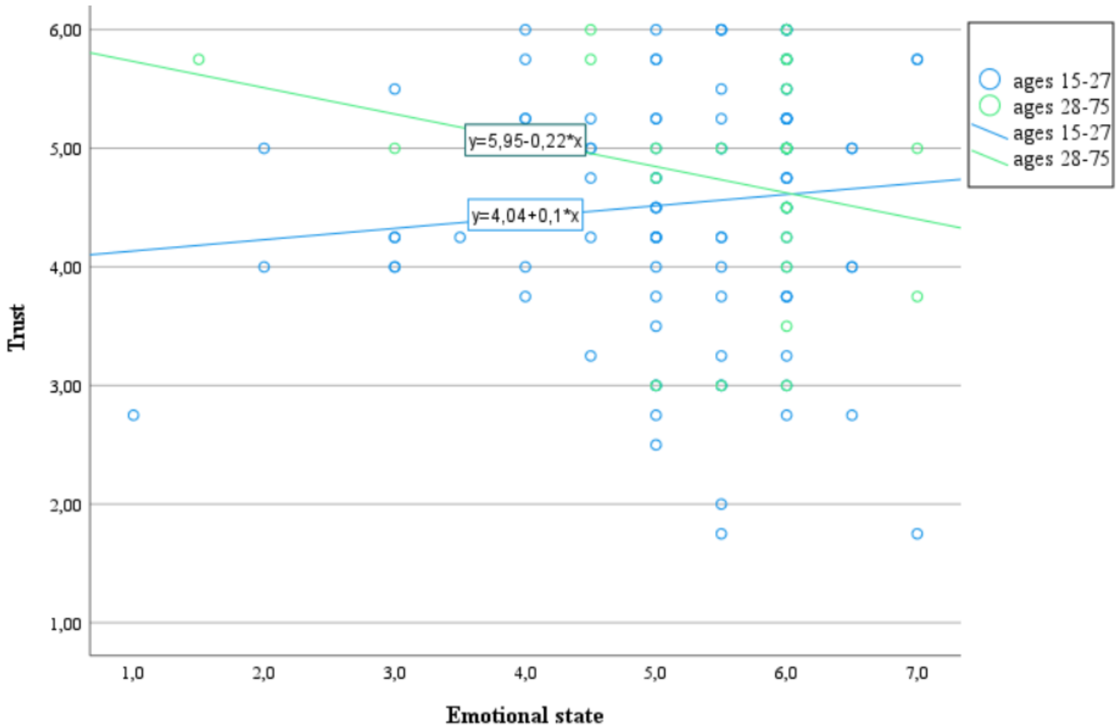
Additionally, hypothesis 4 states that perceived privacy risk has a negative effect on trust in voice assistants. Studies have shown that consumers have privacy concerns when using voice assistants, which could negatively influence trust (McLean and Osei-Frimpong, 2019; Brill, Munoz & Miller, 2022). In Model I ($p= 0.086$), model II ($p= 0.067$), model III ($p= 0.087$), model IV ($p= 0.079$), model V ($p= 0.071$), and model VI ($p= 0.062$), the coefficient of perceived privacy risk is only significant on a ten percent significance level, but not on a five percent significance level. Nevertheless, model VII ($\beta= -0.156$, $p< 0.050$) does show a significant negative effect of perceived privacy risk on trust on a five percent significance level. However, as model III has the lowest adjusted R square and the other models show no significant effect, there is not enough evidence that perceived privacy risk has a significant negative effect on trust in voice assistants. Therefore, hypothesis 4 cannot be accepted.

Moderation effects

Models II, VI and VII are used to analyse the moderation effect of age on emotional state. Hypothesis 5a states that age negatively moderates the effect of emotional state of consumers on trust in voice assistants. Model II (β= -0.014, p= 0.087) and model VI (β= -0.017, p= 0.065) do show a significant effect on a ten percent significance level, but not on a five percent significance level of the interaction term Age x Emotional state. However, model VII (β= -0.032, p< 0.050) does show a significant effect of the interaction term on a five percent significance level. Additionally, it is interesting that there is a large increase of the adjusted R square between models I (0.137) and II (0.145), indicating that the model explains significantly more variance of the dependent variable when the interaction between age and emotional state is added in the model. To better understand the interaction effect, a scatterplot with fit lines was created to visualise the effect of the moderator, as shown in figure 3.

Figure 3

Line plot moderation of age on emotional state



In the scatterplot, age is divided into a younger group of 15-27 and an older group of 28-75 to be able to analyse how the moderator age influences the effect of emotional state on trust. The groups are divided based on the mean age of 28 of the sample. This figure shows additional evidence that the effect of emotional state on trust is moderated by age. For the younger age group, the slope of the line is positive, indicating that trust in voice assistants increases when the emotional state of the respondent gets more positive. However, the slope of the line of the older age group is negative, indicating that trust in voice assistants decreases when the emotional state of the respondent gets more positive. Therefore, one possible explanation for the insignificant effect of emotional state while the interaction term is significant, is that the effect differences across age groups rule out the main effect. In conclusion, the significant interaction effect in model VII and the visual representation of figure 3 provide enough evidence to support hypothesis 5a. As the respondents get older, the sign of the effect of emotional state on trust changes from positive to negative, indicating that age negatively moderates the effect of emotional state on trust in voice assistants. This is in line with previous mentioned studies, as this also indicates that younger generations are more influenced by positive emotions to make the decision whether to trust the voice assistant (Peters et al., 2007). In contrast, for older consumers the effect even turns negative.

Additionally, hypothesis 5b states that age positively moderates the effect of perceived human-likeness on trust in voice assistants. Models III, VI and VII are used for this hypothesis. Table 6 shows that the sign of the coefficient of perceived human-likeness is negative in all models and that the sign of the coefficient does turn positive when perceived human-likeness is moderated by age in the interaction term. However, the interaction term Age x Perceived human-likeness is not significant in model III (β= 0.001, p= 0.929), model VI (β= 0.006, p= 0.351) and model VII (β= 0.011, p= 0.109). Furthermore, the adjusted R square decreases from 0.137 in model I to 0.124 in model III, indicating that when the interaction term is added, the model has a worse fit. Therefore, while the sign turns positive, there is still not enough evidence that age positively moderates the effect of perceived human-likeness.

Furthermore, models IV, VI and VII are used to analyse the moderation effect of age on perceived expertise. Hypothesis 5c states that age positively moderates the effect of perceived expertise on trust in voice assistants. However, the value of the coefficients decreases when the moderator is added in the interaction term, instead of the expected positive increase of the coefficient. Furthermore, while perceived expertise is significant in all models, models IV (β= 0.010, p= 0.296), VI (β= 0.008, p= 0.451) and VII (β= 0.009, p= 0.362) show no significant effect of the interaction term Age x Perceived expertise. Therefore, there is not enough evidence that age moderates the effect of perceived expertise on trust and hypothesis 5c cannot be accepted.

Lastly, hypothesis 5d states that age positively moderates the effect of perceived privacy risk on trust in voice assistants. Models V, VI and VII are used for this hypothesis. In these models, the value of the coefficient of the interaction term weakens compared to the value of perceived privacy risk, instead of the expected increase of the value when the moderation is added. Furthermore, in model V (β= -0.005, p= 0.502) model VI (β= -0.005, p= 0.504) and model VII (β= -0.008, p= 0.336) the interaction term Age x Perceived privacy risk shows no significance. Therefore, hypothesis 5d is rejected, as there is not enough evidence that age positively moderates the effect of perceived privacy risk. Table 7 shows a summary of the analysis of the hypotheses.

Table 7

Overview hypotheses analysis

Hypothesis	**Supported/ rejected**
H1: Emotional state of consumers has a positive effect on trust in voice assistants.	Rejected
H2: Perceived human-likeness has a positive effect on trust in voice assistants.	Rejected
H3: Perceived expertise of the voice assistant has a positive effect on trust in voice assistants.	Supported
H4: Perceived privacy risk has a negative effect on trust on voice assistants.	Rejected
H5a: Age negatively moderates the effect of emotional state on trust in voice assistants.	Supported
H5b: Age positively moderates the effect of perceived human-likeness on trust in voice assistants.	Rejected
H5c: Age positively moderates the effect of perceived expertise on trust in voice assistants.	Rejected
H5d: Age positively moderates the effect of perceived privacy risk on trust in voice assistants.	Rejected

Control variables

In model III, demographic variables are added as control variables to reduce the possibility of confounding effects. Table 6 shows that there is not a significant difference between males and females in trusting a voice assistant. Furthermore, all educational variables show no significance on a five percent significance level, indicating that the educational level of the sample does not significantly influence trust in voice assistants. Lastly, the variable age also does not have a significant effect on trust. This indicates that trust in voice assistants does not significantly differ between different age groups in the sample.

Conclusion

Main findings

This thesis aims to find the determinants of trust in voice assistants. Trust has shown to be an important factor for the adoption of technology. Therefore, finding the determinants of trust in voice assistants can attribute to a greater adoption of voice assistants. In the literature review, previous studies were analysed to find factors which possibly influence the trust in voice assistants. Additionally, the moderator age is also found, which could potentially influence those effects. An online survey is used to gather data from respondents. Here, questions were related to the voice assistant Siri, as in this way respondents could imagine their experience with Siri while answering the questions. In total, 128 responses were used in the analysis. Finally, after analysing the results, the answer to the following research question can be discussed:

"What are the determinants of consumers' trust in voice assistants?"

This study found a significant effect in all models of perceived expertise on trust in voice assistants on a one percent significance level. Table 6 of the results indicates that higher perceived expertise increases the respondent's trust in voice assistants. This is in line with previous studies, where was found that consumers find it important that voice assistants correctly answer their questions and are able to complete tasks accurately (Cowan, 2017; Poushneh, 2021). Furthermore, no significant effect on a five percent significance level was found for the factors emotional state and perceived human-likeness. Therefore, it cannot be concluded from this study that these factors significantly influence trust in voice assistants. However, perceived privacy risk has shown to have a significant effect on five percent significance level in model VII. As in the other six models this was not the case, it could not be concluded that perceived privacy risk has a significant effect on trust in this study. However, this factor might still be interesting to study for future research.

Regarding the moderator age, a significant effect was found of the interaction term Age x Emotional state on a five percent significance level. This indicates that the effect of emotional state on trust is moderated by age. Figure 3 has shown that the effect of emotional state changes from positive to negative as respondents get older. This shows that age negatively moderates the effect of emotional state on trust in voice assistants. Younger respondents are more likely to be influenced by their emotions when making certain decisions. A positive emotional state could therefore have more positive effect on their trust in voice assistants, compared to older respondents. Furthermore, age did not significantly moderate the effect of the other factors on trust in this study. In conclusion, this study has found that perceived expertise and the moderation between age and emotional state have a significant effect on trust in voice assistants.

Academic implications

Currently, much academic research is available regarding trust in technology. However, existing research regarding trust in voice assistants specifically is scarce. This study contributes to existing literature by providing more information on the determinants of trust in voice assistants.

This study provides more evidence that a higher perceived expertise not only increases the satisfaction of consumers mentioned by previous research (Cowan, 2017; Poushneh, 2021), but also increases trust. As the study of Nordheim, Følstad and Bjørkli (2019) already found that expertise positively influences trust in chatbots, this study concludes that this is also the case with voice assistants. Furthermore, a significant effect of perceived privacy risk was found in model VII. While there was not enough evidence to conclude that perceived privacy risk really influences trust, it is still interesting for future research. This is in contrast with the study of Pitardi and Marriott (2021), where no significant effect was found for privacy risk.

Furthermore, this study provides deeper insights into how age moderates the various factors influencing trust in voice assistants. Currently, there is limited research available where age is used as a moderator regarding this topic. This study introduces a new finding that age negatively moderates the effect of emotional state on trust in voice assistants. This also supports existing research that younger consumers are more influenced by their emotions compared to older consumers (Peters et al., 2007).

Managerial implications

This study provides valuable insights for managers of voice assistant companies and marketers. Since trust has shown to be crucial for the adoption of voice assistants, managers need to understand the factors that influence trust. This study has shown that perceived expertise is important for trust and therefore also might be important for the adoption of voice assistants. Therefore, managers should put more focus on the possibilities to improve the capability of their voice assistant to accurately understand the consumer and accurately answer questions and complete tasks. This improvement could enhance their product and attract more potential customers.

Furthermore, both managers and marketers should be aware that the effect of emotional state of consumers on trust varies across different age groups. When advertising their voice assistant, marketers can tailor their approach to target different age groups in specific ways. For example, they can create advertisements for younger consumers that evoke positive emotions, as this age group is more influenced by their emotional state when making decisions.

Limitations

Despite the academic and managerial implications, this study also has some limitations that must be considered. First, there are some limitations regarding the sample. The sample size of 128 is large enough to be able to conduct the analysis as discussed in the research methodology. However, a larger sample size gives more accurate estimates and often gives a better representation of the population. Due to the time constraint of the study, a minimum sufficient sample size is used for the analysis. Furthermore, the majority of the respondents is between 15 and 35 years old. Therefore, this sample mainly represents this age group and does not represent the whole population of voice assistant users. As age was used as a moderator in the analysis, this could bias the results and less could be concluded for older generations. Additionally, 71.9% of the sample completed higher professional education or university. Therefore, this sample mainly represents higher educated consumers, and this might not be in line with the population of voice assistant users. These limitations are mainly due to the sampling techniques that are used to gather respondents. Convenience sampling and snowball sampling were used due to time constraints, where mainly the social network is used to gather respondents. As a student, the majority of the social network consists of students with a higher educational background. Furthermore, as non-random sampling techniques were used, selection bias could occur.

There are also some limitations regarding the use of an online survey for data collection. The questions used are specifically about Siri so respondents can imagine their experience with this voice assistant when answering the questions. As a result, the findings might not be fully representative of other voice assistants as these might differ from Siri. Moreover, survey responses may vary from real-life behavior. Individuals could for example answer based on what they think is the aim of the study, or fatigue effects could occur due to the number of questions. However, this method was chosen, as this allows to easily collect data in a short time.

Suggestions for further research

For future research, it is important to use random sampling for data collection. This method will ensure a more representative sample of the population of voice assistant users and eliminates the possibility of selection bias. Additionally, random sampling ensures that the different age groups are equally represented in the sample. This allows a more accurate analysis of the moderation effect of age. Furthermore, a bigger sample size would be optimal for future research, as this will give more accurate estimates and enhance the representativeness of the data.

Another recommendation would be to apply this study to other voice assistants. Currently, in this study the questions are specifically about Siri. By applying this study to other voice assistants, researchers can gain a better understanding of all voice assistants in general and how the behaviour of consumers varies across different voice assistants. Additionally, this approach will give the opportunity to compare different voice assistants and show how some voice assistants could improve to satisfy their users.

Lastly, while no direct evidence was found as already discussed, perceived privacy risk remains an interesting factor to study for future research. With a better sampling technique and a larger sample size, the estimate might become significant. Additionally, the significant interaction between age and emotional state is interesting for future research. Future research could for example examine whether trust in voice assistants varies when respondents' emotions are positively versus negatively manipulated. This change in behavior could then be compared across different age groups. This will provide more information on the effect of emotion on trust between different age groups.

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Appendix

Appendix A. Survey voice assistants

Start of Block: Default Question Block

Q1 Dear respondent,

I am currently writing my Master's thesis at Erasmus University Rotterdam. For my thesis, I am interested in voice assistants and consumer behaviour. Therefore, in the survey you will find several statements regarding the voice assistant Siri. Here, you are asked to answer to what extent you agree with these statements. If you have never used Siri before, please do <u>not</u> fill in this survey. After the questions about Siri, a few demographic questions will be asked regarding your gender, age, and level of education. Furthermore, an attention check question will be asked, where you are asked to fill in a certain answer to check if you are paying attention. It will take around 5 minutes to fill in the survey.

The data collected from this survey will be kept strictly confidential and will only be used for research purposes for my thesis. All data will be deleted once I finish writing my thesis. By completing the survey, you give permission to use the personal information provided. However, you will always stay anonymous. You always have the option to withdraw your consent by not completing the survey. If you have any questions, please contact me at 575026ks@student.eur.nl.

Thank you in advance for taking your time to complete the survey!
Kim van der Sar

PS. SurveyCircle and SurveySwap users will receive a survey code at the end of the survey.

End of Block: Default Question Block

Start of Block: Block 1

Q2 Have you ever used the voice assistant Siri?

○ No (1)

○ Yes (2)

End of Block: Block 1

Start of Block: Block 2

Q3 To what extent do you agree with the following statements?

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Right now, I feel happy. (1)	○	○	○	○	○	○	○
Right now, I feel glad. (2)	○	○	○	○	○	○	○
Right now, I feel pleased. (3)	○	○	○	○	○	○	○

End of Block: Block 2

Start of Block: Block 3

Q4 To what extent do you agree with the following statements?

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I feel like the voice assistant Siri has intentions. (1)	o	o	o	o	o	o	o
I feel like the voice assistant Siri has free will. (2)	o	o	o	o	o	o	o
I feel like the voice assistant Siri can experience emotions. (3)	o	o	o	o	o	o	o
I feel like the voice assistant Siri has consciousness. (4)	o	o	o	o	o	o	o
I feel like the voice assistant Siri has a mind of its own. (5)	o	o	o	o	o	o	o

End of Block: Block 3

Start of Block: Block 4

Q5 To what extent do you agree with the following statements?

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Voice assistant Siri has the information it needs to conduct its tasks. (1)	○	○	○	○	○	○	○
Voice assistant Siri competently handles all my requests. (2)	○	○	○	○	○	○	○
Voice assistant Siri is efficient. (3)	○	○	○	○	○	○	○
Voice assistant Siri is knowledgeable. (4)	○	○	○	○	○	○	○

End of Block: Block 4

Start of Block: Block 5

Q6 To what extent do you agree with the following statements?

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I have my doubts over the confidentiality of my interactions with voice assistant Siri. (1)	○	○	○	○	○	○	○
I am concerned to perform a financial transaction via the voice assistant Siri. (2)	○	○	○	○	○	○	○
I am concerned that my personal details stored with voice assistant Siri could be stolen. (3)	○	○	○	○	○	○	○
I am concerned that voice assistant Siri collects too much information about me. (4)	○	○	○	○	○	○	○

End of Block: Block 5

Start of Block: Block 6

Q7 To what extent do you agree with the following statements?

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I feel that voice assistant Siri makes truthful claims. (1)	○	○	○	○	○	○	○
I feel that voice assistant Siri is trustworthy. (2)	○	○	○	○	○	○	○
I believe what voice assistant Siri tells me. (3)	○	○	○	○	○	○	○
I feel that voice assistant Siri is honest. (4)	○	○	○	○	○	○	○

End of Block: Block 6

Start of Block: Block 8

Q11 Please answer this question with "Somewhat agree".

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
Answer this question with somewhat agree. (1)	○	○	○	○	○

End of Block: Block 8

Start of Block: Block 7

Q8 What is your gender?

○ Male (1)

○ Female (2)

Q9 What is your age?

____

Q10 What is the highest level of education you completed?

○ Primary school (basisschool) (1)

○ Lower or intermediate secondary education (MAVO/VMBO) (2)

○ Higher secondary education (HAVO) (3)

○ Pre-university secondary education (VWO) (4)

○ Higher professional education (HBO) (5)

○ University (6)

○ PhD (Doctorate) (7)

End of Block: Block 7

Appendix B. Output demographics

Figure 4

Demographic statistics gender

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	35	27,3	27,3	27,3
	2	93	72,7	72,7	100,0
	Total	128	100,0	100,0	

Figure 5

Demographic statistics education

Education

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	1	,8	,8	,8
	2	10	7,8	7,8	8,6
	3	9	7,0	7,0	15,6
	4	16	12,5	12,5	28,1
	5	33	25,8	25,8	53,9
	6	59	46,1	46,1	100,0
	Total	128	100,0	100,0	

Figure 6

Demographic statistics age

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age	128	15	75	27,57	11,427
Valid N (listwise)	128				

Appendix C. Output factor- and reliability analysis

Figure 7

Correlation matrix determinant when including all items

Correlation Matrix[a]

a. Determinant = 9,62E-006

Figure 8

Pearson's bivariate correlation matrix including all items

Correlations

		Emotion1	Emotion2	Emotion3	Humanlikeness1	Humanlikeness2	Humanlikeness3	Humanlikeness4	Humanlikeness5	Expertise1	Expertise2	Expertise3	Expertise4	PrivacyRisk1	PrivacyRisk2	Privacyrisk3	PrivacyRisk4	Trust1	Trust2	Trust3	Trust4
Emotion1	Pearson Correlation	1	,776**	,836**	,018	,059	,059	-,043	,157	-,027	,087	-,002	,040	-,063	-,031	,025	-,064	-,083	,034	-,011	,055
	Sig. (2-tailed)		,000	,000	,838	,507	,510	,630	,077	,762	,331	,985	,656	,481	,724	,776	,473	,352	,702	,901	,537
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Emotion2	Pearson Correlation	,776**	1	,815**	,182*	,206*	,121	,157	,266**	-,044	,072	,029	,047	-,088	-,056	,086	-,010	,006	,098	,056	,092
	Sig. (2-tailed)	,000		,000	,039	,020	,173	,077	,002	,622	,418	,749	,595	,322	,532	,334	,908	,944	,272	,529	,302
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Emotion3	Pearson Correlation	,836**	,815**	1	,113	,057	,075	,063	,192*	-,041	,108	,038	,020	-,047	-,001	,080	,019	-,029	,152	,082	,046
	Sig. (2-tailed)	,000	,000		,203	,525	,399	,477	,030	,649	,224	,672	,827	,595	,992	,371	,831	,746	,087	,357	,609
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Humanlikeness1	Pearson Correlation	,018	,182*	,113	1	,547**	,535**	,612**	,533**	,061	,047	,043	,067	,069	-,033	,163	,086	-,008	,018	-,020	-,043
	Sig. (2-tailed)	,838	,039	,203		,000	,000	,000	,000	,495	,600	,630	,450	,440	,715	,066	,336	,930	,842	,823	,632
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Humanlikeness2	Pearson Correlation	,059	,206*	,057	,547**	1	,496**	,620**	,727**	,000	,092	,047	,118	,026	-,040	,146	,162	-,068	-,094	,053	,013
	Sig. (2-tailed)	,507	,020	,525	,000		,000	,000	,000	1,000	,303	,602	,186	,769	,655	,101	,068	,446	,292	,555	,882
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Humanlikeness3	Pearson Correlation	,059	,121	,075	,535**	,496**	1	,595**	,509**	-,035	,096	-,063	-,093	,001	-,148	,108	,083	-,051	-,043	-,036	-,098
	Sig. (2-tailed)	,510	,173	,399	,000	,000		,000	,000	,694	,279	,479	,297	,995	,096	,225	,352	,569	,628	,685	,270
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Humanlikeness4	Pearson Correlation	-,043	,157	,063	,612**	,620**	,595**	1	,639**	,033	,217*	,116	,115	,021	-,154	,204*	,095	,079	,023	,095	,050
	Sig. (2-tailed)	,630	,077	,477	,000	,000	,000		,000	,712	,014	,191	,198	,817	,082	,021	,288	,376	,798	,288	,579
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Humanlikeness5	Pearson Correlation	,157	,266**	,192*	,533**	,727**	,509**	,639**	1	-,063	,215*	,088	,105	-,006	-,129	,148	,116	-,040	-,027	,068	-,005
	Sig. (2-tailed)	,077	,002	,030	,000	,000	,000	,000		,478	,015	,323	,236	,946	,147	,095	,191	,656	,762	,445	,955
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Expertise1	Pearson Correlation	-,027	-,044	-,041	,061	,000	-,035	,033	-,063	1	,549**	,651**	,576**	-,021	-,076	,015	,030	,294**	,323**	,316**	,275**
	Sig. (2-tailed)	,762	,622	,649	,495	1,000	,694	,712	,478		,000	,000	,000	,811	,394	,865	,734	,001	,000	,000	,002
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Expertise2	Pearson Correlation	,087	,072	,108	,047	,092	,096	,217*	,215*	,549**	1	,629**	,606**	-,110	-,033	-,029	,070	,228**	,275**	,281**	,160
	Sig. (2-tailed)	,331	,418	,224	,600	,303	,279	,014	,015	,000		,000	,000	,218	,708	,747	,435	,010	,002	,001	,071
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Expertise3	Pearson Correlation	-,002	,029	,038	,043	,047	-,063	,116	,088	,651**	,629**	1	,637**	,001	-,011	,065	,054	,237**	,279**	,329**	,258**
	Sig. (2-tailed)	,985	,749	,672	,630	,602	,479	,191	,323	,000	,000		,000	,995	,901	,467	,547	,007	,001	,000	,003
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Expertise4	Pearson Correlation	,040	,047	,020	,067	,118	-,093	,115	,105	,576**	,606**	,637**	1	-,067	,088	-,029	,088	,126	,197*	,288**	,318**
	Sig. (2-tailed)	,656	,595	,827	,450	,186	,297	,198	,236	,000	,000	,000		,454	,322	,743	,325	,156	,025	,001	,000
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
PrivacyRisk1	Pearson Correlation	-,063	-,088	-,047	,069	,026	,001	,021	-,006	-,021	-,110	,001	-,067	1	,320**	,640**	,556**	-,058	-,186*	-,119	-,194*
	Sig. (2-tailed)	,481	,322	,595	,440	,769	,995	,817	,946	,811	,218	,995	,454		,000	,000	,000	,519	,035	,181	,028
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
PrivacyRisk2	Pearson Correlation	-,031	-,056	-,001	-,033	-,040	-,148	-,154	-,129	-,076	-,033	-,011	,088	,320**	1	,310**	,357**	-,004	-,097	-,026	-,082
	Sig. (2-tailed)	,724	,532	,992	,715	,655	,096	,082	,147	,394	,708	,901	,322	,000		,000	,000	,968	,277	,770	,359
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Privacyrisk3	Pearson Correlation	,025	,086	,080	,163	,146	,108	,204*	,148	,015	-,029	,065	-,029	,640**	,310**	1	,690**	-,064	-,096	-,039	-,112
	Sig. (2-tailed)	,776	,334	,371	,066	,101	,225	,021	,095	,865	,747	,467	,743	,000	,000		,000	,470	,283	,664	,206
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
PrivacyRisk4	Pearson Correlation	-,064	-,010	,019	,086	,162	,083	,095	,116	,030	,070	,054	,088	,556**	,357**	,690**	1	-,047	-,206*	-,007	-,160
	Sig. (2-tailed)	,473	,908	,831	,336	,068	,352	,288	,191	,734	,435	,547	,325	,000	,000	,000		,595	,019	,941	,072
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Trust1	Pearson Correlation	-,083	,006	-,029	-,008	-,068	-,051	,079	-,040	,294**	,228**	,237**	,126	-,058	-,004	-,064	-,047	1	,610**	,585**	,480**
	Sig. (2-tailed)	,352	,944	,746	,930	,446	,569	,376	,656	,001	,010	,007	,156	,519	,968	,470	,595		,000	,000	,000
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Trust2	Pearson Correlation	,034	,098	,152	,018	-,094	-,043	,023	-,027	,323**	,275**	,279**	,197*	-,186*	-,097	-,096	-,206*	,610**	1	,616**	,617**
	Sig. (2-tailed)	,702	,272	,087	,842	,292	,628	,798	,762	,000	,002	,001	,025	,035	,277	,283	,019	,000		,000	,000
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Trust3	Pearson Correlation	-,011	,056	,082	-,020	,053	-,036	,095	,068	,316**	,281**	,329**	,288**	-,119	-,026	-,039	-,007	,585**	,616**	1	,653**
	Sig. (2-tailed)	,901	,529	,357	,823	,555	,685	,288	,445	,000	,001	,000	,001	,181	,770	,664	,941	,000	,000		,000
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Trust4	Pearson Correlation	,055	,092	,046	-,043	,013	-,098	,050	-,005	,275**	,160	,258**	,318**	-,194*	-,082	-,112	-,160	,480**	,617**	,653**	1
	Sig. (2-tailed)	,537	,302	,609	,632	,882	,270	,579	,955	,002	,071	,003	,000	,028	,359	,206	,072	,000	,000	,000	
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128

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

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

Figure 9

Pearson's bivariate correlation matrix after removing item 3 of emotional state

Correlations

		Emotion1	Emotion2	Humanlikeness1	Humanlikeness2	Humanlikeness3	Humanlikeness4	Humanlikeness5	Expertise1	Expertise2	Expertise3	Expertise4	PrivacyRisk1	PrivacyRisk2	Privacyrisk3	PrivacyRisk4	Trust1	Trust2	Trust3	Trust4
Emotion1	Pearson Correlation	1	,776**	,018	,059	,059	-,043	,157	-,027	,087	-,002	,040	-,063	-,031	,025	-,064	-,083	,034	-,011	,055
	Sig. (2-tailed)		,000	,838	,507	,510	,630	,077	,762	,331	,985	,656	,481	,724	,776	,473	,352	,702	,901	,537
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Emotion2	Pearson Correlation	,776**	1	,182*	,206*	,121	,157	,266**	-,044	,072	,029	,047	-,088	-,056	,086	-,010	,006	,098	,056	,092
	Sig. (2-tailed)	,000		,039	,020	,173	,077	,002	,622	,418	,749	,595	,322	,532	,334	,908	,944	,272	,529	,302
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Humanlikeness1	Pearson Correlation	,018	,182*	1	,547**	,535**	,612**	,533**	,061	,047	,043	,067	,069	-,033	,163	,086	-,008	,018	-,020	-,043
	Sig. (2-tailed)	,838	,039		,000	,000	,000	,000	,495	,600	,630	,450	,440	,715	,066	,336	,930	,842	,823	,632
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Humanlikeness2	Pearson Correlation	,059	,206*	,547**	1	,496**	,620**	,727**	,000	,092	,047	,118	,026	-,040	,146	,162	-,068	-,094	,053	,013
	Sig. (2-tailed)	,507	,020	,000		,000	,000	,000	1,000	,303	,602	,186	,769	,655	,101	,068	,446	,292	,555	,882
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Humanlikeness3	Pearson Correlation	,059	,121	,535**	,496**	1	,595**	,509**	-,035	,096	-,063	-,093	,001	-,148	,108	,083	-,051	-,043	-,036	-,098
	Sig. (2-tailed)	,510	,173	,000	,000		,000	,000	,694	,279	,479	,297	,995	,096	,225	,352	,569	,628	,685	,270
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Humanlikeness4	Pearson Correlation	-,043	,157	,612**	,620**	,595**	1	,639**	,033	,217*	,116	,115	,021	-,154	,204*	,095	,079	,023	,095	,050
	Sig. (2-tailed)	,630	,077	,000	,000	,000		,000	,712	,014	,191	,198	,817	,082	,021	,288	,376	,798	,288	,579
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Humanlikeness5	Pearson Correlation	,157	,266**	,533**	,727**	,509**	,639**	1	-,063	,215*	,088	,105	-,006	-,129	,148	,116	-,040	-,027	,068	-,005
	Sig. (2-tailed)	,077	,002	,000	,000	,000	,000		,478	,015	,323	,236	,946	,147	,095	,191	,656	,762	,445	,955
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Expertise1	Pearson Correlation	-,027	-,044	,061	,000	-,035	,033	-,063	1	,549**	,651**	,576**	-,021	-,076	,015	,030	,294**	,323**	,316**	,275**
	Sig. (2-tailed)	,762	,622	,495	1,000	,694	,712	,478		,000	,000	,000	,811	,394	,865	,734	,001	,000	,000	,002
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Expertise2	Pearson Correlation	,087	,072	,047	,092	,096	,217*	,215*	,549**	1	,629**	,606**	-,110	-,033	-,029	,070	,228**	,275**	,281**	,160
	Sig. (2-tailed)	,331	,418	,600	,303	,279	,014	,015	,000		,000	,000	,218	,708	,747	,435	,010	,002	,001	,071
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Expertise3	Pearson Correlation	-,002	,029	,043	,047	-,063	,116	,088	,651**	,629**	1	,637**	,001	-,011	,065	,054	,237**	,279**	,329**	,258**
	Sig. (2-tailed)	,985	,749	,630	,602	,479	,191	,323	,000	,000		,000	,995	,901	,467	,547	,007	,001	,000	,003
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Expertise4	Pearson Correlation	,040	,047	,067	,118	-,093	,115	,105	,576**	,606**	,637**	1	-,067	,088	-,029	,088	,126	,197*	,288**	,318**
	Sig. (2-tailed)	,656	,595	,450	,186	,297	,198	,236	,000	,000	,000		,454	,322	,743	,325	,156	,025	,001	,000
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
PrivacyRisk1	Pearson Correlation	-,063	-,088	,069	,026	,001	,021	-,006	-,021	-,110	,001	-,067	1	,320**	,640**	,556**	-,058	-,186*	-,119	-,194*
	Sig. (2-tailed)	,481	,322	,440	,769	,995	,817	,946	,811	,218	,995	,454		,000	,000	,000	,519	,035	,181	,028
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
PrivacyRisk2	Pearson Correlation	-,031	-,056	-,033	-,040	-,148	-,154	-,129	-,076	-,033	-,011	,088	,320**	1	,310**	,357**	-,004	-,097	-,026	-,082
	Sig. (2-tailed)	,724	,532	,715	,655	,096	,082	,147	,394	,708	,901	,322	,000		,000	,000	,968	,277	,770	,359
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Privacyrisk3	Pearson Correlation	,025	,086	,163	,146	,108	,204*	,148	,015	-,029	,065	-,029	,640**	,310**	1	,690**	-,064	-,096	-,039	-,112
	Sig. (2-tailed)	,776	,334	,066	,101	,225	,021	,095	,865	,747	,467	,743	,000	,000		,000	,470	,283	,664	,206
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
PrivacyRisk4	Pearson Correlation	-,064	-,010	,086	,162	,083	,095	,116	,030	,070	,054	,088	,556**	,357**	,690**	1	-,047	-,206*	-,007	-,160
	Sig. (2-tailed)	,473	,908	,336	,068	,352	,288	,191	,734	,435	,547	,325	,000	,000	,000		,595	,019	,941	,072
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Trust1	Pearson Correlation	-,083	,006	-,008	-,068	-,051	,079	-,040	,294**	,228**	,237**	,126	-,058	-,004	-,064	-,047	1	,610**	,585**	,480**
	Sig. (2-tailed)	,352	,944	,930	,446	,569	,376	,656	,001	,010	,007	,156	,519	,968	,470	,595		,000	,000	,000
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Trust2	Pearson Correlation	,034	,098	,018	-,094	-,043	,023	-,027	,323**	,275**	,279**	,197*	-,186*	-,097	-,096	-,206*	,610**	1	,616**	,617**
	Sig. (2-tailed)	,702	,272	,842	,292	,628	,798	,762	,000	,002	,001	,025	,035	,277	,283	,019	,000		,000	,000
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Trust3	Pearson Correlation	-,011	,056	-,020	,053	-,036	,095	,068	,316**	,281**	,329**	,288**	-,119	-,026	-,039	-,007	,585**	,616**	1	,653**
	Sig. (2-tailed)	,901	,529	,823	,555	,685	,288	,445	,000	,001	,000	,001	,181	,770	,664	,941	,000	,000		,000
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128
Trust4	Pearson Correlation	,055	,092	-,043	,013	-,098	,050	-,005	,275**	,160	,258**	,318**	-,194*	-,082	-,112	-,160	,480**	,617**	,653**	1
	Sig. (2-tailed)	,537	,302	,632	,882	,270	,579	,955	,002	,071	,003	,000	,028	,359	,206	,072	,000	,000	,000	
	N	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128	128

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

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

Figure 10

Correlation matrix determinant after excluding item 3 of emotional state

Correlation Matrix[a]

a. Determinant = 5,23E-005

Figure 11

KMO statistic exploratory factor analysis after removing item 3 of emotional state

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,742
Bartlett's Test of Sphericity	Approx. Chi-Square	1181,335
	df	171
	Sig.	,000

Figure 12

Communalities exploratory factor analysis after removing item 3 of emotional state

Communalities

	Initial	Extraction
Emotion1	,666	,859
Emotion2	,670	,741
Humanlikeness1	,516	,498
Humanlikeness2	,627	,614
Humanlikeness3	,485	,485
Humanlikeness4	,652	,719
Humanlikeness5	,656	,670
Expertise1	,574	,568
Expertise2	,601	,595
Expertise3	,596	,695
Expertise4	,602	,626
PrivacyRisk1	,491	,553
PrivacyRisk2	,264	,211
Privacyrisk3	,647	,753
PrivacyRisk4	,594	,645
Trust1	,499	,522
Trust2	,601	,671
Trust3	,581	,663
Trust4	,570	,570

Extraction Method: Principal Axis Factoring.

Figure 13

Eigenvalues exploratory factor analysis after removing item 3 of emotional state

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,995	21,026	21,026	3,617	19,035	19,035	3,045	16,026	16,026
2	3,563	18,754	39,780	3,182	16,746	35,781	2,476	13,029	29,055
3	2,478	13,040	52,819	2,085	10,972	46,753	2,415	12,710	41,765
4	1,714	9,019	61,838	1,491	7,849	54,602	2,106	11,086	52,851
5	1,668	8,781	70,619	1,285	6,764	61,365	1,618	8,514	61,365
6	,838	4,408	75,027						
7	,688	3,619	78,646						
8	,615	3,236	81,882						
9	,492	2,590	84,473						
10	,433	2,277	86,750						
11	,406	2,136	88,886						
12	,372	1,957	90,843						
13	,348	1,831	92,674						
14	,322	1,697	94,371						
15	,273	1,436	95,806						
16	,241	1,270	97,076						
17	,220	1,159	98,235						
18	,175	,922	99,157						
19	,160	,843	100,000						

Extraction Method: Principal Axis Factoring.

Figure 14

Rotated factor loadings after removing item 3 of emotional state

Rotated Factor Matrix[a]

	Factor				
	1	2	3	4	5
Humanlikeness4	,839				
Humanlikeness5	,799				
Humanlikeness2	,776				
Humanlikeness1	,703				
Humanlikeness3	,691				
Expertise3		,810			
Expertise4		,779			
Expertise2		,743			
Expertise1		,711			
Trust2			,787		
Trust3			,782		
Trust4			,719		
Trust1			,708		
Privacyrisk3				,846	
PrivacyRisk4				,784	
PrivacyRisk1				,732	
PrivacyRisk2				,435	
Emotion1					,925
Emotion2					,836

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 5 iterations.

Figure 15

Correlation matrix determinant after excluding item 2 of perceived privacy risk

Correlation Matrix[a]

a. Determinant = 7,10E-005

Figure 16

Final KMO statistic exploratory factor analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,744
Bartlett's Test of Sphericity	Approx. Chi-Square	1147,848
	df	153
	Sig.	,000

Figure 17

Final communalities exploratory factor analysis

Communalities

	Initial	Extraction
Emotion1	,665	,863
Emotion2	,669	,739
Humanlikeness1	,509	,503
Humanlikeness2	,623	,624
Humanlikeness3	,483	,477
Humanlikeness4	,643	,710
Humanlikeness5	,650	,669
Expertise1	,556	,572
Expertise2	,600	,595
Expertise3	,596	,697
Expertise4	,588	,624
PrivacyRisk1	,487	,550
Privacyrisk3	,640	,808
PrivacyRisk4	,589	,605
Trust1	,493	,522
Trust2	,601	,672
Trust3	,580	,661
Trust4	,569	,570

Extraction Method: Principal Axis Factoring.

Figure 18

Final eigenvalues exploratory factor analysis

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,982	22,120	22,120	3,605	20,028	20,028	2,996	16,644	16,644
2	3,563	19,794	41,914	3,182	17,680	37,708	2,475	13,752	30,396
3	2,258	12,546	54,460	1,921	10,673	48,381	2,420	13,447	43,843
4	1,699	9,440	63,899	1,473	8,184	56,565	1,948	10,825	54,667
5	1,649	9,159	73,059	1,277	7,097	63,662	1,619	8,995	63,662
6	,739	4,104	77,162						
7	,616	3,421	80,584						
8	,494	2,743	83,326						
9	,437	2,427	85,754						
10	,415	2,305	88,059						
11	,376	2,086	90,145						
12	,366	2,031	92,176						
13	,324	1,800	93,976						
14	,276	1,532	95,508						
15	,244	1,354	96,863						
16	,220	1,223	98,086						
17	,184	1,024	99,110						
18	,160	,890	100,000						

Extraction Method: Principal Axis Factoring.

Figure 19

Final rotated factor loadings

Rotated Factor Matrix[a]

	Factor				
	1	2	3	4	5
Emotion1	,005	,027	-,030	-,037	,927
Emotion2	,192	,001	,071	-,003	,835
Humanlikeness1	,705	,026	-,004	,068	,026
Humanlikeness2	,781	,056	-,035	,064	,072
Humanlikeness3	,686	-,060	-,049	,014	,022
Humanlikeness4	,831	,091	,078	,065	-,032
Humanlikeness5	,798	,079	-,016	,033	,160
Expertise1	-,039	,712	,242	,028	-,058
Expertise2	,139	,742	,142	-,039	,057
Expertise3	,018	,810	,192	,058	-,004
Expertise4	,045	,778	,128	-,010	,035
PrivacyRisk1	-,016	-,048	-,107	,729	-,066
Privacyrisk3	,141	-,008	-,018	,885	,068
PrivacyRisk4	,095	,087	-,093	,761	-,030
Trust1	-,019	,127	,708	-,009	-,068
Trust2	-,032	,167	,789	-,130	,054
Trust3	,038	,222	,781	-,007	,006
Trust4	-,022	,174	,720	-,127	,069

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 5 iterations.

Figure 20

Case processing summary reliability analysis emotional state

Case Processing Summary

		N	%
Cases	Valid	128	100,0
	Excluded[a]	0	,0
	Total	128	100,0

a. Listwise deletion based on all variables in the procedure.

Figure 21

Cronbach's Alpha emotional state

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,872	,874	2

Figure 22

Statistics when item is deleted emotional state

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Emotion1	5,23	1,346	,776	,602	.
Emotion2	5,29	1,593	,776	,602	.

Figure 23

Case processing summary reliability analysis perceived human-likeness

Case Processing Summary

		N	%
Cases	Valid	128	100,0
	Excluded[a]	0	,0
	Total	128	100,0

a. Listwise deletion based on all variables in the procedure.

Figure 24

Cronbach's Alpha perceived human-likeness

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,874	,874	5

Figure 25

Statistics when item is deleted perceived human-likeness

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Humanlikeness1	11,13	26,772	,666	,454	,857
Humanlikeness2	11,20	24,462	,729	,584	,841
Humanlikeness3	11,76	26,909	,632	,418	,864
Humanlikeness4	11,42	24,167	,753	,570	,835
Humanlikeness5	11,30	24,371	,737	,595	,839

Figure 26

Case processing summary reliability analysis perceived expertise

Case Processing Summary

		N	%
Cases	Valid	128	100,0
	Excluded[a]	0	,0
	Total	128	100,0

a. Listwise deletion based on all variables in the procedure.

Figure 27

Cronbach's Alpha perceived expertise

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,859	,861	4

Figure 28

Statistics when item is deleted perceived expertise

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Expertise1	13,83	12,348	,682	,481	,830
Expertise2	14,57	10,656	,689	,480	,830
Expertise3	13,93	11,278	,752	,570	,800
Expertise4	13,92	11,427	,706	,500	,819

Figure 29

Case processing summary reliability analysis perceived privacy risk

Case Processing Summary

		N	%
Cases	Valid	128	100,0
	Excluded[a]	0	,0
	Total	128	100,0

a. Listwise deletion based on all variables in the procedure.

Figure 30

Cronbach's Alpha perceived privacy risk

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,835	,836	3

Figure 31

Statistics when item is deleted perceived privacy risk

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PrivacyRisk1	9,56	8,138	,651	,435	,817
Privacyrisk3	9,69	6,531	,756	,572	,709
PrivacyRisk4	9,63	6,740	,693	,499	,776

Figure 32

Case processing summary reliability analysis trust

Case Processing Summary

		N	%
Cases	Valid	128	100,0
	Excluded[a]	0	,0
	Total	128	100,0

a. Listwise deletion based on all variables in the procedure.

Figure 33

Cronbach's Alpha trust

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
,853	,854	4

Figure 34

Statistics when item is deleted trust

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Trust1	13,64	10,138	,647	,443	,833
Trust2	13,89	9,421	,725	,531	,801
Trust3	13,84	8,847	,731	,543	,799
Trust4	13,55	10,155	,684	,501	,819

Appendix D. Output linear regression assumptions and models

Figure 35

Residual statistics multiple linear regression before removal of potential outlier

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3,4011	5,8023	4,5762	,44073	128
Std. Predicted Value	-2,666	2,782	,000	1,000	128
Standard Error of Predicted Value	,141	,968	,313	,140	128
Adjusted Predicted Value	2,7637	9,3842	4,6065	,63501	127
Residual	-2,65533	2,34887	,00000	,90938	128
Std. Residual	-2,742	2,426	,000	,939	128
Stud. Residual	-2,814	2,735	-,011	1,026	127
Deleted Residual	-4,88420	2,98633	-,03367	1,13770	127
Stud. Deleted Residual	-2,906	2,819	-,013	1,037	127
Mahal. Distance	1,692	126,008	14,883	17,910	128
Cook's Distance	,000	1,166	,020	,109	127
Centered Leverage Value	,013	,992	,117	,141	128

a. Dependent Variable: Trust

Figure 36

Residual statistics multiple linear regression after removal of potential outlier

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3,5094	6,4534	4,5768	,49621	127
Std. Predicted Value	-2,151	3,782	,000	1,000	127
Standard Error of Predicted Value	,137	,943	,306	,137	127
Adjusted Predicted Value	1,9043	6,9602	4,5769	,61156	126
Residual	-2,64574	2,24065	,00000	,88490	127
Std. Residual	-2,806	2,377	,000	,939	127
Stud. Residual	-2,880	2,683	-,001	1,012	127
Deleted Residual	-3,19839	3,09573	-,00352	1,07023	126
Stud. Deleted Residual	-2,980	2,762	-,003	1,026	126
Mahal. Distance	1,672	125,008	14,882	17,854	127
Cook's Distance	,000	,478	,016	,061	126
Centered Leverage Value	,013	,992	,118	,142	127

a. Dependent Variable: Trust

Figure 37

Pearson's Bivariate Correlation matrix of the whole model

Correlations

		Trust	Female	primary school	Higher secondary education	Pre-university secondary education	Higher professional education	University	Age	Emotion	Humanlikeness	Expertise	Privacyrisk	EmotioncXAgec	HumanlikenesscXAgec	ExpertisecXAgec	PrivacyriskcXAgec
Pearson Correlation	Trust	1,000	-,045	,037	,069	,059	-,027	-,047	,028	,037	-,007	,375	-,144	-,108	,048	-,003	-,010
	Female	-,045	1,000	-,144	,015	-,031	,004	,151	-,041	,041	-,111	-,061	-,006	,049	-,077	-,074	-,098
	primary school	,037	-,144	1,000	-,023	-,034	-,053	-,083	,174	-,185	,083	,067	-,057	-,372	,088	,170	-,139
	Higher secondary education	,069	,015	-,023	1,000	-,098	-,154	-,242	,158	,050	-,011	,010	-,123	,132	,078	-,014	-,173
	Pre-university secondary education	,059	-,031	-,034	-,098	1,000	-,225	-,354	-,150	,073	-,036	,101	,054	-,071	,013	,048	,048
	Higher professional education	-,027	,004	-,053	-,154	-,225	1,000	-,552	-,045	,073	,097	-,051	,015	-,101	-,134	-,072	,018
	University	-,047	,151	-,083	-,242	-,354	-,552	1,000	-,275	-,092	-,148	-,122	,035	-,116	-,222	-,006	-,112
	Age	,028	-,041	,174	,158	-,150	-,045	-,275	1,000	,161	,400	,035	,084	,414	,664	,167	,204
	Emotion	,037	,041	-,185	,050	,073	,073	-,092	,161	1,000	,126	,065	-,030	-,188	,114	,020	,001
	Humanlikeness	-,007	-,111	,083	-,011	-,036	,097	-,148	,400	,126	1,000	,110	,136	,175	,266	,125	,007
	Expertise	,375	-,061	,067	,010	,101	-,051	-,122	,035	,065	,110	1,000	,014	,017	,066	-,214	,041
	Privacyrisk	-,144	-,006	-,057	-,123	,054	,015	,035	,084	-,030	,136	,014	1,000	,003	,004	,046	-,135
	EmotioncXAgec	-,108	,049	-,372	,132	-,071	-,101	-,116	,414	-,188	,175	,017	,003	1,000	,571	,000	,133
	HumanlikenesscXAgec	,048	-,077	,088	,078	,013	-,134	-,222	,664	,114	,266	,066	,004	,571	1,000	,156	,228
	ExpertisecXAgec	-,003	-,074	,170	-,014	,048	-,072	-,006	,167	,020	,125	-,214	,046	,000	,156	1,000	-,028
	PrivacyriskcXAgec	-,010	-,098	-,139	-,173	,048	,018	-,112	,204	,001	,007	,041	-,135	,133	,228	-,028	1,000
Sig. (1-tailed)	Trust	.	,309	,339	,222	,254	,381	,299	,377	,341	,467	,000	,053	,113	,295	,486	,457
	Female	,309	.	,053	,434	,363	,483	,046	,322	,324	,108	,247	,474	,293	,196	,204	,137
	primary school	,339	,053	.	,398	,353	,278	,177	,026	,019	,177	,227	,263	,000	,163	,028	,060
	Higher secondary education	,222	,434	,398	.	,135	,042	,003	,038	,289	,450	,456	,084	,070	,191	,440	,026
	Pre-university secondary education	,254	,363	,353	,135	.	,005	,000	,046	,207	,345	,129	,272	,214	,441	,297	,295
	Higher professional education	,381	,483	,278	,042	,005	.	,000	,306	,206	,140	,285	,434	,130	,066	,210	,420
	University	,299	,046	,177	,003	,000	,000	.	,001	,151	,048	,086	,348	,098	,006	,472	,105
	Age	,377	,322	,026	,038	,046	,306	,001	.	,035	,000	,349	,175	,000	,000	,030	,011
	Emotion	,341	,324	,019	,289	,207	,206	,151	,035	.	,079	,233	,367	,017	,100	,411	,494
	Humanlikeness	,467	,108	,177	,450	,345	,140	,048	,000	,079	.	,109	,064	,025	,001	,081	,468
	Expertise	,000	,247	,227	,456	,129	,285	,086	,349	,233	,109	.	,439	,424	,230	,008	,325
	Privacyrisk	,053	,474	,263	,084	,272	,434	,348	,175	,367	,064	,439	.	,488	,482	,306	,064
	EmotioncXAgec	,113	,293	,000	,070	,214	,130	,098	,000	,017	,025	,424	,488	.	,000	,499	,068
	HumanlikenesscXAgec	,295	,196	,163	,191	,441	,066	,006	,000	,100	,001	,230	,482	,000	.	,040	,005
	ExpertisecXAgec	,486	,204	,028	,440	,297	,210	,472	,030	,411	,081	,008	,306	,499	,040	.	,375
	PrivacyriskcXAgec	,457	,137	,060	,026	,295	,420	,105	,011	,494	,468	,325	,064	,068	,005	,375	.
N	Trust	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	Female	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	primary school	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	Higher secondary education	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	Pre-university secondary education	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	Higher professional education	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	University	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	Age	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	Emotion	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	Humanlikeness	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	Expertise	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	Privacyrisk	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	EmotioncXAgec	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	HumanlikenesscXAgec	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	ExpertisecXAgec	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127
	PrivacyriskcXAgec	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127	127

Figure 38

Statistics R square and Durbin-Watson test model VII

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,489[a]	,239	,136	,94280	1,889

a. Predictors: (Constant), PrivacyriskcXAgec, Emotion, ExpertisecXAgec, Pre-university secondary education, Female, Privacyrisk, Higher secondary education, Humanlikeness, Expertise, Higher professional education, primary school, HumanlikenesscXAgec, Age, EmotioncXAgec, University

b. Dependent Variable: Trust

Figure 39

Statistics significance of model VII

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31,024	15	2,068	2,327	,006[b]
	Residual	98,665	111	,889		
	Total	129,689	126			

a. Dependent Variable: Trust

b. Predictors: (Constant), PrivacyriskcXAgec, Emotion, ExpertisecXAgec, Pre-university secondary education, Female, Privacyrisk, Higher secondary education, Humanlikeness, Expertise, Higher professional education, primary school, HumanlikenesscXAgec, Age, EmotioncXAgec, University

Figure 40

Coefficients model VII, including Tolerance and VIF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3,572	,862		4,142	,000					
	Female	-,093	,201	-,041	-,461	,645	-,045	-,044	-,038	,867	1,154
	primary school	-2,516	1,438	-,220	-1,750	,083	,037	-,164	-,145	,433	2,309
	Higher secondary education	,542	,514	,130	1,054	,294	,069	,100	,087	,448	2,231
	Pre-university secondary education	,511	,504	,168	1,014	,313	,059	,096	,084	,250	3,993
	Higher professional education	,454	,464	,197	,978	,330	-,027	,092	,081	,169	5,919
	University	,463	,463	,228	,999	,320	-,047	,094	,083	,131	7,621
	Age	,019	,013	,206	1,427	,157	,028	,134	,118	,327	3,055
	Emotion	-,158	,096	-,173	-1,639	,104	,037	-,154	-,136	,618	1,618
	Humanlikeness	-,046	,078	-,056	-,586	,559	-,007	-,056	-,048	,759	1,318
	Expertise	,399	,082	,433	4,860	,000	,375	,419	,402	,864	1,158
	Privacyrisk	-,156	,070	-,198	-2,235	,027	-,144	-,208	-,185	,876	1,141
	EmotioncXAgec	-,032	,012	-,377	-2,550	,012	-,108	-,235	-,211	,314	3,186
	HumanlikenesscXAgec	,011	,007	,222	1,615	,109	,048	,152	,134	,363	2,756
	ExpertisecXAgec	,009	,010	,081	,916	,362	-,003	,087	,076	,866	1,154
	PrivacyriskcXAgec	-,008	,008	-,092	-,967	,336	-,010	-,091	-,080	,760	1,316

a. Dependent Variable: Trust

Figure 41

Histogram of the multiple linear regression

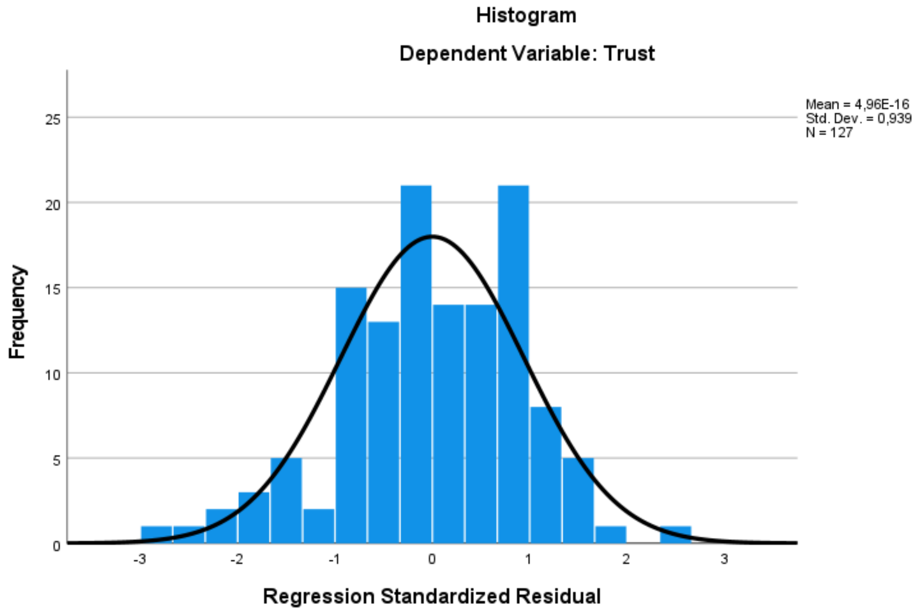

Figure 42

Q-Q plot

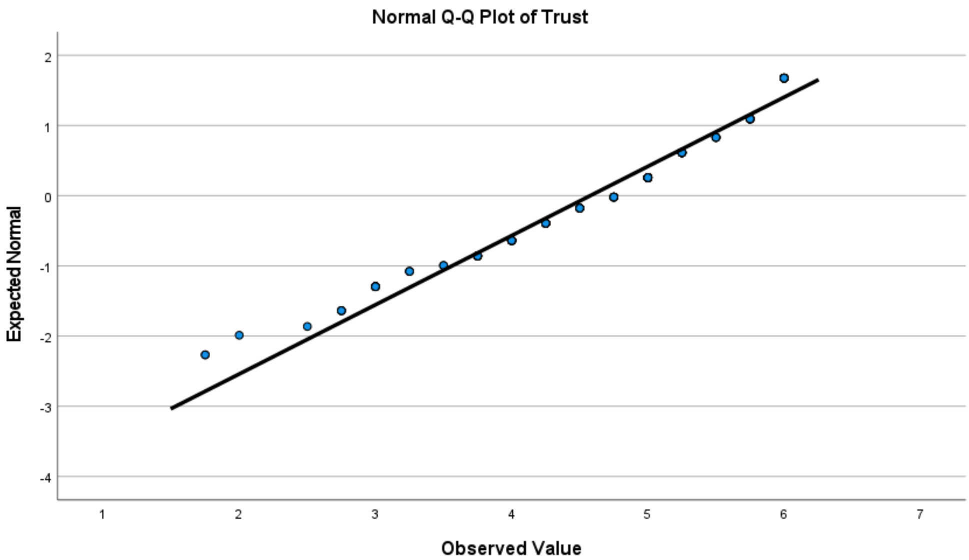

Figure 43

P-P plot

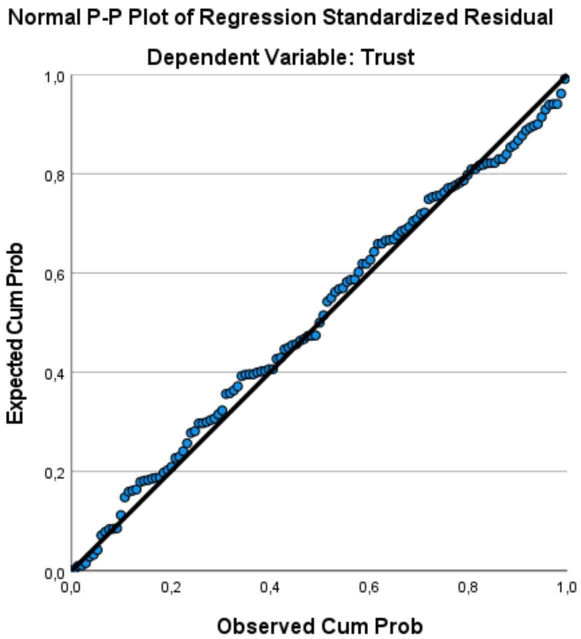

Figure 44

Scatterplot

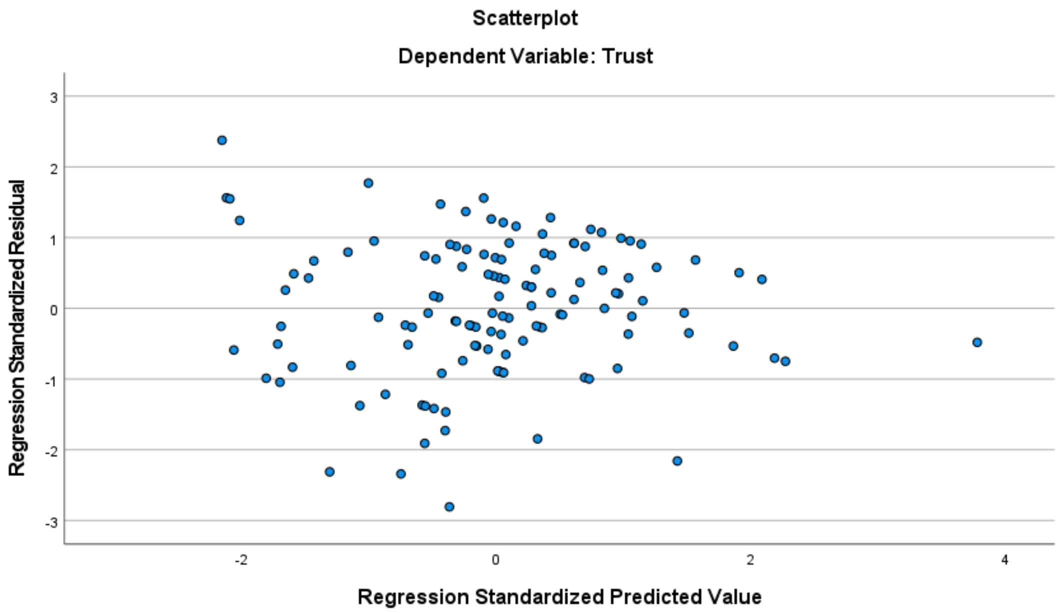

Figure 45

Statistics R square model VI

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,447[a]	,200	,138	,94181	1,887

a. Predictors: (Constant), PrivacyriskcXAgec, Emotion, ExpertisecXAgec, Privacyrisk, Humanlikeness, Expertise, EmotioncXAgec, Age, HumanlikenesscXAgec

b. Dependent Variable: Trust

Figure 46

Statistics significance of model VI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25,910	9	2,879	3,246	,001[b]
	Residual	103,779	117	,887		
	Total	129,689	126			

a. Dependent Variable: Trust

b. Predictors: (Constant), PrivacyriskcXAgec, Emotion, ExpertisecXAgec, Privacyrisk, Humanlikeness, Expertise, EmotioncXAgec, Age, HumanlikenesscXAgec

Figure 47

Coefficients model VI

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3,685	,660		5,588	,000					
	Age	,006	,011	,062	,520	,604	,028	,048	,043	,486	2,059
	Emotion	-,046	,082	-,050	-,560	,576	,037	-,052	-,046	,862	1,160
	Humanlikeness	-,043	,076	-,052	-,565	,573	-,007	-,052	-,047	,805	1,242
	Expertise	,366	,079	,396	4,609	,000	,375	,392	,381	,925	1,081
	Privacyrisk	-,126	,067	-,160	-1,887	,062	-,144	-,172	-,156	,952	1,050
	EmotioncXAgec	-,017	,009	-,201	-1,865	,065	-,108	-,170	-,154	,592	1,690
	HumanlikenesscXAgec	,006	,007	,119	,936	,351	,048	,086	,077	,427	2,343
	ExpertisecXAgec	,008	,010	,066	,756	,451	-,003	,070	,063	,891	1,122
	PrivacyriskcXAgec	-,005	,007	-,058	-,671	,504	-,010	-,062	-,055	,912	1,097

a. Dependent Variable: Trust

Figure 48

Statistics R square model I

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,405[a]	,164	,137	,94275	1,863

a. Predictors: (Constant), Privacyrisk, Expertise, Emotion, Humanlikeness

b. Dependent Variable: Trust

Figure 49

Statistics significance of model I

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21,259	4	5,315	5,980	,000[b]
	Residual	108,430	122	,889		
	Total	129,689	126			

a. Dependent Variable: Trust

b. Predictors: (Constant), Privacyrisk, Expertise, Emotion, Humanlikeness

Figure 50

Coefficients model I

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3,504	,621		5,645	,000		
	Emotion	,010	,077	,011	,136	,892	,979	1,021
	Humanlikeness	-,025	,070	-,031	-,365	,716	,955	1,048
	Expertise	,350	,077	,380	4,553	,000	,985	1,015
	Privacyrisk	-,114	,066	-,145	-1,730	,086	,979	1,021

a. Dependent Variable: Trust

Figure 51

Statistics R square model II

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,431[a]	,186	,145	,93803	1,928

a. Predictors: (Constant), EmotioncXAgec, Privacyrisk, Expertise, Emotion, Humanlikeness, Age

b. Dependent Variable: Trust

Figure 52

Statistics significance of model II

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24,100	6	4,017	4,565	,000[b]
	Residual	105,589	120	,880		
	Total	129,689	126			

a. Dependent Variable: Trust

b. Predictors: (Constant), EmotioncXAgec, Privacyrisk, Expertise, Emotion, Humanlikeness, Age

Figure 53

Coefficients model II

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3,521	,625		5,636	,000					
	Emotion	-,034	,080	-,037	-,426	,671	,037	-,039	-,035	,884	1,131
	Humanlikeness	-,035	,075	-,043	-,468	,641	-,007	-,043	-,039	,816	1,226
	Expertise	,354	,077	,383	4,615	,000	,375	,388	,380	,985	1,016
	Privacyrisk	-,121	,066	-,154	-1,847	,067	-,144	-,166	-,152	,975	1,026
	Age	,011	,009	,118	1,184	,239	,028	,107	,098	,679	1,473
	EmotioncXAgec	-,014	,008	-,163	-1,725	,087	-,108	-,156	-,142	,759	1,318

a. Dependent Variable: Trust

Figure 54

Statistics R square model III

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,407[a]	,166	,124	,94956	1,865

a. Predictors: (Constant), HumanlikenesscXAgec, Privacyrisk, Expertise, Emotion, Humanlikeness, Age

b. Dependent Variable: Trust

Figure 55

Statistics significance of model III

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21,489	6	3,581	3,972	,001[b]
	Residual	108,200	120	,902		
	Total	129,689	126			

a. Dependent Variable: Trust

b. Predictors: (Constant), HumanlikenesscXAgec, Privacyrisk, Expertise, Emotion, Humanlikeness, Age

Figure 56

Coefficients model III

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	3,474	,650		5,344	,000					
	Emotion	,006	,078	,006	,072	,943	,037	,007	,006	,964	1,037
	Humanlikeness	-,040	,076	-,048	-,524	,601	-,007	-,048	-,044	,817	1,224
	Expertise	,351	,078	,380	4,515	,000	,375	,381	,377	,982	1,019
	Privacyrisk	-,115	,067	-,146	-1,725	,087	-,144	-,156	-,144	,973	1,028
	Age	,004	,011	,039	,329	,743	,028	,030	,027	,497	2,010
	HumanlikenesscXAgec	,001	,006	,010	,089	,929	,048	,008	,007	,554	1,805

a. Dependent Variable: Trust

Figure 57

Statistics R square model IV

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,416[a]	,173	,132	,94526	1,835

a. Predictors: (Constant), ExpertisecXAgec, Emotion, Privacyrisk, Humanlikeness, Expertise, Age

b. Dependent Variable: Trust

Figure 58

Statistics significance of model IV

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	22,467	6	3,745	4,191	,001[b]
	Residual	107,222	120	,894		
	Total	129,689	126			

a. Dependent Variable: Trust

b. Predictors: (Constant), ExpertisecXAgec, Emotion, Privacyrisk, Humanlikeness, Expertise, Age

Figure 59

Coefficients model IV

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	3,425	,629		5,442	,000					
	Emotion	,005	,077	,006	,070	,944	,037	,006	,006	,964	1,037
	Humanlikeness	-,047	,076	-,057	-,615	,540	-,007	-,056	-,051	,811	1,234
	Expertise	,370	,079	,401	4,668	,000	,375	,392	,388	,932	1,073
	Privacyrisk	-,117	,066	-,149	-1,769	,079	-,144	-,159	-,147	,977	1,023
	Age	,003	,008	,033	,360	,719	,028	,033	,030	,813	1,230
	ExpertisecXAgec	,010	,010	,091	1,050	,296	-,003	,095	,087	,915	1,092

a. Dependent Variable: Trust

Figure 60

Statistics R square model V

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,411[a]	,169	,127	,94780	1,868

a. Predictors: (Constant), PrivacyriskcXAgec, Emotion, Expertise, Privacyrisk, Humanlikeness, Age

b. Dependent Variable: Trust

Figure 61

Statistics significance of model V

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21,889	6	3,648	4,061	,001[b]
	Residual	107,800	120	,898		
	Total	129,689	126			

a. Dependent Variable: Trust

b. Predictors: (Constant), PrivacyriskcXAgec, Emotion, Expertise, Privacyrisk, Humanlikeness, Age

Figure 62

Coefficients model V

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	3,472	,630		5,506	,000					
	Emotion	,004	,078	,004	,047	,963	,037	,004	,004	,963	1,039
	Humanlikeness	-,043	,076	-,053	-,569	,570	-,007	-,052	-,047	,813	1,230
	Expertise	,354	,077	,383	4,563	,000	,375	,385	,380	,983	1,017
	Privacyrisk	-,122	,067	-,155	-1,820	,071	-,144	-,164	-,151	,956	1,046
	Age	,005	,009	,060	,639	,524	,028	,058	,053	,783	1,278
	PrivacyriskcXAgec	-,005	,007	-,058	-,674	,502	-,010	-,061	-,056	,928	1,078

a. Dependent Variable: Trust