Faculty of Economics and Business, MSc Business Administration: Entrepreneurship & Innovation

How Intelligent Personal Assistants Impact User Perceptions of Risk and Usefulness in E-commerce: Moderation Effect of Personalization and Responsiveness

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Date of Submission and Version: 06.08.2024 - Final

The EBEC Approval Number: EB-6013

2024

Table of Contents

List of Tables and Figures

Abstract: This paper examines the interplay between perceived risk and perceived usefulness in e-commerce, enabled by Intelligent Personal Assistants (IPAs). It highlights how the interactive functional features of IPAs, specifically personalization and responsiveness, can moderate this relationship. Utilizing the Technology Acceptance Model (TAM), perceived risk is hypothesized to negatively impact perceived usefulness. It is further hypothesized that personalization and responsiveness positively moderate this relationship. An online survey was conducted to gather data. 101 participant answers were analyzed and the hypotheses were tested using regression analyses. The findings reveal that while perceived risk alone does not significantly impact perceived usefulness, responsiveness positively moderates this relationship. In contrast, personalization did not demonstrate a significant moderating effect. The outcomes contribute to the literature by explaining the roles of personalization and responsiveness in shaping user interactions with IPAs in e-commerce settings, offering practical insights for enhancing user experience.

Keywords: Intelligent Personal Assistants, e-commerce, perceived usefulness, perceived risk, user value, personalization, responsiveness.

1. Introduction

A crisp autumn afternoon under a clear sky, where the sun gently warms your face and your breath forms a mist as you exhale. You've just left the gym and are cycling home, excited about the dinner party you're hosting for friends. As you lie down on your couch, you initiate a conversation with your IPA.

YOU: I have invited friends over for dinner tonight. Could you assist in creating a menu?

IPA: Of course. More details about the dinner would enable me to tailor a more suitable menu.

YOU: Well, we are celebrating our graduation. I'm planning to serve red wine and would like three main courses and a dessert that complements it.

IPA: Thank you. Based on your preferences, I have created the menu and merged it with today's beverage choice. Let me know if you wish to order this menu or need any assistance.

YOU: Great! Let's proceed to checkout…

The story depicted above serves as an example of how artificial intelligence (AI) backed IPAs can ease e-commerce experiences. Nowadays, customers can fulfill their informational needs in the pre-purchase stage, conveniently proceed through purchasing, and easily access after-sales services during their e-commerce journeys simply by using their voice. Thus, the shopping stages for IPA users are arguably more convenient than ever thanks to enhancements in generative AI technologies that are being integrated into today's smart products. IPAs are the most readily accessible smart products that employ data-based programs to interact with people and answer their voice commands (McLean and Osei-Frimpong, 2019; Mishra et al., 2021; Guo and Luo, 2023). The usage and popularity of IPAs in e-commerce have been spreading widely, with 8.4 billion IPAs in use today compared to 3.25 billion in 2019 (Voicebot.ai, 2018). As demand for this type of product increases, companies seek convenient ways to bring voice-enabled e-commerce to their customers and gain an advantage in a highly competitive e-commerce market. Hence, these products have already entered our lives as physical assets or as applications and built-in features in mobile phones. Amazon (Alexa), Apple (Siri), Microsoft (Cortana), Alibaba (Tmall Genie), and Xiaomi (Xiaoxia) are some of the examples that notable companies have been providing to their customers (Guo and Luo, 2023).

Throughout the e-commerce journey, IPAs are likely to contribute to the perceived usefulness due to their distinct features from other services. Firstly, IPAs can perform tasks solely through voice without the need for another medium, thus providing users with multitasking options (Fernandes and Oliveira, 2021; Guo and Luo, 2023; McLean & Osei-Frimpong, 2019; Poushneh, 2021; Statista, 2019). Moreover, IPAs can autonomously learn from user usage data, empowering them to deliver personalized services and respond to customer inquiries promptly (Ki et al., 2020). This ability of provide personalized services highlights IPAs' personalization feature, while their capacity of respond quickly underscores their responsiveness. Although these characteristics are prominent as distinct interactive functional features of IPAs that can contribute to perceived usefulness, they also bring about concerns regarding customers' perceived risk. Perceived risk is related to the issues that individuals face regarding the use of the personal information that they share with organizations and how much control they have over it (Yun, Lee, & Kim, 2019). This is due to the exchange of user data for enhanced services. The disclosure of data may include personal information, usage information, and sometimes sensitive information such as transactional information. The tremendous increase in the amount of data has made it critically important to consider how and in what manner data should be utilized. Thus, companies need to prove that their guidelines for gathering and using data, which are usually shared through user privacy policies (Bélanger, 2011; Hong, 2013; Pavlou, 2011; Smith, 2011), fulfill ethically righteous standards, such as security and privacy by design (Cavoukian & Chanliau, 2013; Kroener & Wright, 2014). The correlated and complex nature of perceived risk and perceived usefulness has led to intensive studies on the interaction between these elements. However, studies specifically investigating the direct relationship between perceived risk and perceived usefulness in IPA-enabled e-commerce and how interactive functional features can play a role in this relationship are quite rare. Hence, the first aim of this study is to understand the relationship between perceived risk and perceived usefulness and the second goal is to explore the moderation effect of personalization and responsiveness on the perceived usefulness-perceived risk relationship.

In this thesis, it is hypothesized that perceived risk negatively affects perceived usefulness. Moreover, further hypotheses were constructed for personalization and responsiveness. It is claimed that both personalization and responsiveness moderate the main construct positively.

Additionally, the study aims to contribute to the existing literature on IPAs. The findings are intended to provide practical applications for establishing solid strategies for targeted customer segments.

2. Literature Review

2.1. Technology Acceptance Model (TAM)

It has been over 50 years since scholars began to intensively study perceived usefulness and perceived ease of use as determinants of user behavior. In the mid-1970s, Schultz and Slevin (1975) examined the impact of these determinants on system utilization. Their findings suggested that performance was linked to how much a manager expected to use the system in the future. Subsequently, the relationship between performance and system utilization theorized by Robey (1979) argued that a system that does not assist people in performing their tasks is not likely to be accepted favorably. Over the years, effort has been devoted to predicting user acceptance of computers and computer-advanced information technologies. Eventually, in his study "*Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology"* where the Technology Acceptance Model (TAM) was introduced, Davis, F. D. (1989) highlighted a key statement. He defined perceived usefulness as "People tend to use or not use an application to extent they believe it will help them perform their job better." (Davis, 1989, p. 321). Furthermore, he developed new assessment tools to gauge perceived usefulness and perceived ease of use, and theorized these factors as determinants of computer usage. The TAM model is the theoretical basis of this study, and one of the most crucial outcomes of TAM is that the perceived usefulness-system use relationship is significantly more powerful compared to the ease of use-system use relationship. In research findings, the prominence of perceived usefulness is explained as *'users are driven to adopt an application primarily because of the functions it performs for them, and secondarily for how easy or hard it is to get the system to perform those functions. For instance, users are often willing to cope with some* *difficulty of use in a system that provides critically needed functionality. Although difficulty of use can discourage adoption of an otherwise useful system, no amount of ease of use can compensate for a system that does not perform a useful interaction.'* (Davis, 1989, pp.333-334). This outcome establishes two significant pillars for this study. First, it explains why perceived usefulness has been used as a sole determinant of perceived user value. This is primarily due to its strong correlation with system use, emphasizing the importance of not overlooking the functionality perspective while overemphasizing ease of use. Secondly, it provides positive contributions to the claim that personalization and responsiveness of IPAs' can positively moderate the relationship between perceived risk and perceived usefulness.

2.2. Intelligent Personal Assistants

The increasing competition among firms in e-commerce and the growing expectation of users to access online services necessitate companies to offer a wide range of online services and products to users. In order to preserve revenue streams and existing users, and draw in new customers, e-commerce enterprises must innovate and create new products that enhance their existing offerings (Maroufkhani et al., 2022). IPAs are a new class of smart products that can interpret users' intentions into operational commands and respond to users through voice (de Barcelos Silva et al., 2020; Fernandes and Oliveira, 2021; Maroufkhani et al., 2022). Certain unique features distinguish IPAs from other services and provide a seamless experience to customers through online purchasing. Firstly, IPAs are equipped with machine learning and recommendation algorithm technology, they can recognize and gather data, become self-learning, and suggest services based on user interests and preferences (Guo & Luo, 2023; Hu et al., 2021; Kang & Shao, 2023; Poushneh, 2021). Secondly, IPAs can take advantage of natural language understanding technologies. Therefore, it can assist users in making knowledgeable decisions and managing other devices by voice (Choi & Drumwright, 2021; Aw et al., 2022; Guo & Luo, 2023).

The significant potential for IPAs to alter future online shopping habits has brought about considerable academic interest. Research in this field is currently focused on adoption, continuous intention to use, and privacy (Guo & Luo, 2023). However, studies examining the moderation effect of IPAs' interactivity features on the relationship between perceived risk and perceived usefulness are limited. This thesis aims to fill this gap in academic studies and provide practical guidance.

2.3. Intelligent Personal Assistants in E-commerce

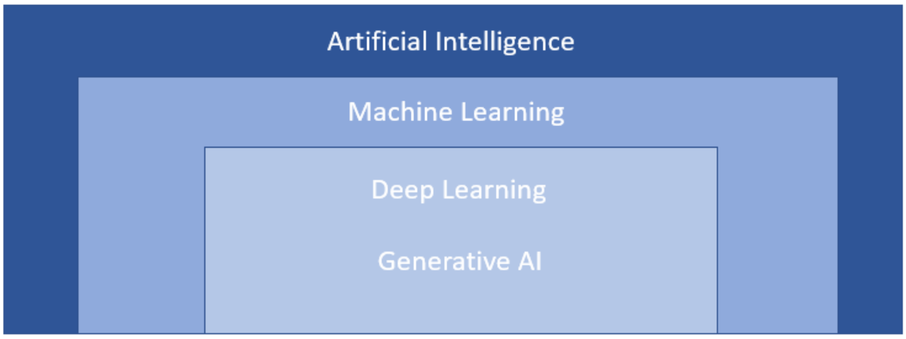
One of the first definitions used for commerce is described by Nissen (1997) as the process flow associated with a relationship or transaction, including activities such as purchasing, marketing, sales, and customer support. Over time, the undeniable dominance that the internet has exerted on the business world and consequently on business models has added an 'e' to the commerce terminology. This addition has moved the concepts of relationship and transaction mentioned in the definition of commerce to a web-based context. Thus, Web-based commerce (e-commerce) has become a fundamental factor in companies' operations (Oppong, Yen, & Merhout, 2005).

Technological advancements allow companies to find new communication channels with their customers through multiple touchpoints and provide consistent quality services within these channels. The ultimate aim is to create an ecosystem for users, ensuring a seamless experience across every channel. Using IPAs in e-commerce is a new and increasingly popular channel, allowing customers to perform e-commerce activities using their voice. Thus, it is crucial to examine the advantages and disadvantages involved in IPA usage in e-commerce. Regarding the advantages, IPAs are considered convenient and user-friendly compared to websites (Luger & Sellen, 2016; McLean & Osei-Frimpong, 2019), efficient in interactions (Luger & Sellen, 2016; Rzepka, 2019), and enjoyable for users (Pal, Arpnikanondt, & Razzaque, 2020; Yang & Lee, 2019). As the disadvantages, they also contain reliability risks that negatively impact users' performance expectancy (Zaharia & Würfel, 2020) and exert privacy concerns that can prevent the adoption of the technology (Easwara Moorthy & Vu, 2015; McLean & Osei-Frimpong, 2019). Arising privacy concerns necessitates exploring factors that can affect the perceived risk-perceived usefulness relationship, not only to contribute to the insufficient literature in this specific domain but also to provide insights for companies looking to shape their strategies.

2.4. Artificial Intelligence and Generative Artificial Intelligence

IPAs rely on AI algorithms. While AI is not a new concept, enhancements in generative AI algorithms have made interaction with AI-based technologies convenient. Thus, it is important to understand AI and generative AI to have a complete picture of how IPAs can contribute to the e-commerce journey. However, it is difficult to define AI since human intelligence is already a concept that is hard to define. A good definition is "A system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019b, p. 17). AI is an umbrella term covering a variety of computational algorithms capable of carrying out operations that normally call for human intelligence such as understanding natural language, recognizing patterns, making decisions, and learning from experience (Banh & Strobel, 2023; Castelvecchi, 2016; Winston, 1993). Under the umbrella, there are machine learning (ML) and deep learning (DL). ML is a sub-category of AI that is capable of independently completing tasks without explicit programming (Brynjolfsson & Mitchell, 2017). DL, on the other hand, is a more sophisticated subset of ML and uses artificial neural networks to automatically find patterns and correlations in vast datasets and to model complicated data representations (Janiesch et al., 2021; Samtani et al., 2023). Neural networks are algorithms that are trying to imitate the structure and function of the actual human brain, which are composed of linked layers of artificial neurons (Goodfellow et al., 2016). DL, due to neural networks, is capable of processing multidimensional data such as images, videos, and audio (LeCun et al., 2015). Unlike the discriminative models, generative models are unique in their structure. Generative AI can learn the nature of the data structure and generation processes (Jebara, 2004). This part is particularly interesting since generative AI can generate new data unlike other models which process, learn, and create output in the boundaries of existing data. By design, generative AI

Figure 1.
AI to Generative AI



outputs are probabilistic and nonreplicable as compared to deterministic AI models (Weisz et al., 2023). Currently, IPAs utilize, ML and DL algorithms and operate as follows; The device utilizes speech recognition technology to convert voice prompts of users. Then, uses natural language understanding technology to categorize phrases or words. Afterward, with the help of dialogue management technology, the device identifies the context of the interaction and provides answers accordingly. Eventually, speech synthesis technology to convert the related answer into speech (de Barcelos Silva et al., 2020; Aw et al., 2022; Guo & Luo, 2023).

3. Research Model and Hypotheses

3.1. Perceived Risk

Privacy concerns are related to people's concerns about how organizations will use the personal information they disclose to companies (Yun, Lee, & Kim, 2019). Even though the definition of privacy concerns may differ depending on the context, perceived risk is one of the most suitable terms when understanding IPA-human interaction. Perceived risk is the extent to which people believe that there will be a potential loss in the event of a release of personal information (Dinev & Hart, 2006; Malhotra, Kim, & Agarwal, 2004). The information that customers disclose may be comparatively less sensitive or may include sensitive information such as transactional data of customers. Regardless of the content of the information, users may hesitate to share data containing information about themselves (Bansal et al., 2016; Yun et al., 2019), and the use of IPAs does not present a contrary example in this regard. Many studies discuss how an increase in perceived risk adversely affects the usage of IPAs. Dinev and Hart (2006) noted that people are less inclined to trust digital technologies at higher perceived privacy risk levels. Consequently, customers' adoption of virtual assistants and other automated technologies depends on their perception of the privacy risk (Fernandes and Oliveira, 2021). According to Hernâdez Acosta and Reinhardt (2022), users who refuse to use voice assistants such as Alexa, Siri, and Google Assistant usually do so out of worry for their privacy. The main concern for users is the device's listening capability, which gives the impression of constant surveillance. Additionally, there is concern over the possible mishandling of personal information (Guo & Luo, 2023). In the shade of rising worries, studies by Yun, Han, and Lee (2013) demonstrate that a high level of privacy concern reduces performance expectancy, and performance expectancy in turn decreases continuous usage. Given that performance expectancy is an equivalent construct of perceived usefulness (Martins, Oliveira, & Popovic, 2014), it can be argued that an increase in privacy concerns will decrease the perceived usefulness of IPAs. Building on the theoretical framework of the TAM, it can be argued that an increase in perceived risk, while using IPAs in e-commerce, would decrease perceived usefulness. Therefore, this thesis proposes the following.

H1: An increase in perceived risk will negatively affect perceived usefulness in the context of IPA usage in e-commerce.

3.2. Moderation Effect of Personalization

Every day, following nearly every digital interaction, users leave traces behind that companies can use. These traces enable businesses to tailor their products, prices, services, marketing messages, and media content to suit individual preferences and needs (Martin & Murphy, 2017), namely personalized content. However, disclosure of personal information also elicits privacy concerns (Goldfarb and Tucker 2011; Okazaki, Li, and Hirose 2009; Turow et al. 2009). The primary term associated with perceived risk is trust. Trust is defined as "willingness to rely on an exchange partner in whom one has confidence" (Moorman, Zaltman, and Deshpandé 1992, p. 315). When consumers shop online, they often rely on trust as the only factor that influences their buying choices. (McStay 2011; Urban, Amyx, and Lorenzon 2009; Urban, Sultan, and Qualls 2000). Through e-commerce, IPAs collect user information and listen for instructions from the user at all times, which puts smart speaker owners in a weak position (Bawack, Wamba, & Carillo, 2021). As a consequence, customers may worry more about trust issues than the advantages of personalization, which can prevent customers from buying products with the help of IPAs. When looking at this perspective, it is logical to assume that personalization may negatively moderate the perceived risk and perceived usefulness. However, As IPAs become more sophisticated in personalization, their role in e-commerce will likely grow significantly. Advancements in generative AI technology may encourage users to more readily disclose their information due to the perceived advantages of customized services. Such an interaction could create a positive feedback loop where enhanced personalization leads to increased user engagement and data sharing, which in turn, further improves personalization. In this context, numerous studies have been conducted. In the literature, this is called the privacy-personalization paradox. In one piece of research, Pal et al. (2020) approach to privacy-personalization paradox through the lens of the Privacy Calculus Framework. The framework explains users' privacy perceptions and behavioral reactions to a specific object. In this study, the authors addressed the phenomenon as a dual path (Pal et al., 2020). The first path represents the positive effects of perceived benefits and it is related to a higher level of personalization of IPAs in exchange for personal information (Smith, Dinev, & Xu, 2011). The second path represents the negative effects of perceived risks and is related to the perception of customers of a potential loss in the event of disclosure (Dinev et al., 2006; Malhotra et al., 2004). In that sense, it is a cost-benefit analysis for individuals. Since most users today are aware of their privacy rights and the potential negative consequences of revealing their personal information without proper assurances, users often evaluate the pros and cons they will have to undergo in case of such an event (Pal et al., 2020). Moreover, today, users are more eager to exchange their personal information for personalized services such as receiving birthday greetings, special discount coupons, book recommendations, travel advice, or even recipe suggestions tailored to their needs (Li, 2014; Chen et al., 2019). According to another study by Rubini (2001), consumers are happy to receive individualized care and are even prepared to watch commercials in exchange for a particular item they have been wanting. The benefits are not only limited to the customer's perspective. While users get tailored service and monetary benefits, firms collect and analyze data to design a better service and tap into their potential customer base (Pal et al., 2020). All in all, considering the sophisticated features of IPAs and the increased awareness of their privacy choices among customers, personalization could potentially create greater perceived usefulness as compared to perceived risk. Thus, this thesis proposes the following.

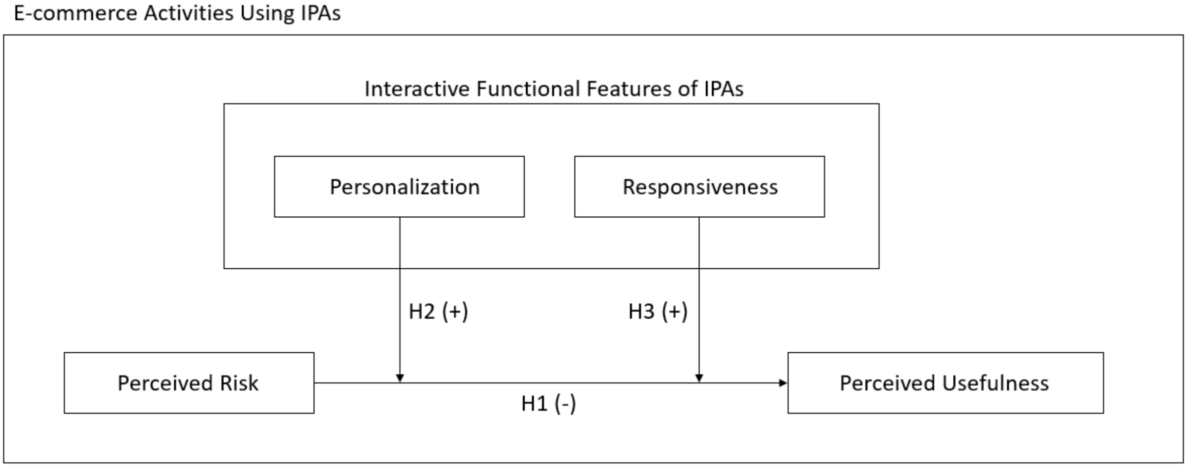
H2: The degree of personalization in IPAs used in e-commerce will positively moderate the relationship between perceived risk and perceived usefulness.

3.3. Moderation Effect of Responsiveness

In every interaction between IPAs and users, regardless of the context, customers ask questions and IPAs answer them. Through any interaction, one of the most important interactive functional features of IPAs is responsiveness, which can be defined as the capacity to quickly and accurately identify, comprehend, and respond to the needs of customers (Alalwan et al., 2020; Johnson et al., 2006; Lee, 2005; Zhao & Lu, 2012). This interaction can simply be divided into two main parts: internal process and outcome. The internal process involves the power of the algorithm and servers, where IPAs should effectively recognize and understand user queries. The outcome part is what customers receive as a result of internal processes and is where IPAs should provide timely answers to user queries. Timeliness, accuracy, relevancy, and interactivity are the key capabilities of IPAs (Alalwan et al., 2020; Guo & Luo, 2023) in the context of responsiveness, which influences people and is assumed to determine the moderation path between perceived risk and perceived usefulness. This effect is twofold. First of all, research indicates that IPA responsiveness, especially timeliness, is positively correlated with hedonic benefits, namely happiness (Mo, Zhang, Sun, & Zhou, 2024). Hedonic benefits are the emotional experiences of individuals, such as the excitement and satisfaction they derive from utilizing modern technology, like voice assistants in their homes (Schuitema, Anable, Skippon, & Kinnear, 2013). In the study of Mo et al. (2024), it is also found that perceived risk negatively affects user happiness. Considering the significant enhancements in AI-based technologies in recent years, it is assumed that, the responsiveness of IPAs can suppress the negative influence of perceived risk on happiness. Secondly, responsiveness includes accuracy and relevancy elements, which are linked to outcome quality. Improved outcome quality can positively contribute to utilitarian benefits. Utilitarian benefits in this context are the capability of IPAs which can offer useful and convenient ways of performing tasks (Hoy, 2018). Since the use of technology in the future due to utilitarian benefits is one of the main perceived usefulness components according to the TAM, it can be assumed that responsiveness will have a positive impact on perceived usefulness. Overall, IPA responsiveness is assumed to positively moderate the perceived risk-perceived usefulness relationship due to its positive contributions to both utilitarian and hedonic benefits. The following hypothesis is constructed accordingly.

H3: The degree of responsiveness in IPAs used in e-commerce will positively moderate the relationship between perceived risk and perceived usefulness.

Figure 2.
Research Model



4. Methods

4.1.Measures and Survey Construct

The questionnaire comprises three parts. The first part provides a description of the study, outlines the duration of the survey, explains how personal information will be used, details data protection, and includes a consent question for respondents regarding the utilization of data. The second part consists of two screening questions to ensure that responses are gathered from a representative sample. The screening questions are 'Have you ever experienced an IPA device or software?'(with a definition of the IPA provided), and 'Have you ever used an IPA for e-commerce purposes?'(with a definition of e-commerce provided). The survey is designed to exclude individuals who have not experienced an IPA device or software, or who have experienced it but have not used it for e-commerce purposes. The last part of the questionnaire is designed to gather respondents' answers for specific measures: perceived risk, perceived usefulness, personalization, and responsiveness.

Table 1 details the items of independent variable (perceived risk), dependent variable (perceived usefulness), and moderation variables (personalization and responsiveness).

Additionally, the survey collects data on six control variables: Age, years of experience with an IPA device or software, weekly usage frequency of an IPA device or software, type of IPA, gender, and occupation. Among these, age, years of experience with an IPA device or software, and weekly usage frequency of an IPA device or software were three numerical, ratio-type data. Age was transformed into a dummy variable to observe the impact of Gen Z and Gen Y. This was done because all respondents fell under either Gen Z or Gen Y, allowing to study to reveal possible generational differences in IPA usage in e-commerce. Gen Z was selected as the reference variable. The other two variables were kept as continuous numerical data. Gender is composed of either females or males. For this variable, dummy coding was performed by selecting females as the reference category. Likewise, occupation is categorized as either student or employed. Dummy Coding was utilized by picking the employed as the reference category. Lastly, for the IPA type, respondents were allowed multiple selections throughout the survey, resulting in non-mutually exclusive responses. Considering this, instead of dummy coding, binary categories were established for each IPA type based on the responses. All items introduced in the survey were measured using a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). Lastly, to ensure clarity, wording, understandability, and length of the measurement instruments, two academics and one fellow student from the University of Amsterdam were asked to complete and provide feedback on the questionnaire. The survey was distributed online to the University of Amsterdam, Middle East Technical University, and Ihsan Dogramaci Bilkent University members. University members such as students, alumni, and academics were intentionally selected to acquire comparably reliable outcomes, assuming, these people were inclined to answer questions with greater conscientiousness. The data collection process took place between April and May 2024.

Table 1.
Measures of Construct.

Constructs	Items	Sources
Personalization	Q1 - Intelligent Personal Assistants offer me personalized services. Q2 - Intelligent Personal Assistants understand my specific needs. Q3 - Using the Intelligent Personal Assistants can provide me with the type of products that I might like.	Roy et al. (2017) Pal et al. (2020)
Responsiveness	Q1- Intelligent Personal Assistant respond my input quickly. Q2 - Intelligent Personal Assistant are always ready to serve me. Q3 - Intelligent Personal Assistants are always able to respond to me in time. Q4 - Whenever I seek assistance from Intelligent Personal Assistants, I consistently receive responses quickly.	Chen et al. (2022a)
Perceived Usefulness	Q1 - Using Intelligent Personal Assistant increases my consumption ability. Q2 - Using Intelligent Personal Assistant enables me to search for products or services faster. Q3 - Using Intelligent Personal Assistants enhances my effectiveness when shopping. Q4 - Overall, Intelligent Personal Assistants are useful when shopping.	Hsiao & Chang (2014)
Perceived Risk	Q1 - I can trust that my Intelligent Personal Assistant will not misuse my financial/personal information. Q2 - I can rest assured that my Intelligent Personal Assistant will protect my financial/personal information with the highest security standards. Q3 - I am not worried about the possibility of my Intelligent Personal Assistant misusing the financial or personal information that I provide	Bawack et al. (2021)

4.2. Data Collection

A total of 400 responses were obtained. First, 5 respondents who did not give their consent for the study were eliminated. Then, 248 individuals who could not pass the screening questions were cleared. Afterward, 11 respondents who provided incorrect answers to attention check questions were excluded. Subsequently, outlier boundaries were determined using the interquartile range (IQR) method (Tukey, 1977), and 35 outlier answers were eliminated. Finally, a meanwise substitution was used for 13 respondents to handle missing data. After these steps, 101 respondents remained for the analysis.

Table 2 presents the demographics of the respondents. Among the 101 respondents analyzed, females comprised 71.3% and males 28.7%. All respondents are either GenZ or GenY. GenZ respondents, aged 18 to 27 years, constitute 73.3% of the sample. GenY respondents, aged 28 to 43 years, make up 26.7%. Almost all respondents, 97%, hold a higher education diploma. Only 1% have some college or an associated degree, and 2% percent have a high school diploma or below. Additionally, 58.4% of the participants are students and the remaining 41.6% are employed. Lastly, 25.7% of the respondents have an annual household income of $10K or less, followed by 36.6% with an income between $10K and $50K (inclusive). Additionally, 23.8% have an income between \$50K and \$100K (inclusive), 12.9% have an income between \$100K and \$150K (inclusive), and only 1% have more than \$150K.

Table 2
Demographic Information of Respondents (n=101).

Measure	Category	Frequency	Percent
Age			
	Gen Z: Borned between and including 1997-2010	74	73.3
	Gen Y: Borned between and including 1981-1996	27	26.7
Gender			
	Female	72	71.3
	Male	29	28.7
Education			
	High school diploma and below	2	2.0
	Some college or associated degree	1	1.0
	Higher education (Bachelor's degree and above)	98	97.0
Annual Household Income (in USD)			
	≤ 10K	26	25.7
	10K < Annual Household Income ≤ 50K	37	36.6
	50K < Annual Household Income ≤ 100K	24	23.8
	100K < Annual Household Income ≤ 150K	13	12.9
	≥ 150K	1	1.0
Occupation			
	Student	59	58.4
	Employed	42	41.6

Table 3 shows control variable descriptive statistics. The age, gender, and occupation descriptive statistics were already discussed in '*4.1. Measures and Survey Construction'*. In addition to these, the numerical control variable, "years of experience with an IPA device or software" has a mean value of 3.51 years with a standard deviation of 2.37 years. Another numerical control variable, "weekly usage frequency of IPA devices or software" has a mean value of 11.99 times per week with a standard deviation of 10.14 times per week. The last control variable is the type of IPA, which is composed of four types: Type 1: Alexa (Amazon), Type 2: Google Assistant (Google), Type 3: Siri (Apple), and Type 4: ChatGPT (OpenAI) with frequencies of 16, 34, 57, and 66, respectively.

4.3. Models

Four models were constructed to analyze the research model. In Model 1, the direct relationship between perceived risk and perceived usefulness was analyzed by using linear regression analysis. In SPSS, Perceived risk, perceived usefulness, personalization, and responsiveness constructs were transformed into composite scores. Control variables and

Table 3
Control Variable Descriptive Statistics.

Measure	Category	Mean	Standar Deviation	Frequency	Percent
Experience with an IPA Device or Software (Years)		3.50	2.37		
Usage frequency of IPA devices or software		11.99	10.14		
Age					
	Gen Z: Borned between and including			74	73.27
	Gen Y: Borned between and including			27	26.73
Gender					
	Female			72	71.29
	Male			29	28.71
Occupation					
	Student			59	58.40
	Employed			42	41.60
Type of IPA					
	Type 1: Alexa (Amazon)			16	
	Type 2: Google Assistant (Google)			34	
	Type 3: Siri (Apple)			57	
	Type 4: ChatGPT (OpenAI)			66	

composite scores of perceived risk and perceived usefulness were included in the regression analysis. For Models 2 and 3, the moderation effects of personalization and responsiveness were analyzed, respectively. Analyzing these moderation effects required interaction terms. To create these terms, first, the independent variable and moderator variables are centered to avoid multicollinearity. Then, the independent variable was multiplied by each moderator variable to create two interaction terms. In Model 2, the interaction term for perceived risk and personalization was labeled as PR_PA. In Model 3, the interaction term for perceived risk and responsiveness was labeled as PR_RE. Regression analysis was then conducted to reveal the moderation effects. Finally, in Model 4, composite scores of main constructs, interaction terms, and control variables were used together in the regression analysis to understand the overall construct. Table 4 contains the summary of each model.

Table 4.
Model Summary.

Model	Aim	Variables Used	Analysis Method
1	Analyze the direct relationship between Perceived Risk and Perceived Usefulness	CVs + CmpPR	Linear Regression
2	Analyze the moderation effect of Personalization on the relationship between Perceived Risk and Perceived Usefulness	CVs + CmpPR + CmpPA + PR_PA	Moderated Regression
3	Analyze the moderation effect of Responsiveness on the relationship between Perceived Risk and Perceived Usefulness	CVs + CmpPR + CmpRE + PR_RE	Moderated Regression
4	Analyze the combined effects of Perceived Risk, Personalization, and Responsiveness on Perceived Usefulness	CVs + CmpPR + CmpPA + CmpRE + PR_PA + PR_RE	Combined Regression

Note: CVs = Control variables, CmPR = Composite scores of perceived risk, CmpPA = Composite scores of personalization, CmpRE = Composite scores of responsiveness, PR_PA = Interaction effect of perceived risk and personalization, PR_RE = Interaction effect of perceived risk and responsiveness

4.4. Measurement Assessment

To confirm scale reliability, Cronbach's alpha values were calculated and shown in Table 5 for the independent, dependent, and moderator variables. Except for the personalization element (α = 0.633), all values exceeded the 0.7 threshold, confirming scale reliability. For personalization, three elements that constitute personalization were examined by item-total statistics to determine whether reliability could be improved if an item was deleted. None of the constitutions improved internal consistency in case of deletion. Furthermore, Exploratory Factor Analysis (EFA) was performed for the same three elements to check if items contributed to the same underlying factor. All items had greater loadings than the threshold value of 0.4, indicating they contributed to the same underlying factor. Thus, personalization value was retained without a change. Item-total statistics are detailed in Table 6. Before proceeding to

Table 5.
Cronbach's Alpha Values.

Constructs	Cronbach's Alpha
Perceived risk	0.749
Perceived Usefulness	0.832
Personalization	0.633
Responsiveness	0.811

Table 6.
Item-Total statistics values.

Item	Cronbach's Alpha if Item Deleted
Personalization_1	0.580
Personalization_2	0.524
Personalization_3	0.508

regression analysis, skewness and kurtosis values of the main constructs and continuous control variables were examined to ensure normal distribution. A normality test was also conducted for this purpose. Skewness and Kurtosis values for independent, dependent variables and moderators were within the range of [-1,1], meaning that they follow a normal distribution. However, the normality test rejected the null hypotheses (H0: The data follows a normal distribution) for all but perceived risk. Due to this contradiction, residual investigation was performed for direct relationships, moderator analysis, and control variables since regression analysis assumes normally distributed residuals, not predictors. Skewness and kurtosis values for unstandardized residuals were measured, and Q-Q plots were observed. Consequently, all residuals were determined to be normally distributed.

5. Results

Table 7 shows the means, standard deviations, and correlations among the variables of this study. The correlation levels are lower than 0.4 in all cases, confirming the variables' discriminant validity. Table 8 is composed of four models. The first model, Model 1, tests Hypothesis 1. Hypothesis 1 was constructed to understand the direct relationship between perceived risk and perceived usefulness. A linear regression model was run to test it. The coefficient of perceived risk turned out positive (β=0.133), indicating a positive correlation, but

Table 7.
Descriptive Statistics and Correlations.

	Mean	Std. Deviation	1	2	3	4	5	6
(1) Perceived Risk	3.890	1.199	1					
(2) Perceived usefulness	5.245	1.012	0.103	1				
(3) Personalization	5.263	0.565	0.132	0.203*	1			
(4) Responsiveness	5.899	0.742	-0.057	-0.009	0.071	1		
(5) Experience	3.510	5.512	0.092	-0.126	0.138	-0.083	1	
(6) Frequency	3.506	2.307	0.022	0.128	0.177	0.013	0.058	1

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

it was insignificant. Additionally, none of the control variables showed statistical significance in explaining perceived usefulness. The overall model is also statistically insignificant, meaning that H1 is not supported.

Model 2 tests Hypothesis 2. Hypothesis 2 was established to understand the moderation effect of personalization on the main construct. The results indicated that the moderation effect of personalization is negative (β=-0.024) and insignificant. On the other hand, the direct effect of personalization in the model has a positive impact (β=0.347) and is significant at a 10% significance level. Furthermore, the effect of years of experience with an IPA becomes apparent

Table 8.
Results of regression analysis.

Variable	Direct Relationship Model 1		Moderation Effect - Personalization Model 2		Moderation Effect - Responsiveness Model 3		Full Model Model 4	
	β	SE	β	SE	β	SE	β	SE
Perceived risk	0.133	$(0.090)^{n.s}$	0.108	$(0.091)^{n.s}$	0.149	(0.089)†	0.124	$(0.091)^{n.s}$
Personalization			0.347	$(0.189)^{\dagger}$			0.319	(0.189)†
Responsiveness					0.020	$(0.150)^{n.s}$	-0.005	$(0.150)^{n.s}$
PR_PA			-0.024	$(0.147)^{n.s}$			-0.022	$(0.146)^{n.s}$
PR_RE					0.232	(0.114)*	0.217	(0.113)†
Experience	-0.072	$(0.048)^{n.s}$	-0.083	(0.049)†	-0.089	(0.049)†	-0.098	(0.049)*
Frequency	0.016	$(0.011)^{n.s}$	0.012	$(0.011)^{n.s}$	0.021	(0.011)*	0.018	$(0.011)^{n.s}$
GenY	0.106	$(0.312)^{n.s}$	0.078	$(0.311)^{n.s}$	0.170	(0.311)†	0.145	$(0.311)^{n.s}$
Gender	0.151	$(0.236)^{n.s}$	0.130	$(0.239)^{n.s}$	0.109	$(0.236)^{n.s}$	0.095	$(0.237)^{n.s}$
Occupation	-0.293	$(0.268)^{n.s}$	-0.287	$(0.266)^{n.s}$	-0.231	$(0.266)^{n.s}$	-0.229	$(0.265)^{n.s}$
Alexa	-0.055	$(0.293)^{n.s}$	-0.063	$(0.297)^{n.s}$	-0.088	$(0.306)^{n.s}$	-0.078	$(0.311)^{n.s}$
Google Assistant	0.005	$(0.224)^{n.s}$	-0.059	$(0.226)^{n.s}$	0.083	$(0.227)^{n.s}$	0.013	$(0.230)^{n.s}$
Siri	-0.206	$(0.224)^{n.s}$	-0.208	$(0.224)^{n.s}$	-0.259	$(0.223)^{n.s}$	-0.255	$(0.223)^{n.s}$
ChatGPT	0.165	$(0.240)^{n.s}$	0.179	$(0.239)^{n.s}$	0.143	$(0.237)^{n.s}$	0.156	$(0.237)^{n.s}$
Intercept	4.905	(0.470)*	3.285	(0.997)*	4.705	(1.016)***	3.376	(1.283)*
R	0.327		0.374		0.384		0.419	
R^2	0.107		0.140		0.148		0.176	
Adjusted R^2	0.006		0.021		0.030		0.040	
p-value	0.400		0.309		0.259		0.229	
F value	1.062		1.181		1.257		1.293	
Observations	101		101		101		101	

†p < 0.1
*p < 0.05
**p < 0.01.
***p < 0.001
n.s = not significant (two-tailed).
Notes: PR_PA = Interaction term of personalization and perceived risk. PR_RE = Interaction term of responsiveness and perceived risk.

with the introduction of the personalization element and, has a negative (β=-0.083) and significant (p<0.1) impact. Model 2 fails to reject the null hypothesis, and thus H2 is not supported.

Model 3 tests Hypothesis 3. Similar to the second hypothesis, the model aims to understand the moderation effect of responsiveness. According to the results, the moderation effect of responsiveness is positive (β=0.232) and statistically significant (p<0.05). Thus, Hypothesis 3 is supported. The finding of the moderation effect is shown in Figure 3. In contrast, the direct responsiveness effect is insignificant with a positive contribution (β=0.020). For control variables, experience, frequency, and generational effects become significant with the presence of responsiveness. Experience has a negative impact (β=-0.089), frequency has a positive contribution (β=0.021), and Gen Y shows a positive inclination (β=0.170) compared to Gen Z.

The last model, Model 4, contains all elements and shows the overall construct of the research. While direct contributions of perceived risk and personalization are positive (β=0.124 and β=0.319 respectively), responsiveness has a weak, negative impact (β=-0.005). The direct effect of personalization is statistically significant at the 90% confidence interval (p<0.1).

Figure 3.
Effect of responsiveness.

Moreover, the moderation effect of responsiveness shows a positive, significant effect (β=0.217, $p<0.1$) while the moderation term for personalization indicates a negative, insignificant impact (β=-0.022). Additionally, only the experience control variable indicated a significant impact ($p<0.05$), again, in the negative direction (β=-0.098).

6. Discussion

6.1. Key Insights, Theoretical and Practical Implications

Customers are inclined to use IPAs for shopping for several reasons, particularly, time efficiency and seamless shopping (Klaus & Zaichkowsky, 2020; Reisinger, 2018). However, using these devices brings privacy concerns as IPAs offered through continuous listening features (Cloarec, 2020; Kinsella & Mutchler, 2018b). Companies rely on listening features to meet customers' expectations as customers deem more and more quality. This situation creates a paradox of disclosure of a certain degree of privacy in exchange for getting enhanced service. This significant phenomenon contains customers on one hand, and businesses on the other. Examining the direct relationship between perceived risk and perceived usefulness and understanding the possible moderations of the main construct in this context is crucial both for contributing to the literature and encompassing the practical implications for service providers. The study revealed several key takeaways, highlighting the bidirectional nature of the interactions between customers and businesses, as well as between perceived risk and perceived usefulness.

First of all, perceived risk was found statistically insignificant element in explaining the perceived usefulness when using IPA for e-commerce purposes, contrary to several academic articles. As explained in the study by Yun et al. (2013), a high level of privacy concerns reduces performance expectancy, and performance expectancy in turn declines continuous usage. The differentiation of this study's results from the existing literature could lie in the different expectations and perceptions of generations. Most of the past articles including Yun, Han, and Lee, (2013) and Martins, Oliveira, and Popovic, (2014), consider and measure perceived usefulness mostly from a utilitarian perspective, focusing on the performance aspect of new technologies. Additionally, TAM shows a similar approach in explaining intended behavior. TAM is a method of understanding the intended behavior of individuals when a new, task-related IT is introduced (Gefen, Karahanna, & Straub, 2003). However, the sample of this study is mostly composed of Gen Z individuals who were born into the center of technological advancements. New generations of IPA users might not view the e-commerce experience as merely a task-related endeavor but rather perceive it as an entertaining activity, closely related to hedonic factors, and influenced by psychological or emotional elements. From this perspective, TAM might not be the best-suited theoretical base for examining e-commerce activities that use new technologies for new generations. According to the results, the uses and gratification theory (U&GT) (Katz et al., 1974) can establish a more fundamental and inclusive perspective. This theory explains that people select media according to hedonic and symbolic gratifications, and psychological (utilitarian) demands (Grellhesl and Punyanunt-Carter, 2012; Katz et al., 1974; McLean and Osei-Frimpong, 2019). Among these three categories, hedonic gratifications, in particular, could be the main reason influencing the relationship between perceived risk and perceived usefulness. New generations, as opposed to older ones, may focus more on hedonic gratifications, whereas older generations mostly emphasize a utilitarian perspective. In this sense, this study reveals the complex nature of perceived usefulness when a new IT is introduced. It also encourages further research on the interplay of perceived risk, perceived usefulness, and hedonic gratifications from the perspective of new generations.

Secondly, valuable findings are acquired regarding the moderation effect of personalization. As can be recalled, there are two schools of thought on the moderation effect of personalization in the literature. On one hand, primarily due to IPAs' continuous listening features and the collection of users' personal information, people hesitate to use these devices for voice shopping (Bawack et al., 2021). Moreover, the disclosure of personal information brings trust issues in e-commerce, which is the main influence on buying intentions (McStay, 2011; Urban, Amyx, and Lorenzon, 2009; Urban, Sultan, and Qualls, 2000). Eventually, the rise in privacy concerns and hesitation due to continuous listening features leads to a negative contribution of personalization on the perceived risk-perceived usefulness relationship. On the other hand, some studies, including this thesis, stand on the opposite side of the privacy-personalization paradox. Pal et al. (2020) claim that people are now more aware of their privacy choices and can better assess the consequences of information disclosure. Furthermore, consumers are happy to share personal information in exchange for tailored products and services (Rubini, 2001). As a result, enhanced personalized recommendations improve the main relationship. The outcomes of this study showed results contrasting with the initial hypothesis, revealing indications that support the first school of thought.

Thirdly, the p-value of the interaction effect for responsiveness is significant at the 5% significance level, indicating a significant moderation for the perceived risk and perceived usefulness relationship in the positive direction. As can be seen in Figure 3, intercept values for the two lines are almost the same. This indicates that for the low level of perceived risk, the level of responsiveness does not distinguishably influence the perceived usefulness. However, as the perceived risk increases, the high responsiveness of IPAs contributes meaningfully to the perceived usefulness. The outcome suggests that when these devices can provide accurate, timely, and relevant information interactively, they can mitigate the detrimental effects of risk perception of customers. This is a significant insight for developers in practical implications. Responsiveness can be used strategically to enhance user acceptance of these devices, especially for risk-averse customers.

Another key insight according to the results is the negative contribution of the years of experience on perceived usefulness. Even though the effect is small, the impact of experience is apparent with the introduction of personalization and responsiveness. This can be caused simply by a mismatch between experienced customers' expectations and the current offerings of IPAs. While people using IPAs in e-commerce for the first time, might be amazed by its capabilities, responses to queries, and level of interaction, experienced users might expect more than what IPAs currently provide. Even though generative AI technologies have been rapidly evolving toward a more useful landscape, these implementations are still in their early stages and may not yet satisfy the demands of experienced customers. As the years pass and generative AI-backed technologies become more sophisticated, this relationship is likely to change. Determining the interplay of timeliness, accuracy, relevancy, and interactivity in user experience can be crucial for companies aiming to understand the complex nature of user value perception. This understanding could help entities develop solid e-strategies. E-strategies can be formulated based on the customer's mindset, which can be examined based on functional or hedonistic needs (Quix, 2022). While functional needs focus on efficiency and convenience, hedonic elements are based on experience. The results indicate that enhancing the responsiveness capabilities of IPAs can play a crucial role in effectively integrating hedonistic and functional needs of customers which will lead to a seamless e-commerce experience.

The introduction of responsiveness also highlights the positive contribution of weekly IPA usage frequency to perceived usefulness. People using these technologies more frequently are assumed to be technology-savvy and integrate modern, technology-based products and services into their daily lives. These individuals are likely to understand the capabilities of these devices, prompting better, and know what to expect. Infrequent users, on the other hand, may encounter challenges when utilizing these devices for e-commerce, as they might lack understanding of the optimal methods for voice inputs or the expected responses, potentially leading to decreased satisfaction. The outcome indicates different behavioral segments towards IPA products (frequent users and infrequent users) and could help companies with the behavioral segmentation of their customers. Behavioral segmentation, also known as ex-post-facto segmentation, can help precisely detect customer needs related to product requirements and usage. This insight allows companies to develop IPAs in a more customer-centric manner in the future.

Lastly, responsiveness brings significance to generational differences. All respondents of this study were either Gen Z or Gen Y. This provides a chance to see whether there are generational differences. The results revealed that being part of Gen Y is associated with an increase in perceived usefulness as compared to Gen Z when responsiveness is introduced. This difference could stem from expectations of new technologies. As GenY grew up during the rise of the internet and witnessed the transition from basic to sophisticated technologies, they might be inclined to value to functional perspective of IPAs during e-commerce. In contrast to that, Gen Z are digital natives, born and surrounded by advanced technologies. They are likely to focus on the experience, entertainment, and interaction aspects of IPAs rather than the functionality.

6.2. Limitations and Further Research

The study's main limitation is the sample size. The target group, people who use Intelligent Personal Assistants (IPAs) for e-commerce, is niche. While 89% of the initial 400 respondents owned IPAs, only 45% used them for e-commerce. Moreover, after handling missing data, only 25% (101 respondents) of the total respondents were valid for the study. This means that approximately 1,550 people would have been needed to capture a sufficient sample size, as the common rule of thumb suggests 385 participants for a 95% confidence interval and 5% margin error in a large population (>100,000). Due to time and resource limitations, the broad range could not be reached. However, several techniques were used to mitigate the margin of error. With the increased adoption of IPAs for e-commerce, future studies can achieve greater accuracy by capturing a sufficient sample size.

As AI-based technologies become more integrated into daily life, further studies can explore how IPA features can impact perceived usefulness in e-commerce. In upcoming research, diversifying control variables is crucial and could help identify influencing factors on user value, as this study shows the complex nature of these interactions. Additionally, theories containing hedonic factors when explaining the adoption of new technology, such as U&GT, can be selected and utilized for upcoming studies to reveal more comprehensive results.

7. Conclusion

Perceived risk and perceived usefulness in the context of e-commerce by using IPAs were investigated in this study, with a focus on the moderating roles played by responsiveness and personalization. The aim was to understand how the risk-usefulness relationship dynamics work, how interactive functional characteristics affect this relationship, and which elements could be the contributors to user value when generative AI hype becomes a key part of our lives. The findings indicate that while perceived risk alone is not statistically significant in explaining perceived usefulness, the responsiveness of IPAs can mitigate negative perceptions of risk. This suggests that users value timely, accurate, and relevant responses from their IPAs, which can mitigate privacy concerns and enhance the overall user experience. Additionally, Personalization anticipated to play a positive moderating role was found not to show a significant effect in this study. The findings highlight the complex interplay between user expectations, privacy concerns, and perceived usefulness. The research contributes to the academic understanding of user interactions with AI-driven e-commerce technologies by illustrating the importance of responsive design. Additionally, it also provides practical insights for entities aiming to improve user experience with IPAs. Lastly, the study highlights how years of experience, weekly usage frequency, and generational differences can play a role in enhancing perceived usefulness.

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