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Can I trust my AI friend? The role of emotions, feelings of friendship and trust for consumers' information-sharing behavior toward AI

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Keywords: *artificial intelligence; consumers; self-disclosing behavior; emotion; friendship*

Abstract

Research background: AI devices and robots play an increasingly important role in consumers' everyday life, by accompanying the consumer all day long. This presence has several utilitarian and social benefits, but at the same time the optimal functioning of AI requires personal information from the consumer.

Purpose of the article: Starting from the premise that people share more information with friends, we have tested empirically whether an emotional behavior of AI can evoke the same emotions in the relationship between consumers and their AI devices, leading to a higher self-disclosing behavior.
Methods: To validate the proposed hypotheses, three mediation models were tested using structural equation modelling in Smart-PLS 3.3.3, based on data collected with the help of an online survey.
Findings & value added: We prove empirically that AI's emotional behavior can increase consumers' trust, it can evoke feelings of friendship and it can determine a higher perceived control over the shared private information, thus leading to lower perceived threats regarding the consumers' vulnerability and exposure related to sharing of private data. These results have important implications for designing consumer-AI interactions.

Introduction

The attribution of social roles and empathetic behavior to artificial intelligence (Van Doorn *et al*., 2017; Ki *et al*., 2020; Youn & Jin, 2021) has caused several challenges for the current business environment and for the entire society (Kaplan & Haenlein, 2020; Gursoy *et al*., 2019). Using empathetic AI devices in the service industry and marketing increases the satisfaction of the interaction between human consumers and AI (Pelau *et al*., 2021). Similar to human employees, empathetic AI devices can focus more on the needs and desires of consumers, having a higher ability to individualize the offered products due to their greater capacity to store and process consumer data (Ashfaq *et al*., 2020; Anica-Popa *et al*., 2021). The main disadvantage in this process is the fact that an optimal functioning of AI requires access to the consumers' personal information (Martin *et al*., 2017). In this sense, a key aspect for the use of AI are the perceived risks regarding the sharing of personal information with AI devices. In the present day, there is a big debate on this topic as companies can have considerable financial benefits from the use of private information (Balcerzak *et al*., 2023; Erevelles *et al*., 2016; Lazaroiu *et al*., 2022) and, at the same time, consumers can perceive increased threats from excessive exposure of their private data (Bilal *et al*., 2024; Chang *et al*., 2023; Rasheed *et al*., 2023). Using AI can definitely help companies to be more customer centric and allows them to increase customer experience by providing tailor made products (Bilal *et al*., 2024), but at the same time it is important to see how to develop the relationship between consumer and AI, in order not to be seen as intrusive and to have the consumers' acceptance (Chang *et al*., 2023; Rasheed *et al*., 2023).

The main risks associated with exposure of private data are a higher vulnerability to manipulation and the insecurity of using private information for inadequate purposes (Chang *et al*., 2023; Martin *et al*., 2017; Rasheed *et al*., 2023). To be willing to be exposed to the threats of sharing private data, consumers must receive incentives or rewards (Constant *et al*., 1994; Song & Kim, 2021). Several predictors of the willingness of consumers to share private information have been tested (Aiello *et al*., 2020; Pizzi *et al*., 2022), but this trend will gain importance as AI will become more and more prevalent in the daily life of consumers.

Self-disclosing behavior and data sharing are topics that have been much studied in the context of social media, sharing economies and interpersonal relations, but several psychological characteristics can be transposed to the interaction with AI. Among the factors predicting the willingness to share data with AI are trust, system usefulness and enjoyment of using the machine (Song & Kim, 2021; Rese *et al*., 2020; Schroeder & Schroeder, 2018; Song & Kim, 2020). The relationship type between consumer and AI is another factor that affects the acceptance and inclusion of AI (Rasheed *et al*., 2023; Pelau *et al*., 2023). Martelaro *et al*. (2016) prove in their study that trust, feelings of companionship and the robots' expressivity are important predictors for the willingness to share information, while Bilal *et al*. (2024) prove that the emotional bond enhances this relationship (Bilal *et al*., 2024). Studies also show, that the perceived relationship between consumer and AI will determine the way AI will be integrated as partner or intruder in the life of consumers (Chang *et al*., 2023). Consequently, it is important to understand the type of relationship, in order to face the challenges of implementing AI in consumers' life. Depending on the context, consumer-AI relationship can take different forms of social companionship (Chaturvedi *et al*., 2023; Leo-Liu, 2022).

Starting from the idea that in human interactions, people are more willing to share information with friends and people they know, the objective of our paper is to determine if an emotional, empathetic behavior of an AI device impacts the severity of perceived threats regarding data sharing with AI devices. The role of emotional bond in the consumer-AI relationship has been previously studied to determine trust and acceptance towards AI and robots (Pelau *et al*., 2021; Bilal *et al*., 2024). Our research extends the existent models, by focusing on a particular type of trust, namely the one related to the use of personal information. In comparison to previous research, we investigate if an emotional bond in consumer-AI relations decreases the perceived threats of data-sharing and the trust that personal data is not misused. Our research question is based on the idea that if an AI device behaves in an empathetic and friendly way, then the individual will perceive in a different way the risks regarding data sharing with AI. An emotional empathetic behavior of AI impacts the trust the human has towards the AI device, it develops feelings of friendship, and it will increase the perception of control related to the use of personal data shared with AI. This research direction extends the social penetration theory (Altman & Taylor, 1973) to consumer-AI relations. Based on this theory, the type of exchanged information depends on the depth of the relationship. The closer a relationship is, the more information will be exchanged. In our research, we have empirically tested the impact of an emotional relation between humans and AI on the perceived risks regarding the use of personal information by AI. As an emotional and empathetic relationship between humans and AI can trigger trust and feelings of friendship, we have measured the mediating role of these constructs, as well as the mediating role of the perceived control over the shared information for the mentioned relation. Based on data collected with the help on an online questionnaire, we have applied structural equation models in Smart-PLS to validate the proposed hypotheses. The paper follows the structure of scientific article. It begins with the research questions, hypotheses and main constructs, followed by the methodology of research. Afterwards results, discussions and conclusions are presented.

Literature review

Consumer willingness to share private information

As personal information is essential for the individualization of services, the topic of willingness of consumers to share private data has gained increased attention from scholars (Aiello *et al.*; 2020; Kim *et al.*, 2018). The willingness to share data is defined as consumers' openness of providing relevant personal data to a marketing or business-related context (Song & Kim, 2021). It is not a new concept, as it has been previously studied in different other contexts such as social media (Carlson *et al.*, 2022), sharing economies (Tran *et al.*, 2022), online commerce (Pizzi *et al.*, 2022; Fernandes & Pereira, 2021; Urbonavicius *et al.*, 2021) or even in psychology in the in-between human interactions (Altman & Taylor, 1973; Li *et al*., 2011). Based on these previously studied contexts, several theories and models have been developed to explain the motivations and fears of consumers' willingness to share private information, such as social penetration theory (Altman & Taylor, 1973; Tran *et al*., 2022), social exchange theory (Bagozzi, 1975), the personalization-privacy paradox (Barth & De Jong, 2017; Hayes *et al*., 2021; Bright *et al*., 2022; Ameen *et al*., 2022) and other similar studies.

The social penetration theory describes the role of information exchange in the relationship between individuals (Altman & Taylor, 1973). On the basis of this theory, the depth of the relationship between two persons is described by the type of information they exchange. The more individuals reveal personal information, the higher the trust and closeness of the relationship (Carpenter & Greene, 2015). Several authors have classified the different fields of the closeness of a relationship by defining several layers that an individual has in his/her interactions. According to Carpenter and Greene (2015), there are four layers of communication ranging from a superficial and middle layer to an inner and core personal one. In a similar way Clark and Mills (1993) categorize the relationship between individuals in exchange and communal relationships, while Reis and Patrick (1996) divide them in a similar way into descriptive and evaluative. Several authors agree that good relationships have to be reciprocal (Altman & Taylor, 1973) and that a high level of self-disclosure leads to a sentiment of intimacy, which is a key aspect for the success of a relationship (Sprecher & Hendrick, 2004).

The social exchange theory assumes that information is one valuable resource that can be exchanged for social support, recognition and other benefits (Bagozzi, 1975; Urbonavicius *et al*., 2021). According to the theory of social exchange, economic or informational transactions are negotiated and reciprocal. In negotiated transactions, the parties discuss the terms of exchange before the transaction, while the reciprocal one is based on the expectation that the other party will have a similar behavior based on the delivered resources (Molm *et al*., 2000). Based on this theory, the disclosure of personal data depends on formal assurances, trust and uncertainties (Bansal *et al*., 2016; Mothersbaugh *et al*., 2012).

Consumer decision to provide personal data to receive personalized services is known as the personalization-privacy paradox (Barth & De Jong, 2017; Hayes *et al*., 2021; Bright *et al*., 2022; Ameen *et al*., 2022). According to the gratification theory (Katz *et al*., 1973), consumers are willing to provide personal data for information and social purposes. Consumers seeking informational benefits have a lower trust in social media, while consumers looking to enhance social interactions and entertainment are more willing to share personal information (Carlson *et al*., 2022). Consequently, it can be stated that consumer seek value in exchange for personal information (Pallant *et al*., 2022). This cost-benefit analysis of sharing private information is also known as the "privacy calculus" (Li *et al*., 2011; Dinev & Hart, 2006). There are two aspects that are associated with the risk of sharing private information. On one hand, there is privacy protection, which refers to consumers' trust towards the technology or the vendor collecting the data. On the other hand, there is the privacy risk, associated with the potential dangers that might occur by exposing private information (Li *et al*., 2011).

The idea that consumers are willing to share private information as an exchange for other benefits has also been found at other authors. For instance, Constant *et al*. (1994), in their information sharing theory, prove that the predictors of data sharing can be divided into self-interest (service, quality, enjoyment, usefulness and ease of use) and social interaction (social cognition, collaborativeness and trust). Several other authors state that conscious data sharing can happen in return for tangible or intangible benefits of the consumers, such as exchange of information, communication and social relations and trust in case of companies (Song & Kim, 2021; Rese *et al*., 2020; Schroeder & Schroeder, 2018).

Motivations and fears about data sharing and the self-disclosing behavior of consumers

According to a study by Gutierrez *et al*. (2023), data privacy concerns are a major predictor of the willingness of consumers to interact with companies and also a determinant of the buying decision (Gutierrez *et al*., 2023). However, not providing personal data may also determine a lower personalization degree of services. From a company perspective, data sharing is important to provide personalized, custom-designed offers to the consumer. On the other hand, providing too much data can jeopardize the privacy of the consumer and increase his/her vulnerability toward manipulation of even data theft (Song & Kim, 2021). The willingness to share information depends on the type of information, traits of the individual, the relationship between the company and the consumer and the context (Aiello *et al*., 2020). Consumers are usually reluctant to share sensitive information, such as financial data, personal identification data or embarrassing information (Phelps *et al*., 2000; White, 2004).

Trust is an essential component of the disclosure of personal data. Only if a consumer trusts a company or technology, will he/she be willing to share more of his/her private information. Studies show that higher involvement with a platform or social media network, determines consumer to share more information, while requiring a certain level of trust (Urbonavicius *et al*., 2021). Based on the previously described social exchange theory (Bagozzi, 1975), consumers also share private information for social exchange and acceptance, and it depends on the context if they are willing to disclose personal information. In this sense, not only material and informational benefits matter when it comes to data sharing. A study by Aiello *et al*. (2020) confirms that perceived warmth in the relationship between consumer and company can increase the willingness of consumers to share personal information. Moreover, they show that in the customer journey, perceived warmth is important in the post-purchase phase, so the best way to ask for personal information is at the end of the buying process (Aiello *et al*., 2020). Trust is also important, as self-disclosing behavior is frequently associated by consumers with a certain vulnerability (Tran *et al*., 2022). By sharing information with other people, an individual may be exposed to emotional harm, financial damage (Moon, 2000), critics and judgment. Based on this fear, there is a particular type of self-disclosing behavior, which occurs in the context of sharing economy and refers to the self-disclosing behavior to strangers. Some consumers might feel less vulnerable and may perceive less risks in sharing information with strangers, as these have a lower influence on their everyday lives (Derlega & Chaikin, 1977). The same behavior can be transposed in the context of interaction with technology. As long as technology is perceived as providing digital anonymity, consumers will feel less vulnerable to judgement or rejection in the technology-mediated communication (Qian & Scott, 2007). According to a study by Tran *et al*. (2022), the consumer has a stronger self-disclosing behavior if he/she interacts with people with similar characteristics. In addition, self-esteem plays a moderating role in the relationship between self-disclosing behavior and consumer response (Tran *et al*., 2022). Self-disclosure in the sharing economy might be beneficial, as individuals with similar personalities share information (Tran *et al*., 2022), but this is not the case for service employees, for whom self-disclosure is perceived as superficial and less competent (Andersson *et al*., 2016). Based on this, we formulate the following two hypotheses:

H1: *The emotional connection to AI devices increases perceived threats related to vulnerability and exposure of the individual in relation to the personal data shared and used by the AI device.*

H2a: *Trust mediates the relation between the emotional connection to AI by decreasing perceived threats related to the use and exposure of personal data.*

Perceived control over shared data, as well as legal regulations on data protection are important predictors in the disclosure of personal data (Urbonavicius *et al*., 2021). If a consumer is not sure that the legal entities responsible for data protection are efficient enough, they will be reluctant in sharing data (Meier *et al*., 2020). The lack of control over what happens with data once it is disclosed is another aspect that inhibits consumers from providing data (Wang *et al*., 2016; Hong & Thong, 2013; Stanescu *et al*., 2021). In some cases, consumers expect discounts and preferential data to disclose private information (Pizzi *et al*., 2022). Despite the cost-benefit analysis of sharing private information, the consumer still finds the online collection of data as an intrusive practice (Fernandes & Pereira, 2021). However, sharing private data can depend on the context (Bansal *et al*., 2016) or it may be influenced by several biases such as habits or non-conscious factors (Barth & De Jong, 2017). In the long run, privacy concerns can lead to tiredness, fatigue (Bright *et al*., 2022) or discontinuous use of a certain technology. Based on this, we formulate the following hypothesis:

H2b: *Perceived control over the shared personal data mediates the relationship between the emotional behavior of AI, decreasing the perceived threats regarding the use of personal data.*

Emotions and feelings of friendship also play an important role in the relationship consumers have with other people (Schweitzer *et al*., 2019) but also with brands and companies (Kumar & Pansari, 2016) and even technological devices such as AI (Van Doorn *et al*., 2017; Huang & Rust, 2021). Several studies have shown that consumers can attach to different brands and objects (Kumar & Pansari, 2016) and this can also be transposed to AI devices (Van Doorn *et al*., 2017; Nass & Moon, 2000). Considering the fact that AI devices will play an increasingly important role in consumer lives (Guzman, 2019), it is expected that a certain attachment or feelings of friendship can arise (Kim *et al*., 2022; Sundar *et al*., 2017). The idea of having robots as friends has already been parodied in several movies (Oliveira & Yadollahi, 2024), while also research shows that empathetic and friendly behavior of AI devices may enhance trust and willingness to increasingly use them (Pelau *et al*., 2021; Huang & Rust, 2021). Several authors discuss the development of para-social friendships between consumers and their AI devices (Ki *et al*., 2020; Youn & Jin, 2021). Based on the definition of friendship, a para-social friendship between consumer and their intelligent device will include social support and self-disclosing behavior (Ki *et al*., 2020). This idea is supported empirically by research by Ki *et al*. (2020), who show that para-social presence of AI devices may enhance a para-friendship between consumer and its technological device. Based on this, we formulate the following hypothesis:

H2c: *Feelings of friendship mediate the relationship between the emotional connection to AI, decreasing the perceived vulnerability and threats related to the use of personal data.*

In order to test these hypotheses an online questionnaire was developed (see Appendix), to measure the proposed constructs. Based on the proposed hypotheses, we have AI's emotional behavior as independent variable, perceived threats related to consumers' data sharing with AI as dependent variable and trust, feelings of friendship and perceived control as mediators.

Research methods

Data collection took place with the help of an online survey in the urban population of Romania in December 2021. The survey started with a picture with an interaction between a human consumer and AI, in order to create an image and context for the interaction. The respondents had the scenario in which they had to imagine that they need to solve a problem with the AI presented in the picture. Based on this scenario, they had to evaluate the measured constructs. The convenience sample consisted out of 678 valid responses, out of which 61% were women and 39% were men.

Most of the consumers were younger than 40 years, having 50.5% respondents younger than 25 years, 35.2% with ages between 26 and 40 years and 14% respondents older than 41 years. As samples greater than 200 are considered adequate for structural equation models (Dash & Paul, 2021; Hair *et al*., 2017), our sample fulfills the criteria for structural equation models. Taking into consideration that younger generations are more likely to use AI in the present time and in the future, we consider that the sample reflects the existent situation.

To measure the reliability of the proposed constructs, a confirmatory factor analysis was performed, using the principal component extraction method, with varimax rotation in SPSS 20.0. The Kaiser-Meyer-Olkin value of 0.885 and the significance of the Bartlett test of 0.000 showed good adequacy of the data for the model. Based on eigenvalues greater than 1, the model showed an ideal number of five factors, explaining 73.06% of the total variance.

In order to validate the constructs, pre-defined scales have been adapted for this research. The used scales together with validation measures are presented in table 1. The first construct refers to the emotional relationship between consumer and AI, containing items about the ability of the AI device to experience emotions (CFA=0.752), similarity to humans (CFA=0.749), emotional involvement to AI (CFA=0.741), emotional affection of interaction with the AI (CFA=0.725), emotional connection to AI (CFA=0.802) and the caring way of AI (CFA=0.606). The items for this variable have been adapted after Bagchi *et al*. (2016), Bruner (2019), Kim *et al*. (2017) and Lu *et al*. (2019). This variable has a Cronbach-alpha value of 0.867, a CR value of 0.877 and an AVE vale of 0.548, all proving its reliability.

The second construct refers to trust towards AI. It contains items that refer to AI's ability to be honest (CFA=0.841), sincere (CFA=0.866), not manipulative (CFA=0.682) and trustworthy (CFA=0.796). The items have been adapted after Bruner (2019) and Kirmana *et al*. (2017). The reliability of the variable is tested with the Cronbach-alpha value of 0.868, the CR value of 0.910 and the AVE value of 0.718. The third variable refers to feelings of friendship towards AI. It includes items about consumers believe that AI is friendly (CFA=0.828), kind (CFA=0.856) and warm (CFA=0.713). These items have been adapted after Bagchi *et al*. (2016) and Bruner (2019). The variable has good reliability having a Cronbach-alpha value of 0.870, a CR value of 0.919 and an AVE value of 0.791.

The last two constructs refer to personal information exchanged with the AI device. Two variables have been defined for this: one variable measures the perceived threats related to sharing of personal information with AI and the second one the perceived control over the exchanged information. The variable about perceived threats includes items about the consumers' perception that the use of their personal data is insecure (CFA=0.793) and makes them exposed (CFA=0.872), threatened (CFA=0.879), vulnerable (CFA=0.890) and susceptible to manipulation (CFA=0.828). The reliability of this variable is given by the Cronbach-alpha value of 0.916, CR value of 0.932 and AVE value of 0.773. The second variable related to the control over what happens to the data includes items about perceived control over the use of private data (CFA=0.767), the amount of shared personal information (CFA=0.885), the way in which the personal data is used (CFA=0.906) and the control over the sharing of private data (CFA=0.867). This variable has a Cronbach-alpha value of 0.912, a CR value of 0.939, an AVE value of 0.793 and F=7.377 (p=0.000), showing its reliability. The items for the last two variables have been adapted after Martin *et al*. (2017) and Bruner (2019). These results and the applied items can be observed in Table 1. Convergent validity is confirmed by the factor loadings of the confirmatory factor analysis. Discriminant validity is confirmed by the heterotrait-monotrait criterion, for which all values are lower than 0.7.

Results

To validated the proposed hypotheses, three mediation models were tested using structural equation models in Smart-PLS 3.3.3. A bootstrapping method using 5000 distinct subsamples has been applied (software developed by Ringle *et al*., 2015). We have used structural equation models in Smart-PLS to test our hypotheses, because this method is adequate for research with a small sample size and non-normally distributed data (Hair *et al*., 2017) and because it is a tool for evaluating complex models (Hair *et al*., 2014), such as the one we proposed in our research.

The first mediation model has the emotional relationship between consumer and AI as an independent variable, the perceived trust towards the AI device as mediator and the perceived threat of data sharing as dependent variable. The results confirm that emotional behavior positively affects the perceived trust towards AI (β=0.434, t=14.133, p=0.000, CI=[0.386; 0.487]). There is a significant negative relation for the b-path, demonstrating that increased trust decreases perceived threats and vulnerability regarding the AI's use of personal data (β= -0.191, t=4.187, p=0.000, CI=[-0.268; -0.117]). The direct effect of the mediation model has a significant positive value (β=0.317, t=7.309, p=0.000, CI=[0.246; 0.390]) showing that the consumer is aware that an emotional relation with AI, increases his/her vulnerability of sharing data with it. However, the total effect of the mediation (β=0.234, t=5.546, p=0.000, CI=[0.163; 0.302]) shows that if the individual trusts the AI, then the perceived threat and vulnerability are lower. This is confirmed by the significant negative indirect effect (β= -0.083, t=3.922, p=0.000, CI=[-0.119; -0.050]) and the fact that trust diminishes perceived risks regarding the use of personal information by AI devices. The results of the mediation model can be observed in table 2.

The second mediation model includes the emotional relation between consumer and AI as independent variable, threats related to data sharing as dependent variable and feelings of friendship as mediator. For this model, there is a significant positive relation for the a-path, which shows that feelings of friendship between consumers and AI may occur, if AI has the ability to connect emotionally with the consumer (β=0.553, t=20.560, p=0.000, CI=[0.509; 0.597]). These feelings of friendship reduce the perceived vulnerability regarding AI's use of private data (β= -0.152, t=3.172, p=0.002, CI=[-0.232; -0.072]), confirming the b-path of the mediation model. Similar to the previous model, the direct effect shows that an emotional relationship impacts the perceived threats regarding the vulnerability of data sharing (β=0.318, t=6.945, p=0.000, CI=[0.243; 0.396]), however, this effect is reduced by feelings of friendship. This is proven both in the value of the total effect (β=0.234, t=5.734, p=0.000, CI=[0.167; 0.302]) and in the indirect effect (β= -0.084, t=3.138, p=0.002, CI=[-0.129; -0.040]). The results for this mediation model can be observed in Table 3.

The last mediation model contains the emotional AI relation as independent variable, the perceived threats of data sharing as dependent variable and perceived control over the use of shared data as mediator. This model also shows significant positive results for the a-path (β=0.251, t=6.876, p=0.000, CI=[0.190; 0.312]) showing that an emotional relation increases perceived control over the use of shared data by the AI device. Perceived control over the use of shared private information significantly decreases perceived threats regarding the exposure of the private information (β= -0.330, t=7.933, p=0.000, CI=[-0.398; -0.260]). Moreover, perceived control over the use of shared data by AI has a mediating effect for the proposed relation, reducing perceived threats of vulnerability and exposure in case of an emotional relationship between human and AI device. This is proven by the significant result for both the total effect (β=0.237, t=5.759, p=0.000, CI=[0.170; 0.305]) and the indirect effect (β= -0.083, t=5.040, p=0.000, CI=[-0.111; -0.057]). The results can be observed in table 4.

In order to test which of the constructs has the strongest impact on reducing the perceived threats regarding AI's use of private data, we have tested a combined model having all mediators simultaneously. These results show that perceived control over private information impacts most (β= -0.300, t=6.916, p=0.000, CI=[-0.370; -0.229]) the reduction of perceived threats with respect to vulnerability to data exposure in an emotional relationship with the AI device. Trust has a lower impact (β= -0.093, t=1.992, p=0.046, CI=[-0.171; -0.016]) compared to perceived control, while the feelings of friendship (β= -0.036, t=0.765, p=0.445, CI=[-0.110; 0.042]) are completely eclipsed by the other two constructs. The cumulative total effect has a value of β=0.231 (t=5.561, p=0.000, CI=[0.161; 0.297]), while the indirect effect is higher than in the case of the previous mediation models (β= -0.137, t=4.511, p=0.000, CI=[-0.188; -0.088]). The results for this model are presented in table 5.

The results of our research show that in simple mediation models, all three mediators influence the relationship between the emotional connection between consumer and AI and information sharing behavior, reducing the perceived threats by having a negative indirect effect. However, in a combined model, perceived control overshadows the other two variables, being the most important variable that reduces threats associated to information sharing. This combined model can be observed in figure 1.

Discussion

The results of our research show that perceived control, trust and feelings of friendship mediate the relationship between an emotional behavior towards AI and perceived threats regarding the use of consumers' personal data by AI, confirming all proposed hypotheses. As expected, an emotional relation between consumer and AI increases the perception of threats regarding the use of personal data, as the consumer is aware that it can increase his/her vulnerability to manipulation and that the data can be used by third parties and by algorithms developed within the AI. Consequently, it is not enough to have an emotional connection in order to determine the consumer to share private information, but a deeper relationship is needed. This is in line with previous studies, which show that a higher degree of intimacy, understanding and involvement is needed in order to determine consumers to share private information (Ki *et al*., 2020; Carpenter & Green, 2015; Sprecher & Hendrick, 2004).

Perceived control over the use of shared personal information is the most significant mediator in decreasing perceived threats regarding the vulnerability and exposure of the individual. Believing that an individual can have control over the amount of shared personal information or the way this information is used can reduce the perceived risks regarding giving his/her personal data to the AI device. Similar data have been obtained in studies performed for the online environment, where formal assurances, trust and uncertainties are important factors in disclosing personal information (Bansal *et al*., 2016; Mothersbaugh *et al*., 2012; Urbonavicius *et al*., 2021). However, we have measured a subjectively perceived control and there is no real proof that the consumer really controls the information he/she gives to the AI device. Several studies confirm that a big part of the data provided to intelligent devices are gathered in an unconscious way, so it is difficult to evaluate the real control over the shared data (Stanescu *et al*., 2021). But, as long as consumers have the impression that he/she controls the shared data, the perceived risk are lower.

Trust is another important construct that mediates the relationship between the emotional connection between consumer and AI and perceived threats regarding the use of personal data. If, in addition to developing an emotional relationship, an AI device can develop trust, then the consumer will perceive fewer risks in providing his/her personal data. The relationship between trust and AI devices is considered one of the most important determinants of acceptance of these new technologies (Gursoy *et al*., 2019; Urbonavicius *et al*., 2021). The concept of trust is a very complex one as it can be analyzed from different points of view. Therefore, in future research, it is important to further develop the concept of trust in the consumer-AI relationship.

Several studies point out the feelings of friendship between consumer and AI, trying to optimize this relationship (Chang *et al*., 2023; Chaturvedi *et al*., 2023; Huang & Rust, 2021; Ki *et al*., 2020; Leo-Liu, 2022; Schweitzer *et* *al.*, 2019), while fewer studies analyze the willingness of consumers to disclose private information with robots, but in a social sales context, not in a friendship context (Song & Kim, 2021). Our research fills this gap, by analyzing the consumers' willingness to disclose personal information with AI, in a friendship context. It can be debated how far consumers and AI can be considered as friends, as it is rather a para-social friendship. However, in our research, we kept the friendship term in order to test if consumers can imagine to have AI as friends and if AI can be placed at the same level as human friends. This situation can have implications on real friendships as human friends might be replaced by AI friends.

The results show that feelings of friendship have the smallest mediating effect in reducing the perceived threats of data sharing. However, in the absence of the control over the shared data, feelings of friendship, kindness and warmth can decrease the perceived vulnerability of data sharing. This is in line with other studies that show that warmth and an emotional bond are important factors in shaping consumer-AI interactions (Bilal *et al*, 2024; Chang *et al.*, 2023) and that they can influence the sharing of private information (Aiello *et al.*, 2020). It must also be mentioned that perceived control is a construct closer related to personal data, in comparison to feelings of friendship and trust, which are more general constructs that define the relation between human and AI. Having control over personal data is more difficult to accomplish, while trust and feelings of friendship rely on the consumers' perception of the relationship.

Conclusions

Analyzing all these factors shows the complexity of consumer-AI relationships and their impact on consumers' self-disclosing behavior towards AI. These developments have major implications for theory, business practice and society in general. From a managerial point of view, our research results have major implications on the design of AI that interacts with consumers in business, service industries and even in the consumers' private environment. Understanding the way in which an emotional connection, trust or feelings of friendship can be developed will have major implications for the design of the future consumer-AI relationships and it will shape AI' social role in the future society. Compared to the initial technological devices that were assigned with a social role, the inclusion of AI in consumers' life is far more complex. These devices will have the ability to show emotions and empathy, they will have free will as well as the power to make own decisions. Therefore, their role in society will have deeper implications, in comparison to the social role of computers and other technologies.

From a theoretical perspective, the paper adds value to the literature by extending existing theories that define human relationships to consumer-AI relations. Depending on the type of AI, the human consumer will develop formal or more emotional reaction, having implications on the involvement of AI in human decision. The higher the bond between consumer and AI, the greater AI's influence will be. In present research, much of the attention regarding the implementation of AI has focused on its general acceptance. From the perspective of sharing personal data with AI, acceptance theories will go deeper in investigating the relation between consumers and AI. If consumers are willing to share personal and private data, they will increase the functionality of AI devices and will also consolidate their role in society. From this perspective, it is important to understand the factors that affect this relation, as they will have major implications for the integration of AI in the private environment of each individual.

From the marketing perspective, this aspect is important as the communication between companies, brands and consumers will happen with the interference of AI, as it will have the role to recommend or select the appropriate products/ brands for the consumer. Consequently, it is important to determine in how far the human consumer trusts an AI device, how much information is he/she willing to provide to AI and which are the factors that affect the sharing of personal data. According to the present research, an emotional relation between consumer and AI, mediated by perceived control over the shared data, trust and feelings of friendship are significant determinants for the perceived risks regarding data sharing with AI, having major implications on the future development of AI.

The main limitation of our research refers to the fact that it is a scenario-based study, in which respondents had to imagine the interaction with the AI, while in real life they did not do it. The survey used a third person perspective, so the respondents had to evaluate the feelings of friendship and emotions towards an AI with which they did not interact. A first-person perspective as well as a real interaction between consumer and AI might change the evaluations and the reactions towards emotional constructs as well as trust, feelings of friendship and perceived control. Another limitation is the fact that data collection took place in Romania, where people don't have much experience in interacting with AI. In our future studies, we aim to improve the context in which the consumer-AI interaction takes place and to measure the construct based on a real interaction and not a scenario-based one. However, our study reveals important implications the consumer-AI relationship has on the disclosure of private data.

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Annex

Table 1. Results of the confirmatory factor analysis

Item	Mean	CFA loading
Emotional relationship (Adapted after Bagchi *et al.*, 2016; Bruner, 2019; Kim *et al.*, 2017; Lu *et al.*, 2019) Cronbach-Alpha=0.867, CR=0.877, AVE=0..548, M=2.270		
AI devices will experience emotions.	2.06	0.752
AI devices are like humans	2.06	0.749
I felt emotionally involved with the robot	2.55	0.741
The interaction with the robot affected me emotionally	2.44	0.725
I was able to connect with the robot emotionally	2.24	0.802
To what extent do you believe the robot is caring	2.23	0.606
Trust (Adapted after Bruner, 2019; Kirmani *et al.*, 2017) Cronbach-Alpha=0.868, CR=0.910, AVE=0.718, M=3.769		
I feel that the relationship to the robot is honest	3.57	0.841
I feel that the relationship to the robot is sincere	3.60	0.866
I feel that the relationship to the robot is not manipulative	4.04	0.682
I feel that the relationship to the robot is trustworthy	3.84	0.796
Feelings of friendship (Adapted after Bagchi *et al.*, 2016; Bruner, 2019) Cronbach-Alpha=0.870, CR=0.919, AVE=0.791, M=3.432		
To what extent do you believe the robot is friendly	3.79	0.828
To what extent do you believe the robot is kind	3.62	0.856
To what extent do you believe the robot is warm	2.87	0.713
Threats of sharing personal information (Adapted after Martin *et al.*, 2017; Bruner, 2019) Cronbach-Alpha=0.916, CR=0.932, AVE=0.773, M=3.668		
The personal information used by robot makes me insecure	3.72	0.793
The personal information used by robot makes me exposed	3.84	0.872
The personal information used by robot makes me threatened	3.47	0.879
The personal information used by robot makes me vulnerable	3.63	0.890
The personal information used by robot makes me susceptible to manipulation	3.65	0.828
Perceived control over exchanged information (Adapted after Martin *et al.*, 2017; Bruner, 2019) Cronbach-Alpha=0.912, CR=0.939, AVE=0.793, M=4.186		
I believe that I have control over what happens to my personal information in relation to the robot	4.08	0.767
It is up to me how much the robot uses my information	4.32	0.885
I have a say in how my information is used by the robot	4.18	0.906
I have a say in whether my information is shared with others	4.14	0.867

Table 2. Results of mediation model 1

Relation	β	SD	t	CI
Emotional relationship → Trust (a-path)	0.434	0.031	14.133***	[0.386; 0.487]
Trust → Info sharing threats (b-path)	-0.191	0.046	4.187***	[-0.268; -0.117]
Emotional relationship → Info sharing threats (direct effect, c-path)	0.317	0.043	7.309***	[0.246; 0.390]
Emotional relationship → Info sharing threats (total effect, c′-path)	0.234	0.042	5.546***	[0.163; 0.302]
Emotional relationship → Info sharing threats (indirect effect, ab-value)	-0.083	0.021	3.922***	[-0.119; -0.050]

Where β=path coefficient, SD=standard deviation, t=t-test, CI=confidence interval and *** for p<0.01, ** for p<0.05, * for p<0.10.

Table 3. Results of mediation model 2

Relation	β	SD	t	CI
Emotional relationship → Friendship (a-path)	0.553	0.027	20.560***	[0.509; 0.597]
Friendship → Info sharing threats (b-path)	-0.152	0.048	3.172***	[-0.232; -0.072]
Emotional relationship → Info sharing threats (direct effect, c-path)	0.318	0.046	6.945***	[0.243; 0.396]
Emotional relationship → Info sharing threats (total effect, c′-path)	0.234	0.041	5.734***	[0.167; 0.302]
Emotional relationship → Info sharing threats (indirect effect, ab-value)	-0.084	0.027	3.138***	[-0.129; -0.040]

Where β=path coefficient, SD=standard deviation, t=t-test, CI=confidence interval and *** for p<0.01, ** for p<0.05, * for p<0.10.

Table 4. Results of mediation model 3

Relation	β	SD	t	CI
Emotional relationship → Control (a-path)	0.251	0.036	6.876***	[0.190; 0.312]
Control → Info sharing threats (b-path)	-0.330	0.042	7.933***	[-0.398; -0.260]
Emotional relationship → Info sharing threats (direct effect, c-path)	0.320	0.041	7.718***	[0.252; 0.389]
Emotional relationship → Info sharing threats (total effect, c′-path)	0.237	0.041	5.759***	[0.170; 0.305]
Emotional relationship → Info sharing threats (indirect effect, ab-value)	-0.083	0.016	5.040***	[-0.111; -0.057]

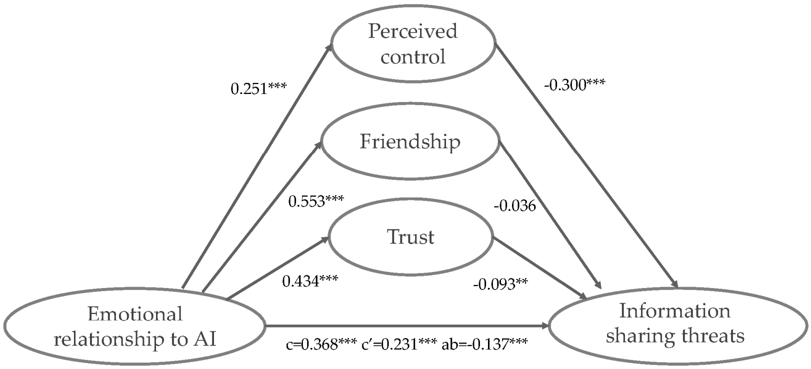
Where β=path coefficient, SD=standard deviation, t=t-test, CI=confidence interval and *** for p<0.01, ** for p<0.05, * for p<0.10.

Table 5. The combined model

Dependent variable: Info sharing threats				
Independent variable/ mediator	β	SD	t	CI
Emotional relationship (direct effect)	0.368	0.048	7.634***	[0.289; 0.447]
Trust	-0.093	0.047	1.994**	[-0.171; -0.016]
Friendship	-0.036	0.047	0.765	[-0.110; 0.042]
Control	-0.300	0.043	6.916***	[-0.370; -0.229]
Emotional relationship (total effect)	0.231	0.041	5.561***	[0.161; 0.297]
Emotional relationship (indirect effect)	-0.137	0.030	4.511***	[-0.188; -0.088]

Where β=path coefficient, SD=standard deviation, t=t-test, CI=confidence interval and *** for p<0.01, ** for p<0.05, * for p<0.10.

Figure 1. The proposed model



Appendix

Questionnaire used in the research

Scenario: Please imagine that you have to solve a problem with the following AI. Based on this, evaluate the following affirmations on a scale from 1 to 7, where 7 represents total agreement and 1 represents total disagreement.

Nr.	**Affirmation**	**7**	**6**	**5**	**4**	**3**	**2**	**1**
1	AI devices will experience emotions.							
2	AI devices are like humans							
3	I felt emotionally involved with the robot							
4	The interaction with the robot affected me emotionally							
5	I was able to connect with the robot emotionally							
6	To what extent do you believe the robot is caring							
7	I feel that the relationship to the robot is honest							
8	I feel that the relationship to the robot is sincere							
9	I feel that the relationship to the robot is not manipulative							
10	I feel that the relationship to the robot is trustworthy							
11	To what extent do you believe the robot is friendly							
12	To what extent do you believe the robot is kind							
13	To what extent do you believe the robot is warm							
14	The personal information used by robot makes me insecure							
15	The personal information used by robot makes me exposed							
16	The personal information used by robot makes me threatened							
17	The personal information used by robot makes me vulnerable							
18	The personal information used by robot makes me susceptible to manipulation							
19	I believe that I have control over what happens to my personal information in relation to the robot							
20	It is up to me how much the robot uses my information							
21	I have a say in how my information is used by the robot							
22	I have a say in whether my information is shared with others							
23	Gender:							
	Female							
	Male							
24	Age:							
	< 25 years							
	25-40 years							
	41-55 years							
	> 55 years							

Source: Questionnaire developed by authors, adapted after scales mentioned in table 1.