‘Okay Google, What About My Privacy?’: User’s Privacy Perceptions and Acceptance of Voice Based Digital Assistants

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Abstract

Conversational Artificial Intelligence (AI) backed Alexa, Siri and Google Assistants are examples of Voice-based digital assistants (VBDA) that are ubiquitously occupying our living spaces. While they gather an enormous amount of personal information to provide bespoke user experience, they also evoke serious privacy concerns regarding the collection, use and storage of personal data of the consumers. The objective of this research is to examine the perception of the consumers towards the privacy concerns and in turn its influence on the adoption of VBDA. We extend the celebrated UTAUT2 model with perceived privacy concerns, perceived privacy risk and perceived trust. With the assistance of survey data collected from tech-savvy respondents, we show that trust in technology and the service provider plays an important role in the adoption of VBDA. In addition, we notice that consumers showcase a trade-off between privacy risks and benefits associated with VBDA while adopting the VBDA such technologies, reiterating their calculus behaviour. Contrary to the extant literature, our results indicate that consumers’ perceived privacy risk does not influence adoption intention directly. It is mediated through perceived privacy concerns and consumers’ trust. Then, we propose theoretical and managerial implications to conclude the paper.

Keywords:

Voice Based Digital Assistants, Privacy Concerns, Privacy Risk, Trust, Technology Adoption

1. Introduction

Over the last few years, VBDA backed by cutting-edge AI technologies have emerged as an important trend in consumer electronics goods (Kowalski, 2020). Though they were originally intended to be a voice-based, AI-driven, interactive feature that would allow consumers to use their smartphones in a novel way, digital assistants such as Siri, Alexa, and Google Assistant are now being integrated into consumer devices such as speakers, vehicles, TVs, and wearables (Fowler, 2018). One of the most significant advantages of a digital assistant is the conversational interface. As interaction is through natural language, it is more intuitive and easier to use than hand-keypad input-based web and mobile interfaces (Zhong & Yang, 2018). Using cutting-edge AI technologies, digital assistants observe and process complex data in real-time to facilitate information retrieval based on user input. They can also perform tasks on behalf of users such as booking appointments, playing music, and ordering groceries. Digital assistants refine their responses based on past task feedback and thus improve over time, which allows for extensive personalisation (Wollerton, 2019).

However, despite their benefits, AI-based digital assistants have given rise to far-reaching privacy and security concerns (Agrawal, Gans, & Goldfarb, 2018; Shin, Zhong, & Biocca, 2020). Digital assistants collect sensitive and private data related to users' location history, contacts, calendars, voice queries, browsing history, and purchase history (Gardiner, 2018). According to a report by Microsoft Bing Ads, 41 per cent of those surveyed expressed distrust of digital assistants and believed that they compromise privacy through passive listening; further, about 52 per cent said that they were worried that their personal information is not secure (Olson & Kemery, 2019).

Despite the ubiquity of VBDA, there have been limited studies to understand adoption challenges (Ostrom, Fotheringham, & Bitner, 2019), where adoption refers to acceptance of technology into everyday life of the consumers and subsequent use (Vannoy & Palvia, 2010). Table 2 lists the extant research exploring the adoption of VBDA. Existing studies related to the adoption of digital assistants are limited to a western individualistic socio-technical context (Liao, Vitak, Kumar, Zimmer, & Kritikos, 2019) and sheds limited exposure to the eastern collectivist societies like India. Given privacy concerns related perspective vary considerably between the individualistic and collectivists (Leidner & Kayworth, 2006; Milberg, Burke, Smith, & Kallman, 1995) and these concerns are central to the adoption of VBDA, studies exploring them in the collectivist society are essential for our overall understanding of these phenomenon. Further, the studies have also called for the development of comprehensive models of adoption of AI based technologies such as VBDA (Fernandes & Oliveira, 2021). Thus, there is a need to go beyond the technological approach to develop a theory-based understanding of acceptance of AI-based digital technologies, which takes into account both enablers such as its value to users and inhibitors such as privacy and security concerns from the perspective of a collectivist society such as India.

The current study attempts to address this gap by analysing the factors affecting consumers' acceptance and subsequent use of AI-based digital assistants. We identify the factors that influence the acceptance of AI-based technologies and conceptualise and test a research model based on the extant literature and theoretical background. Our theoretical model expands the set of antecedents beyond the established constructs of the Unified Theory of Acceptance and Use of Technology model (UTAUT2) and investigates the acceptance and use of digital assistants by including AI-specific variables such as Perceived Trust, Perceived Privacy Concerns, and Perceived Privacy Risk. We adopt and extend UTAUT2 in the context of VBDA because we believe this is the most compressive technology adoption model from the consumer technology perspective and the privacy related constructs and relationships are borrowed from the seminal work by Dinev and Hart (2006). Thus, this research integrates two seminal works to develop an integrated and comphrensive theoretical framework for adoption of VBDA and thus address the research calls for comphensive theories.

Thus, the aim and potential contributions of this study are two-fold:

1. To develop a comprehensive theory of adoption of VBDA by integrate the UTAUT2 and privacy calculus theories and
2. To examine the efficacy of the integrated theory for adoption VBDA from perspective of a collectivist society

Through an empirical investigation our results depict that all the relationships established in the UTAUT2 were significant in the context of VBDA. However, the privacy related relationships produced interesting results and thus are significant contribution to the literature. The privacy risk had a strong negative influence on the perceived trust and positively associated with concerns. The trust has positive influence on performance expectance and behavioural intention. Surprisingly, despite having a significant influence on PPC and trust, perceived privacy risk did not show any significant influence on the adoption behaviour of consumers. The post-hoc analysis also show that people who believe VBDA to be useful cared less about privacy concerns compared to those who perceived VBDA are not so useful. Thus, iterating the privacy calculus behaviour when adopting the VBDA.

The rest of the paper is organised as follows. First, we begin with a brief literature review of VBDA, UTAUT2, and privacy concerns. Then, we will propose an extended model of UTAUT2 that includes privacy-related variables such as perceived risk, trust, and privacy concerns. Further, we test the proposed model with data collected from over 250 individuals and present the results. Finally, we conclude our paper with a brief discussion of theoretical and practical implications.

2. Theoretical Background and Related Work

2.1 VBDA as a Cutting-edge Technology: A Review of Characteristics

People have always dreamed of computers as virtual buddies and attempts to realise this dream have been on-going since the early twentieth century. One of the unique capabilities of humans that separate us from other living entities is our linguistic capabilities and our ability to communicate thoughts through spoken languages (Harari, 2014). Thus, attempts to make computers human-like have centred on making them understand natural languages and communicate through voice. The introduction of the voice-activated toy, Radio Rex, in 1911 (Krazit, 2010), IBM Shoebox, a voice-based calculator, in 1962, and ELZA, a chatbot based on natural language processing in the 1960s (Epstein & Klinkenberg, 2001) were all attempts to make computers more human-like assistants. However, technology in this arena has made some astonishing leaps in the past decade. The introduction of Apple's Siri in 2012 as part of iPhone 4S marked this transition. Then Google Assistant and Amazon's Alexa entered the fray with their amazing capabilities. Technological advancements such as conversational AI, the exponential growth in the processing power of modern computers, and the sheer amount of information available over the internet to these tech giants helped transform these VBDA into cutting-edge technologies. Though they appear simple from the outside, the sheer level of innovation and their amazing learning capabilities will surely enhance their reach. As more and more things get internetised through the Internet of Things, these VBDA will become a central point of contact to connect with and control multiple devices. Such proliferation will change the fundamental landscape of consumer interactions with these artefacts. However, to customise such VBDA, tech organisations collect enormous amounts of personal data, making them a significant threat to privacy and protection of personal information. In this context, it is necessary to understand the attitudes of consumers in adopting these technologies and their apprehensions with regards such technologies, if any.

VBDAs are unique and different from other technologies (Table 1). These technologies emulate human like traits by conversing with the consumers in natural language. They are hands free and controlled by voice-based interface (McLean & Osei-Frimpong, 2019). Their human personification and conversational style have made consumers to perceive and interact with them in intimate ways. Given their access to cutting edge technologies and data collected by tech-giants have made them efficient and capable of delivering personalised services (Fernandes & Oliveira, 2021). These unique characteristics of VBDAs such as Alexa, Siri or Google have made them ubiquitous on all them mobile phones (Kaplan & Haenlein, 2019) and are expected to adopted by one-third of US population by 2021 (E-Marketer, 2019).

While on the one hand, cutting-edge technologies like VBDA are proliferating in our daily life, and on the other, privacy and personal data concerns are multiplying, the literature on the adoption of these technologies are still in early stages. Given the highly sensitive micro-phones, always listening functionality and their presence in private spaces have raised severe privacy and data security concerns among the western developed societies (Foehr & Germelmann, 2020). Theory of reasoned action (TRA; Fishbein and Ajzen 1975), theory of planned behaviour (TPB; Ajzen 1985), and the technology acceptance model (TAM; Davis 1989) have thus far been the most common theories to explain technology adoption. Particularly, technical reviews of IT adoption literature (Dwivedi & Williams, 2008; Williams, Rana, & Dwivedi, 2015) report that TAM and its extensions such as UTAUT/UTAUT2 are the most popularly used theories to study IT acceptance behaviours in general. We believe that TAM can provide us with a suitable starting point to understand users' adoption of VBDA, and thus we will first discuss TAM and UTAUT/UTAUT2. Then, we will explore the literature on privacy to investigate the theoretical frameworks available to examine the influence of privacy concerns on adoption behaviour.

Table 1: Unique Characteristics of Voice Based Digital Assistants

Sr. No.	Characteristics of VBDA
1	Human personification in its interaction
2	Natural and Conversational style of Interface
3	Highly sensitive always-on microphones for always listening
4	Personalized and efficient service delivery
5	Hands free, controlled by voice

2.2 Adoption of Technology

The generalisability, measurability, and simplicity of TAM make it one of the most cited, mature, and established theories in information systems (IS) (V Venkatesh, Thong, & Xu, 2016). TAM was first proposed by Davis et al. (1989). Over the years, TAM has evolved, as researchers have enhanced the theory with additional constructs and extensions that have improved the applicability of the theory (Singh, Chandwani, & Kumar, 2018). In 2003, Venkatesh et al. (2003) aggregated different models of technology acceptance into a unified theory of acceptance and use of technology (UTAUT). UTAUT identifies four key factors and four moderators and is intended to study technology acceptance at the organisational level. Recognising the penetration of mobile phones, PCs, and the internet at the individual consumer level, Venkatesh et al. (2012) proposed a newer version of UTAUT (popularly known as UTAUT2) that had an additional construct. The newer UTAUT2 was able to explain almost 74 per cent of the variations in the adoption and use of technology at the individual level (Venkatesh, Thong, & Xu, 2016).

Technology adoption can be studied among different levels of users in an organisation, different types of users, and for different technologies. Some studies have examined technology adoption at the group and organisation level (e.g., Sarker and Valacich 2008; Sarker et al. 2005; Sia et al. 2002, 2004); among employees at different levels within organisations, such as senior managers, middle-level managers, and operational personnel (Hong, Thong, Chasalow, & Dhillon, 2011); and among a targeted group of users such as teachers (Pynoo et al., 2011) or physicians (Chang, Hwang, Hung, & Li, 2007). Studies have also looked into the adoption of mobile services (Wang, Liu, & Fan, 2011) and e-government services (Viswanath Venkatesh & Sykes, 2013) at the individual level and in different types of organisations such schools (Pynoo et al., 2011), government organisations (Gupta, Dasgupta, & Gupta, 2008), and hospitals (Chang et al., 2007). They have also looked at the adoption of different types of technologies such as the internet (Gupta et al., 2008), agile IS (Hong et al., 2011), digital learning (Pynoo et al., 2011), mobile banking (Alalwan, Dwivedi, & Rana, 2017), and e-government services (Venkatesh, Thong, Chan, & Hu, 2016).

Our literature survey of studies examining VBDA shows the current literature have used various theories of adoption and even the earlier versions of TAM and UTAUT (Table 2). However, we could not find any studies utilising the consumer centric technology adoption models like UTAUT2 on cutting-edge technologies like VBDA. Artificial intelligence and machine learning (ML)–driven VBDA have radically changed the way we interact with technology. Users can simply speak to their devices without even raising a finger. Since the introduction of Siri in 2012, the technology behind digital assistants has advanced in leaps and bounds. The growing penetration of mobile phones, low-cost internet access, and the increased support for native languages has made these VBDA accessible to ordinary individuals in a developing country like India. However, access to technology does not always lead to adoption. Thus, we believe this is an important moment to examine the challenges and opportunities in the adoption of VBDA.

Table 2: Empirical Studies on VBDA in the extant literature

Sr.	Paper Ref.	Objective	Key constructs	Context	Findings	Future Call
1	(Kowalczuk, 2018)	Building on technology acceptance research, this study aims to develop and test an acceptance model for investigating consumers' intention to use smart speakers.	Perceived Usefulness, Perceived Enjoyment, Privacy Risk and Surveillance Risk, System Qualtiy, System Diversity and Technology Optimism	Germany	Besides perceived ease of use and perceived usefulness, the quality and diversity of a system, enjoyment, consumer's technology optimism and risk (surveillance anxiety and security/privacy risk) strongly affect the acceptance of smart speakers. Among these variables, enjoyment had the strongest effect on behavioral intention to use smart speakers.	Data is gathered from Germany and in order to assess the generalisability, studies need to focus on other countries
2	(McLean & Osei-Frimpong, 2019)	This research aims to further our understanding by taking a Uses and Gratification theory (U&GT) approach to understand the use of voice assistants focusing on voice interactions,	Utilitarian benefits, Hedonic Benefits, Symbolic Benefits, Social presence, Social Attraction	United Kingdom	Individuals are motivated by the (1) utilitarian benefits, (2) symbolic benefits and (3) social benefits provided by voice assistants	Future research should further consider the role of perceived privacy concerns. Researchers should further examine the concerns of users in their interactions with voice assistants.
3	(Yang & Lee, 2019)	To develop a comprehensive research model, based on perceived value theory, to explain potential customers' intentions to adopt and use VPA devices.	Perceived Usefulness, Perceived Enjoyment, Portability, Automation, Content Quality, Visual Attractiveness	United States	Though, PU and PE both are significantly influencing the adoption, PE has higher impact than PU. Content Quality influencess PU and Attractivenss influences both PU and PE.	Need to Study Security and Privacy related risks associated with Virtual personal assistance

4	(Fernandes & Oliveira, 2021)	Examine the user's motivation to adopt AI Based digital assistance in service encounters	Ease of Use, perceived usefulness, Social norms, Perceived Humaness, Social Interactivity, Social Presence, Trust and Rapport	Portugal (not specified, assumed from the authors affiliation)	Functional elements like PU and PEOU are most important influencers of adoption, followed by Relational elements like trust and rapport. Social presence and interactivity also has sjown influence on the motivation to adopt digita virtual assistance.	Future studies might need to look at the other inhibitors like privacy concerns to explain the users acceptace of DVA
5	(Pitardi & Marriott, 2021)	To examine how trust and attitude towards virtual assistance are developed	Perceived Usefulness, Perceived ease of use, Enjoyment, Social Presence, Social Cognition, Privacy, Attitude, Trust, Intention to Use	United Kingdom	The results indicate the importance of direct and indirect relationships between the functional, hedonic, social, and privacy factors on trust, attitude, and subsequent usage	This study is representative of only British consumers and hence it will be interesting for future research to investigate the development of trsut in other cultural settings.
6	(Foehr & Germelmann, 2020)	How consumers build and maintain trust in their devices?	Qualitative Study - NA	Germany	Our findings suggest that consumers follow four paths to trust in smart technology: On one path, in which consumers relate their trust to the perceived personality of the technology's voice -interface and three non-anthropomorphism-based trust paths.	NA

2.3 UTAUT and Privacy Concerns

Other studies have tried to extend the UTAUT model by adding either new external factors that influence adoption behaviours or new moderators that influence the relationship between the predictors and technology adoption. For example, Alalwan et al. (2017) extended the UTAUT2 model by including trust as an exogenous factor that influences technology adoption in the context of Jordanian Bank. In another study, the model was extended by including risk (Alalwan, Dwivedi, Rana, & Williams, 2016). Similarly, Isabelle and Sandrine (2009) conceptualised social influences and facilitating conditions as multi-dimensional constructs, and Venkatesh et al. (2012) included price value and habit to extend UTAUT. Studies have also added new moderation mechanisms to understand the relationship between the predictors and adoption behaviour, including income, education, and culture differences. For instance, Im et al. (2011) used nationality as to represent cultural differences, Niehaves and Plattfaut (2010) used income and education, and Thong et al. (2011) used technology characteristic as the moderating variable.

However, the cutting-edge technologies that underlie VBDA, along with the universal and open nature of the internet, make it possible for corporations to collect, store, process, and use the personal information of an individual beyond the boundaries of a particular nation, thereby making information privacy concerns a significant issue for technology adoption (H. Smith, Dinev, Xu, & 2011, 2011). Given the fact that VBDAs are equipped with highly sensitive micro-phones, there always listening functionality and their presence in private spaces of the individuals have raised severe privacy and data security concerns among the western developed societies (Foehr & Germelmann, 2020). This makes privacy concerns the next logical candidate for inclusion in the UTAUT2 model.

Though there are studies attempting examine the privacy concerns with respect to adoption of technologies (e.g. (Herrero, San Martín, & Garcia-De los Salmones, 2017; Merhi, Hone, & Tarhini, 2019) and particularly with respect to AI technologies like VBDA (e.g. Kowalczuk 2018, Pitardi & Marriott 2021), the need for studies developing a comprehensive models integrating privacy calculous and UTATU2 for examining the adoption of VBDA still exist (Fernandes & Oliveira, 2021; McLean & Osei-Frimpong, 2019; Yang & Lee, 2019). Further, the extant literature on the adoption of VBDA and privacy concerns mostly focus on western, individualistic and developed countries (See Table 2). However, the literature shows that the privacy concerns and related behaviour significantly vary between western-individualistic societies (Bellman, Johnson, Kobrin, & Lohse, 2004; Miltgen, Henseler, Gelhard, & Popovič,

2016) and eastern-collectivistic societies (Leidner & Kayworth, 2006; Milberg et al., 1995). Thus, a study contextualising the eastern-collectivistic perspective on the privacy concern related to adoption of AI based VBDA technologies may enhance our understanding and assist us in developing comprehensive technology adoption theories.

Though privacy is considered a human right, it is also one of the oldest, most complex, and most debated topics in IS literature. The literature on privacy is complicated as it has been studied from multiple perspectives—law, economics, psychology, management, marketing, and information system. The origins of the debate can be traced to an article in the *Harvard Law Review* by Warren and Brandéis (1890), in which they define privacy as "the right to be left alone". Clarke (1999) identifies four different types of privacy: the privacy of a person, behaviour privacy, communication privacy, and data or information privacy.

Bélanger and Crossler (2011) reviewed multiple definitions of information privacy in the literature. They agree that we can define information privacy as controlling how the personal information of an individual is acquired and used (Stone et al. 1983; Warren and Brandéis 1890; Westin 1967). IS deals with information privacy in three broad areas: (1) the conceptualisation of information privacy; (2) the relationship between information privacy and related constructs; and (3) the contextual nature of information privacy and its relations in various contexts (H. Smith et al., 2011). In addition, special attention has been paid in the literature to how information privacy deals with the protection of personal information (Bélanger & Crossler, 2011). Bélanger and Crossler (2011) conclude that control over the personal information of an individual, particularly the secondary use of the information, is the common theme across most of the studies on information privacy.

One of the repeatedly raised questions in the literature about personal information privacy is this: *do people care about their privacy while adopting technology?* (Kokolakis, 2017). Studies show that information privacy is a primary concern for citizens of the digital age (Pew Research, 2014). However, contextual shreds of evidence show that though individuals reported that they were highly concerned about privacy, they readily provided their personal information in several instances (Krasnova et al., 2009; Spiekermann, Grossklags, & Berendt, 2001; Zeng, Ye, Li, & Yang, 2020). This dichotomy between attitudes towards privacy and actual behaviour is popularly known as the "privacy paradox" (Acquisti & Grossklags, 2007; Knijnenburg et al., 2018; Kokolakis, 2017; Lee, Park, & Kim, 2013; Norberg, Horne, & Horne, 2007). This paradox provides us with the opportunity to re-examine privacy concerns and its effects on technology adoption. In the next section, we will propose an extended model of UTAUT2 that includes privacy concerns.

3. Hypothesis Development

To begin, we employ the UTAUT2 model and assume that in line with the model, the factors identified will influence the adoption of VBDA. The original model proposed six constructs that directly influence the consumers' intention to adopt a technology. In line with the original model by Venkatesh et al. (2012), we include performance expectancy (PE), effort expectancy (EE), social influence (SI), hedonic motivation (HM), and price value (PV) as the direct determinants that influence consumers' intentions to adopt a voice-based digital assistant. We dropped the habit construct as one of the direct determinants. This is in line with the extant literature that shows that consumers need sufficient time to formulate a habitual behaviour in relation to a technology (Alalwan et al., 2017), and VBDA are relatively new. Further, as conceptualised in UTAUT2, behavioural intention (BI) and facilitating conditions (FC) are both postulated as key predictors for the adoption of a voice-based digital assistant. We also examined the relationship between effort expectancy (EE) and performance expectancy as hypothesised in UTAUT (V Venkatesh et al., 2003).

3.1 Privacy and Adoption of a Voice-based Digital Assistant

As the proliferation of VBDA increases in our daily life, the potential risk of them collecting personal information also increases. The objective of this research is to understand how consumers perceive risk and privacy concerns in relation to VBDA and the influence of such perceptions on their adoption behaviour. We believe that the privacy calculus model proposed by Dinev and Hart (2006), which offers a framework to understand how consumers weigh perceived risk, privacy concerns and trustworthiness when adopting new technologies, can provide us with the theoretical foundation for our analysis. Thus, to understand the adoption of VBDA, we propose an extended UTAUT2 model that includes a privacy calculus framework. In the following section, we postulate the hypothesis related to the extended model.

3.1.1 Perceived Privacy Risk

Risk is inherently a subjective notion, and it can be defined as the probability of losing something. It is the probability of the service provider exhibiting an opportunistic behaviour that leads to a loss on the part of the consumer (Peter & Tarpey, Sr., 1975). Privacy risk can be defined as the degree of loss a consumer associates with the potential disclosure of personal information by the users in general (Featherman & Pavlou, 2003; Malhotra, Kim, & Agarwal, 2004; H. Smith et al., 2011; Iyer & Singh 2018). Though there are different concerns associated with privacy, the literature on privacy risks treats it as a single-dimensional construct that captures the loss of control over personal information (H. Smith et al., 2011). Recently, there have been a lot of debate and concerns raised regarding how information is being collected and used by tech giants like Google, Facebook, and Apple (Agrawal et al., 2018; Kak, 2018). Consumers are concerned about how this information is being gathered and used without their prior knowledge. Studies show that consumers perception of privacy risk, particularly secondary uses of information reduces the trust in a website (Martin, 2018). Given that voice-based assistants are the products of these tech giants, consumers may perceive privacy risks about these cutting-edge technologies as well (Gardiner, 2018), which can negatively influence adoption (Rauschnabel, He, & Ro, 2018) . The greater the PPR, the lesser the trust in VBDA (Dinev & Hart, 2006). Such risks can also influence the privacy concerns of the consumer. There are studies related to general privacy that supports this finding (Malhotra et al., 2004). Thus, we hypothesise:

H1: *Perceived privacy risk positively influences PPC*

H2: *PPR negatively influence perceived trust*

H3: *PPR negatively influence behavioural intentions*

3.1.2 Perceived Privacy Concerns (PPC)

Privacy concerns are similar to perceived risk, but it is the internalisation of probable loss due to compromised personal information (Dinev, Albano, Xu, D'Atri, & Hart, 2016) such as misusing or unforeseeable usage of the data. That is, risk is belief about the loss and privacy concern is the assessment of the loss. Perceived privacy risk and privacy concerns are closely related but are distinct and the former influences the latter directly (Dinev & Hart, 2006). The increasing sophistication of the technology used in terms of data collection, retrieval, and mining has increased the privacy concerns of consumers enormously. Privacy concerns mainly centre on the collection of data, data errors, unauthorised access, and unauthorised secondary use of the information collected (Dinev et al., 2016). Privacy concerns are negative attitude beliefs, and they can negatively influence the attitude of a person towards a technology. In the context of VBDA, the consumer might express many concerns, particularly the loss of sensitive personal information, financial information, and other related information, particularly when these applications are used in a public space such as the living room. For instance: Alexa Dot answers to the commands of anyone, and anyone can access the primary user's Amazon shopping list information. Such access can lead to a loss of personal information, ultimately leading to economic loss. Many studies related to e-commerce have empirically verified that PPC negatively influences the usage behaviours of consumers (Cozzarin & Dimitrov, 2016; Dai, Viken, Joo, & Bente, 2018; Robinson, 2017; Bao, Ni, & Singh 2018). Thus, we hypothesise that privacy concerns negatively influence the behavioural intentions of consumers.

H4: *PPC negatively influence the adoption of VBDA by consumers.*

3.1.3 Perceived Trust

Consumer trust can be defined as consumers' accumulated beliefs regarding the integrity, benevolence, and ability of the service provider to safeguard their interests (Mayer, Davis, & Schoorman, 1995; McKnight, Choudhury, & Kacmar, 2002). Trust has been widely examined and has been proven to be a crucial factor that predicts customer's perceptions and intention to adopt a technology (Alalwan et al., 2017). Trust is an essential element in helping individuals overcome PPR and concerns, especially in the case of privacy concerns related to technology (Dinev et al., 2016; Dinev & Hart, 2006). However, recently, tech giants have under scrutiny for violating consumer trust. For instance, the case of Cambridge Analytica and the role of Facebook in it (Willson & Kinder-Kurlanda, 2019). Another recent example is the antitrust case against Google (Casey Newton, 2020; Duhigg, 2018). Such examples cast doubt on the trustworthiness of tech giants in general, and this, in turn, can affect the trust consumers place in VBDA, and by extension, their intention to adopt these technologies (Dinev et al., 2016). The literature also notes that trust can also influence the consumer's expectations of performance from those technologies (Alalwan et al., 2017; Sharma et al. 2016; Luo, Li, Zhang, & Shim, 2010). Thus, we hypothesise:

H5: *perceived trust can positively influence performance expectations from VBDA.*

H6: *Perceived trust can positively influence consumers' intentions to adopt VBDA.*

Since the extant literature provides sufficient evidence for the influence of constructs of UTAUT2, (i.e. PE, EE, SI, HM, PV, FC and BI) on adoption of consumer technologies (Alalwan et al., 2017; Baptista & Oliveira, 2015; Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019; Venkatesh et al., 2012), this paper has not hypothesised them separately here. We focus more on the constructs related to privacy that we propose to add to the model. Further, considering all these hypotheses and the UTAUT2 model, we propose the following conceptual model of adoption of VBDA (Figure 1).

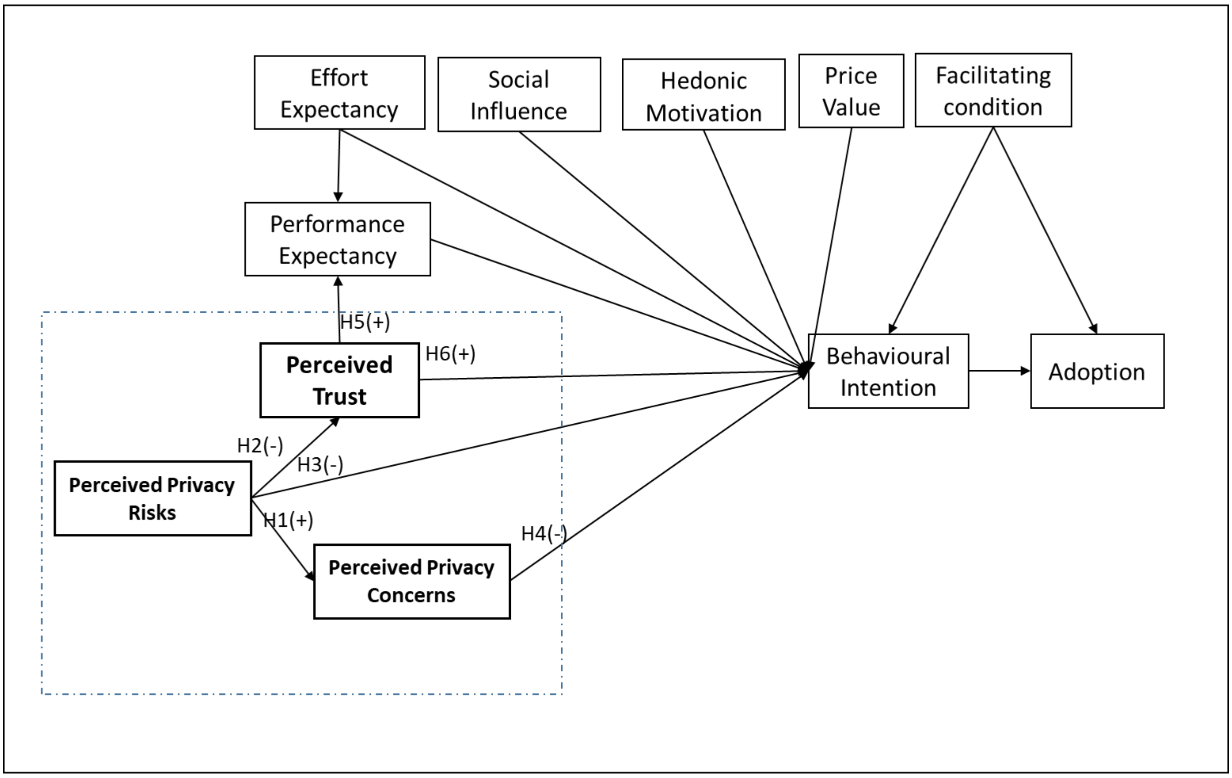

Figure 1 - Research Model

4. Research Methodology

4.1 Data Collection and Measurement of Indicators

A quantitative survey methodology was adopted to achieve the objectives of the study. To corroborate the research model and conduct hypotheses testing, we surveyed Indian respondents who use VBDA such as Siri, Alexa, Google Assistant, and Bixby. A survey questionnaire was developed to test and validate the research model. We explained the objectives of the study and assured the respondents of data confidentiality at the beginning of the survey.

The survey questionnaire was divided into two overarching sections. In the first section, a set of 39 indicators was given (see Appendix A for details, including descriptive statistics). We adapted basic constructs, namely performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and price value, from the UTAUT2 model (Venkatesh et al., 2012). In addition to the constructs from the UTAUT2, we adapted other tested and validated indicators from the literature, namely perceived risk, PPC, and trust

(Alalwan, 2020; Bansal, Zahedi, & Gefen, 2016; H. Smith et al., 2011; H. J. Smith, Milberg, & Burke, 1996). The constructs mentioned above were indirectly measured by asking respondents to rate statements on a five-point Likert scale starting from 1 "strongly disagree" to 5 "strongly agree". We included demographic variables such as age, gender, education, the model of mobile phone and experience with smart devices in the second section of the survey questionnaire. The research team validated the survey questionnaire using a pilot study to minimise problems such as inconsistencies in the language indicators and the use of several indicators for each construct. The pilot study included a few professors with expertise in technology acceptance and smart technologies and eight adopters of VBDA such as Siri and Alexa. We revised and finalised the survey questionnaire based on the feedback received. Overall, it was observed that the pilot study helped in improving the readability of the survey questionnaire.

Smart technologies are emerging phenomena in developing countries like India, and hence it is difficult to find a trustworthy sampling frame in India for data collection purposes. Data collection using a web-based approach is faster and more affordable; however, it may lead to bias in the sample selection (Bhattacherjee, 2012; Patil, Tamilmani, Rana, & Raghavan, 2020). A web link for the survey questionnaire was created with the help of Google Forms, a freely available cloud service. As VBDA is a new and emerging technology, the sampling frame for this study was target population who are studying in premier management schools in India and who are active on social media platforms like LinkedIn and Facebook. We identified two premier management schools in India offering MBA and PhD programmes to collect data. A survey questionnaire was sent using a web link which could be used once and also respondents were not allowed to submit their file with incomplete responses. In addition, we provided instructions to the respondents in the beginning of the survey questionnaire that collected data will be used strictly for research purposes and will not be shared with third parties. We received 164 responses in the month of February 2020 using all three modes namely, web links sent to students in two premier management schools, professionals on social media platforms and students in the aforementioned schools who wanted to fill paper based survey questionnaire. We sent two reminders in the beginning of march 2020 and received 102 responses using aforementioned modes. Finally, we received 206 responses from two premier management schools in India who used survey link so there were no missing data in 206 responses. Next, we received 24 responses from social media platforms including Facebook and LinkedIn using web link so all responses we received were with no missing values. In addition, we received

36 paper based responses from the same two management schools out of which were 22 usable responses and 14 responses discarded due to missing entries. Finally, we managed to get a sample size of 252 which we used in the further analysis.

In survey-based studies, non-response bias is a severe concern for researchers. The research team used the Kolmogorov-Smirnov (K-S) statistical tool (Bryson, 1974) to assess the level of non-response sample bias. Through the aforementioned statistical test, the distributions of the samples obtained from the two respondent groups (group 1 data collected in February 2020 and group 2 data collected in March 2020) were compared. The findings revealed that the difference between the two groups was insignificant, and, therefore, we concluded that there was no significant non-response bias present in the collected sample.

4.2 Sample Statistics

In total, the research team received 252 complete and usable responses from the respondents who willingly participated in the survey. The data were coded and analysed using IBM SPSS 22.0. The summary of the descriptive statistics of the collected sample is presented in Table 3. Out of the 252 respondents who participated in the survey, 63 per cent were male and 35 per cent were female, while 2 per cent belonged to the other category. The gender representation in the survey was in the acceptable limits. In terms of educational qualification and age of respondents, about 55 per cent of respondents had a bachelor’s or master’s degree in the technology or business disciplines, and 86 per cent were below 35 years of age. It was also observed that most of the respondents were using Android devices (72 per cent) and had more than one year of experience using smart devices. We can conclude that the demographic profile of the sample was appropriate to collect the information needed for the study.

Table 3: sample summary

Characteristics (N = 252)	**Indicators**	**Frequency**	**Percentage**
Gender	Male	159	63.10
	Female	88	34.92
	Others	5	1.98
Education	Technology Degree	50	19.84
	Ph.D.	15	5.95
	Business Degree	90	35.71
	Others	97	38.49
Years of Experience (smart devices)	Less than 1 year	12	4.76
	1 to 5 years	113	44.84
	5 to 10 years	39	15.48
	10 to 20 years	42	16.67

	More than 20 Years	12	4.76
	Unknown	34	13.49
Mobile phone OS	Iphone	31	12.30
	Android	181	71.83
	Unknown	40	15.87
Age	Less than 25 Years	42	16.67
	25-30 Years	121	48.02
	30-35 Years	55	21.83
	35-40 Years	21	8.33
	40-50 Years	10	3.97
	above 50 Years	3	1.19

4.3 Normality

The univariate normality of the indicators of all the constructs was tested based on the acceptable limits of skewness and kurtosis, as recommended by Byrne (Byrne, 2011). Each indicator was tested for normality to ensure the suitability of structural equation modelling for testing the proposed research model. IBM SPSS Statistics 22.0 was used to compute the descriptive statistics of the required variables. The values of parameters such as mean, standard deviation, skewness, and kurtosis are presented in Appendix A. Descriptive statistics reveal that the values of parameters such as skewness and kurtosis fell with the acceptable ranges of ±2 and ±3 (Byrne, 2011).

4.4 Structural Equation Modelling Analysis

Structural equation modelling (SEM) is a prominent second-generation statistical modelling technique that is adopted to test the proposed relationships among constructs in complex research models. SEM tests the relationships among decision variables at one point in time by integrating factor analysis with multiple regressions. In comparison to first-generation statistical models, namely multiple linear regression, SEM provides more accurate results. Therefore, IT/IS adoption researchers preferring second-generation statistical models to first-generation statistical models. SEM offers two types of approaches: variance-based structural equation modelling, which is employed when variables do not satisfy the necessary condition, i.e., data normality; second, co-variance based structural equation modelling, which is used when indicators meet the data normality condition. In this study, we adopted the latter approach. In co-variance-based SEM, there are two types of models we need to test, i.e., the measurement and structural models. First, we examine a measurement model to assess the fitness of the research model, i.e., the reliability and validity of the constructs under consideration. Second, we use the structural model to test the relationships among constructs. AMOS 21.0 is the appropriate software for co-variance SEM.

5. Hypothesis Testing and Results

5.1 Confirmatory Factor Analysis (CFA) for Assessing Measurement Model

To test the fitness of the data with respect to the proposed research model, we assessed the measurement model. The purpose of the measurement model is to test the convergent and discriminant validity of all the constructs under consideration. We begin with testing the fitness of the measurement model by assessing the popular indices—CMIN/DF, GFI, AGFI, TLI, CFI, and RMSEA. The fitness indices obtained from the CFA results were as follows: CMIN = 983.50, DF = 647, CMIN/DF = 1.520, IFI = 0.950, TLI = 0.942, CFI = 0.949, and RMSEA = 0.046. These indicate the appropriateness of the measurement model for this research study. Next, Cronbach's alpha (CA) was computed to assess the internal consistency of all the constructs. The CA values for the constructs are presented in table 4 – column 1. The CA values met the minimum recommended value of 0.50 as suggested by Hair et al. (2010) and hence ensure the reliability of the constructs in the research model. Furthermore, we ensured the reliability of each construct by computing and reporting composite value (CR) and average variance extracted (AVE) in Table 2. It was observed that CR and AVE for all constructs were more than 0.70 and 0.50, respectively, ensuring their reliability (Hair et al., 2010). It was further observed that the values of CR were greater than the values of AVE for all constructs, and the AVEs were also reported to be greater than 0.50, and hence the convergent validity of all the constructs was guaranteed (Byrne, 2011). Finally, the CFA showed that the values of AVEs were greater than the MSVs of all the constructs (see Table 4) and also the square root of AVEs of all constructs is higher than their corresponding correlation values to ensure the discriminant validity of all the constructs as recommended by Hair et al. (2010). Based on the results reported in Table 2, we can conclude that the fitness of data in the measurement model is satisfactory. Therefore, we can use the aforementioned constructs in the structural model to assess the strength of the relationships among constructs, i.e., hypotheses testing.

Table 4: Reliability and validity of constructs

	CA	CR	AVE	MSV	ASV	TR	PV	HM	PE	PPC	PPR	SI	EE	FC	BI	ADD
TR	0.865	0.866	0.564	0.504	0.224	0.751										
PV	0.849	0.847	0.649	0.454	0.223	0.509	0.806									
HM	0.896	0.897	0.743	0.501	0.250	0.372	0.674	0.862								
PE	0.882	0.882	0.653	0.552	0.272	0.497	0.552	0.644	0.808							
PPC	0.935	0.935	0.782	0.425	0.094	-0.447	-0.195	-0.206	-0.149	0.885						
PPR	0.888	0.895	0.685	0.425	0.110	-0.557	-0.234	-0.155	-0.205	0.652	0.827					
SI	0.887	0.886	0.723	0.504	0.185	0.710	0.394	0.346	0.531	-0.308	-0.377	0.850				
EE	0.826	0.831	0.622	0.552	0.203	0.338	0.482	0.560	0.743	-0.135	-0.030	0.394	0.789			
FC	0.778	0.780	0.542	0.334	0.156	0.153	0.513	0.578	0.487	-0.014	-0.003	0.149	0.569	0.736		
BI	0.867	0.881	0.712	0.501	0.257	0.550	0.612	0.708	0.626	-0.304	-0.285	0.522	0.408	0.481	0.844	
ADD	0.882	0.886	0.661	0.222	0.117	0.381	0.307	0.398	0.471	-0.057	-0.128	0.326	0.394	0.347	0.391	0.813

PE: Performance Expectancy, EE: Effort Expectancy, SI: Social Influence, FC: Facilitating Conditions, TR: Trust, PV: Perceived Value, HM: Hedonic Motivation, PPC: PPC, PPR: Perceived Privacy Risk, BI: Behavioral Intention, ADD: Adoption.

5.2 The Structural Model for Testing the Hypotheses

The structural model was examined to assess the strength of the relationships among the decision variables proposed in the research model. A set of 13 relationships were examined using the structural model. We accepted or rejected hypotheses based on β-values along with p-values. It was observed that all the hypotheses adapted from the UTAUT2 model were supported as p-values in all the relationships were less than 0.05, which implies that relationships were supported at the 5 per cent significance level (see Table 5).

We further noticed that perceived privacy risk was positively and strongly related to PPC (β = 0.657, p-value < 0.05) as well as negatively and strongly associated with perceived trust (β = -0.565, p-value < 0.05), hence supporting H1 and H2. However, the direct effect of perceived privacy risk on behavioural intentions did not show any significant effect (β = 0.070, p-value = 0.444), thus not supporting H3. Next, perceived trust had a positive and significant relationship with performance expectancy (β = 0.328, p-value < 0.05), supporting H5. Perceived trust was also related to behavioural intention (β = 0.188, p-value < 0.05), supporting H6. On the other hand, PPC had a negative relationship with behavioural intentions as postulated, but had a weak relationship significant at 10 per cent (β = -0.137, p-value < 0.10). Thus, we consider H4 as not supported and warranting further analysis.

Table 5: Hypotheses testing

Relationships	β-values	p-Value	Supported
UTAUT2 Constructs and relationships			
Performance-Expectancy → Behavioral-Intention	0.370	***	Yes
Effort-Expectancy→ Behavioral-Intention	-0.311	0.002	Yes
Social-Influence → Behavioral-Intention	0.212	***	Yes
Perceived-Value→ Behavioral-Intention	0.138	0.020	Yes
Hedonic-Motivation → Behavioral-Intention	0.504	***	Yes
Facilitating-Conditions → Behavioral-Intention	0.203	0.001	Yes
Facilitating-Conditions →Adoption	0.155	0.035	Yes
Behavioral-Intention→ Adoption	0.306	***	Yes
Effort-Expectancy →Performance-Expectancy	0.686	***	Yes
Additional Privacy related constructs and relationships			
H1: Perceived-Risk → Perceived-Privacy Concern	0.657	***	Yes
H2: Perceived-Risk→Perceived-Trust	-0.565	***	Yes
H3: Perceived-Risk → Behavioral-Intention	0.070	0.444	No
H4: Perceived-Privacy Concerns→ Behavioral-Intention	-0.137	0.080	No

H5: Perceived-Trust → Performance-Expectancy	0.328	***	Yes
H6: Perceived-Trust→ Behavioral-Intention	0.188	0.026	Yes

(*** represents coefficients significant at $p<0.001$ level)

The validated research model shows β-values, p-values, and the values of the coefficient of determination for each of the dependent constructs, namely PPC, perceived expectancy, perceived trust, behavioural intention, and adoption. It is interesting to note that effort expectancy had the maximum influence on performance expectancy with a coefficient of determination of 68 per cent. In the similar vein, all the statistically significant relationships between perceived trust, PPC, behavioural intention, and adoption were explained with the coefficients of determination of 32 per cent, 43 per cent, 53 per cent, and 14 per cent, respectively.

5.3 Post-hoc Analysis

Using SEM analysis, we found answers to a set of questions we proposed at the beginning of this research study. However, these answers also triggered some new interesting research questions. Post-hoc analysis is an appropriate extension of a study in the current methodology (Beaudry & Pinsonneault, 2010). For example, we found that perceived risk significantly influences PPC, but it does not significantly influence the behavioural intention of users to adopt VBDA, though there is a weak relationship between PPC and behavioural intention. These phenomena are interesting and worth further investigation.

To investigate the causes of the weak relationship between PPC and behavioural intentions, as well as the non-significant relationship between perceived risk and behavioural intentions, we explored the concept of the privacy paradox (Dinev & Hart, 2006; Kokolakis, 2017; Lee et al., 2013). The most interesting and widely accepted explanation of the privacy paradox comes from the theory of "calculus of behaviour" (Knijnenburg et al., 2018), coined by Laufer and Wolfe (1977) to describe the cognitive process behind the privacy-related behaviour of an individual.

The idea of the privacy calculus is rooted in economic principles where privacy is viewed as a commodity (Bennett, 1994). According to this perspective, privacy can be assigned an economic value. Individuals, being economic agents, make a cost(risk)–benefit analysis before disclosing any private information, and they disclose information only if they perceive the benefits of revealing the private information to be greater than the risk. Privacy calculus is the trade-off between the risk and benefit (Bélanger & Crossler, 2011; Dinev & Hart, 2006;

Knijnenburg et al., 2018; Kokolakis, 2017; H. Smith et al., 2011; Xu, Teo, Tan, & Agarwal, 2009). The cognitive process behind this trade-off is considered a rational and conscious decision, where the economic agent attempts to maximise its utility (Knijnenburg et al., 2018). For example, when a consumer encounters a request for personal information online or through social networking sites, they perform a risk–benefit analysis to assess the outcomes they would encounter in return for the information shared and will respond accordingly.

To examine the calculus behaviour of the individuals in our scenario, we decided to conduct a post-hoc analysis of the two critical relationships that did not support our hypotheses: (1) between PPC and behavioural intentions; and (2) between perceived risk and behavioural intentions. In our model, the calculus behaviour can be postulated by considering performance expectancy. In line with the privacy paradox, if consumers expect high performance, then privacy concerns are less of a deterrent. On the other hand, if the expected performance from the technology is low, then privacy concerns significantly influence adoption behaviour. To examine this behaviour, in our post-hoc analysis, we categorised the sample into two groups of high and low-performance expectance based on their mean response to the performance expectance items. Then, the analysis was performed to examine the relationships mentioned above. The results of the post-hoc analysis are presented in Table 6.

Table 6: Post hoc analysis

Relationships	Low-performance expectancy			High-performance expectancy		
	β-	p-Value	Supported?	β-	p-Value	Supported?
Perceived-Privacy Concerns→ BI	-0.209	0.015	Yes	-0.019	0.904	No
Perceived-Risk → BI	0.104	0.315	No	0.009	0.961	No

The post-hoc analysis results revealed that there is a statistically significant and negative relationship between PPC and behavioural intention for users who anticipate low benefits from using VBDA. However, this relationship is not significant for those who expect higher benefits from VBDA. It is interesting to note that perceived risk does not significantly influence the likelihood of users adopting VBDA, indicating that perceived risk is fully mediated through trust and perceived concerns.

6. Discussion

This study employed an extended UTAUT2 model with privacy-related variables to examine the adoption of VBDA in India. Along with all the causal relationships established in the UTAUT2, we considered PPR, PPC, and perceived trust as the additional privacy-related variables that might influence the adoption intentions of consumers. We postulated six hypotheses and examined 13 relationships, including the established UTAUT2, in our SEM model. Our results support all the relationships established in the UTAUT2, and four of the six hypotheses of privacy-related relationships postulated in this research.

In line with the existing research on technology adoption research (Venkatesh et al., 2012), all the relationships were significant. Hedonic motivation seems to have the most influence on the behavioural intention to adopt a voice-based digital assistant, followed by performance expectancy. This indicates that consumers perceive VBDA to be entertainment devices rather than utility tools. As expected, effort expectancy had a negative influence on adoption and an impact on performance expectancy, indicating the individuals' perception of the relationship between effort and performance.

When it comes to our hypotheses regarding privacy concerns, we see some interesting relationships. As expected, perceived privacy risk had a strong negative and significant influence on perceived trust (Dinev et al., 2016; Dinev & Hart, 2006). This indicates that higher the perceived risk, people recognise the technology to be lesser trustworthy. Thus, to increase trust, one has to address the risk perception towards technology.

Then, we see that trust has a positive influence on performance expectancy and behavioural intention. That is, the higher the trust in the technology, the greater the expected performance of the technology (Alalwan et al., 2017). Higher trust also leads to a greater intention to adopt the technology. This indicates that trust is an important factor in the adoption of VBDA and that enhancing trust in the technology can greatly enhance adoption behaviour.

Further, perceived risk also had a very high positive relationship with PPC, which is in line with the literature (Dinev & Hart, 2006). This indicates that people who consider VBDA a potential threat to their privacy also exhibit a higher level of concern about the technology. That is, perceived risk directly leads to perceived concerns. This also means that addressing perceived risk will also help address privacy concerns.

Surprisingly, contrary to the literature (Dinev et al., 2016), despite having a significant influence on perceived privacy concerns and trust, perceived privacy risk did not show any significant influence on the adoption behaviour of consumers. Therefore, we can conclude that privacy risk might not affect technology adoption directly, but it is mediated by privacy concerns and the trust of the consumers on the product, which in turn affect adoption.

Finally, our initial results showed that privacy concerns do not have a significant influence on the behavioural intention to adopt VBDA at the 5 per cent significance level. This was completely counter-intuitive (Dinev & Hart, 2006) and warrants further analysis. Based on the privacy calculus theory (Knijnenburg et al., 2018; Kokolakis, 2017), we further conducted a post-hoc analysis to understand the influence of performance expectance. We categorised the data into two groups: high-performance expectancy and low-performance expectancy individuals. We then again examined the relationship between PPC and behavioural intentions. In line with the privacy calculus theory, we showed that people who believe VBDA to be useful cared less about privacy concerns. But when people think that voice-based assistants are not so useful, then privacy concerns tend to have a significant impact on behavioural intentions. This confirms the privacy calculus behaviour of the consumers in the adoption of VBDA.

6.1. Theoretical Contributions

This paper is an attempt to develop a comprehensive theoretical model of the adoption of VBDA by integrating UTAUT2 and privacy calculus theories. Then we tested the model in the context of eastern collectivist like India, which provides a unique perspective for the privacy concerns against the extant literature which mostly examines privacy concerns associated with the western individualistic societies (as noted in Table 2). While the results reaffirm that the relationships established by UTAUT2 are valid and significant even in the context of a cutting-edge consumer technology like VBDA, some relationships related to privacy did not find support. Given that the study is from different context, the findings add some significant contributions to the literature.

Firstly, we believe that privacy concerns are a significant influencer of technology adoption, and a comprehensive model technology adoption of AI technologies like VBDA with privacy-calculus variables will increase the generalisability of the model. Thus, we believe the extension is a significant contribution to the technology adoption literature.

Further, our results initially depicted that Indian users do not care about privacy while adopting a voice-based digital assistant. However, a more in-depth analysis shows that individuals who consider the technology to be useful are ready to compromise their privacy to enjoy its benefits. On the other hand, people sceptical about the usefulness of the technology are less likely to adopt the technology due to privacy concerns. Overall, this is a study that aims to integrate and successfully showcase the privacy calculus behaviour of the Indian consumer and its influence on technology adoption. This is contrary to the findings from the studies on western consumers, where privacy concerns are central to the adoption such AI based technologies (see Table 2 for earlier studies).

Moreover, this study did not postulate users' privacy calculus behaviour. But our post-hoc analysis indicates that the relationship between privacy-related concerns and the intention to adopt a voice-based digital assistant are moderated by performance expectancy. Given the prominence of privacy concerns and its probable significance for technology adoption, we believe that future models of technology adoption should consider privacy concerns in their theorisation and find a way to incorporate privacy calculus behaviour. We believe that without incorporating privacy concerns, the model will not provide the complete picture regarding cutting-edge technologies that require enormous personal information to work efficiently.

Finally, the study also shows that privacy risk does not influence behavioural intention directly. It is mediated through privacy concerns and consumer trust. Thus, we conclude that privacy risk is fully mediated by privacy concerns and trust in the case of adoption of VBDA, contrary to the partial intervention established in privacy literature.

6.2. Implications for Practice

The paper provides a holistic model to estimate customers' perceptions towards the adoption of VBDA in India and provides some interesting results. For instance, the impact of hedonic motivations on the adoption of a voice-based digital assistant being higher than even performance expectancy depicts the kind of expectations individuals have of these technologies. This shows, for now, that consumers perceive VBDA to be amusement devices than a utility tool. This implies that tech companies need to work toward changing the perception of consumers towards VBDA.

As noted in the beginning, most individuals raised concerns regarding the trustworthiness of these technologies and the companies that produce them. Because these technologies need an enormous amount of personal data to perform efficiently, and customers can provide personal information only when they trust the technology and service provider, trust is an important factor for the adoption these technologies. Thus, practitioners need to invest in securing consumer trust regarding the safety of their personal information. There are multiple ways to improve trust: (1) organisations can bring in transparency in their algorithms and data usage. (2) they can clearly communicate their business models and how the data is used, (3) by educating the consumers about the privacy and personal information protection and (4) strong and reliable privacy laws.

Further, when it comes to privacy risks and privacy concerns, we see that most consumers make decisions based on a privacy calculus. That is, consumers who believe that the technology offers greater utility do not worry about privacy and personal information, but consumers who do not see their utility are more likely to not adopt the technology due to privacy concerns. This increases the responsibility of the service provider two-fold: first, they have to safeguard the interests of the consumer who is handing over their personal data in exchange for utility, and second, they have to take necessary steps to reduce privacy concerns so that other consumers also adopt VBDA.

Finally, since these technologies collect lots of sensitive personal information, we believe that local governments also need to establish strong privacy norms to protect the interests of consumers. Such norms can help both service providers as well as consumers as they can help safeguard consumers' interest while helping to increase adoption by reducing privacy concerns.

6.3. Limitations and Future Directions

Like all other research, this study too bears some shortcomings and limitations. Firstly, the research data were collected from users of India who were highly educated and had a technology background, making it a non-representative and non-probabilistic sample. As the respondents included in the sample had access to smartphones and were familiar with VBDA, and since such an approach to data collection is widely accepted in the literature, we believe that using such a sample better showcases the influence of privacy concerns on adoption behaviour. However, future studies can employ representative sampling techniques to explore privacy concerns and its influence on the technology adoption of non-tech-savvy users.

Secondly, the questionnaire was in English and data collection assumed that the respondents are well-versed in the language. Since our respondents were well-educated, we could safely make this assumption. However, if representative sampling is to be adopted in a country like India with more than 22 scheduled languages and hundreds of spoken languages, with wide disparities in education levels, we need to be more inclusive in terms of the questionnaire format and language. Future studies also need to keep this in mind.

Third, this research used a quantitative approach that does not allow an in-depth exploration of consumers views on the adoption of VBDA. An in-depth mixed-method approach could have helped us understand the phenomenon better. However, time and resources constraints prevented us from conducting such an exploration. Future studies can utilise a mixed-method approach to generate a deeper understanding.

Fourth, the effect of moderating variables like gender was not considered in this study. Future studies can explore the role of these moderating variables on privacy calculus behaviour. Extant literature has also provided evidence for the influence of the past experience with the technology influencing the adoption behaviour and hence future studies can also account for it as moderator (Pappas, Pateli, Giannakos, & Chrissikopoulos, 2014). Future studies can also explore the effects of privacy concerns and trust on emotion and affective perception that in turn affect the adoption of technologies like VBDA (Pappas, 2018). Finally, in line with the popular approach, we have measured technology adoption through a self-reported usage scale. Future research can enrich this by exploring actual usage information, exploring the contrary cases and employ methods like FsQCA which is gaining popularity (e.g. (Pappas, Giannakos, & Sampson, 2019).

7. Conclusion

This research article is a first of its kind that attempts to understand consumers' adoption of VBDA and the influence of privacy concerns on the same. To fulfil these two objectives, the paper extends the celebrated UTAUT2 model with privacy-related variables such as risk, privacy concerns, and trust. The results show some interesting behaviours. As expected, trust has a positive and significant influence on adoption behaviour. Privacy risk did not show any direct influence on adoption behaviour. But its considerable influence on trust and privacy concerns indicated the full mediation of risk through these variables. Further, consumers exhibit a privacy calculus behaviour when considering the trade-offs between privacy concerns and utility, where individuals who expect higher utility from the technology ignore privacy concerns and individuals who are sceptical about its usefulness are more likely to be influenced by privacy concerns. Finally, we discussed the theoretical and practical implications of the findings.

Appendix A: Indicators with basic statistics

Indicators	Mean	S.D.	Skewness	Kurtosis
PPR1: PDA data may be sold to third parties?	3.75	1.137	-.712	-.204
PPR2: Personal Data in PDA may be misused?	3.71	1.102	-.613	-.261
PPR3: PDA data could be given to unidentified persons or companies without my consent	3.82	1.129	-.784	-.095
PPR4: PDA Data could be made available to government agencies?	3.41	1.132	-.199	-.709
PPC1: I am concerned that the information I submit to (PDA) could be misused.	3.36	1.265	-.339	-.905
PPC2: I am concerned that a person can find private information about me through PDA.	3.34	1.236	-.258	-.897
PPC3: I am concerned about submitting information to PDA, because what others might do with it.	3.27	1.203	-.196	-.816
PPC3: I am concerned about submitting information to PDA, because it could be used in a way I did not foresee	3.37	1.243	-.292	-.931
TR1: PDAs are safe environments in which to exchange information with others	2.85	.995	.103	-.347
TR2: PDAs are reliable environments in which to conduct business transactions	2.84	1.071	-.040	-.562
TR3: PDAs handle personal information submitted by users in a competent fashion	3.12	1.002	-.130	-.422
TR4: I think that PDAs are trustworthy	2.96	1.067	.012	-.586
TR5: I feel assured that legal and technological structures adequately protect me from problems on PDAs	2.90	1.085	-.047	-.634
PE1: I find PDAs useful in my daily life.	3.59	.981	-.458	-.118
PE2: Using PDAs increases my chances of achieving tasks that are important to me.	3.34	.943	-.262	-.295
PE3: Using PDAs helps me accomplish tasks more quickly.	3.51	1.021	-.481	-.273
PE4: Using PDAs increases my productivity	3.40	1.024	-.185	-.516
EE1: Learning how to use PDA is easy for me.	3.95	.928	-.721	.041
EE2: My interaction with PDA is clear and understandable.	3.59	.985	-.568	-.101
EE3: I find PDA easy to use.	3.83	1.056	-.892	.255
SI1: People who are important to me think that I should use PDA.	2.84	.975	.194	-.279
SI2: People who influence my behaviour think that I should use PDA.	2.88	.986	.225	-.130
SI3: People whose opinions that I value prefer that I use PDA.	3.01	.965	-.024	-.012
FC1: I have the resources necessary to use PDA.	3.80	.902	-.857	.950
FC2: I have the knowledge necessary to use PDA.	3.92	.818	-.640	.378
FC3: PDA is compatible with other technologies I use	3.67	.853	-.663	.556
HM1: Using PDA is fun.	3.85	.881	-.688	.427
HM2: Using PDA is enjoyable.	3.82	.889	-.803	1.001
HM3: Using PDA is entertaining.	3.82	.895	-.795	.792
PV1: PDA is reasonably priced.	3.40	.854	-.450	.253
PV2: PDA is good value for the money.	3.44	.853	-.286	.042
PV3: At the current price, PDA provides good value.	3.47	.904	-.373	.198
BI1: I intend to use PDA in the future.	3.75	.928	-.813	.874

BI2: I will always try to use PDA in my daily life.	3.23	1.081	-.271	-.505
BI3: I plan to use PDA in future.	3.72	.900	-.781	.890
Frequency: When was the last time you used a mobile phone to use the following features by Voice-based Digital Assistant (5: Today, 4: Past 7 Days, 3; Past 30 Days, 2; More than 90 days, 1: Never):				
Adotion1: Alarm	3.09	1.524	-.108	-1.451
Adotion2: Reminder	2.82	1.456	.058	-1.405
Adotion3: Weather	2.87	1.460	.075	-1.383
Adotion4: News	2.89	1.588	.075	-1.544

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