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BALANCING PRIVACY AND PERSONALIZATION

Analyzing Consumer Behavior when Using Intelligent Personal Assistants

Patrícia Rosa dos Reis Gomes Vieira Gago

Master Thesis

presented as partial requirement for obtaining the Master Degree in Statistics and Information Management

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação

Universidade Nova de Lisboa

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Master Thesis presented as partial requirement for obtaining the Master's degree in Statistics and Information Management, with a specialization in Risk Analysis and Management

Supervised by

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Patrícia Vieira Gago

Lisboa, 27-05-2024

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Completing my master's degree has been a lifelong aspiration of mine, and this journey has been both challenging and fulfilling. Balancing work, personal life, and school was really tough, but I am overwhelmed with happiness and gratitude for this opportunity.

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ABSTRACT

Nowadays, AI technology is developing at a rapid pace, changing the world and our daily lives every day. Thus, understanding the impacts of these AI developments on their users' ethical concerns and data privacy is essential. This study focuses on the role of *Personalization* in determining whether the desire for personalized content can mitigate users' data privacy concerns when using and disclosing information to Intelligent Personal Assistants (IPAs). To address this question, a model was developed where *Personalization* was the independent variable, and *Risk Perception* and *Trust* served as mediators. The dependent variables were *Willingness to Self-Disclose to IPAs* and *Intention to use IPAs.* A survey was conducted, and the results indicated that *Personalization* significantly enhances users' intention to use IPAs and their willingness to disclose personal information with them. Additionally, having access to personalized content can reduce the perceived risk associated with IPAs and foster greater trust in these technologies. These findings contribute to a deeper understanding of the trade-off users are willing to make to access the benefits provided by IPAs while highlighting the critical role of personalization in influencing user behavior and perceptions.

KEYWORDS

Personalization; Data Privacy; Intelligent Personal Assistants; Artificial Intelligence; Consumer Behavior

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1. INTRODUCTION

In recent years, considerable technological advancements have transformed the world, reshaping it on a daily basis. As a result, there has been a growing interest in understanding the impact of these technological advances on consumers and exploring why, despite numerous options, consumers do not always behave as the rational, utility-maximizing *Homo Economicus*, a rational individual who always makes the most optimal choice available (Cartwright, 2018).

To address this, fields like Behavioral Economics, Marketing, and Sociology use AI tools to gain a better understanding of customer behavior, since AI-based systems such as Intelligent Personal Assistants (IPAs), use machine learning algorithms to analyze large amounts of data and identify patterns, individual behaviors, and preferences (Youvan, 2023), enabling the creation of highly personalized and effective nudges that can influence consumer behavior (Hrnjic & Tomczak, 2019). Although a nudge is considered to be a non-coercive method to influence consumer behavior without limiting their freedom of choice (Youvan, 2023), it may also be regarded as manipulative since it can override the user's own ideas and encourage them to make choices that are not in their best interest (Nyman, 2023), such as social media and its constant nudging strategies to keep users on the platform for longer periods (Agrawal et al., 2022).

Intelligent Personal Assistants (IPAs) like Siri or Alexa are highly multidimensional and interactive software applications (Du & Xie, 2021) powered by artificial intelligence to model human interaction and optimize consumers' daily lives by satisfying their needs. In order to be able to provide faster and more accurate results, the IPAs systems continuously access, collect, and transmit a significant amount of private and sensitive data (Thomaz et al., 2020), which raises ethical challenges related to transparency, data privacy, bias (Huang et al., 2022), cybersecurity, and consumer consent (Xie et al., 2022).

The debate over the ethical implications of AI systems generates polarizing opinions: On one hand, certain scholars argue that technologies remain morally neutral, implying that the technology itself cannot be held accountable for good or bad outcomes, even though it could be employed for either purpose (Du & Xie, 2021). Nevertheless, studies demonstrate that the use of AI technologies can have negative effects on their users, such as cyber addiction and stress (Samaha & Hawi, 2016). Therefore, these systems cannot be determined as morally neutral, given their significant influence on the decision-making process of consumers (Verbeek, 2011).

Some measures have already been implemented to mitigate privacy risks faced by consumers regarding data privacy, such as the EU General Data Protection Regulation (GDPR) that was put in place in 2018 (Xie et al., 2022). However, it is important for companies to implement significant measures to guarantee the protection and well-being of their consumers, such as ensuring transparency in the algorithms used in AI-based systems (Sharma, 2023) and

installing efficient cybersecurity measures to protect consumers' sensitive data, such as firewalls, authentication/access, and encryption (Udo et al., 2018).

Although there are several ethical considerations associated with AI technology in general and with IPAs in particular, this dissertation focuses on the ethical challenges related to data privacy, such as *Risk Perception* and *Trust*. The fact that IPAs continuously gather and store user data to enhance their performance, potentially exposing this information to unauthorized access or misuse can make their users feel vulnerable when sharing their sensitive data with them (Aiello et al., 2020). By examining the impact of data privacy concerns on IPA users, the main goal of this dissertation is to determine how data privacy concerns can influence consumers' use and perception of IPAs - *Do ethical concerns about data privacy outweigh the benefits of IPAs, leading to a decrease in willingness to disclose personal information with IPAs and lower the intention to use them?*

To address this research question, a model was developed where the independent variable was *Personalization.* The goal was to determine whether access to personalized content, which is considered one of the primary benefits of IPAs (Rhee & Choi, 2020), could outweigh the users' data privacy concerns and assess its impact on the consumer's intention to use IPAs and their willingness to disclose personal information to it.

The role of *Risk Perception* and *Trust* as mediator variables was analyzed in relation to consumer usage intentions and their willingness to disclose personal information to an IPA. This analysis seeks to provide valuable insights into how these data privacy concerns impact the *Personalization* aspect of IPAs and the user's overall comfort level in sharing sensitive information with these AI devices. As a moderator variable, we considered the *Type of Information Shared*, which analyzes whether sharing sensitive information with IPAs increases consumers' risk perception or not.

After developing the research model considering these variables, a set of hypotheses was formulated to be tested through a quantitative research method, such as a questionnaire, where consumers' opinions on data privacy risks related to IPAs technology were collected and analyzed. After evaluating which assumptions have been proven true, a theory based on empirical data was developed.

This dissertation (1) identifies the most recent and relevant literature review related to the IPAs, (2) addresses the main ethical challenges and data privacy issues related to the IPAs, such as *Risk Perception* and *Trust*, (3) explains the methodology used in this study, (4) presents the results obtained from it, (5) summarizes the main findings in a theoretical framework and (6) addresses possible future research topics.

The contributions of this dissertation are the following:

- Understanding the impact that *Personalization* has on the *Intention to Use IPAs* and *Willingness to Self-Disclose to IPAs*;
- Understand if ethical concerns related to data privacy such as *Risk Perception* and *Trust* impact the *Intention to Use IPAs* and *Willingness to Self-Disclose to IPAs*;
- Assess if the data privacy concerns override the IPAs benefit of *Personalization*;
- Understand the moderator role of the *Type of Information Shared in the relation between Personalization and Risk Perception.*

The success of AI products and systems heavily relies on the trust that users place in AI technology (Omrani et al., 2022). Therefore, a proper understanding of the impact of AI on consumers' lives prepares them to better deal with it and protects them from its negative aspects, while also promoting the creation of ethical AI tools that improve their well-being and protect their sensitive data.

2. LITERATURE REVIEW

2.1. INTELLIGENT PERSONAL ASSISTANTS

Over the past decade, Intelligent Personal Assistants (IPAs), also referred to as Intelligent Virtual Assistants (IVAs) or Digital Voice Assistants (DVAs), have become very popular across the world. With ongoing technological advancements and predicted future trends, it is safe to assume that the use of these intelligent personal assistants will only continue to rise (Bilos et al., 2023).

According to Statista's report (2023), the number of users of IPAs in the United States was approximately 142 million in 2022. The report also projected an increase of 15 million users by 2026. Moreover, in 2020, around 4.2 billion IPAs were utilized in devices across the globe, and this number is expected to increase to 8.4 billion by 2024 (Statista, 2022).

By using Artificial Intelligence (AI) technologies such as machine learning, natural language processing techniques, and deep learning methods, IPAs have replicated human cognition (Kamoonpuri & Sengar, 2023), which improved their ability to comprehend human language as an input (Delgrange et al., 2019). This has allowed natural, easy, and intuitive interactions between humans and computers (Bilos et al., 2023), which can create effortless and enjoyable experiences for consumers.

These Intelligent Personal Assistants are voice command devices that are activated by a "wake-up word" (Flavián et al., 2023) and can be used to perform everyday tasks such as setting reminders for appointments or alarms, playing music, answering questions (Guo & Luo, 2023), sending and reading texts, conducting basic math calculations, controlling Internet of Things (IoT) enabled devices at home (Pridmore & Mols, 2020) and even understanding the patterns of human behavior which allows them to create a personalized user profile according to the user's preferences, habits and needs (Thomaz et al., 2020).

Whether these voice command devices are used on a mobile phone, such as Siri (from Apple) or Google Assistant or used as a standalone device at home such as Alexa (from Amazon), IPAs have replaced traditional human-computer interactions that rely on typing, offering a more efficient hands-free approach (Furey & Blue, 2019) to accessing and searching for information (Hoy, 2018).

This widespread acceptance of IPAs can be explained by successful developments in technology, both in artificial intelligence algorithms as well as in the data stored on the IoT, which encompasses any technological device connected through a network and/or the internet, sharing its produced data (Conti & Passarella, 2018). The IPAs are included on the Internet of People (IoP), a subcategory of IoT that focuses particularly on collecting and storing data related to individuals (Furey & Blue, 2019).

According to Siau (2018), the users' perception of IPAs is influenced by their brand, meaning that, if consumers are already familiar with and trust the brand of the IPAs, they are more likely to adopt a new technology from the same brand. Moreover, the IPAs' ability to have human-like interactions and engage in lengthy conversations with users promotes trust, resulting in greater acceptance (Cerekovic et al., 2017).

Recent studies indicate that consumers mostly use IPAs for utilitarian purposes (Bilos et al., 2023; Fernandes & Oliveira, 2021; McLean & Osei-Frimpong, 2019;) such as asking questions, getting directions, dictating text messages, and setting reminders or for hedonic purposes such as asking silly or funny questions, playing music (Bilos et al., 2023) or simply out of curiosity (Liao et al., 2019).

Alternatively, some research has analyzed the main reasons why consumers do not use IPAs, with the main ones being: perceived privacy risks and data security, fear of IPAs listening to private conversations even when on standby mode (McLean & Osei-Frimpong, 2019), low usefulness, and design flaws (Bilos et al., 2023; Liao et al., 2019).

Additionally, according to Liao et al. (2019), the environment where the IPA is used can also play a determinant role in its usage, since users often feel hesitant to use voice-controlled devices in public spaces due to concerns about privacy invasion by those around them.

2.2. PERSONALIZED EXPERIENCE

IPAs are designed to offer users a highly interactive and multifunctional experience (Du & Xie, 2021). By utilizing machine learning and recommendation algorithms (de Barcelos Silva et al., 2020), IPAs are capable of autonomously collecting a vast amount of data from their users, learning and understanding human behavior from it, and creating a personalized user profile based on their preferences, habits, and needs (Flavián et al., 2023). By providing targeted and tailored recommendations for products and services, these AI-enabled products can offer unique and customized experiences for each user, which can be understood as nudging techniques to incentivize consumers to self-disclose their personal information (Thomaz et al., 2020).

Additionally, it is also important to differentiate the recommendations provided by IPAs from the ones provided by regular recommendation agents such as chatbots. IPAs are prepared to respond to natural language vocal commands (Guo & Luo, 2023), which has been shown to be more efficient for the consumer as it decreases effort and optimizes their time (Fernandes & Oliveira, 2021). Consumers highly appreciate the personalized experience provided by IPAs since according to Georgiev (2022), 72% of Google users consult their smartphones' IPAs daily, and 52% of this 72% use them to access product and brand recommendations.

Personalization is considered to be the primary benefit offered by IPAs (Rhee & Choi, 2020). This benefit leads to a perceived value and favorable engagement between consumers and IPAs, which means that when consumers have a positive experience with the recommendations made by an IPA, they are more likely to recommend the IPA to others, continue using it, and follow its recommendations (Akdim & Casalo, 2023; Flavián et al., 2023; Mishra & Shukla, 2020).

According to Melzner et al. (2023), consumers weigh the benefits against the costs before deciding to disclose personal information. Thus, whenever consumers feel that using IPAs provides more benefits, such as receiving personalized recommendations, than the risks associated with its usage, they decide to disclose their personal information. Self-disclosure refers to the voluntary act of sharing any information regarding oneself, including opinions, emotions, thoughts, or personal information (Posey et al., 2010).

Thus, personalized content gives consumers a reason to disclose their personal information to the IPAs, since the more personal information the IPA is provided with, the better its personalization content and service recommendations will be, which in turn, will help the consumers to make informed decisions and improve their lives.

After considering these points, the following hypotheses were formulated:

H1. *Personalization* has a positive impact on *Willingness to Self-Disclose to IPAs*

H2. *Personalization* has a positive impact on the *Intention to Use IPAs*

2.3. ETHICAL CHALLENGES RELATED TO DATA PRIVACY

2.3.1. RISK PERCEPTION

To be able to provide faster and more accurate results, the IPAs systems continuously access, collect, and transmit (Du & Xie, 2021) a significant amount of private and sensitive information, including real-time voice data, lifestyle habits, and behavioral patterns (Melzner et al., 2023). However, this can raise privacy concerns, as consumers may experience anxiety or discomfort over the fact that companies can misuse their personal information (Du & Xie, 2021). Additionally, there is also the risk of data breaches, where malicious actors may gain access to users' personal and detailed information through wiretapping, exploring security vulnerabilities, impersonating the user, or eavesdropping unintentional recordings (Chung et al., 2017).

After controversies such as the Cambridge Analytica (Isaak & Hanna, 2018), consumers have become more cautious about sharing their personal information with AI-enabled devices. They now want to comprehend (1) how their data is stored, (2) exactly what it is used for, (3) who can access it, and (4) what security measures are in place to safeguard their data from

malicious use (Bilos et al., 2023; & Blue, 2019). These privacy concerns have been identified as a major factor that negatively affects customers' willingness to disclose personal information (Jain et al., 2022). In fact, some users will even refuse to use IPAs due to them (Hernandez Acosta & Reinhardt, 2022; Pal et al., 2022).

Although consumers appreciate personalized content and offers, privacy concerns regarding the collection, utilization (Thomaz et al., 2020), and storage of their personal data (Pal et al., 2022), can make them feel uneasy when using IPAs, which can lead them to not trust IPAs. Additionally, these devices are "always on" (Hernandez Acosta & Reinhardt, 2022) collecting verbal information willingly shared by the consumer but also collecting nonverbal information, that most times the consumer is not aware of sharing, such as their emotional state or household activities (Melzner et al., 2023), which can increase their risk perception when using these devices.

Thus, to better understand the impact of *Personalization* on the *Risk Perception* felt by the users and their *Trust in the IPAs* manufacturer, the following hypotheses were formulated:

H3. *Personalization* has a positive impact on the *Risk Perception*

H4. *Personalization* has a negative impact on *Trust in the IPA*

The IPA's voice control feature is one of its greatest benefits for its users (McLean & Osei-Frimpong, 2019). However, using these devices can also increase consumers' risk perception, as they may collect not only verbal personal data that users willingly disclose but also nonverbal information. According to Melzner et al (2023), this type of information goes beyond users' words and can even reveal details about their health conditions, emotional states, and daily habits. Additionally, this feature can also intensify the risk perception felt by the users as any individual within the range of the IPAs may issue verbal queries to access their sensitive and personal data. This feature becomes particularly threatening when IPAs are synchronized with other devices, such as wearable health monitors like smartwatches (Graziano, 2016) because then any individual can access *Personally Identifiable Information* and *Personal Health Information* with just a voice command (Daubert et al., 2015).

If the consumers feel that disclosing information to the IPA will make them susceptible to any harm, they will refrain from it, adopting behaviors that will protect their privacy (Gao et al., 2018). This aligns with previous research where it was shown that individuals who perceive higher levels of risk online usually avoid sharing their information online and may even stop buying online (Miyazaki & Krishnamurthy, 2005). Thus, since *Risk Perception* can decrease the desire to disclose personal data and the use of these AI devices, the following hypothesis is proposed:

H5a. *Risk Perception* has a negative impact on *Willingness to Self-Disclose to IPAs*

H5b. *Risk Perception* has a negative impact *Intention to Use IPAs*

2.3.2. TRUST

When predicting the future of IPAs, experts anticipate that these devices will have deeper interactions with their users by using an individual's gestures, images, voice, and emotional recognition (Kepuska & Bohouta, 2018). This suggests that this type of AI technology will require greater trust, permissions, and access to sensitive consumer data. If users do not trust IPAs with their personal information, the future of IPAs as well as their development and expansion might be compromised (McLean & Osei-Frimpong, 2019).

In a study conducted by Bonilla & Martin-Hammond (2020) with older adults, it was found that trust plays a key role for consumers when using IPAs. The participants reported that their lack of trust in the security measures implemented by the manufacturers to safeguard their sensitive information, as well as in the operational mechanism of the IPAs themselves, prevented them from continuing to use these devices. This finding is also in line with a report carried out by PricewaterhouseCoopers (2017), where 88% of consumers state that their willingness to share personal data is determined by how much they trust a company.

Researchers have found that one of the primary reasons for consumers not to use IPAs is the "always on" listening feature, which can make users feel like they are being surveilled at all times (Pal et al., 2022), and the potential misuse of the data collected and processed by the IPA company (Hernandez Acosta & Reinhardt, 2022). These two factors significantly contribute to increased feelings of vulnerability among consumers, leading to higher levels of concern about disclosing personal information to IPAs (Aiello et al., 2020).

On the other hand, even though trust between consumers and IPAs can take some time to develop (Pal et al., 2022), consumers have shown that when there is trust in the customer-company relationship, they are more inclined to disclose their personal information (Lappeman et al., 2023). As so, it is relevant to measure the influence of *Trust o*n the *Willingness to Self-Disclose to IPAs* and on *the Intention to Use IPAs*, with the following hypothesis:

H6a. *Trust in the IPA* has a positive impact on *Willingness to Self-Disclose to IPAs*

H6b. *Trust in the IPA* has a positive impact on the *Intention to Use IPAs*

2.4. TYPE OF INFORMATION SHARED

The sensitivity level of personal information disclosed by consumers can vary according to the type of information that is being shared and the risk perception associated with it.

The General Data Protection Regulation (GDPR) defines sensitive personal information as data that can uniquely identify an individual, including biometric data, racial or ethnic origin, and health information (GDPR - European Parliament and Council, 2016). Prior research indicates

that the severity of harm is proportional to the sensitivity of the information being shared (Acquisti et al., 2012). Consequently, the higher the identifiability of the shared information, the greater its sensitivity, which is associated with an increased perceived risk by users (Melzner et al., 2023). Financial data and incriminating behaviors are considered more sensitive than information related to marital status or routine behaviors (Melzner et al., 2023), as the potential negative impact on consumers is significantly greater in the event of a data breach.

A study performed by Uchida et al. (2017) found that when comparing an AI robot with a human mental health counselor, the sensitivity of the shared information had an impact on the disclosure of information since users preferred to disclose sensitive negative topics to AI robots rather than to other humans. These findings were confirmed in a study conducted by Kim et al. (2022) where it was reported that disclosure of sensitive personal information is higher when interacting with an AI agent than when interacting with a human due to the concern of being negatively judged by other humans. This effect did not occur for non-sensitive information.

When sharing sensitive information with IPAs, such as personal financial data or medical records consumers may perceive a higher level of risk, since they understand that such information can be misused or harmful to them if it falls into the wrong hands (Naeini et al., 2017).

To better understand the impact that sharing highly sensitive information or sharing low sensitive information can have on the consumers' risk perception toward IPAs, the following hypothesis was formulated:

H7. The *Type of Information Shared* will moderate the relationship between *Personalization* and *Risk Perception*

2.5. RESEARCH MODEL

A research model was developed to understand the relationship between the benefits of personalized content and the use and disclosure of personal data to IPAs (see Figure 1). This model also aims to examine how ethical concerns related to data privacy, such as *Risk Perception* and *Trust in IPAs*, impact this relationship.

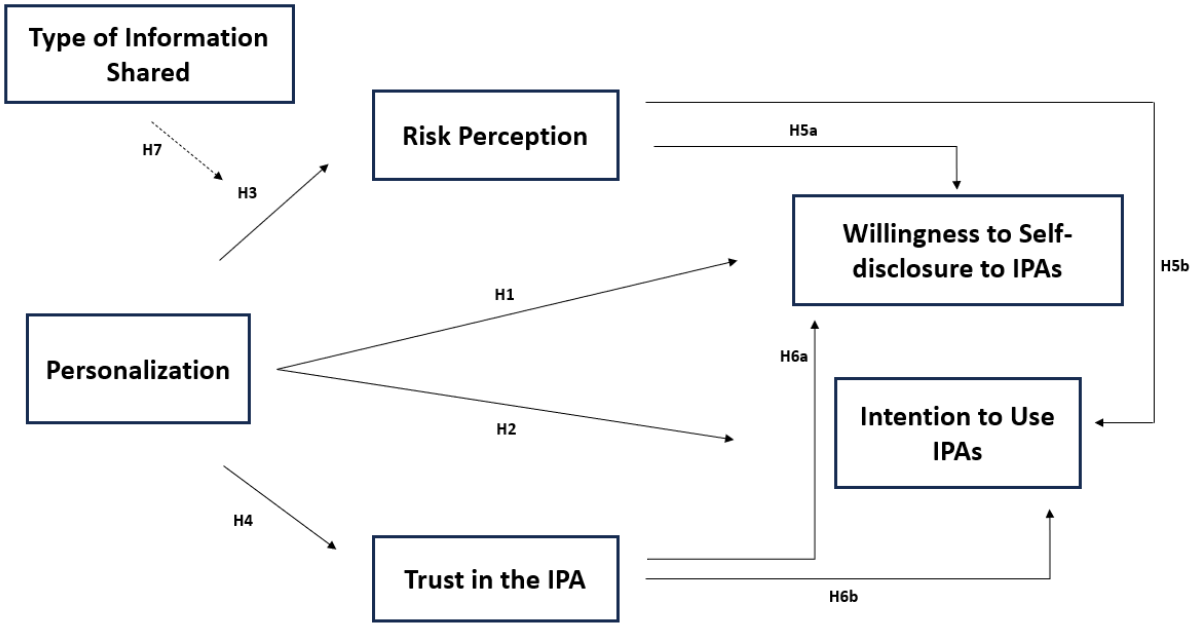

Figure 1 – Research Model

3. METHODOLOGY

3.1. RESEARCH DESIGN

The main purpose of this study is to understand the impact of data privacy concerns on consumers' intention to use an IPA and their willingness to disclose personal data to it, in order to access personalized content and recommendations. Our model explores factors such as *Risk Perception* and *Trust*, which are known to play a critical role in shaping users' attitudes towards data privacy (Gao et al., 2018; Aiello et al., 2020).

To gain a comprehensive understanding of the relationship between the variables in our model, a quantitative research method was used. Quantitative research, such as surveys, involves the systematic collection and analysis of numerical data to understand patterns, relationships, and trends within a population (Khan et al., 2022). This approach also allows for statistical inference and generalization of the findings to a larger population, as they facilitate the gathering of a large and diverse sample (Abraham & Ledolter, 2009). Thus, to test the hypotheses of our model and establish relevant statistical relationships, a survey was conducted, and the collected data was analyzed using SPSS software.

3.2. MEASURES

The survey used to test our model was structured into four distinct sections:

Section 1: The initial section served as the questionnaire's introduction, outlining the survey's objectives, the confidential handling of responses, consent queries, and, where applicable, the Prolific ID.

Section 2: This segment included five questions to help characterize our sample when it comes to familiarity with IPAs, frequency of use, the most used IPA, primary tasks involving IPAs, and preferred devices for IPA usage. These variables offer a deeper understanding of the study's sample, which is crucial for developing the theoretical framework and determining its applicable scope.

Section 3: In this section, the scales in Table 1 were used to measure the impact of *Personalization*, *Risk Perception*, *Trust*, *Intention to Use IPAs,* and *Willingness to Self-Disclose to IPAs* using the following 7-point Likert scale: *Strongly Agree, Agree, Somewhat Agree, Neither Agree Nor Disagree, Somewhat Disagree, Disagree and Strongly Disagree.* This scale was selected for the questionnaire since it accurately reflects the respondents' true feelings and allows for greater differentiation in opinions and feelings toward IPAs, contributing to accurate results and conclusions (Joshi et al., 2015).

Section 4: The final section encompassed four control variables: *Gender, Age, Education Level,* and *Employment Status*. These variables were integrated into the study to delineate the

characteristics of our respondent pool and sustain the validity and reliability of the questionnaire's conclusions.

Table 1 – Summary of Measurement Items. Source: Author

Variable	Items	Scale	Adapted from
Personalization	My personal assistant provides me with relevant promotional information tailored to my preferences or personal interests. My personal assistant provides me with the kind of deals/ads I might like. My personal assistant makes purchase recommendations that match my needs. My personal assistant makes me feel that I am a unique customer. I believe my personal assistant is customized to my needs.	7-point Likert scale	Hayes et al (2021)
Risk Perception	I have my doubts over the confidentiality of my interactions with my personal assistant. I am concerned about performing a financial transaction via a personal assistant. I am concerned that my personal details stored with the personal assistant could be stolen. I am concerned that the personal assistant collects too much information about me. Providing the personal assistant with my personal information could involve many unexpected problems. It could be risky to disclose my personal information to the personal assistant. There would be a high potential for loss in disclosing my personal information to the personal assistant	7-point Likert scale	McLean et Osei-Frimpong (2019) Hayes et al (2021)
Trust	I feel I can rely on a personal assistant to do what is supposed to do. I believe the personal assistant provides accurate information. My digital assistant provides unbiased information and recommendations. My digital assistant provides honest answers. I trust my personal assistant.	7-point Likert scale	Fernandes & Oliveira (2021) Brill et al (2019) Thompson & Siamagka (2021)
Type of Information Shared	When using a personal assistant, I usually share the following information: - Personal Information (e.g., name, age, contact details) - Financial Information (e.g., bank account details, credit card information) - Health Information (e.g., medical history, symptoms) - Preferences and Interests (e.g., hobbies, favorite products) - General Queries or Requests (e.g., asking for directions, setting reminders) Sharing sensitive personal information with a personal assistant makes me feel vulnerable. I will share sensitive personal information with a personal assistant if it allows me to have access to personalized content.	7-point Likert scale	-
Willingness to Self-Disclose to IPAs	When personal assistant asks for my personal information, I reveal a large amount. When it comes to my personal assistant, I disclose quite extensive personal information. I would be willing to share my personal information when using personal assistants in the future. I would probably disclose information about myself to the personal assistant. I would likely share my personal information with the personal assistant if necessary.	7-point Likert scale	Thompson & Siamagka (2021) Wang et al (2017)
Intention to Use IPAs	I will try to use a personal assistant in the future. I plan to use a personal assistant in the future. I intend to use a personal assistant in the future.	7-point Likert scale	Fernandes & Oliveira (2021)

Table 2 – Summary of Measurement Items (cont). Source: Author

Variable	Items	Scale	Adapted from
Control Variable: Gender	-	3-point scale	Author
Control Variable: Age	-	N/A	Author
Control Variable: Education Level	-	5-point scale	Author
Control Variable: Employment Status	-	6-point scale	Author

3.3. DATA COLLECTION

The sample used in the study was obtained through convenience sampling, which is a non-probability sampling method, where participants are selected based on their availability and willingness to participate in the study (Golzar et al., 2022). From March 1st to March 27th, the survey was distributed on open-source platforms population and 197 people responded.

However, between March 27th and March 29th, the survey was also published on Prolific, and 202 people responded. It was decided to use this platform, mainly for practical reasons since it allowed us to collect the remaining responses in a shorter period. The primary criteria used to select participants for the study on Prolific was their familiarity with IPAs, regardless of whether they were regular users of these devices or not. This ensured that all participants had a basic understanding of IPAs, which was important to provide meaningful answers from all the participants and to include consumers with varying perceptions and usage habits of IPAs.

Since the survey data was collected through two different methods, an A-NOVA test analysis was performed on SPSS to assess if there was a difference in the *Personalization* mean between both groups. The respondents who answered the survey on open-source platforms, such as social media, reported a similar level of *Personalization* (M = 3.80, SD = 1.34) when compared with the respondents who filled the survey on Prolific (M = 3.53, SD = 1.44). The ANOVA results were not significant (F = 2.58, p = 0.109), which means that even though the respondents' answers had two different sources, they can be analyzed with the same approach.

4. EMPIRICAL STUDY

The survey was developed on Qualtrics and out of 399 answered surveys, only 305 were considered for this study since 67 respondents did not finish their survey and 27 did not use IPAs.

The final sample was composed of respondents ranging from 18 to 74 years old (M = 32 years old, SD = 10.09), where 53.8% of the respondents were *Female*, 45.6% were *Male*, and 0.7% *Prefer Not to Say*. More than half of the respondents have a bachelor's degree (52.5%), and the majority are employees (65.9%).

According to the analysis performed, the respondents are familiar with the use of IPAs (M = 1.94, SD = 1.11), and 35.7% use them occasionally. As shown in Chart 1, the respondents use Google Assistant the most (35.7%), followed by Siri (31.8%) and Alexa (29.8%). When it comes to the use of IPAs, practicality is a factor, as the phone (57.4%) and home devices (33.1%) are the main places where respondents use IPAs.

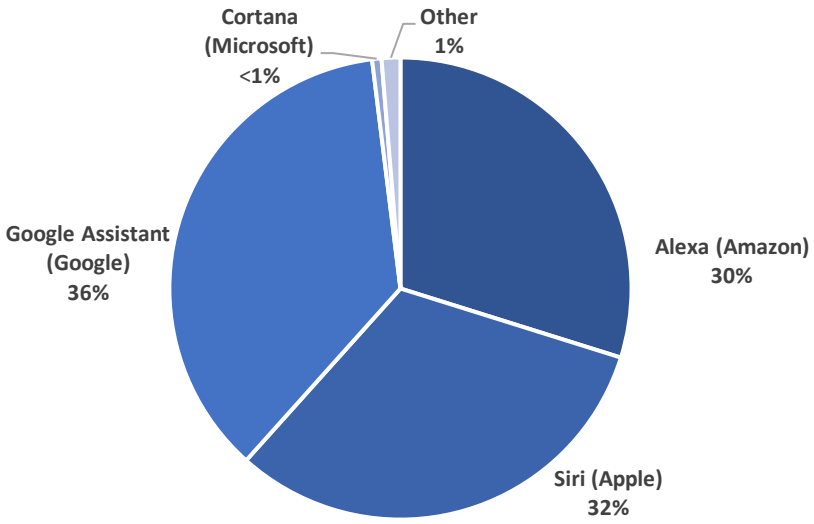

Chart 1 - Frequency of IPA Usage. Source: Author

The results also indicated that the respondents primarily use IPAs for efficiency reasons, as the most common tasks reported were the following: *Playing music or podcasts* (25.3%), *Asking general questions* (23.0%), and *Setting reminders or alarms* (22.5%), as shown in Chart 2. This is aligned with recent studies that indicate that users mostly use IPAs for utilitarian purposes (Bilos et al., 2023; Fernandes & Oliveira, 2021; McLean & Osei-Frimpong, 2019).

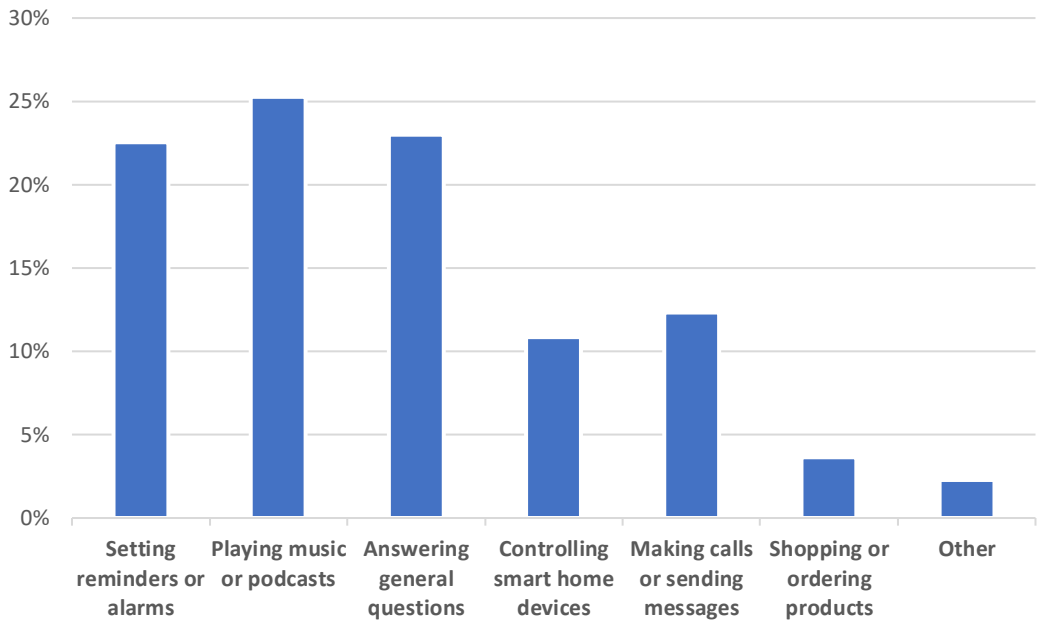

Chart 2 – Tasks performed when using an IPA. Source: Author

To analyze the reliability of the questionnaire, Cronbach's alpha was calculated. This coefficient measures the reliability of a set of survey items, meaning, it is used to assess if a collection of items consistently measures the same characteristic (Izah et al., 2023). This index ranges from 0 to 1 and for a variable to be considered acceptable, it needs to have a Cronbach's alpha > = 0.7. In Table 2 below, it is shown that the following variables used in this survey are classified as Good or Excellent as they present a Cronbach's alpha higher than 0.8.

Table 2 – Summary of Internal Consistency Analysis. Source: Author

Variables	Cronbach's Alpha	Internal Consistency
Personalization	0.904	**Excellent**
Risk Perception	0.930	**Excellent**
Trust	0.869	**Good**
Willingness to Self-Disclose to IPAs	0.906	**Excellent**
Intention to use IPAs	0.961	**Excellent**

Table 3 – Model Variables - Descriptive Statistics. Source: Author

Variables	N	Number of Items	Min	Max	Mean	Standard Deviation
Personalization	305	5	1	7	3.62	1.41
Risk Perception	305	7	1	7	3.06	1.34
Trust	305	5	1	7	2.98	1.05
Willingness to Self-Disclose to IPAs	305	5	1	7	4.36	1.34
Intention to Use IPAs	305	3	1	6.67	2.43	1.24

To analyze the impact of the moderator *Type of Information Shared*, a scale was developed comprising the following questions: *When using a personal assistant, which of the following information do you usually share?*, *Sharing sensitive personal information with a personal assistant makes me feel vulnerable* and *I will share sensitive personal information with a personal assistant if it allows me to have access to personalized content*. This scale was designed to assess how different types of information moderate the relationship between *Personalization* and *Risk Perception* felt by the users.

When analyzing the responses given to the question: *When using a personal assistant, which of the following information do you usually share?,* it is clear that users avoid sharing sensitive personal information with IPAs, such as financial and health information. Naeini et al. (2017) found that this can be explained due to the fear users have that their information may be misused or used against them in the event of a data breach. According to Chart 3, the information users share the most with IPA are *General questions* they might have (36.7%), their *Preferences and hobbies* (28.7%), and General personal information, like name or age (19.6%).

The second question examines users' emotional responses to sharing sensitive information. According to the respondents' answers, the majority tend to agree that they feel vulnerable when sharing sensitive personal information with IPAs (M = 3.09, SD = 1.54). Lastly, the third question assesses the extent to which users are willing to share sensitive personal information with IPAs to access personalized content, with most respondents showing indifference (M = 3.90, SD = 1.49).

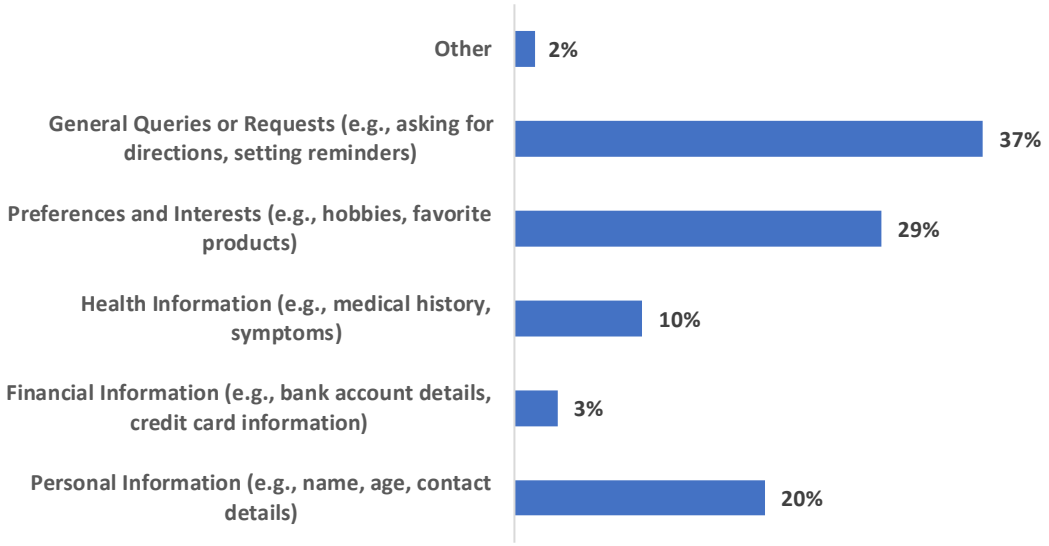

Chart 3 – Type of Information Shared when using an IPA. Source: Author

4.1. Regression Model

To analyze the impact of *Personalization* on the *Willingness to Self-Disclose to IPAs* and on the *Intention to use IPAs*, two linear regression models were used. In the first model, the Dependent Variable (DV) was the *Willingness to Self-Disclose to IPAs* and the Independent Variable (IV) was *Personalization*. According to the results of this first model, *Personalization* has a significant positive effect on the *Willingness to Self-Disclose to IPAs* ($\beta = 0.48$, $t = 9.58$, $p < 0.001$). When analyzing the R^2, we concluded that this model explains 23.2% of the variation in *Willingness to Self-Disclose to IPAs*, therefore the H1 was supported.

In the second model, the IV remained the same, however, the DV was *Intention to use IPAs*. Even though this model presents a lower explanatory power than the first one ($R^2 = 11\%$), *Personalization* still had a significant positive effect on the *Intention to use IPAs* ($\beta = 0.33$, $t = 6.13$, $p < 0.001$), confirming H2.

4.1.1. Covariates Analysis

An additional analysis was performed to understand the impacts of the following continuous covariates in each of the regression models: *Familiarity with IPAs* and *Frequency of Use*. For that, the ANCOVA analysis was used on SPSS, where the Independent Variable was Personalization, the covariates were *Familiarity with IPAs* and *Frequency of Use, and the*

Dependent Variables were Willingness to Self-Disclose to IPAs (model 1) and Intention to use IPAs (model 2).

- **Regression Model 1 – Personalization - Willingness to Self-Disclose to IPAs:**

According to table 4, considering our first regression model, for the covariates analysis, we understand that *Familiarity* and *Frequency of Use* are positively significant in our model, even though their partial eta squared is low, which means that higher familiarity and frequency of use are associated with higher willingness to disclose personal information to the IPAs. *Personalization* was shown to be the most significant predictor of *Willingness to Self-Disclose to IPAs*, indicating that personalized content strongly encourages users to share personal information with IPAs.

When considering these covariate variables in our model, its explanatory power increased, now explaining 27% of the variation in *Willingness to Self-Disclose to IPAs* (R^2= 0.268, $p < 0.001$).

Table 4 – Willingness to Self-Disclose to IPAs Coefficients Source: Author

Variables	F	p	η^2
Familiarity	4.40	0.037	0.016
Frequency of Use	7.81	0.006	0.028
Personalization	4.27	0.001	0.312

- **Regression Model 2 – Personalization - Intention to use IPAs:**

For the second regression model, the same independent and covariate variables were considered, only changing the dependent variable for *Intention to use IPAs*. In this model, the covariates and independent variables had a considerable impact on the model, since its explanatory power increased from 11% to 33% ($R^2 = 0.331$, $p < 0.001$).

Following the results presented in table 5, we understand that *Familiarity and Frequency of Use* have a highly significant positive effect on the *Intention to use IPAs*. However, contrary to model 1, when we consider covariates in our model, *Personalization* becomes non-significant. In model 2, the covariates variables seem to capture the effect that was being previously explained by *Personalization*, when the covariates were not present in the model.

Table 5 – Intention to use IPAs Coefficients Source: Author

Variables	F	p	η^2
Familiarity	22.66	0.001	0.077
Frequency of Use	49.19	0.001	0.153
Personalization	1.28	0.158	0.120

4.2. MEDIATION PROCESS ANALYSIS

To analyze the mediation effect of *Risk Perception* and *Trust* on the DVs, the macro *Process* by Hayes was used on SPSS (Model 4).

- **Personalization – Risk Perception - Willingness to Self-Disclose to IPAs:**

The impacts of *Personalization* on *Risk Perception* were revealed to be negatively significant ($\beta = -0.29$, $t = -5.57$, $p < 0.001$) which means that as *Personalization* increases the consumer's *Risk Perception* associated with IPAs usage decreases. These results reject H3.

The impact of *Risk Perception* on *Willingness to Self-Disclose to IPAs* was also negatively significant ($\beta = -0.22$, $t = -4.34$, $p < 0.001$), suggesting that higher levels of *Risk Perception* were associated with decreased *Willingness to Self-Disclose to IPAs*, which supports H5a. The direct effect of *Personalization* on users' *Willingness to Self-Disclose to IPAs* was positively significant ($\beta = 0.39$, $t = 8.06$, $p < 0.001$). Additionally, the indirect effect of *Risk Perception* as a mediator variable confirmed a partial mediation (LLCI = 0.026, ULCI = 0.120).

- **Personalization – Risk Perception - Intention to use IPAs:**

Considering the *Intention to use the IPA* as the DV, the mediator *Risk Perception* revealed a significant negative impact on the users' *Intention to use IPAs* ($\beta = -0.17$, $t = -3.26$, $p = 0.0013$). This indicates that higher levels of *Risk Perception* are associated with decreased *Intention to use IPAs*, confirming H5b. The direct effect of *Personalization* on *Intention to Use IPAs* was significantly positive ($\beta = 0.24$, $t = 4.93$, $p < 0.001$), which means that increased personalized content leads to a higher intention among consumers to use IPAs. The mediation analysis also revealed a significant indirect effect of *Personalization* on the *Intention to Use IPAs* through *Risk Perception,* confirming a partial mediation (LLCI = 0.019, ULCI = 0.096).

- **Personalization – Trust - Willingness to Self-Disclose to IPAs:**

When performing a similar analysis having *Trust* as the mediator variable, we observe that there is a significant positive impact of *Personalization* on *Trust* ($\beta = 0.42$, $t = 11.94$, $p < 0.001$). Thus, as the degree of personalization increased, the consumers' trust in the IPAs also increased. This evidence rejects H4.

Trust showed a significant positive impact on *users' Willingness to Self-Disclose to IPAs* ($\beta = 0.26$, $t = 3.32$, $p = 0.001$), suggesting that higher levels of *Trust* were associated with increased *Willingness to Self-Disclose to IPAs*, which supports H6a. The direct effect of the IV on *Willingness to Self-Disclose to IPAs* is significant and positive ($\beta = 0.35$, $t = 6.15$, $p < 0.001$). The indirect effect is also significant (LLCI = 0.038, ULCI = 0.187), confirming the role of *Trust* as a mediator between the IV and the DV.

- **Personalization – Trust - Intention to use IPAs:**

Considering the *Intention to use IPA* as the DV, the results show that the mediator *Trust* has a significant positive impact on users' *Intention to Use IPAs* ($\beta = 0.55$, $t = 7.71$, $p < 0.001$), indicating that higher levels of *Trust* were associated with an increased *Intention to Use IPAs*. Therefore, H6b was supported.

The direct effect of *Personalization* on *Intention to use IPAs* showed to be not significant when considering *Trust* in the model ($\beta = 0.06$, $t = 1.16$, $p = 0.247$). Nevertheless, the indirect effect of *Trust* as a mediator between the IV and the DV is significant (LLCI = 0.174, ULCI = 0.357), indicating a full mediation, which means that the impact on *Intention to use IPAs* is fully explained by *Trust.*

Table 6 – Summary of Mediation Analysis without Covariates. Source: Author

			Path A		Path B		Direct Effect		Indirect Effect		Mediation
Mediator	**Independent Variable**	**Dependent Variable**	**t-test**	**p-value**	**t-test**	**p-value**	**t-test**	**p-value**	**BootLLCI**	**BootULCI**	
Risk Perception	Personalization	Willingness to Self-Disclose to IPAs	-5.57	< 0.001	-4.34	< 0.001	8.06	< 0.001	0.026	0.120	Partial Mediation
Risk Perception	Personalization	Intention to use IPAs	-5.57	< 0.001	-3.26	0.0013	4.93	< 0.001	0.019	0.096	Partial Mediation
Trust	Personalization	Willingness to Self-Disclose to IPAs	11.94	< 0.001	3.32	0.001	6.15	< 0.001	0.038	0.187	Partial Mediation
Trust	Personalization	Intention to use IPAs	11.94	< 0.001	7.71	< 0.001	1.16	0.247	0.174	0.357	Full Mediation

Since the covariate variables *Familiarity with IPAs* and *Frequency of Use* were shown to be significant in both of our models, a mediation analysis was performed, including them in the final model.

Table 7 – Summary of Mediation Analysis with Covariates. Source: Author

			Path A		Path B		Direct Effect		Indirect Effect		Mediation
Mediator	**Independent Variable**	**Dependent Variable**	**t-test**	**p-value**	**t-test**	**p-value**	**t-test**	**p-value**	**BootLLCI**	**BootULCI**	
Risk Perception	Personalization	Willingness to Self-Disclose to IPAs	-4.97	< 0.001	-3.73	0.0002	8.08	< 0.001	0.018	0.104	Partial Mediation
Risk Perception	Personalization	Intention to use IPAs	-4.97	< 0.001	-1.92	0.0557	2.81	0.0053	-0.003	0.063	No Mediation
Trust	Personalization	Willingness to Self-Disclose to IPAs	9.98	< 0.001	3.36	0.0009	6.50	< 0.001	0.034	0.167	Partial Mediation
Trust	Personalization	Intention to use IPAs	9.98	< 0.001	6.16	< 0.001	0.10	0.9166	0.088	0.244	Full Mediation

Using model 4 by Hayes, the same analysis was performed to assess the impact of including the following covariate variables *Familiarity with IPAs* and *Frequency of Use* in our mediation process. As shown in table 7, the results remained unchanged for most of the cases tested. The only relation that was changed was the one between *Personalization* and *Intention to Use IPAs* mediated by *Risk Perception*.

When including the covariates, the classification went from a *Partial Mediation* to a *No Mediation*. This may be explained by the fact that when covariates were included in this model, the effect that *Risk Perception* had on the *Intention to use IPAs* decreased since the p-value went from 0.0013 (significant) to 0.0557 (not significant). This suggests that *Familiarity with IPAs* and *Frequency of* Use have a strong explanatory power to account for the variance in the *Intention to Use IPAs*, reducing the explanatory power previously attributed to *Risk Perception.*

4.3. MODERATION PROCESS ANALYSIS

In the developed research model, the variable *Type of Information Shared* was defined as our moderator, to assess if sharing sensitive personal information with IPAs to have access to personalized content would increase consumers' *Risk Perception* or not.

In the survey, the moderator variable was measured with a multiple-choice question. However, to better analyze this relation a new variable was created based on the information shared by the respondents with the IPAs, which considered the following developed scale:

- Option 1 » General Queries - **Public Information**
- Option 2 » Preferences and Hobbies - **Low Sensitive Information**
- Option 3 » Personal Information - **Moderately Sensitive Information**
- Option 4 » Information Financial Information - **Sensitive Information** (Melzner et al., 2023)
- Option 5 » Health Information - **Highly Sensitive Information** (GDPR - European Parliament and Council, 2016)

This new variable considered only the most sensitive information shared. For instance, if a respondent reported sharing both health information and preferences or interests, the health information was used for moderation purposes as it is the most sensitive option.

To analyze this relation, Model 7 of the macro *Process* by Hayes was used on SPSS since it described exactly the interaction of the studied variables in our model. *Personalization* was our independent variable, *Risk Perception* was our mediator, *Willingness to Self-Disclose to IPAs* and *Intention to Use IPAs* were our dependent variables, and *Type of Information Shared* was our moderator.

Based on the results obtained from the SPSS analysis, it was concluded that the interaction between the *Type of Information Shared* and the relationship between *Personalization* and *Risk Perception* was not significant. This conclusion is verified when considering both *Willingness to Self-Disclose to IPAs* (LLCI = -0.024, ULCI = 0.014) and *Intention to Use IPAs* (LLCI = -0.020, ULCI = 0.010) as dependent variables.

These findings indicate that the *Type of Information Shared* does not influence the strength or direction of the relationship between *Personalization* and *Risk Perception,* which rejects H7. Therefore, regardless of the type of information being shared, the perceived risk associated with the personalized content presented by IPAs does not change significantly.

This analysis was replicated to include the covariate variables *Familiarity with IPAs* and *Frequency of Use* in our model. The results proved to be similar to the model without covariates since the moderator *Type of Information Shared* was also not significant when considering Willingness to Self-Disclose to IPAs (LLCI = -0.018, ULCI = 0.012) and *Intention to Use IPAs* (LLCI = -0.010, ULCI = 0.006) as dependent variables.

5. RESULTS AND DISCUSSION

After analyzing the survey results, we gained a deeper understanding of the role of *Personalization* in decreasing the levels of *Risk Perception* and improving *Trust* felt by the users when interacting with IPAs.

Table 8 presents a summary of all the hypotheses of our model, as well as their final verification.

Table 8 – Hypothesis Verification. Source: Author

Hypothesis	Verification
H1. Personalization has a positive impact on Willingness to Self-Disclose to IPAs	Confirmed
H2. Personalization has a positive impact on the Intention to Use IPAs	Confirmed
H3. Personalization has a positive impact on the Risk Perception	Rejected
H4. Personalization has a negative impact on Trust in the IPA	Rejected
H5a. Risk Perception has a negative impact on Willingness to Self-Disclose to IPAs	Confirmed
H5b. Risk Perception has a negative impact Intention to Use IPAs	Confirmed
H6a. Trust in the IPA has a positive impact on Willingness to Self-Disclose to IPAs	Confirmed
H6b. Trust in the IPA has a positive impact on the Intention to Use IPA	Confirmed
H7. The Type of Information Shared will moderate the relationship between Personalization and Risk Perception	Rejected

Our analysis confirmed H1 and H2, indicating that increased content personalization leads to higher user engagement with IPAs and greater willingness to disclose personal information. These findings confirm the users' preferences for a personalized and unique experience tailored to their needs when using these AI systems, as they understand that sharing their personal information with IPAs will improve their interaction and experience when using them.

Contrary to our expectations, H3 and H4 were rejected. This suggests that greater *Personalization* does not increase *Risk Perception* and that higher levels of *Personalization* are in fact associated with increased *Trust* in IPAs.

A possible explanation for this can be the fact that when the user has a clear understanding of the real use of the information they are providing to IPA, they are more prone to disclose that information. In these cases, the users see that all the information they disclose is intended to create a unique experience for them, which generates an increase in *Trust* and a decrease in the *Risk Perception* felt when they interact with the IPA.

The survey results confirmed Hypotheses H5a and H5b, showing that higher perceived risk correlates with reduced intention to use IPAs and willingness to disclose personal information with them. This finding aligns with existing literature, demonstrating that if users feel that they are at risk of being negatively affected by sharing their personal information with IPAs, they will not want to do it or continue to use it (Gao et al., 2018).

Risk Perception was also confirmed to be a partial mediator between *Personalization* and the dependent variables (*Willingness to Self-Disclose to IPAs* and *Intention to use IPAs*), which means that personalized content reduces the perceived risk of disclosing personal data, which in turn increases the willingness to share information. Thus, while users acknowledge potential risks, the benefits of *Personalization* partially mitigate these concerns.

Hypothesis H6a and H6a were also found to be in line with the results. Increased *Trust* leads to users willingly sharing their information with IPAs, as they understand that to access certain benefits, such as personalized content, which optimizes time and reduces mental fatigue, they must give the IPAs the proper data. Thus, when users share information and have positive experiences with IPAs, their confidence in these systems grows. Users begin to perceive IPAs as tools that understand them, and they are there to assist their needs and desires.

Trust was shown to be a partial mediator in the relationship between *Personalization* and *Willingness to Self-Disclose to IPAs*, which means that *Trust* partly explains how *Personalization* influences user behavior regarding data disclosure. Additionally, when analyzing *Trust* as a mediator for the *Intention to Use IPAs*, we observed a full mediation. This indicates that the effect of *Personalization* on users' *Intention to Use IPAs* is entirely explained by the trust they have in these systems.

6. CONCLUSIONS AND FUTURE WORKS

The objective of this study was to examine the role of *Personalization* when it comes to the user's data privacy concerns associated with the use and disclosure of information with the IPAs. To achieve this, a model was developed where *Personalization* served as the independent variable, while *Risk Perception* and *Trust* were proposed as mediators. The dependent variables were defined as *Willingness to Self-Disclose to IPAs* and *Intention to Use IPAs* and the moderator variable was *Type of Information Shared.*

6.1. THEORETICAL IMPLICATIONS

This research contributes to existing literature on the ethical implications and consumer behavior related to IPAs, illustrating the relation between *Personalization, Risk Perception*, *Trust*, and user behavior in the context of IPAs.

Personalization, a key feature of IPAs, was shown to positively impact users' *Willingness to Self-Disclose to IPAs* and their *Intention To Use* these AI systems, confirming that consumers are more inclined to engage with IPAs and share personal data when they have access to personalized content (Isidore & Arun, 2023). These results align with existing literature, which suggests that personalized content is highly valued by users (Rhee & Choi, 2020) as it plays a central role in user satisfaction and engagement (Thomaz et al., 2020).

Contrary to our initial hypotheses, increased *Personalization* did not lead to increased *Risk Perception*, nor did it negatively impact *Trust*. This suggests that when users understand the specific uses of the information they share, they become more inclined to disclose it. Consequently, they perceive the disclosed information as essential in order to create a unique, personalized experience. As a result, *Personalization* was understood to be a complex variable as it has the potential to reduce perceived risks and foster trust, not being overshadowed by data privacy concerns. These findings support the results of Huang et al. (2022), who highlight that transparency in data usage can mitigate users' privacy concerns.

When it comes to ethical concerns such as the *Risk Perception* felt by the users when using IPAs, results confirmed that users who perceive greater risks associated with sharing their data are less likely to engage with IPAs. This finding highlights the importance of focusing on users' privacy concerns to foster greater acceptance and usage of IPAs. *Trust*, on the other hand, was found to have a positive impact on both the *Willingness to Self-Disclose to IPAs* and the *Intention to Use IPAs*, which consolidates the critical role *Trust* has in mitigating privacy concerns and enhancing user engagement with IPAs (Lappeman et al., 2023; Bonilla & Martin-Hammond, 2020).

Lastly, our study confirmed that sharing sensitive data with an IPA to benefit from personalized content does not significantly impact the user's *Risk Perception*. A possible explanation for this finding is that *Personalization* may reduce *Risk Perception* and foster *Trust*.

When users already trust the IPA, they are more inclined to share information with it. This trust in the technology likely leads users to feel that their data is safe, allowing them to share more sensitive information without feeling negatively judged or at risk (Uchida et al., 2017).

Overall, this research highlights the importance of analyzing both the benefits of IPAs, such as constant access to personalized content, and the ethical challenges surrounding their adoption, since these aspects are intrinsically and powerfully related. The findings from this study contribute to a clearer understanding of consumer behavior regarding IPA usage and it aims to equip consumers with a better understanding of how these technologies impact their daily lives.

6.2. MANAGEMENT IMPLICATIONS

The results of this dissertation provide valuable insights for business owners and policymakers as it provides suggestions to leverage the contributions of this work and improve their companies and policies.

The positive impact of personalization on user engagement and data disclosure emphasizes the necessity for companies to prioritize personalized user experiences. This finding indicates that consumers are willing to share their personal information when they perceive a clear benefit, such as enhanced interaction and tailored content, which aligns with their preferences and needs.

This study also revealed that personalization does not increase risk perception or decrease trust. Instead, when users understand how their data is being used, trust in the AI system increases, and perceived risk decreases. This highlights the importance of transparency and clear communication about data usage from the companies to the consumers. Therefore, companies should focus on educating users about the benefits of data sharing; while explaining the measures they are putting in place to safeguard their data. By doing this, it will help foster trust in the IPA and mitigate privacy concerns.

An example of this approach would be to display an overview table during the registration process for using the IPA or any AI-based system. This table would clearly show the direct connection between the data collected and its use in the personalized experience. For example, it could show users that data related to their music habits would be used to build their profile, create new playlists, determine the best time of day to play certain songs, and recommend new artists, or inform them that their search history and liked products will be used to tailor all advertisements they will see, only showing them products that are aligned with their profile.

Risk perception remains a critical factor that can influence user behavior. Our findings suggest that while personalization can mitigate perceived risks, companies must continue to address

potential privacy concerns proactively. Showing consumers the exact ways in which they are implementing robust data protection measures and ensuring compliance with regulations like the EU General Data Protection Regulation (GDPR) can help build user confidence and trust.

Trust was identified as an important mediator in the relationship between personalization and user engagement. Based on this, companies should invest in building and maintaining trust relationships with their users through transparent practices, reliable performances, and safeguarding user data. Ensuring that IPAs provide consistent and positive user experiences will further reinforce trust and encourage greater adoption and data sharing.

In conclusion, companies that are developing IPAs should focus on creating transparent, trustworthy, and personalized experiences for their users. By doing so, they can ensure their users feel comfortable using and self-disclosing to their IPA, which will mitigate their privacy concerns, and create lasting relations based on trust. These strategies will improve customer satisfaction and promote long-term growth and competitive advantage in the AI market.

6.3. LIMITATIONS AND FUTURE RESEARCH

This research has contributed to a deeper understanding of the ethical challenges surrounding IPAs adoption and usage while highlighting its main impacts on consumers and companies. Nevertheless, there are some limitations to this work.

When it comes to the analysis of the variable *Type of Information Shared* instead of developing a construction, an approved scale could have been selected. By using validated scales, we can have a higher Cronbach's Alpha, ensuring the reliability of the results. Additionally, since there is not a lot of information regarding this variable, a quantitative study, such as an interview, could have been performed to better understand the impact that sharing sensitive personal information has on the consumers' data privacy concerns and risk perception when using IPAs.

In this study, a few variables were analyzed to better describe the respondent sample, such as *Familiarity with IPAs* and *Frequency of Use*. However, more variables could be studied, such as country of residence, to assess if, for example, *Risk Perception* is constant between the same age groups in different countries or not. This would provide managers and policymakers with a comprehensive analysis of the specific policies to adopt in each country to maximize their benefits.

Concerning future work, even though IPAs are very a researched topic because they are an ongoing changing AI system, there is always room for new and deeper studies. A suggestion for further exploration could be to investigate the impact that social influence could have on the users' risk perception. In a world where there is pressure to have a strong social presence, whether online or in real life, and where there is so much competition to keep up with the

latest trends, it would be interesting to understand the impact that adopting technology due to social pressure or social advice, can have on a user's *Risk Perception*.

Following the results obtained concerning Personalization, it could be interesting to dive deeper into this analysis and have a clearer understanding of the situations where Personalization can lead to feelings of vulnerability due to the high amount of data that is collected and the situations where it decreases the perception of risk felt by the users.

Moreover, IPAs are gaining new features every day, which is making them more sophisticated and user-intuitive. Voice biometrics and emotional recognition are some examples of news features IPAs can adopt and they can impact the current trade-off between *Personalization* and *Risk Perception*, which means this topic could be further analyzed to understand if, under these new circumstances, *Personalization* would continue to have a negative impact on *Risk Perception* or not.

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APPENDIX A

This is to certify that
Project No.: **DDMKT2024-7-151019**
Project Title: **BALANCING PRIVACY AND PERSONALIZATION - Analyzing Consumer Behaviour when Using Intelligent Personal Assistants**
Principal Researcher: **Patrícia Vieira Gago**

according to the regulations of the Ethics Committee of NOVA IMS and MagIC Research Center this project was considered to meet the requirements of the NOVA IMS Internal Review Board, being considered **APPROVED** on 7/15/2024.

It is the Principal Researcher's responsibility to ensure that all researchers and stakeholders associated with this project are aware of the conditions of approval and which documents have been approved.

The Principal Researcher is required to notify the Ethics Committee, via amendment or progress report, of
- Any significant change to the project and the reason for that change;
- Any unforeseen events or unexpected developments that merit notification;
- The inability of the Principal Researcher to continue in that role or any other change in research personnel involved in the project.

Lisbon, 7/15/2024

NOVA IMS Ethics Committee
ethicscommittee@novaims.unl.pt

APPENDIX B - SURVEY

Survey - Personal Assistants

Hello!

Thank you for taking the time to participate in this survey! This survey aims to help us better understand how individuals perceive and interact with Intelligent Personal Assistants (also known as Voice Assistants), such as Alexa, Siri, and Google Voice Assistant.

Your responses are completely confidential, and your anonymity is guaranteed. All data collected will be used for research purposes only and will be kept strictly confidential.

The survey should take approximately 5 minutes to complete.
Your thoughtful and honest responses will contribute significantly to our research efforts.

Let's get started!

Q1. Do you consent to participate in this research study?

- ○ Yes
- ○ No

Q2. Please enter your Prolific ID:

- ○ Prolific ID _____
- ○ Not Applicable / I'm not using Prolific

Q3. Familiarity with the Intelligent Personal Assistant

	Strongly Agree	Agree	Somewhat Agree	Neither Agree Nor Disagree	Somewhat Disagree	Disagree	Strongly Disagree
I am familiar with the use of personal assistants	○	○	○	○	○	○	○

Q4. Frequency of Use

	Rarely or never	Occasionally	Several times a week	Daily	Multiple times a day
How often do you interact with a personal assistant?	○	○	○	○	○	○

Q5. Which Intelligent Personal Assistant you use the most?

- ○ Alexa (Amazon)
- ○ Siri (Apple)
- ○ Google Assistant (Google)
- ○ Cortana (Microsoft)
- ○ Other _____
- ○ I do not use personal assistants

Q6. For which of the following tasks do you typically use an Intelligent Personal Assistant? (select all that apply)

- [ ] Setting reminders or alarms
- [ ] Playing music or podcasts
- [ ] Answering general questions
- [ ] Controlling smart home devices
- [ ] Making calls or sending messages
- [ ] Shopping or ordering products
- [ ] Other _____
- [ ] I do not use personal assistants

Q7. Where do you usually use your Intelligent Personal Assistant?

- ○ Phone
- ○ Smartwatch
- ○ Computer
- ○ Home device
- ○ Other _____

Q8. Personalization: How much do you agree with the following sentences?

	Strongly Agree	Agree	Somewhat Agree	Neither Agree Nor Disagree	Somewhat Disagree	Disagree	Strongly Disagree
My personal assistant provides me with relevant promotional information tailored to my preferences or personal interests	○	○	○	○	○	○	○
My personal assistant provides me with the kind of deals/ads I might like	○	○	○	○	○	○	○
My personal assistant makes purchase recommendations that match my needs	○	○	○	○	○	○	○
My personal assistant makes me feel like a unique customer	○	○	○	○	○	○	○
I believe my personal assistant is customized to my needs	○	○	○	○	○	○	○

Q9. Risk Perception: How much do you agree with the following sentences?

	Strongly Agree	Agree	Somewhat Agree	Neither Agree Nor Disagree	Somewhat Disagree	Disagree	Strongly Disagree
I have my doubts over the confidentiality of my interactions with my personal assistant	○	○	○	○	○	○	○
I am concerned about performing a financial transaction via a personal assistant	○	○	○	○	○	○	○
I am concerned that my personal details stored in the personal assistant could be stolen	○	○	○	○	○	○	○
I am concerned that the personal assistant collects too much information about me	○	○	○	○	○	○	○

Providing the personal assistant with my personal information could involve many unexpected problems	○	○	○	○	○	○	○
It could be risky to disclose my personal information to the personal assistant	○	○	○	○	○	○	○
There would be a high potential for loss in disclosing my personal information to the personal assistant	○	○	○	○	○	○	○

Q10. Trust: How much do you agree with the following sentences?

	Strongly Agree	Agree	Somewhat Agree	Neither Agree Nor Disagree	Somewhat Disagree	Disagree	Strongly Disagree
I feel I can rely on a personal assistant to do what is supposed to do	○	○	○	○	○	○	○
I believe the personal assistant provides accurate information	○	○	○	○	○	○	○
My digital assistant provides unbiased information and recommendations	○	○	○	○	○	○	○
My digital assistant provides honest answers	○	○	○	○	○	○	○
I trust my personal assistant	○	○	○	○	○	○	○

11. Type of Info Shared: When using a personal assistant, which of the following information do you usually share? (select all that apply)

- ☐ Personal Information (e.g., name, age, contact details)
- ☐ Financial Information (e.g., bank account details, credit card information)
- ☐ Health Information (e.g., medical history, symptoms)
- ☐ Preferences and Interests (e.g., hobbies, favorite products)
- ☐ General Queries or Requests (e.g., asking for directions, setting reminders)
- ☐ Other _____
- ☐ I do not use personal assistants

Q12. Type of Information: How much do you agree with the following sentences?

	Strongly Agree	Agree	Somewhat Agree	Neither Agree Nor Disagree	Somewhat Disagree	Disagree	Strongly Disagree
Sharing sensitive personal information with a personal assistant makes me feel vulnerable	○	○	○	○	○	○	○
I will share sensitive personal information with a personal assistant if it allows me to have access to personalized content	○	○	○	○	○	○	○

Q13. Willingness to self: How much do you agree with the following sentences?

	Strongly Agree	Agree	Somewhat Agree	Neither Agree Nor Disagree	Somewhat Disagree	Disagree	Strongly Disagree
When my personal assistant asks for my personal information, I reveal a large amount	○	○	○	○	○	○	○
When it comes to my personal assistant, I disclose quite extensive personal information	○	○	○	○	○	○	○
I would be willing to share my personal information when using personal assistants in the future	○	○	○	○	○	○	○
I would probably disclose information about myself to the personal assistant	○	○	○	○	○	○	○
I would likely share my personal information with the personal assistant if necessary	○	○	○	○	○	○	○

Q14. Intention to use: How much do you agree with the following sentences?

	Strongly Agree	Agree	Somewhat Agree	Neither Agree Nor Disagree	Somewhat Disagree	Disagree	Strongly Disagree
I will try to use a personal assistant in the future	○	○	○	○	○	○	○
I plan to use a personal assistant in the future	○	○	○	○	○	○	○
I intend to use a personal assistant in the future	○	○	○	○	○	○	○

Q15.Gender

- ○ Male
- ○ Female
- ○ Prefer not to say

Q16. Age (only write numbers please)

_____

Q17. Education Level

- ○ Basic school
- ○ High school
- ○ Bachelor's degree
- ○ Master's degree
- ○ PhD's degree

Q18. Employment Status

- ○ Student
- ○ Student worker
- ○ Self-employed
- ○ Employee
- ○ Retired
- ○ Unemployed

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