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Alexa, You Freak Me Out – Identifying Drivers of Innovation Resistance and Adoption of Intelligent Personal Assistants

Completed Research Paper

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Abstract

Intelligent Personal Assistants (IPAs) are increasingly being integrated in many consumer products such as smartphones or cars. However, according to recent research only 50% of the population is using IPAs displaying a certain resistance behavior. Moreover, studies on the reasons for IPA resistance are not available. Consequently, our study strives to close this research gap by identifying key drivers of innovation resistance and adoption behavior of IPAs. Using a large-scale online survey (n=168) we find that individual differences, data privacy concerns, trust in AI and perceived creepiness play an important role for innovation resistance. More specifically, trust in AI applications partially mediates the relationship between individual differences and innovation resistance. Additionally, perceived creepiness fully mediates the relationship between AI data privacy concerns and innovation resistance. Our results provide valuable implications for the development and marketing of IPAs emphasizing the importance of trust and perceived creepiness for a customer's innovation resistance.

Keywords: Innovation resistance, intelligent personal assistants, perceived creepiness of ai, trust in ai

Introduction

Due to tremendous progress in the field of artificial intelligence (AI), specifically in voice recognition and natural language processing, intelligent personal assistants (IPAs) are rapidly increasing in importance (Liao et al. 2019). IPAs are capable of performing increasingly complex tasks by the day (Han and Yang 2018). They help remember meetings, play music, control smart homes, shop online and provide information about the weather (Cao et al. 2019). Thus, it is not surprising that IPAs such as the Google Assistant, Amazon's Alexa, Apple's Siri, and Microsoft's Cortana have become mainstream, with a global market size of 4.1 Billion IPAs in 2021 (T4.ai 2021). However, market size can be a misleading indicator in regard to IPA adoption, as all of these IPAs are integrated or can be bought in combination with other products, such as smartphones, smart TVs and even cars (Liao et al. 2019).

Moreover, representative studies in the US and Germany identified that across all ages, only half of the population used IPAs in recent years (Beyto 2020; Olmstead 2017). Considering the high availability of IPAs as part of almost every smartphone, the question arises why more than every second person is not using IPAs. Additionally, interest in academia on IPA functionality, usage and interaction with users has consistently risen in the last couple of years (e.g., Cao et al. 2019; Diederich et al. 2020; Maedche et al. 2019). Given the importance of IPAs to academia and practice alike (e.g., Adner et al. 2019; Furman and Teodoridis 2020; Haefner et al. 2021), it is surprising that, to the best of our knowledge, no study is available that identifies the key drivers of innovation resistance and derives implications to increase the adoption of IPAs.

Thus, our paper strives to close this research gap by developing and testing an innovation resistance and adoption model for AI-based IPAs. The contributions of our paper are as follows. First, we examine the effects of AI privacy concerns such as data control, awareness of privacy practices and actual data collection on innovation resistance. Second, we test the effect of individual differences (need for interaction, self-efficacy, technological innovativeness and inherent novelty seeking) on innovation resistance. By doing so, we will answer a call made by Ostrom et al. (2019) stating that AI privacy concerns, as well as individual differences, should be studied. As anecdotal evidence suggests, these factors could play an important role in explaining innovation resistance and adoption behavior of AI applications such as IPAs. Third, as trust builds the basis for describing any interaction between humans and AI (Hengstler et al. 2016), we will integrate it into our model. Specifically, we will analyze whether trust in AI applications will act as a mediator between individual differences and innovation resistance, emphasizing its key role in the adoption process. Fourth, AI-enabled applications such as IPAs can be perceived as "creepy" by the customer if the underlying algorithms are optimized without considering social norms and consumer psychology (Tene and Polonetsky 2013). Thus, our study examines the role of a customer's perceived creepiness towards AI applications analyzing its function as a mediator between AI privacy concerns and innovation resistance. Our study results will provide product managers with valuable information on key drivers of innovation resistance for AI-based IPA applications. More specifically, product managers can create new IPA applications based on our results, reducing customers' innovation resistance and boosting the adoption of their applications.

Moreover, our study will also enrich the IS and innovation management literature by providing an empirical explanation for the relatively low observed adoption rates of AI-based applications such as IPAs. The remainder of the paper is structured as follows: In the next section, we provide a literature overview of the existing IPA literature followed by the conceptual foundation of our research model, which is based on the IS and innovation management literature. Subsequently, we develop our hypotheses and perform our analysis. The last sections evaluate our model results, provide implications for theory and practice and identify future research avenues based on the study's limitations.

Related Work

Although AI has recently gained importance in the IS and management literature (e.g., Furman and Teodoridis 2020; Gursoy et al. 2019; Haefner et al. 2021), the related research field on intelligent assistants is rather underdeveloped, with only a few publications available on the topic (e.g., Bentley et al. 2018; Diederich et al. 2020; Maedche et al. 2019). However, more than 20 years ago, the first conceptual study dealt with intelligent assistants describing them as integrated systems of intelligent software supporting the customer with communication and information management (Azvine et al. 2000). The main functions of this intelligent assistant were supporting diary, mail and telephone activities. The authors conclude that the ability to learn and customize intelligent assistants will provide great potential for the personalization of future services (Azvine et al. 2000). In the following years, further conceptual studies were published using many different terms to describe intelligent assistants, such as conversational agents, digital assistants, voice assistants and intelligent personal assistants (Fernandes and Oliveira 2021; Maedche et al. 2019). However, the most commonly used term for describing intelligent assistants is intelligent personal assistant (IPA) (Cao et al. 2019; Han and Yang 2018; Liao et al. 2019). Consequently, we will define IPA as "an application which has the ability to respond to user's demands synchronically, engage in humanoid interaction, even learn users' behavior preferences and evolve over time" (Cao et al. 2019, p. 3).

Apart from these earlier studies on IPAs, which provided a good conceptual overview, recent studies focus on IPA usage. A study by Bentley et al. (2018) analyzed the voice history logs of Google Home devices and identified different usage patterns concerning content and time. Based on these usage patterns, the authors defined four different user groups and provided user group-specific implications for further improving the user experience of the IPA. Another study developed a model for predicting user satisfaction with IPAs based on interaction signals from search dialogs (Kiseleva et al. 2016). Moreover, the potential of IPA speech interaction was tested using Apple's Siri to help elderly people access their smartphone. This study found that elderly users valued the simplicity of interacting with smartphones (Wulf et al. 2014). Finally, some studies examine the user's relationship with IPAs, focusing on IPA's anthropomorphic features (Han and Yang 2018; Purington et al. 2017). For example, the study by Han and Yang (2018) identified interpersonal attraction as well as security and risks as key drivers of IPA continuance intention. The authors conclude that developers should focus their efforts on improving the parasocial features of IPAs, thereby making them more human-like (Han and Yang 2018).

Additionally, the personification of IPAs leads to more interaction with the device and increases user satisfaction (Purington et al. 2017). This result underlines the importance of anthropomorphic features for user adoption of IPAs. However, if an IPA is behaving too human-like, there is always the possibility that customers are afraid and perceive the IPA behavior as creepy (Stevens 2016). Thus, examining the role that perceived creepiness of an AI application plays in the resistance and adoption of IPAs merits further study.

Another research stream addresses the data security and privacy challenges that IPAs produce (e.g., Furey and Blue 2019; Liao et al. 2019). IPAs collect vast amounts of real-time voice data and send it to cloud servers (Liao et al. 2019). In the case of a hacker attack, these data could be accessed by criminals who could retrieve valuable information such as customers' buying behavior, passwords or credit card information (Dorai et al. 2018). Studies by Fernandes and Oliveira (2021) and Nasirian et al. (2017) identified that trust plays an important role for the user of an IPA. However, these studies did not link trust to the topic of data security and data privacy concerns. The issue of data security and privacy concerns itself also plays an important part in a related research stream on automation and self-service technologies – SSTs (e.g., Featherman and Hajli 2016; Kaaz et al. 2017). Using smart AI-enabled SSTs often requests a tremendous amount of personal data from the customer, resulting in negative feelings as customers experience a loss of privacy (Bitner et al. 2002; Featherman and Hajli 2016).

Moreover, a recent study by Portes et al. (2020) examined how data privacy concerns affect a customer's perception of digital transparency concerning the use of SSTs. The authors found that privacy concerns negatively influence perceived digital transparency, finally reducing customer engagement. These results are in line with a study on user perceptions of privacy concerning the use of home automation (Kaaz et al. 2017). The users of the home automation devices expected a certain level of data security and privacy protection, representing a main barrier to using such SST devices.

Overall, the existing studies already provide a good overview of IPAs, their functionalities and usage behavior. However, although some studies have found drivers of IPA usage (Fernandes and Oliveira 2021; Han and Yang 2018), no study has yet identified the antecedents predicting innovation resistance and adoption behavior of IPAs. Moreover, our study is the first to test the effects of personality traits such as individual differences and data privacy concerns on innovation resistance. Finally, our study is unique, examining the importance of perceived creepiness and trust for a customer's resistance to IPAs.

IPA Innovation Resistance and Adoption Model

The goal of this study is to focus on the customer and why she or he is resisting the adoption of an AI-based application such as an IPA. Consequently, our research model is based on a theoretical framework for customer acceptance and adoption of AI applications (Ostrom et al. 2019), which has its roots in the adoption literature on self-service technologies (Meuter et al. 2005). As IPAs deliver digital services to the customer, it is logical that our model heavily builds on the recent customer acceptance framework of AI for service encounters (Ostrom et al. 2019). The framework provides a sound theoretical basis to study antecedents of innovation resistance and adoption of AI-based applications. More specifically, the AI customer acceptance framework features individual differences as well as privacy concerns, trust and perceived creepiness as key antecedents of adoption behavior (Ostrom et al. 2019).

Thus, in line with previous literature, our model will feature key individual differences as antecedent predictors of IPA innovation resistance and adoption intention (e.g., Blut et al. 2016; Heidenreich and Handrich 2015). Specifically, individual differences "capture characteristics that describe the (potential) adopter of an innovation" (Heidenreich and Handrich 2015, p. 48). As the adoption process, in general, is strongly influenced by a customer's personality (Arts et al. 2011) and research on AI adoption also suggests that individual differences will affect the adoption of AI-based technology, we integrate them in our model. Based on the AI customer acceptance framework, we also add AI context-specific variables capturing AI data privacy concerns (Malhotra et al. 2004; Ostrom et al. 2019). Additionally, and in line with the AI customer acceptance framework, perceived creepiness and trust are integrated as mediators in our model, as they are specifically important for AI applications such as IPAs (Hengstler et al. 2016; Ostrom et al.

2019). As our study strives to identify why half of the people are not adopting IPAs despite having access to them via built-in functions of various devices such as smartphones, a central variable of our model is innovation resistance. In line with previous research, we conceptualize innovation resistance as a negative attitude formation (Kleijnen et al. 2009; Nabih et al. 1997). Figure 1 depicts our research model.

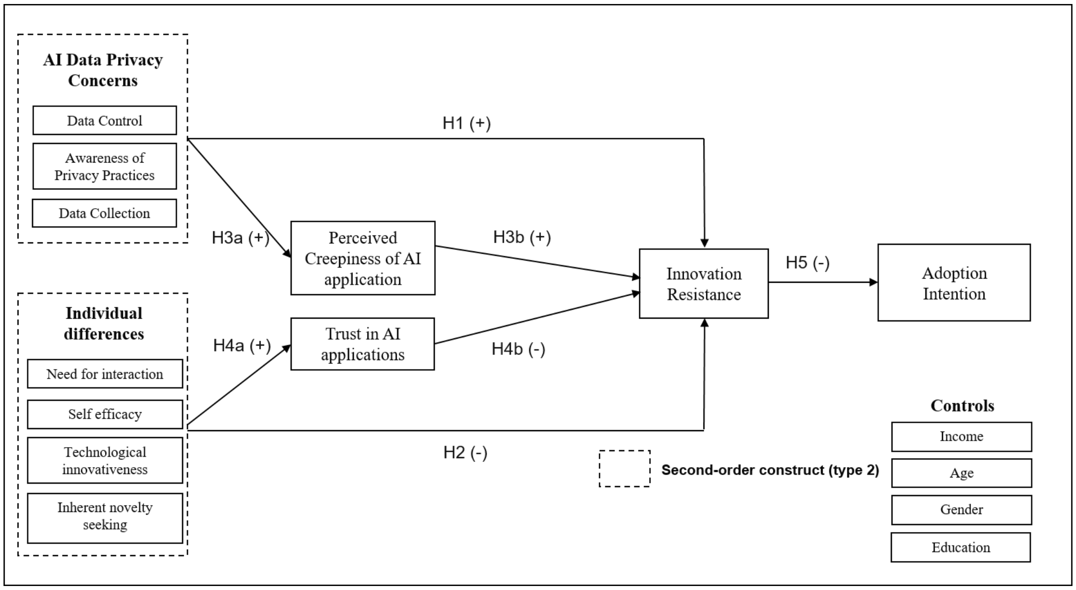

Figure 1. Research Model

Hypothesis Development

Although AI-based applications can perform many tasks with higher efficiency and greater quality than humans, these applications are not without danger (Haefner et al. 2021). In particular, AI-based IPAs raise security and privacy concerns, as they collect vast amounts of behavioral data and send it to the cloud even without the customer realizing it (Liao et al. 2019). Customers need to share personal information to receive the benefits of customized offerings from the IPA. However, this can result in a personalization-privacy paradox forcing the customer to balance benefits from customization with the risk of disclosing personal information (Awad and Krishnan 2006). Therefore, drawing on the AI customer acceptance framework, we decided to include data privacy concerns as antecedent predictors of innovation resistance in our model. In line with Malhotra et al. (2004), we conceptualized AI data privacy concerns as a 3-dimensional construct consisting of data control, awareness of privacy practices and data collection. The construct captures the degree to which a customer is concerned with the collection of personal data, the customer's control over the collected data and the awareness of how the collected data are being used (Malhotra et al. 2004).

More specifically, the data collection dimension measures the extent to which a customer is worried about the amount of data that other parties possess in relation to the received benefits (Malhotra et al. 2004). In general, many customers are currently reluctant to share personal data online, which has negative effects on their purchasing behavior (Rust and Chung 2006). Moreover, a recent study on IPAs found that the perceived security and privacy risk associated with data collection negatively influences the parasocial relationship, ultimately leading to dissatisfaction and a reduction in IPA usage (Han and Yang 2018). Thus, based on the arguments above and looking from an innovation resistance perspective, we suggest that with increasing concerns regarding data collection, innovation resistance will also rise. The second dimension of AI data privacy concerns is the data control dimension capturing the fact that customers expect to have control over their personal data (Phelps et al. 2000). Losing control over their personal data reduces a customer's willingness to use an application, whereas being in control of the data increases the willingness to use it (Ostrom et al. 2019). Additionally, customers with a high need for control over their personal data see a violation of that control as unfair, making them more likely to resist an innovation (Stewart and Segars 2002). Therefore, we assume that a higher need for data control will increase innovation resistance. Finally, the third dimension of AI data privacy concerns consists of the awareness of privacy practices. Contrary to data control, which is an active component of data privacy implemented by data approval or opt-in/optout, the awareness of privacy practices describes the extent to which a customer is worried about his or her awareness of the information privacy practices defined by companies, thereby capturing the passive component (Malhotra et al. 2004). Customers who highly value company policies on data and information transparency are less willing to be profiled online to obtain a personalized service (Awad and Krishnan 2006). As a customer's willingness to be profiled online for a personalized service represents an attitude (Awad and Krishnan 2006) and innovation resistance also captures an attitude formation, albeit a negative one (Heidenreich and Spieth 2013), we conclude that customers with a high awareness of data privacy practices will have a higher resistance to innovations.

Based on our arguments in the preceding paragraph, we expect positive relationships between AI data privacy concerns and innovation resistance:

H1: AI data privacy concerns are positively related to innovation resistance.

Based on the AI customer acceptance framework (Ostrom et al. 2019) and on the fact that the adoption process is highly influenced by the personality of a customer, we include key individual differences (need for interaction, self-efficacy, inherent novelty seeking and technological innovativeness) as antecedent predictors of innovation resistance (Arts et al. 2011). We chose these 4 individual difference constructs, as they have been shown to be the most consistently used constructs in the technology-based service resistance and adoption literature (e.g., Heidenreich and Handrich 2015). IPA applications provide a digital, technology-based service to the customer using these individual differences as antecedents of innovation resistance. The first individual difference construct need for interaction, captures the wish of a person to stay in contact with others during the use of a service or application (Dabholkar 1992). However, AI-based applications such as IPAs cannot provide this interpersonal interaction. Nevertheless, many of today's customers with a high need for interaction prefer a digital interaction over a personal interaction, as they want to stay anonymous or do not want to be disappointed by a bad interpersonal customer experience (Meuter et al. 2005). Thus, we expect a negative relationship between the need for interaction and innovation resistance. Self-efficacy, which we also include as individual differences in our model, measures a customer's belief in his or her capability to perform a certain task (Gist 1987). A study by Cho and Chang (2008) found a negative relationship between self-efficacy and innovation resistance toward salesforce automation. In line with this study, we assume that self-efficacy negatively affects innovation resistance. The third individual difference construct, technological innovativeness, describes the degree to which a customer is motivated to adopt a new technological product or service (Bruner and Kumar 2007). Existing studies have found a positive relationship between a customer's technological innovativeness and adoption intention (Bruner and Kumar 2007; Heidenreich and Handrich 2015). Moreover, customers with high technological innovativeness are more willing to actively participate in cocreation activities of technology-based services (Heidenreich and Handrich 2015). Consequently, as customers high in technological innovativeness will have lower resistance to innovations, we expect a negative relationship between technological innovativeness and innovation resistance. The last individual difference construct, inherent novelty seeking, captures a customer's wish to look for new stimuli (Dabholkar and Bagozzi 2002). Inherent novelty seeking is also known to positively affect the early stages of innovation adoption (Manning et al. 1995). Moreover, customers high in inherent novelty seeking have an intrinsic motivation to try out new technologies and approach problems in new ways (Hirschman 1980). Thus, and in line with the presented studies, we suggest that people high in inherent novelty seeking will have lower innovation resistance.

Considering our arguments above, we expect negative effects of individual differences on innovation resistance:

H2: Individual differences are negatively related to innovation resistance.

In general, AI data privacy concerns capture a person's subjective views of fairness about information privacy (Campbell 1997). For instance, if customers are not aware of what happens with their personal data and they do not have any control over the process or have any transparency regarding the data privacy practices or the amount of data being collected, they feel unfairly treated, which provokes negative feelings (Pavlou 2011; Smith et al. 2011). Additionally, if these data have also been used in an unexpected manner and customers suddenly get confronted with it, they feel that traditional social norms are violated and thus perceive this as "creepy" (Tene and Polonetsky 2013). More specifically, perceived creepiness describes "an emotional reaction to an experience, interaction, technology or unsolicited communication where personal information has been collected with your knowledge or unknowingly and used in an unexpected or surprising manner invoking negative feelings" (Stevens 2016, p. 229). One example that could be perceived as creepy would be that an IPA knows your search history on Amazon as well as your contacts from your phone and asks if you would like to buy a certain item for the birthday of your friend John. In particular, customers with high data privacy concerns will experience high levels of creepiness toward AI in such a situation (Stevens 2016). Moreover, a study by Sohn and Kwon (2020) on the adoption of AI-based intelligent products suggests that negative feelings, such as those evoked by perceived creepiness, will increase innovation resistance toward the products. This suggestion is in line with recent theory based on the AI customer acceptance framework (Ostrom et al. 2019) and with the results of empirical studies arguing that negative emotions such as fear or stress lead to higher innovation resistance (Fuglseth and Sørebø 2014; Marakas and Hornik 1996).

Based on the discussion of the relationships in the previous paragraph, we suggest that the perceived creepiness of AI mediates the positive relationship of AI data privacy concerns on innovation resistance. Thus, we hypothesize:

H3. Perceived creepiness of AI mediates the positive effects of AI data privacy concerns on innovation resistance

H3a. AI data privacy concerns are positively related to the perceived creepiness of AI

H3b. Perceived creepiness of AI is positively related to innovation resistance

The IS and innovation management literature has acknowledged the central role that trust plays in innovation adoption in the AI context (e.g., Malhotra et al. 2004; Nasirian et al. 2017). This is why the AI customer acceptance framework features trust as an important antecedent of resistance behavior (Ostrom et al. 2019). In line with McKnight et al. (2002), we define trust in AI applications as a belief measuring the extent to which an AI application is reliable and can be trusted. Moreover, we identified individual differences such as self-efficacy or technological innovativeness as antecedent variables of trust, as they represent important personality traits that determine a customer's disposition to trust (McKnight et al. 2002). Thus, these individual differences will positively influence trust, which empirical studies in that field can confirm (e.g., Malhotra et al. 2004; McKnight et al. 1998). Additionally, a study on mobile payment systems identified trust as one of the most important determinants regarding adoption and resistance behavior (Zhou 2013). This is in line with Kim et al. (2004) and Yu et al. (2015), who found that trust significantly reduces innovation resistance, leading to higher adoption of internet banking services. Overall, trust generally helps to reduce uncertainties associated with using AI applications, thereby considerably minimizing innovation resistance (Gefen 2002; Hengstler et al. 2016).

Based on our arguments above, we suggest that trust in AI applications mediates the negative relationship of individual differences of innovation resistance. Thus, we hypothesize:

H4. Trust in AI applications mediates the negative effects of individual differences on innovation resistance

H4a. Individual differences are positively related to trust in AI applications.

H4b. Trust in AI applications is negatively related to innovation resistance.

Innovation resistance plays a key role in the adoption process (Rogers 2003). Existing research shows that customers with high innovation resistance are less likely to adopt a new product or service (e.g., Kleijnen et al. 2009; Kuisma et al. 2007). For instance, a study by Heidenreich and Spieth (2013) found a negative relationship between active innovation resistance and adoption intention. Thus, based on our preceding arguments, we state that innovation resistance will have a negative effect on adoption intention:

H5: Innovation resistance is negatively related to adoption intention.

Methodology

Research Design and Sample Description

To collect suitable data for our research, we used a large-scale online survey based on a German online research panel. We asked the participants beforehand about their experience with IPAs in general, naming the most prominent examples (Google Nest/Assistant, Siri, Alexa, Apple Home pod and Cortana). We also ensured that each participant received a definition of an IPA and its general functionalities. Using panel data prevents problems of self-selection and multiple participation (Wood et al. 2004). Moreover, we applied procedural and statistical remedies to exclude a common method bias (Podsakoff et al. 2003). Concerning procedural remedies, we ensured that each independent and dependent variable in the survey was disconnected. Additionally, during item construction, we took care to minimize ambiguity and reduced the difficulty of the questions (Weber and Heidenreich 2018). With respect to statistical remedies, Harman's single factor test (Podsakoff et al. 2003) and a full collinearity assessment approach were performed (Kock 2015). The single-factor test results showed that no single factor developed and that the initial factor was only responsible for 26.4% of the total variance, not reaching the common threshold level of 50% (Podsakoff et al. 2003). Furthermore, the collinearity assessment approach results show that the highest variance inflation factor (VIF) of all constructs was 3.060, clearly beneath the threshold value of 5 (Kock 2015). Thus, based on both tests, we can conclude that no common method bias is present (Klein et al. 2021).

To improve the internal validity and reliability of the survey, we performed a pretest to refine the questions. We obtained 268 participants who successfully completed the online survey. Of those 268, 168 already had some experience with IPAs but were not active users. Thus, we reduced our sample to 168 to better assess innovation resistance and adoption behavior. Our descriptive statistics indicate that 46.4 percent of the participants were female with an average age of 32.7, 53.0% were male with an average age of 37.4 and 0.6% were divers with an average age of 51. Most of our participants had a university degree (48.2%) or a high-school diploma (26.8%). Furthermore, the incomes were distributed normally. The descriptive statistics show that our sample is generally younger and highly educated. Considering that the majority of IPA users are currently younger, higher educated people (Han and Yang 2018), we consider our sample representative in this respect.

Measures

For our model, we used well-established constructs and adapted them to the context of IPAs where needed. All constructs were measured on a 7-point Likert scale. We modeled the individual differences as a second-order construct of type 2 (Jarvis et al. 2003). More specifically, the constructs on the first-order level capturing key consumer psychographics (need for interaction, self-efficacy, inherent novelty seeking and technological innovativeness) are reflective constructs. On the second-order level, the individual difference construct is modeled formative as the sum of the psychographic first-order constructs (Jarvis et al. 2003). We used the repeated indicator approach to model the second-order construct, as every first-order construct level consists of the same number of indicators (Chin 2010).

Furthermore, the second-order construct of AI privacy concerns is based on a validated scale by Malhotra et al. (2004). To model AI data privacy concerns (data control, awareness of privacy practices and data collection), we followed the same approach as with the individual differences and modeled them as a second-order construct of type 2 using the repeated indicator approach (Chin 2010). The perceived creepiness of AI, trust in AI applications and innovation resistance were all modeled as reflective constructs using established scales (see Table 1). Innovation resistance is measured using a three-item scale by Peracchio and Tybout (1996). To measure intention to adopt IPAs, we used a three-item scale anchored by unlikely/likely, improbable/probable and impossible/possible (Kulviwat et al. 2007). Finally, to provide a stronger test for our hypotheses, we integrated income, education, gender and age as control variables for our model. These sociodemographic variables are known to influence adoption intention, especially in the context of technology-based applications such as IPAs (Reinders et al. 2008). Income, education and gender were measured as categorical variables and age was measured in years.

1st order constructs	Item label (all measured on 7- point Likert scale) If not specified otherwise, each item was preceded by: To what extent do you agree with the following statements?
Self-efficacy (Meuter et al. 2005)	I am absolutely capable of using an IPA. I am confident in my ability to use an IPA. I believe that I am qualified to use an IPA.
Novelty seeking (Dabholkar and Bagozzi 2002)	I am always looking for new ideas and experiences. I like my activities to change permanently. I like to experience new things and changes in my daily routine.

Tech. innovativeness (Bruner and Kumar 2007)	I get a kick out of using high-tech products before most other people know they exist. It is cool to be the first to try a new high-tech product. Being the first to try a new high-tech product is very important to me.
Need for interaction (Dabholkar 1996)	Socializing with people during service delivery makes a service more fun. I like to interact with a person providing the service. That service people pay attention to me is important to me.
Data Control (Malhotra et al. 2004)	Consumer online privacy is a matter of consumers' right to control and autonomy in decisions about how their data is collected, used, and shared. Consumer control over their personal data is at the core of consumer protection. I believe that online privacy is violated when control is lost or unintentionally diminished because of a marketing effort.
Awareness of Data Privacy Practices (Malhotra et al. 2004)	Companies seeking information online should reveal how the data is collected, processed, and used. A good online consumer privacy policy should include a clear and visible explanation. It is very important for me to know how my personal data is used and that I am informed about it.
Data Collection (Malhotra et al. 2004)	It usually bothers me when online companies ask me for personal information. It bothers me to give personal information to so many online companies. I worry that online companies collect too much personal information about me.
Perceived Creepiness of AI (Stevens 2016)	I personally feel that through my internet use, information about me exists and my privacy is invaded when it is used. I am uncomfortable with the amount of personal information online companies know about me based on my internet usage. I am concerned about my personal information being at risk.
Trust in AI (Holloway et al. 2009)	An IPA meets my expectations. An IPA can be described as good. An IPA has high quality.
Innovation resistance (Heidenreich and Spieth 2013)	What is your general impression of an IPA? (Individual 7 points scale) Very negative – Very positive Very bad – Very good Very insufficient – Very satisfactory
Adoption Intention (Kulviwat et al. 2007)	How likely is it that you would use an IPA? (Individual 7 points scale) Very unlikely – Very likely Highly improbable – Highly probable Impossible – Possible

Table 1. Constructs and Items

Analysis

To test our hypotheses, we applied variance-based structural equation modeling (PLS: partial least squares). We decided against covariance-based methods (e.g., LISREL: Linear Structural Relations) and favored PLS, as the required sample size is considerably smaller for complex models. Moreover, our model consists of hierarchical constructs using both reflective and formative indicators that cannot be directly modeled in covariance-based structural equation modeling (Chin 2010). However, PLS is variance-based and can handle hierarchical models with reflective and formative indicators (Chin et al. 2003). Thus, PLS (smartPLS 3.0) seemed the logical choice for our analysis. Following the approach of Chin (2010), we separately evaluated the measurement and the structural model to assess the effects of individual differences and innovation characteristics on trust, perceived creepiness, innovation resistance and finally, intention to adopt IPAs. To estimate the outer and inner model parameters, we applied a path r weighting scheme to calculate the inside approximation (Chin 2010). Moreover, we used nonparametric bootstrapping based on 5,000 replications. To determine the standard errors, we applied individual-level preprocessing (Tenenhaus et al. 2005).

Results

Measurement Model Results

To assess the psychometric properties of our measurement model, we evaluated the indicator loadings of all reflective latent and first-order constructs to determine their content validity (Wilson 2010). Our analysis shows that the item loadings all exceeded the critical threshold value of .707, indicating that the items of each construct were loaded appropriately (Barclay et al. 1995). Furthermore, the composite reliabilities of all reflective constructs range between .913 and .971. Moreover, the reliability of our measures is confirmed, as the average variance extracted (AVE) of all measures within the first-order hierarchical measurement model exceeds the cutoff value of .50 (Fornell and Larcker 1981). We also tested for unidimensionality by analyzing the between construct correlations, confirming that the items were more strongly related to like items (Wilson 2010). The Fornell-Larcker criterion is also fulfilled for all first-order constructs, as the square root of the AVE of each latent variable is larger than the correlation of this latent variable with any other variable of the model constructs.

To evaluate whether multicollinearity is present at the second-order construct level, we calculated the variance inflation factor (VIF) (Micheal et al. 2003). We can conclude that multicollinearity should not be an issue, as the maximum VIF value was 2.544 (Henseler et al. 2009). Overall, our analysis confirms a good measurement model fit for each antecedent predictor, allowing us to proceed with the analysis of the structural model.

Structural Model Results

We analyzed our model of IPA resistance and adoption using the reduced sample of n= 168 observations. To evaluate our hypotheses, we calculated the path coefficients and the respective significance levels (Hair Jr. et al. 2016). All relationships were assessed at the 10, 5 and 1 percent significance levels. Moreover, the estimations of our model fit the data well, and the adjusted R^2 for innovation resistance is 0.64 and for intention to adopt 0.44 (Hair Jr. et al. 2016; Henseler et al. 2009). Applying a blindfolding procedure, we assessed the predictive validity (Fornell and Bookstein 1982). Our results show a Q^2 value (Q^2=0.40) different from 0. Therefore, the predictive validity of our construct intention to adopt can be assumed (Tenenhaus et al. 2005). Finally, the first-order factor weights of our second-order constructs AI data privacy concerns and individual differences are significant and in the proposed direction (see Figure 2).

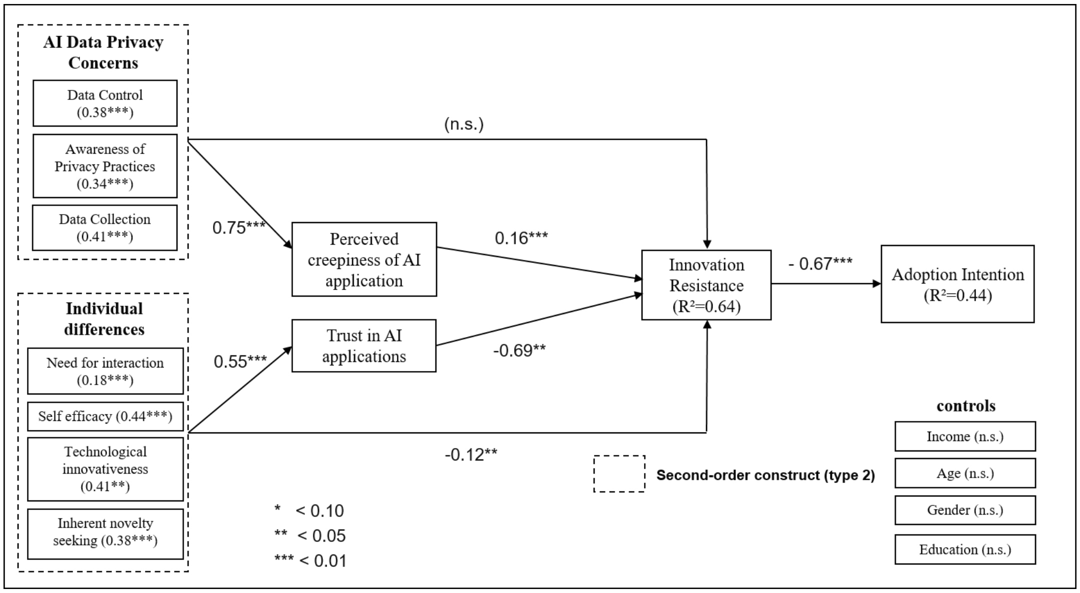

Figure 2. Model Results

As depicted in Figure 2, H1 is not significant. However, H2 is supported (H2: ß=-0.12, p<0.05), showing that individual differences negatively influence innovation resistance. Additionally, we find support for H3, as perceived creepiness fully mediates the relationship between AI data privacy concerns and innovation resistance. More specifically, AI data privacy (H3a: ß=0.75, p<0.01) is positively related to perceived creepiness, and in turn, perceived creepiness positively affects innovation resistance (H3b: ß=0.16, p<0.01). To assess the mediation effect, we applied the procedure proposed by Hair Jr. et al. (2016), as it simultaneously estimates all paths, thereby being superior to the approach by Baron and Kenny (1986). Moreover, we applied bootstrapping to test the indirect effects, as it is “almost always more powerful than Sobel's test”, used in the Baron and Kenny mediation analysis (Zhao et al. 2010, p. 202). Bootstrapping of the indirect effect was performed using 5,000 bootstrap resamples. As Table 2 shows, the mediating effect has an indirect effect size of 0.123 and is significant at the 1% level, confirming the mediating role of perceived creepiness. As the direct effect of AI data privacy concerns on innovation resistance is not significant, we can indeed conclude that perceived creepiness fully mediates the relationship between AI data privacy concerns and innovation resistance. Moreover, H4 is confirmed, as trust in AI applications mediates the relationship between individual differences and innovation resistance. To be more precise, individual differences (H4a: ß=0.55, p<0.01) are positively related to trust in AI applications, and trust in AI applications is negatively related to innovation resistance (H4b: ß=-0.69, p<0.05). We again applied bootstrapping. Our results show a negative indirect effect size of -0.380, which is significant at the 1% level (see Table 2). However, as H2 is also significant (H2: ß=-0.12, p<0.05), we can conclude that trust in AI applications partially mediates the relationship between individual differences and innovation resistance.

Mediator	Mediated Path	Original Sample	Sample Mean (M)	Standard Deviation	T Statistics	P Values
Perceived creepiness of AI	AI Data privacy=> resistance	0.123	0.124	0.052	2.366	0.009
Trust in AI	Indiv. Diff. =>resistance	-0.380	-0.379	0.057	6.653	0.000

Table 2. Mediation Test

Hypothesis 5 can be confirmed, as innovation resistance has a significant negative effect on adoption intention (H5: ß=-0.67, p<0.01). Finally, the effects of our control variables are not significant.

For a summary of all the results see Figure 2.

Discussion and Theoretical Implications

In recent years, AI-based IPAs have exploded, and an increasing number of industries from retail to finance, education, transportation and health care are making use of this technology (Ostrom et al. 2019). Thus, it is not surprising that research on IPAs has recently increased (e.g., Diederich et al. 2020; Maedche et al. 2019). Although there are a few recent studies examining drivers of IPA usage (Fernandes and Oliveira 2021; Nasirian et al. 2017), no study has examined which variables influence innovation resistance and IPA adoption. Thus, our study represents a first step to looking at IPA adoption from a resistance perspective. The theoretical contribution of our study consists of three main points:

First, our study examines, for the first time, the influence of data privacy concerns (comprising data collection, data control and awareness of privacy practices) on innovation resistance. Our results show that there is no direct relationship between data privacy concerns and innovation resistance but an indirect relationship through perceived creepiness. Thus, our model results highlight the importance of perceived creepiness as a mediator of the relationship between data privacy concerns and innovation resistance. This result confirms recent studies suggesting the central role of perceived creepiness in the resistance and adoption of AI applications (Ostrom et al. 2019; Sohn and Kwon 2020). Moreover, our results underline that not only is the sheer amount of data increasing the perceived creepiness of AI applications (0.41, $p<0.01$) but also if the customer is in control of his or her personal data (0.38, $p<0.01$) and aware of the data privacy practices of the company (0.34, $p<0.01$). With these results, we add to the current literature suggesting that data privacy concerns are indeed a multifaceted construct, with its three dimensions being almost equally important in capturing AI-related data privacy concerns (Malhotra et al. 2004). Additionally, our study is the first to identify the perceived creepiness of AI applications as a key predictor of innovation resistance. Overall, our first contribution adds to adoption and resistance theory (Rogers 2003) as well as to IS research (Diederich et al. 2020; Maedche et al. 2019), emphasizing the importance of data privacy concerns and perceived creepiness for the prediction of innovation resistance in the realm of artificial intelligence applications.

Second, as individual differences are a key antecedent predictor of adoption behavior (e.g., Han and Yang 2018; Heidenreich and Handrich 2015), we examined the effect of individual differences (need for interaction, self-efficacy, technological innovativeness and inherent novelty seeking) on innovation resistance. In line with the existing literature (Heidenreich and Handrich 2015; Xu et al. 2016), we find that this relationship is significant. Additionally, our results indicate an indirect relationship of individual differences on innovation resistance via trust in AI applications. More specifically, trust in AI applications partially mediates the relationship between individual differences and innovation resistance. This result underlines that trust builds the foundation for all interactions between humans and AI (Hengstler et al. 2016). Understanding how AI algorithms work directly affects the predictability of the application, which in turn creates trust and finally reduces innovation resistance (Heidenreich and Spieth 2013). Thus, our study highlights that in an AI context, trust is a vital aspect of a customer's innovation resistance.

Furthermore, we identified self-efficacy (0.44, $p<0.01$), inherent novelty seeking (0.38, $p<0.01$) and technological innovativeness (0.41, $p<0.05$) as the most influential individual differences, whereas the need for interaction only plays a minor role (0.18, $p<0.01$). Thus, customers with a personality profile showing high self-efficacy, technological innovativeness and a tendency to look for novel things are more likely to trust AI applications and, in turn, will be less likely to resist innovation. These results are intriguing, as the three individual differences of self-efficacy, inherent novelty seeking and technological innovativeness are typical lead-user characteristics (Schreier and Prügl 2008). Based on these findings, we conclude that lead users are among the first customers of AI-based IPAs, as they have the lowest innovation resistance toward that new technology.

Third, we find that the control variables income, age, gender and education were not significant and thus did not affect the adoption behavior of AI-based IPAs. Studies testing the effect of age and income on adoption behavior for AI-based applications are inconclusive (e.g., Han and Yang 2018; Liao et al. 2019). Therefore, our results provide additional empirical evidence for the theory that the adoption of AI-based applications and products is independent of a customer's age and income.

Implications for Practice

In addition to the theoretical contributions, our study also offers several implications for managers responsible for the development and design of IPAs. First, our results clearly indicate that building trust in the functionality of the IPA is the key lever to reduce innovation resistance and increase adoption. Increasing trust toward IPAs can be established by showing customers how the AI and the corresponding algorithms are working (Goebel et al. 2018).

Second, as our results show that lead users can build trust in AI applications and are among the first to adopt IPAs, product managers should consider integrating famous lead users in marketing campaigns. The lead user could talk about their positive experiences with the IPAs on social media or in commercials and why they trust these applications. Their testimonials will lead to an increase in trust, reduce innovation resistance and increase adoption intention (Chung and Cho 2017).

Third, our study shows that customers are concerned about data privacy. More specifically, customers are worried about the amount of data being collected, the missing control over their data and the transparency about data privacy practices. Together, all these data privacy concerns will increase a customer's perceived creepiness of AI-based IPA. Our model underlines the importance of perceived creepiness, as the construct mediates the effect of data privacy concerns on active innovation resistance. This result provides product managers with valuable information for marketing their products. More specifically, product managers should focus on a clear strategy avoiding the secret collection of an individual's data to personalize product advertising, thereby reducing perceived creepiness and innovation resistance. This result is in line with a recent trend set by Google to stop tracking user behavior data for personalized advertising (BBC 2021). Thus, product managers should follow this trend and publicly communicate that no data are being collected for use in personalized product advertising. Furthermore, product managers should focus on more transparency concerning what data they will use for the IPA in general. They could restrict the amount of data collected to the absolute minimum, which is required to ensure the full functionality of the IPA. To reach this goal, data scientists and developers may have to adapt the underlying AI algorithms. Moreover, product managers could give customers control over their personal data, providing them with options to delete the data if needed. Finally, product managers should think about openly describing their data privacy practices. Additionally, IPA providers should tremendously increase their security measures to prevent cyberattacks and the corresponding misuse of stolen personal data (Han and Yang 2018). Taken together, these measures would significantly reduce a customer's perceived creepiness of the AI application.

Fourth, to reduce the negative effect of a customer's innovation resistance on the adoption intention of IPAs, product managers could more aggressively communicate the benefits of an IPA (e.g., very personalized services), thereby increasing the rate of adoption (Awad and Krishnan 2006). Additionally, IPA developers should focus on providing a more natural language experience by improving natural language processing and making the conversion with the IPA more human-like (but keeping in mind that making the IPA too human may increase a customer's perceived creepiness, thereby increasing innovation resistance). Finally, further pushing third-party integration would increase the skill area of IPAs, adding additional value and thereby making customer adoption more likely (Han and Yang 2018).

Limitations and Avenues for Future Research

As with any other research, our study has some limitations. First, as we wanted to increase the generalizability of our research, we did not specify in which product the IPA is integrated (e.g., smartphone, Smart TV, car) and rather focused on the IPA itself. However, as the functionality, situation and usefulness of IPAs may vary between different product categories (PWC 2018), we suggest that our model should be tested using specific IPAs as the research context.

Second, we used cross-sectional data in our study. As innovation adoption is a dynamic process occurring within a certain time frame, it would be interesting to evaluate the effect of individual differences and AI data privacy concerns on innovation resistance and adoption intention of IPAs in a research setting using longitudinal data. It could be especially interesting to evaluate our model within the different innovation adoption process stages (Rogers 2003).

Third, as our study participants were customers from a single country (Germany), the results could be somewhat limited and specific to German customers. Consequently, we suggest a cross-cultural study, as customers' innovation adoption behavior also depends on cultural value orientations such as power distance, individualism and collectivism (van Everdingen and Waarts 2003).

Apart from these limitations, we also suggest some further research avenues. To identify antecedents of innovation resistance and adoption of IPAs our model focused on the level of interpersonal traits and a customer's personality. However, a customer's perception of IPA product features also plays an important role when studying resistance and adoption behavior (Hengstler et al. 2016). Thus, future studies should integrate product-related innovation attributes such as relative advantage & benefits, compatibility, trialability and complexity to assess their influence on innovation resistance and IPA adoption. Moreover, future studies could study the relationship between innovation resistance and adoption behavior more closely. Within the innovation resistance process, the intensity and the type of user experience can influence the probability of adoption (Talke and Heidenreich 2014). Thus, we suggest incorporating these variables as mediators. Additionally, we found a significant relationship between trust and perceived creepiness ($ß=-0.150$, $p<0.01$). However, we refrained from formulating an additional hypothesis, as this relationship is not central to our study focus. Nevertheless, we suggest that future studies should deeply examine the relationship between trust and perceived creepiness. In this regard, a more detailed analysis of perceived creepiness could also be interesting, as the concept of creepiness toward technology may have multiple dimensions (Woźniak et al. 2021). Moreover, we used the well-established construct (active) innovation resistance to measure a customer's innovation resistance. Nevertheless, recent literature on innovation resistance proposes to differentiate between active and passive innovation resistance (Talke and Heidenreich 2014). More specifically, passive innovation resistance is seen as a customer's predisposition to resist innovation prior to evaluating the new product (Heidenreich and Spieth 2013). Thus, passive innovation resistance is a predictor of active innovation resistance, which captures negative attitude formation after new product evaluation (Kleijnen et al. 2009; Nabih et al. 1997). Consequently, future studies on IPAs could measure active and passive innovation resistance, thereby tapping even further into the innovation and adoption process. Finally, as today an increasing number of innovative self-service technologies (SSTs) have built-in AI capabilities such as hotel booking or car rental websites, it is worth considering our results for the service science community (Kaaz et al. 2017). More specifically, we suggest that service designers and service managers should be aware of the effects that trust and perceived creepiness of AI play in the adoption process. However, as the adoption process for services can be slightly different than that for products (Im et al. 2007), future research is needed to confirm our results for SSTs.

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