Interactive Voice Assistants - Does Brand Credibility Assuage Privacy Risks?

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Abstract

Artificial intelligence-enabled conversational user interfaces, commonly known as voice assistants, are increasingly being used by individuals in their day-to-day lives to fulfill diverse needs (e.g. utility, hedonic, and social). However, the homeostatic (steadily present) attraction of the voice assistants is offset by the privacy risk concerns these devices present to users. Despite the growing literature on the adoption and usage of voice assistants, little has been said on whether brand credibility plays a mitigating role in assuaging the perception of privacy risk. This study combines both empirical and qualitative methods to shed light on the relationship between individuals' perception of the overall value of voice assistants and their behavioral intention towards continued usage of voice assistants. A key study finding is that brand credibility significantly moderates the relationship between VA features and the overall perceived value of VAs – higher brand credibility reduces users' perception of privacy risks.

Keywords: *Brand Credibility, Hedonic, Perceived Privacy Risk, Perceived Value, Social, Utility, Voice Assistants*

1. Introduction

In his work on the transformation of human consciousness under oral and literate societies, Ong (1982) described orality or speech as a powerful practice enabling intersubjective exchange. This is because the immediacy of information flow through speech enables role flexibility, and the sender may be the receiver and vice versa. Ong was accurate in predicting orality or speech gaining momentum in the age of mass electronic communications. Today digital innovations can offer substitution of speech for text or writing, especially with the Voice Assistant (VA) technology featuring as a potently interactive mode of oral communication. Voice recognition is the ability of a machine or program to receive and interpret spoken words and carry out the functions based on user input. The conversational interface is the most significant advantage of a digital assistant (Balakrishnan & Dwivedi, 2021), as the interaction through natural language makes it more intuitive and easier to use than transmitting textual input through a hand-keypad.

As voice-based inputs replace text-based messaging, information exchanges become easy and effective (Mueller, 2018). Voice recognition applications are now diverse ranging from smart home solutions (e.g. adding intelligent voice control to any connected product to enable users to command home features like playing music, switching on the television, etc.), in-car speech recognition (e.g. telling the car call people or navigate to specific destinations) and so on. Digital assistants, through the use of cutting-edge AI technologies, make information retrieval easier based on user input (Balakrishnan & Dwivedi, 2021).

The global voice-based assistants (e.g. smart speakers, voice-based search through browsers, etc.) market size was valued at USD 2.2 billion in 2017 and is expected to exhibit a CAGR of 38.7% over the forecast period of 2018-2025 (Grand View Research, 2018). Voice assistant brands from Amazon, Google, Apple, Alibaba, Xiaomi, and Baidu are adding momentum to this trend as they compete for a share of the market (Kinsella, 2019a). With the evolution of smart technologies such as intelligent assistants, consumers have been presented with a variety of value propositions to satisfy their needs in their physical and social environment (Bawack et al., 2021; Dwivedi et al., 2021; Hu et al., 2021; Krishen et al., 2021; Mishra et al., 2021; Wang et al., 2021). According to Deloitte's Global mobile consumer survey of 2018, the penetration of voice-assisted speakers almost doubled from 12% in 2017 to 20% in 2018. Voice technology offers people the convenience of interaction with technology as users need not always physically interact with the technology other than using voice (Alepis & Patsakis, 2017).

Recent literature has paid significant attention to users' adoption of and interaction with voice assistants. VA usage has been examined from the perspectives of ease of use, privacy risk, human-machine communication, rapport-building, and trust (Moriuchi, 2019, Fernandes & Oliveira, 2020; Nasirian et al., 2017). Concerns have been raised about the wide-ranging security and privacy risks rising from using AI-based digital assistants, despite their many benefits (Vimalkumar et al., 2021; Dubiel, Halvey, & Azzopardi, 2018). At the same time, as also cited by Balakrishnan and Dwivedi (2021), a recent survey (Humanizing Digital 2020, 2019) shows that 88% of consumers demand businesses to integrate digital assistants to help in choosing the right product and brand (Linder, 2020). More tellingly, the higher the perceived risk, the lesser is people's regard for the technology (Balakrishnan & Dwivedi, 2021), and consumers exhibit a trade-off between privacy risk and benefits while adopting virtual-based digital assistants. Thus two counter-intuitive premises can be seen to emerge. On the one hand is the users' perception of heightened value available through the interactive features of the technology, while on the other, there is the perceived privacy risk involved in the technology usage. It may be argued that in such situations, consumers' trust may be elicited if the product is introduced by an established brand

and the brand has made efforts through various communication mechanisms or signals to promote the technology - such as Alexa by Amazon, Cortana by Microsoft, or Siri by Apple.

The issue of brand credibility of VAs is a vital area of concern, as even if a device responds to the user's social and psychological needs, one may still need to be assured of the credible value and trustworthiness of the technology product (Hasan et al., 2020). Intelligent technologies like voice assistants offer many benefits to the users, but they also require users to make trade-off decisions like giving away their private data. There are active concerns regarding VAs listening to private conversations in homes or offices, or digital assistants gathering sensitive information about users' location, contacts, browsing history, etc. (Gardiner, 2018). A pronounced gap exists in the literature around the question – whether privacy concerns of users get assuaged by the credibility of the brand which may lead to continued usage. Similarly, there is little discussion on how brand credibility may impact individuals' perception of the overall value of VAs.

Our study has used the theoretical lenses of Uses and Gratification theory (U&GT), Signaling theory, and Prospect theory to investigate individuals' perception of the overall value of voice assistants and their continued usage of voice assistants. The U&G lens (Rauchnabel et al., 2017; McLean & Osei-Frimpong, 2019) has been used for capturing how the perception of different VA features (utility, hedonic, and social) vary among users from diverse backgrounds and interests. The Signaling theory was used to elucidate the effects of brand credibility (Erdem & Swait, 1998, 2004) – i.e. how brand credibility reduces decision risk by lessening consumers' uncertainty (Akdeniz et al., 2013) when applied to VA usage. The prospect theory (Kahneman & Tversky, 1979, 1992), which proposes that people make risk decisions predominantly in terms of gains and losses, was used to investigate if consumers' expectations of gain in terms of the overall value of VAs, enable them to make the trade-off decision to use VAs despite the risk of privacy.

Accordingly, the research questions driving this study are: (1) If the perceived value of VAs supersedes individuals' concerns of privacy risks? (2) If brand credibility contributes to individuals' perception of the overall value of VAs? And finally, (3) If brand credibility reduces individuals' perceived privacy risk concerning the VAs?

The paper is structured as follows. In section 2, we briefly discuss the theoretical underpinnings of the study. In section 3, we propose the hypotheses and research model. Section 4 explains the research methodology and presents the statistical results. Section 5 presents the discussion including contributions, implications, limitations, and future research directions. Finally, Section 6 presents the key conclusions and implications emerging from this research.

2. Literature Review and Research Hypotheses

2.1 Existing work on VA adoption

The evolution of smart technologies such as voice assistants has presented consumers with options to satisfy their needs in their physical and social environment. Besides the convenience of interaction with technology, as users need only use their voice (Alepis & Patsakis, 2017), VAs have arguably raised people's expectations in terms of fulfilling their subjective/emotional needs (Castelo et al., 2019).

Recent research has examined consumers' adoption of intelligent/voice assistants from rich and diverse perspectives. By adopting the Service Robot Acceptance Model (Wirtz et al., 2018), Fernandes and Oliveira (2020) show that functional, social, and relational elements drive VA adoption, unravel boundary effects between them, and showcase the moderating role of experience and need for human interaction with VAs. McLean and Osei-Frimpong (2019) utilized the Uses and Gratification (U&GT) lens to identify the antecedents of consumers' interaction with in-home voice assistants and found that individuals are motivated by utility features, symbolic, and social benefits provided by the voice assistants. Moriuchi (2019) has investigated the technology acceptance model (TAM) constructs of perceived ease of use and perceived usefulness to uncover their impact on engagement and loyalty between VAs and consumers. On the other hand, Han and Yang (2018) have explored the social relationship that consumers develop with their intelligent personal assistants and their continuance intention by applying parasocial relationship theory. The study findings of Han and Yang (2018) indicate that security or privacy risk, indicating consumers' perceived concern about intelligent personal assistants negatively affected the parasocial relationship. Gursoy et al. (2019) identified six antecedents (social influence, hedonic motivation, anthropomorphism, performance expectancy, effort expectancy, and emotion) spread across three acceptance stages to understand customers' acceptance of AI device use in service encounters. Balakrishnan and Dwivedi (2021) have investigated the aspect of conversational commerce aided by digital assistants: how technology attitude and AI attributes enhanced users' purchase intention through digital assistants. Guzman (2019) has studied voice assistants from the perspective of human-machine communication. Nasirian et al. (2017), examined the voice assistant system from interaction and trust perspectives to suggest that interaction quality significantly affects individuals' trust and adoption of voice assistants. Similar findings have been reported by Hasan et al. (2020).

A broad cache of articles (Cowan et al., 2017; Dubiel et al., 2018; Moorthy & Vu, 2015) explains how contextual social factors play an important role in speech conversational interfaces. Interesting findings by Han and Yang (2018) and Moorthy and Vu (2015) showed that people tend to use their intelligent personal assistants (IPAs) to transmit non-private information in private locations. Furthermore, people are likely to use their smartphone keypad instead of an IPA to transmit information because they think that speaking aloud with a voice agent in public spaces will not be socially acceptable behavior. In a contra situation, as Cowan et al.'s (2017) findings show, users become frustrated when they are asked by the assistant to engage visually with the screen to give confirmation or select options by touching the screen rather than using speech.

No less interesting are the findings by Dubiel, Halvey, and Azzopardi (2018) that the frequency of usage of IPAs does not mean less concern with data privacy. While not many studies exist in the privacy domain of IPAs, Alepis and Patsakis (2017) showed that Siri, Cortana, Google Assistant, and Alexa have susceptibilities on voice activation so that one can easily control and manipulate the voice commands remotely, giving out arbitrary commands which can put the users at risk. Nogueira et al. (2017) also indicated that about 81.8% of users agree that some legislation that protected the privacy of shared data will be helpful, as they felt that the current methods were invasive.

<<**Insert Table 1:** Users' Adoption of Intelligent Devices: Select Review **Here**>>

The literature since long has focused on users' interaction with IT artifacts as social actors and how social rules and expectations apply when interacting with them (Al-Natour, Benbasat & Centefelli, 2011; McLean & Osei-Frimong, 2019). Studies have also focused on privacy concerns associated with the usage of intelligent assistants (Vimalkumar et al., 2021; Dubiel, Halvey, & Azzopardi, 2018). But none yet seems to have dealt with the consumers' perception of brand credibility in eliciting their trust in VAs and in turn contributing to the overall value of VAs. Keeping in view this research gap, the current study has sought to explore if brand credibility contributes to the overall value of VAs, and if brand credibility reduces the perceived privacy risks associated with the VAs.

2.2 Underpinning theoretical frameworks

We have used the U&G lens (Rauchnabel et al., 2017; McLean & Osei-Frimpong, 2019) to propose that utility features, hedonic features, and social presence features lead to consumers' perception of the overall perceived value of voice assistants, which in turn encourage their continued usage intention. The Signaling theory lens (Erdem & Swait, 1998, 2004) has been used to explain how brand credibility serves as a trustworthy signal and a measure to consumers for assessing the quality of a product or service (Dawar & Parker, 1994). Prospect theory (Kahneman & Tversky, 1979, 1992) has been used to explain how consumers' expectations of prospective gains in terms of (overall) value of VAs enable them to make the trade-off decision to use VAs despite the privacy risk.

2.2.1 Uses & Gratification Theory (U&GT):

The foundation of U&GT as a theory is in communication science, and it has been leveraged to understand users' motivation to adopt the technology. Recent research by Rauschnabel et al. (2017) has charted utility features, hedonic features, and symbolic benefits as adding to the gratifications derived from the use of VAs. McLean and Osei-Frimpong (2019) have added social benefits i.e., investing in technology for the sake of the social presence of others and the social attraction of others (e.g. online games or social media) as another driver for the adoption of VAs by individuals. Furthermore, a global study involving two separate surveys (the first one in March-June 2018 with 2000 respondents, and the second one in February 2019 with 5000 respondents) conducted by Microsoft Market Intelligence (2019) reported that on average, the respondents selected five types of productivity tasks such as playing music (70%), asking for directions (65%), news and weather report (68%), fact-checking (over 68%), and researching a product or service (44%). Apart from the utility and hedonic tasks, 41% of respondents considered their voice assistants as a friend, or a person they like talking to. The research also found that more complex functions (e.g. access bank accounts, change passwords, etc.) that require coordination across multiple systems are still farfetched because of a lack of trust in the device. About 41% of respondents reported concerns of data security (52%) and passive listening (41%) (Microsoft, 2019).

Thus drawing on the research findings, both from the academia and industry, we have used the U&GT lens to propose that utility features, hedonic features, and social presence features lead to users' perception of the value of voice assistants, which in turn encourage their behavioral intention towards continued usage.

2.2.2 Signaling Theory

The signaling theory has been used to explain the effects of brand credibility (Erdem & Swait, 1998, 2004). According to the Signaling theory, information asymmetry exists between customers and firms about the quality of products and services provided by firms. As firms have more knowledge about the quality of their products or services than their customers, such information asymmetry creates problems to discern high-quality products from low-quality ones before purchase (Almutairi, 2006). Given this state imbalance of information, firms have been known to use signals to establish the efficacy of product or service quality (Erdem & Swait, 1998; Rao et al., 1999). A signal has been defined as 'an action that the seller can take to convey information credibly about unobservable product quality to the buyer' (Rao et al., 1999, p. 259). According to Erdem and Swait (1998), a brand serves as a credible signal because it is an embodiment of the firm's reputation and aggregated prior marketing mix strategies. Thus, a brand signal can provide an instantaneous heuristic to gauge the quality of a product or service (Dawar & Parker, 1994), especially with experiential products (Nicolao et al., 2009). Firms can signal through brand names which may be perceived by customers as an embodiment of quality which reduces the risk of purchase (Jacoby et al., 1971). The credibility signaled by a brand reduces consumer uncertainty and saves decision-making costs (Akdeniz et al., 2013). Further, a brand is seen as a promise that is continuously assessed by consumers to see if the brand offering measures up to its claim (Dwivedi et al., 2018).

In the case of intelligent technologies like voice assistants, brands may be perceived as signals representing the promise and the believability of the product quality which reduces perceived risk. Therefore, by drawing on the signaling theory, we propose that brand credibility moderates the relationship between individuals' perception of the features and overall value of VAs, and subsequently their behavioral intention towards continued usage of VAs. Similarly, individuals' perceptions of the risk of using VAs may also vary with low or high brand credibility.

2.2.3 Prospect Theory

The Prospect theory, developed by Kahneman and Tversky (1979, 1992) has been used to explain decision-making under risk. Prospect theory predicts that individuals make decisions based on how their brains receive, process, and comprehend information related to an option and not exclusively based on the inherent utility that the option possesses (Kahneman & Tversky, 1979). The theory postulates that risk decisions are made predominantly in terms of gains and losses, and this is attributed to the framing of options (in terms of gains and losses) that yield systematically different preferences. Prospect theory has been extensively used in behavioral finance (Cao, Deng, & Li, 2010), and marketing (Kivetz, 2003). For intelligent technologies like voice assistants, consumers may exhibit a tradeoff between benefits (including brand) and risk of privacy.

By drawing on prospect theory, we propose that individuals make trade-off decisions towards the perception of gain about the overall value of voice assistants.

2.3 Conceptual model and hypotheses development

As argued in the preceding sections, the utility, hedonic, and social features of VAs have been identified as gratifications derived from these intelligent assistants. As per U&G, users are active agents who like to control their actions and media consumptions (Mc Quail, 1994). Since users from diverse backgrounds have varying interests, the perception of the utility, hedonic, and social benefits may vary substantially. At the same time, the risk of privacy cannot be ignored, since VA usage does involve sharing of private data. In such situations, high brand credibility may curb consumers' uncertainty (Akdeniz et al., 2013) and reduce perceived risk associated with intelligent device usage. There may also be a significant difference in the adoption and usage of technology among men and women (Li, Glass, & Records, 2008), and gender could have a moderating effect on varying levels of trust and familiarity with technology (Aeron et al., 2019). It may be conceptualized, therefore, that consumers' expectations of gain in terms of overall perceived value (utility, hedonic, and social features) in addition to trust elicited by a brand, will lead to continued usage of VAs. Fig.1 below presents the conceptual framework.

<< **Insert Fig. 1.** Conceptual Model **here**>>

2.3.1 Utility Features

The utility features propensity of customers has been defined as goal-directed behaviors that aim at reducing risk and acquiring products through the use of heuristics (Park et al., 2012). McLean et al. (2018) found mobile applications providing individuals with utility features benefits. Voice assistants can serve diverse groups of users from the young, senior citizens, differently-abled individuals (e.g. Google's Android application "Voice Access" allows persons with mobility and motor impairments to use voice to tap buttons), and enables users to use voice commands even while multi-tasking during interactions (McLean & Osei-Frimpong, 2019). Given the diverse range of utility features of voice assistants, it may be derived that they will influence users' perception of the usefulness of these devices. Therefore, we propose the following hypothesis:

H1: Utility features have a positive association with the individuals' perceived value of voice assistants.

2.3.2 Hedonic Features

Previous research has drawn attention to the experiential nature of products and services (Holbrook, 2000; Pine, II & Gilmore, 1998). Hedonic values refer to individuals deriving emotional experiences such as pleasure or enjoyment from their interaction with products or interfaces. Individuals interact with technology for hedonistic fulfilments (Wu et al., 2010; Pillai et al., 2020). Hoffman and Novak (1996) have divided online consumers into two segments that of goal-directed consumers and experiential consumers. Goal-directed consumers are those having a specific reason for purchase (Olbrich & Holsing, 2011) in contrast with experiential consumers who seek recreation or pleasure. Hedonic thus relates to individuals' feelings or emotions - such as satisfaction or happiness experienced with the technology (Kamboj et al., 2018). In the case of voice assistants, the enjoyment derived from new interactive experiences is fundamental to the use of such technology. Therefore, we propose the following hypothesis:

H2: Hedonic features have a positive association with the individuals' perceived value of voice assistants.

2.3.3 Social Presence

Social presence has been defined as a 'social or personal liking property' by McCroskey and McCain, (1974, p. 6), a feeling of being with another (Biocca et al., 2003). Studies (Gefen & Straub, 2003a) have shown how human beings assign social roles to their computers to the extent that an artifact can be seen as personal, sociable, and even intimacy is possible when interacting with it. Han and Yang (2018) found social attraction (having regard for intelligent personal assistants as friends) as one of the key elements leading to the adoption of the technology. According to Epley et al. (2008), ‘seeing nonhuman agents is likely to be determined by the relative accessibility and applicability of anthropomorphic representations’ (p.146). AI-enabled voice assistants with their natural language capability can elicit a sense of human companionship, and individual users can build an empathetic connection with their voice assistants (Cerekovic et al., 2017). Therefore, we propose the following hypothesis:

H3: Social presence has a positive association with the individuals' perceived value of voice assistants.

2.3.4 Perceived Privacy Risk

Featherman and Pavlou (2003) defined perceived risk as the potential for loss in the pursuit of the desired outcome. Although consumers’ perception of risk is an inherent factor in the adoption and usage of products, this has not been applied to new technologies and adoption contexts (Featherman & Pavlou, 2003). This is corroborated by Im et al. (2007), that both TAM and UTAUT models of IS adoption have overlooked or given inadequate attention to both perceived risk (PR) and technology type. While intelligent technologies such as voice assistants afford many benefits to users, there are also concerns around VAs listening to conversations in offices, if the information gets recorded, and how organizations intend to use such information (Orra & Sanchez, 2018). AI-enabled voice assistants are capable of performing tasks such as making appointments, placing orders for their users, but this requires giving extensive software permissions to VAs and users end up providing such permissions (Alepis & Patsakis, 2017). As customers get induced by new technology, they may be inclined to overlook their privacy concerns in favor of usage benefits. Therefore, we propose the following hypothesis:

H4: Perceived privacy risk has a negative association with an individuals' perceived value of voice assistants.

2.3.5 Moderating Impact of Brand Credibility

Prior research outlines that brand credibility comprises two important features namely, the trustworthiness of the firm (the sentiment that the firm will not renege on its promises), and belief in the expertise of the firm being capable of carrying out its promises (Erdem & Swait, 1998, 2004). Brand credibility has been defined as the credibility of a brand as a signal of the believability of the product position information encapsulated in a brand, which involves delivering consistently what is being promised (Erdem & Swait, 1998). Brand credibility has also been conceptualized as the relationship the customer has with a brand over a while (Dwivedi et al., 2019). According to Keller (2008), a brand plays a key role in enabling customers to identify a firm's products/services and differentiate them from many other options available in the market. A brand thus functions as an efficient market signal deployed by the firm to mitigate the risk involved in lack of knowledge on the part of customers about the firm's product or service (Sweeney and Swait, 2008).

According to Erdem and Swait (1998), brand credibility can increase perceived quality, decrease information costs, decrease perceived risk, and increase consumers' expected utility of the products and services. Along similar lines, Baek et al. (2010) mention that brand credibility indicates tangible and utilitarian sides of value. Prominent brands are striving hard to improve the utility component of their voice assistants - for example, one can integrate their VAs with mobile apps and improve the navigation search, answer phone calls, book an appointment, etc. Voice and conversational AI like Alexa and Siri have made health services more accessible to anyone unable to leave their home during illness. Given these aspects of brand credibility, we posit that voice assistant devices from known and recognizable brands have better value perception, and have a positive impact on consumers' future intention to use voice assistants. Therefore, we propose the following hypothesis:

H5(a): The association of utility features on overall perceived value tends to be larger when the brand credibility is high.

Prior research has shown that users are motivated by hedonic benefits when interacting with technology (Wu et al., 2010). For many, the functional or utility features of the technology are insufficient to fully embrace the technological products (Venkatesh et al., 2012). Users' enjoyment during technology interaction can influence their actual and future use (Pizzi & Scarpi, 2020). Apart from the enjoyment, the pleasure of interacting with new technology can also affect various aspects of future use. Mattila and Wirtz (2000) show that enjoyment and pleasure can significantly impact individuals' evaluation process followed by establishing trust towards the technology (Gefen et al., 2003b). And as stated in the preceding sections, trust is built through brand credibility. Therefore, it can be hypothesized that:

H5(b): The association of hedonic features on overall perceived value tends to be larger when the brand credibility is high.

When voice assistants were initially launched in 2011, no one could have predicted the extent of popularity or influence these technology innovations have today. Organizations like Amazon, Apple, and Google are continuously striving to offer more individualized experiences to their user base. The voice assistants, with their natural language capability, provide a sense of human companionship to their users (Cerekovic et al., 2017; Pitardi & Marriott, 2021). All this would not be possible if organizations that invest in technology did not continue to demonstrate their willingness to improve the value (through features such as human-like social presence) components for their customers. The natural performance of voice assistants has improved consistently over a decade in terms of quality of answers, voice clarity, modulation, voice response, and recognition, further motivating users to interact more with these devices (Berdasco et al., 2019). Based upon the quality of interaction, there is a possibility that users can differentiate between the brands and recognize their VA brand voice as a distinctive persona. For instance, according to the voice designer Phoebe Ohayon (2020), Siri is "disingenuous and cunning," while Alexa is "genuine and caring." This indicates that the credible design from the brand and its voice persona can be a differentiator for continued usage among its users. Owing to social and symbolic aspects, a human-like social presence is more affable than a robotic presence. Therefore, brand credibility plays a significant role in developing users' perceived social well-being and in enhancing perceived value. Hence we propose:

H5(c): The association of social presence on overall perceived value tends to be larger when the brand credibility is high.

The perceived risk, or in our case perceived privacy risk, is demarcated as the users' subjective belief about potentially negative consequences (in the case of VAs, it is access to personal information) of using a product or a service (Samadi & Yaghoob-Nejadi, 2009). The reviews and recommendations on various online-offline media sites demonstrate trepidations about the wide-ranging security and privacy risks rising from VA usage (Vimalkumar et al., 2021; Dubiel, Halvey, & Azzopardi, 2018). The higher the perceived risk, the lesser is people's regard for the technology (Balakrishnan & Dwivedi, 2021). Therefore, to heighten trust, the risk perception towards technology has to be addressed. Typically, users are seen to reduce their risk perceptions through the selection of brands demonstrating high credibility (Baek, 2007). For innovative technology products such as voice assistants, brands can serve to reduce perceived decision risk and augment perceptions of quality. Credible brands pose smaller risks and hence can improve the users' evaluation. With the purchase of prestigious brands, the perceptions of risks such as performance, social, and psychological risks subside while the value component supersedes (Vimalkumar et al., 2021). Therefore, we hypothesize:

H5(d): The association of perceived privacy risk on overall perceived value tends to be larger when the brand credibility is low.

2.3.6 Moderating Impact of Gender

Prior studies have confirmed that the pattern of adoption and usage of technologies among women can be significantly different from men (Li, Glass, & Records, 2008). This could be because men and women have different value systems (Beutel & Marini, 1995), varying levels of trust, online familiarity (Aeron et al., 2019), self-efficacy (Torkzadeh, & Van Dyke 2002), and usage style (Weiser, 2000). In their study on subjective well-being, Beutel and Martini (1995) found that compared to men, women cherish emotional and social meanings, while men give credence to competitiveness, task orientation (Taylor & Hall, 1982), and materialism. It can be construed that men are likely to pay more attention to the usefulness of the device, as their evaluation of a device or technology could be based on economic, functional (such as ease of use, convenience, effort, and time), or extrinsic motivations (money, recognition, and praise). Therefore, for men, the task-oriented utility features aspect of voice assistants may supersede the hedonic value. Hence we propose:

H6(a): The association between utility features and overall perceived value tends to be stronger for men than women.

When compared to men, women are likely to value the experience which is subjective and personal (Kesari & Atulkar, 2006) over the actual outcome. Hence, there is a possibility that women will appreciate the hedonic features of voice assistants more than men. Therefore, we propose:

H6(b): The association between hedonic features and overall perceived value tends to be stronger for men than women.

According to Pitardi and Mariott (2021), strong and prolonged association with a human being or with the surroundings can enhance para-social relationships (PSRs). Earlier, these relationships were limited to humans (e.g. relation between a celebrity and his/her admirers) but recently, such relationships have been studied with technology as well. For example, users tend to develop an inseparable bond with their mobile phones (Melumad & Pham, 2020), laptops, headphones, wearables, etc. Similarly, with VAs, live and natural interactions between humans and machines have given rise to higher levels of engagement (Guzman, 2019). However, such bonds are found to be stronger among men compared to women, which could be attributed to the fact that men, worldwide, have better access to technology than women (Aeron et al., 2019). Moreover, research shows that compared to men, women are more conservative and cautious towards technology usage while men tend to be more trusting (Yoon & Occena, 2015). The male users are typically, more action-oriented, competitive, and performance-oriented (Schoorman et al., 2007). Hence, we propose:

H6(c): The association between social presence and overall perceived value tends to be stronger for men than women.

In case of perceiving privacy risk, it has been established that the effect of privacy risks on information sharing attitudes is stronger for women (Lin & Wang, 2020). The disclosure of information on digital channels makes women more vulnerable to cyber abuse (Jain & Agrawal, 2020). Therefore, we propose the following hypothesis:

H6(d): The association between perceived privacy risks and overall perceived value tends to be stronger for men compared to women.

2.3.7 Perceived Value and Behavioral Intentions

According to Sigala (2006), perceived value is a primary customer motivation for buying or using a product or service which involves two facets: a 'get' component (involving benefits a buyer derives from offerings by a seller) and a 'give' component (involving monetary cost incurred by the buyer in acquiring the offering). The most favored components of value gathered from marketing literature (Im et al., 2007) lists the following kinds of value: functional or utility features (i.e. the perception of utility associated with the use); emotional or hedonic features (i.e. the state of mind associated with the use); monetary or value-for-money (i.e. utility gained compared to the cost incurred); and social (i.e. the perception of feeling connected with others or self-perception associated with the use). Owing to its multi-faceted approach, the perceived value provides a credible filter to scan the relationship between consumers' perception of value leading to their attitude formation, which in turn impacts their behavioral intention towards continued usage of voice assistants.

The concept of behavioral intention, drawn both from the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), and the Theory of Planned Behaviour (TPB) (Ajzen, 1991), refers to an individual's intention to subscribe or continue to subscribe to a decision. Conferring to Fishbein, Martin, and Ajzen (1975), the formation of an intention to carry out a behavior is a necessary precursor to behavior, and behavior is a direct function of behavioral intention (BI) which is formed by one's attitude of favorableness or un-favorableness towards performing a behavior. According to Taylor and Todd (1995), usage intentions are the sole determinants of usage, thus indicating a positive relationship between behavioral intentions and actions. Many scholars, therefore, have considered behavioral intention towards usage as translating into actual behavior (Chen & Chang, 2018). Voice assistants are increasingly being endorsed by customers as easy to use, having hedonic features, and also having social benefits attached to their usage. Therefore, we propose the following hypothesis:

H7: Overall perceived value has a positive relationship with the individuals' behavioral intention to use voice assistants continuously.

3. Method

The research objective was to explore the impact of various value components on the perception of the overall value of voice assistants in the presence of brand credibility, and how it further affected the users' continued usage intentions. Both qualitative and quantitative methods have been used for data collection and analysis.

For quantitative analysis, an online survey questionnaire was designed for collecting the data. The survey questions were adapted from established scales and analyzed using AMOS and SPSS 23 for causal relationships between them.

For qualitative content analysis, a web-mining script was utilized for extracting the users' reviews about voice assistants (Amazon Alexa and OK Google) from Google Play Store. Text-mining was done to reveal contextual keywords followed by sentiment analysis. However, unlike quantitative data, opinions and sentiments are subjective in nature and express users' actual connection with the technology - in this case, the voice assistants. Therefore, the purpose was to explore whether or not the findings from user reviews are consistent with the findings of the quantitative survey. Another motivation for conducting textual analysis was to understand the values and concerns that affect the users' intention to continue to use voice assistants.

3.1 Measurement scales

An online survey (questionnaire) was hosted to test the proposed research model. The survey was sent only to those respondents who have been using voice assistants consistently for the last 6 months and accessing them at least once a day. The items of all the constructs were adapted from established scales using a five-point Likert scale where 1 represents "strongly disagree" and 5 "strongly agree". The language of the items was changed in the context of voice assistants. Eliminating items from a reflective multi-item scale is commonly referred to as "scale purification" (Frohlich, 2002) and is done to improve the measurement properties of newly developed or existing reflective scales. Thus initially, we had a 44 items survey, which was reduced to 24 items post exploratory factor analysis (EFA). The variables and the source of corresponding items are listed in Table 3, along with their mean value and standard deviation.

3.2 Sampling

Respondents were selected using a mixed multistage sampling method. The purpose of the research was mentioned clearly on top of the survey, along with a qualifier question, "Please proceed with the survey only if you have been using any of the voice assistants (e.g. Alexa, OK Google, Siri, etc.) for at least 6 months and also access it once a day." We initially applied a network and opportunistic sampling strategy by circulating the questionnaire within our networks, as well as to the participants in conferences. Additionally, we used social media platforms to attract more respondents. Later on, using a judgmental sampling method, where the researcher selects the most productive sample to answer the research question (Marshall, 1996) and it has qualities that a researcher expects (Ross, 1979), potential respondents were selected.

3.3 Data collection

The data were collected from January to March 2020 A total of 2265 respondents were approached, 1937 responses were received, and out of which 1820 valid samples were included (the response rate was 80%) in the analysis based on the completeness of the responses. The excluded responses were either partially filled or the standard deviation of item responses was close to zero, which indicated that the respondents have not paid attention to the questions, and marked similar responses to all items. Since the responses were captured online, we tracked respondents' email IDs and restricted one response per email. To eliminate the possibility of non-response bias, we use a time-trend exploration method (Armstrong & Overton, 1977). In the time-trend exploration method, chi-square ($\varkappa^2$) tests are conducted to compare the characteristics (such as age, gender, etc.) of the respondents among early and late respondents. We considered early respondents who answered the survey in the month of January 2020 (within 15 days of the launch of the survey) and late respondents who participated in the last 15 days of March 2020. An insignificant p-value ($p>0.1$) confirmed the non-response bias in the study.

3.4 Data analysis and model testing

The analysis was conducted in two phases. First, we performed tests for reliability, convergent, and discriminant validity by using the statistical tool IBM SPSS 23. Then we tested our structural model using AMOS 23 for the significant path estimates and strength of constructs. Smart PLS is another popular partial least squares (PLS) tool that can assess the measurement and structural models simultaneously. It is a well-suited modeling technique for assessing complex predictive models and for the theory-building stages of an exploratory study (Hair et al., 2014). Furthermore, PLS-SEM enjoys increasing popularity as its ability to model latent constructs even for conditions of non-normality and small to medium-sized samples (Hair, Ringle, & Sarstedt, 2011). We chose the covariance-based AMOS for multiple reasons. First, our data size was very large (1820 responses), the model constructs are mainly reflective in nature, and finally, AMOS is suitable for studies where the analytical focus is to confirm theoretically assumed relationships (Hair et al., 2017), similar to our study.

4. Results

4.1 Sample characteristics

There were 58.1% men and 41.9% women respondents. Most of the samples were from respondents aged less than 35 years (87.6%) totaling 1595 respondents. This distribution is aligned with other similar global studies. For instance, in the research conducted by Han and Yang (2018) (Understanding the adoption of intelligent personal assistants), 76.4% of respondents were less than 35 years of age. Similarly, Kinsella (2019b) mentioned that 75% of the young population, between the age group of 18-29 years globally, are more likely to own a smart speaker than those over 60. However, there was not much difference in terms of the frequency of usage among various age groups. Such findings offer a strong and reasonable premise for our study to conduct research based on this population. The demographics of the respondents are presented in Table 2.

<< **Insert Table 2:** Demographics of Respondents **here**>>

As the demographic data reveals, the majority of respondents are working professionals (73.9%) followed by students, business professionals, and women managing their homes. The mean value of survey item responses is found to be greater than 3.5 with a larger standard deviation value which is above 0.8 (see Table 2). A high standard deviation indicates that the data points are spread out over a large range of values.

<<**Insert Table 3:** Descriptive Statistics Analysis **here**>>

4.2 Reliability & validity (Measurement Model)

The analysis for reliability (Cronbach α), convergent validity, discriminant validity, and Composite Reliability (CR) was performed for the full sample (n=1820). The Cronbach for all the variables ranged from 0.77 to 0.87. The CR value of the latent construct was between 0.74 to 0.88, satisfying the recommended benchmark of 0.7 (Fornell & Larcker, 1981). The reliability and internal consistency of the questionnaire can be verified with the result. For evaluating the measurement model, construct validity was checked. The average variance extracted (AVE) was between 0.50 to 0.63, and all were above the benchmark of 0.5, hence, there was no problem of discriminant validity (Gefen & Straub, 2003a). Subsequently, Table 4 shows that the correlation between each pair of constructs is less than the square root of AVE which confirms that there is no problem of discriminant validity. All the constructs showed good reliability, and the validity of the constructs is also confirmed. The standards for the acceptability of the measurement model are satisfied (Hair et al., 1992).

<< Insert Table 4: Factor Correlation Matrix **here>>**

Since the data were collected using the survey instrument, the common variance bias can be a concern when both the dependent variable and the explanatory variable are perceptual measures derived from the same respondent. (Podsakoff & Organ, 1986). Common Variance bias is “the variance that is attributable to the measurement method rather than to the constructs the measures represent’’ (Podsakoff et al., 2003, p. 879). Hence, it was checked using two different techniques

Harman Single-Factor technique (Harman, 1960), and Common Latent Factor (Eichhorn, 2014). The Harman Single Factor technique uses exploratory factor analysis where all the variables are loaded on a single factor and are constrained to no rotation. Our analysis showed that 32% of the variance was explained by a single factor, that is to say, if the variance explained is more than 50%, then there is a presence of common method bias. After the Harman Single-Factor, the Common Latent Factor technique was applied, in which a new latent variable is introduced in such a way that all the apparent variables are related to it. All the paths are considered equal and the variance of the common factor is constrained to 1 (Eichhorn, 2014, pp. 5). Even though it seems similar to the Harman Single-factor technique, as all the variables are related to a single factor, but in this technique, the latest factors and their relationship are preserved in the analysis, and then the common variance is estimated as the square of each common factor of each path. We extracted two factors where the maximum common variance was no more than 26% which is less than 50% of the threshold value, thus confirming further that there was no common method bias in the study. After this, we conducted a confirmatory factor analysis (CFA). The results of CFA indicate a well-fitting model (Table 5).

<< Insert Table 5: Confirmatory Factor Analysis (Model Fit) **here>>**

All values from the model fit statistics for CFI, GFI and AGFI were above 0.95 way above the permissible threshold level, which showed that our model is acceptable. We even evaluated the model fit parameters for brand credibility subsamples (high/low) and gender (men/women), all parameters were the same as that of the full sample.

4.3 Main effects of U&G and perceived value of AI (H1-H4 and H7)

For the full model, we tested the hypotheses H1-H4 and H7 for the strength of the relationship, path coefficients, and their significance levels at $p<0.01$(Figure 2). The results indicate that there exists a strong and significant relationship between utility features and OPV (0.61, $p<0.001$), medium effects between hedonic features and OPV (0.21, $p<0.001$) low effects between social presence and OPV (0.12, $0<0.001$) and perceived privacy risk and OPV (-0.01, $p<0.01$). Furthermore, a strong, significant, and positive relationship exists between OPV and voice assistant continued usage intentions (VACUI) (0.80, $p<0.001$). Therefore, the hypothesis H1 and H7 displayed strong effects, H2 and H3 have a medium effect, and H4 exhibited low effects (see Table 7). A higher path coefficient between OPV and VACUI further confirms a strong association between the constructs. These effect sizes are supported in extant literature (Cohen, 1988).

The relationships among utility features, hedonic features, and social presence and the overall perceived value are found to be positively significant, whereas the relationship between perceived privacy risks and overall perceived value is negatively significant. Although significant, the path estimate between perceived privacy risks and overall perceived value is very small (-0.01). Based on the analysis, our hypotheses H1, H2, H3, H4, and H7 are supported as conceptualized (see Table 6).

<< **Insert Fig. 1**. Full Model Analysis (without moderators) **here>>**

<< Insert Table 6: Full Model Hypotheses Analysis with Path Estimates **here**>>

4.4 Moderating effect of brand credibility (H5)

As stated in the preceding sections, for multi-group moderation analysis we tested 4 subsamples: 1) effects with high brand credibility 2) effects with low brand credibility, 3) the number of responses from men, and 4) responses from women. Moderation is described as, "the function which partitions a focal independent (predictor) variable into subgroups that establish its domains of maximal effectiveness concerning a given dependent variable" (Baron & Kenny, 1986 p. 1173). When the strength of the relationship between two variables is dependent on a third variable, moderation is taking place (Preacher, Rucker, & Hayes, 2007). Since the construct brand credibility was formulated as a continuous variable (values were captured on the 5-point Likert scales), the procedure proposed by Cohen et al. (2013) was followed:

1. Sort the sample in ascending order
2. Split data across median values of the moderating variables into two subgroups (i.e. low/high, or small/large)
3. Run regression (for small samples) or structured equation modeling (for large samples).

Owing to the large sample size, we chose to proceed with structural equation modeling. The results of the structural model along with their coefficients and significance levels are shown in Figures 3 and 4. The relationship between each pair of constructs and supported hypotheses is exhibited in Table 8. Furthermore, as hypothesized, a difference in perception of users with higher brand credibility was realized except for the construct social presence. All path coefficients were statistically significant (p<0.01) otherwise.

<< **Insert Fig. 2.** Amos Results for the Structural Model with Low Brand Credibility (n=1111) **here**>>

<< **Insert Fig. 3.** Amos Results for the Structural Model with High Brand Credibility (n=709) **here**>>

<<**Table 7:** Hypotheses Results for Brand Credibility as a Moderator **here**>>

The analysis of H5a indicates that the utility features have more importance for respondents paying attention to higher brand credibility. A positive significant relationship exists between utility features and overall perceived value of voice assistants (for low BC path coefficient=0.0.518; for high BC path coefficient = 0.697 for both $p < 0.001$). Furthermore, H5b was supported, which indicates that Hedonic has a positive significant relationship with the individuals' overall perceived value (for low BC path coefficient=0.179; for high BC path coefficient = 0.253 at $p < 0.001$). Unlike H5a and H5b, hypothesis H5c (social presence) was rejected. Although the path coefficients were significant, the polarity of the values reversed (for low BC path coefficient = 0.0.129, $p<0.001$; for high BC path coefficient = -0.03, $p < 0.01$). In the case of low BC, the construct social presence significantly contributes towards overall perceived value, but in a subsample of high BC, it exhibits a negative association with overall perceived value. In the case of hypothesis H5d, the effect of perceived privacy risk becomes negligible with high BC (path coefficient = -0.01, $p<0.01$), while in low BC, the construct perceived privacy risk exhibited a medium negative association with overall perceived value (path coefficient = -0.11, $p<0.01$), which indicates that the perception of risks contributes negatively in the perception of overall value expected from the voice assistants when brand credibility is low. Thus the hypothesis H5d was supported. We also observed that the path estimates for overall perceived value have improved slightly in case of higher brand credibility compared to low brand credibility (for low BC path coefficient=0.875; for high BC path coefficient = 0.904 at $p < 0.001$).

4.5 Moderating effect of gender (H6)

A similar process was followed for the gender subsamples, except for utility features and social presence we could not find any significant differences in path coefficients for the constructs utility features and perceived privacy risks (Table 8). The women were found to be more attracted by the hedonic features of voice assistants than their male counterparts. Similarly, the value of social presence (women path coefficients 0.132, $p<0.001$) was more than men (path coefficients -0.03. We could not find any significant difference between men and women regarding their continued usage intentions of voice assistants. Hence our hypotheses H6b and H6c were supported, while H6a and H6d were rejected.

<<**Insert Table 8:** Hypotheses Results for Gender as a Moderator **here**>>

4.6 Qualitative analysis of voice assistant reviews

Post empirical analysis, we conducted a post-hoc analysis of online user reviews on the app store. The objective was to map the survey findings with the up-front views of users about the voice assistants and observe the pattern.

For analyzing the user-generated content, we extracted reviews from Amazon's Alexa and OKGoogle voice command apps from the Google Play store. The purpose of choosing these two apps was multifold: 1) both apps offer an android based voice assistant, 2) both are freely available and have the largest user base (e.g. by the end of the year 2019, the market percent share of Amazon Alexa was 31.7% whereas for OKGoogle, was 31.4% (Statista, 2020), 3) both are comparable in features, offerings. We used a Google Play Scraper for Python API[1] that helped us in scraping reviews from the Google Play Store. These reviews were rated on a scale of 1-5 where 1 represents "bad experience" and 5 for an "awesome experience". The break-up of these reviews for both voice assistants is exhibited in Table 9.

<< **Insert Table 9:** Rating based Breakup of Number of Reviews **here**>>

The reviews were mined from January 2019 till mid-October 2020. The total number of reviews collected for Alexa was 5861, and for Google, it was 7654. All reviews were text-based and written in the English language. A qualitative data analysis computer software package NVivo 13 was

[1] The Google Play Scrapper was published on April 12, 2020 from the site https://www.curiousily.com/posts/create-dataset-for-sentiment-analysis-by-scraping-google-play-app-reviews-using-python/ API is accessed on 18th August 2020

used for the analysis. First, we prepared the word cloud of both sets of data. The word cloud led us to the top 100 most frequented words (Figure 5 and Figure 6) in user-generated content. Typically, voice assistants are known by their wake words, for example, Amazon's voice assistant's popular wake word is "Alexa", Google's voice assistant's wake word is "OKGoogle". A user calls out these wake words to get the task done by the voice assistant. From word cloud analysis, we observed the following:

1. The most frequent words that emerged in the word cloud were "Alexa", "Amazon", "Echo", "Google" which represent directly, the brand recall by users in their content.
2. In both sets, the emergence of words like "features", "work", "working", "music", "navigate/search", "reminders", "driving", "calls", "alarm", and "questions" represents the utility-based applications (values) of voice assistants.
3. Words like "available", "helpful", "respond" indicate that users were recognizing the social presence of voice assistants around them.
4. We did not find any word in the top 100 words list indicating privacy concerns of users. Therefore, we manually analyzed the reviews and found that in the case of OKGoogle, 20 reviews were exclusively sharing their concerns related to privacy, whereas, in the case of Alexa, the number was 23. Similarly, for OKGoogle, 33 reviews raised security concerns, and for Alexa, it was 28 reviews. The smaller number of reviews could be attributed to higher brand credibility. In 2019, Amazon has overtaken Google (2nd place at $315.5 billion), and Apple (3rd place at $309 billion) to become the world's most valuable brand, (Kantar, 2019).
5. We also found several words expressing frustration and irritation with the voice assistants. For example, words like "frustrating", "fix", "issues", "annoying", "problems", "slow"

indicates glitches in the applications – although this aspect is not covered by the current research.

<< **Insert Fig. 5**. Word Cloud of OKGoogle Reviews **here**>>

<< **Insert Fig. 6.** Word Cloud of Alexa Reviews **here**>>

Next, we performed sentiment analysis for the two voice assistants. For sentiment analysis, the user-generated content was classified into three buckets – Positive, Neutral, and Negative reviews. Ideally, products and services offered by the market leaders (top brands) tend to have more praise than criticism. While both Amazon's and Google's voice assistants have steady recognition as respectable brands, the analysis shows that OKGoogle has witnessed a steady growth in positive reviews followed by negative, and then neutral reviews. However, post-July 2020, there was a sudden drop in the frequency of reviews for OKGoogle (Figure 7). The same was not true for Amazon's Alexa. Although in the initial months of 2019, the total number of reviews for Alexa was less, and there was not much difference in the numbers for positive, neutral, and negative reviews. But in the year 2020, Alexa picked up and got more positive reviews than neutral and negative reviews, thereby surpassing OKGoogle in the count (Figure 8).

<< **Insert Fig. 7.** Sentiment Analysis for OKGoogle Reviews **here**>>

<< **Insert Fig. 8.** Sentiment Analysis of Alexa Reviews **here**>>

5. Discussion

The study results indicate that in the case of the full model, hypotheses H1-H2 are supported, which means that utility features and hedonic features are visible and significantly contributing to the overall perceived value of voice assistants. These findings are consistent with other empirical studies conducted with similar nature of interactive technologies such as shopping assistants Al-Natour, Benbasat, & Centefelli, 2011), intelligent personal assistants (McLean & Osei-Frimpong, 2019), mobile commerce browsing (Zheng et al., 2019), and AI-powered retail stores (Pillai et al., 2020). These previous studies show that higher acceptance can be achieved if interactive technology can assist the users in performing their day-to-day tasks with more ease and efficiency. In the current study, we observed that users have given more weight to utility features than hedonic features, although both values tested as significant. However, our results show divergence from prior studies (Park et al., 2012; Tamilmani et al., 2019), where the findings indicate that in comparison to utility features, hedonic features had a strong and positive effect. The hypothesis H3 is also supported, which suggests that users are using voice assistants as they offer them an artificial presence of humanoid intelligence, such as virtual human agents (Fernandes & Oliveira, 2020). Our next hypothesis H4 is partially supported with a very low value of path coefficients i.e. -0.017. This is inconsistent with earlier studies (Ford & Palmer, 2018; Han & Yang, 2018) where perceived privacy risk was found to have a strong negative impact on the consumers' continuance intentions to adopt and use intelligent or interactive devices. Our results support hypothesis H7, which indicates that there is a significant positive impact of overall perceived value realization on the behavioral intentions of users who affirm to continue their use of voice assistants in the future. Prior studies (Parasuraman, 1997) recognized perceived value as one of the imperative measures for gaining a competitive advantage, and behavioral intentions are viewed as indicators that signal whether customers will continue with, or leave the product. The results achieved in our study are consistent with prior research (Basaran and Aksoy, 2017; Han & Yang, 2018) which states that value realization by users ensures continued intention to use voice assistants.

We further tested our model with brand credibility as a moderator (low BC and high BC). As postulated, the results exhibit that hypotheses H5a, H5b, and H5d are supported when perceived brand credibility is high. The path estimate for perceived privacy risks dropped from -0.11 (high

BC) to -0.01 (low BC) and path estimates for utility and hedonic features show increment (see Table 7). Such results evince the importance of brand credibility as a testimony to the power of a good brand and its impact. Our survey consisted of responses from 1820 users, among them 978 (54%) use Google Assistant, 332 (18%) use Alexa, 385 (21%) use Apple Siri, 70 (4%) use Microsoft Cortana, and 55 (3%) use Samsung Bixby. All of these brands are owned by fortune 500 companies (Fortune 500 (2019); Kantar, 2019). The findings are consistent with studies in the domain of different products (Baek et al., 2010) and services (Jin et al., 2015). It has been established since long that perception of risk is likely to reduce either through the use of brands (Bauer, 1960; Peter & Ryan, 1976), or through extensive information gathered (Mitra et al., 1999) from various sources such as websites, comparator sites, blogs, reviews, influencers, and articles. High perceived risk encourages users to search more, and as they find more and more information available about a product, service, or brand (online or offline), their perception of the concept changes, and they tend to adopt the concept quickly. It is common practice for organizations to use brands as signals to assuage consumers' uncertainty. A good brand acts as a signal for users when considering the unobservable quality (Rao et al., 1999). Online brands like Amazon, Google, Microsoft, and Apple have tremendous opportunities to spread awareness about their offerings in the form of freebies, reports, videos, contests, and blogs. Such actions by brands build trust, improve comfort (Davis et al., 2000), and inculcate in users the tendency to perceive branded products as higher in quality and therefore, less risky (Hasan et al., 2020). Interestingly, the hypothesis H5c with social presence does not get supported with high BC. The results indicate that in the case of high BC, the path estimates reduced drastically with negative polarity (see Table 7), which implies brand credibility does not exert an influence on overall perceived value as far as social presence is concerned. At the same time, there is a significant amount of brand recall in user-generated reviews, which confirms consumers' expectations related to the quality of experience.

Our investigation of gender difference as a moderator in an integrated model is another important contribution of this study. The effect of gender difference has been discussed and tested in prior technology behavioral intention studies. Our findings indicate that women value more hedonic features and social presence than men. These findings are consistent with other technology studies (Borges et al., 2013). Conversely, some studies exhibit that men value hedonic benefits more, and women are attracted by utility features benefits (Li, Glass, & Records, 2008). In the presence of such contradictory findings, it is useful to say that value realization is highly contextual to the technology. The question of how men and women understand the technology and use it could be based on multiple other factors such as para-social attraction (Han & Yang, 2018), perception of similarity with the technology (Lee & Lee, 2018), comfort level, emotional connect, experience (Fernandes & Oliveira, 2020), and engagement (Moriuchi, 2019). As far as social presence is concerned, women attach more value to the social presence (human-like features of voice assistants) than men. This could be due to the current versions of voice assistants that suggest intimacy-like features of a human friend and are always available and answering the users' call as companions or assistants. These factors enhance the overall perceived value and intentions of continued usage.

However, we did not find any significant difference in the perceived risk perceptions between men and women, as it is likely that both have equal concerns about the misuse of private data. In this instance, our findings are aligned with McLean and Osei-Frimpong's (2019) study.

Our qualitative findings largely converged with our empirical findings. The qualitative results suggest the significance of brand association for users, as the most frequently used words emerging from the user reviews were the brand names ("Alexa", "Amazon", "Echo", "Google") exhibiting direct brand recall by the users in their content. The utility values of VAs, similar to quantitative findings, were signaled more by the users. Words like "available", "helpful", "respond" in the users' content indicated that users were acknowledging the social presence of VAs. But this finding was not discrepant from the quantitative results. This is because the quantitative findings show that those favoring brands have more concerns over data privacy and the functional value of VAs, as opposed to users who are less brand conscious and more into social and personal liking. Similar to our empirical findings, privacy was not a predominant concern in the users' content.

6. Conclusions and implications

6.1 Conclusions

The VA market is rising steadily. From the perspective of firms, consumers' choices and perspectives matter greatly in familiarizing and customizing VAs for different contexts. In the present study, we have conducted both empirical research and qualitative analysis (of user-generated content) to show that users prefer gains (value) over the perception of loss of private data in their VA usage. In our empirical investigation, we found that brand credibility is a significant moderator that impacts the relationship between VA features and the overall perceived value of VAs – higher brand credibility reduces users' perception of privacy risks. We found that perceived privacy risks have a negative impact on the overall perceived value of VAs. Further, the utility values of VAs are favored over hedonic features contributing to overall perceived value and continued usage. Our qualitative findings are also consistent with the empirical study. Both investigations confirm that in VAs, the key enablers are associated with the overall perceived value and the brand credibility of the device.

6.2 Theoretical contributions and implications

Concerns have been raised in the academic literature (Vimalkumar et al., 2021; Dubiel, Halvey, & Azzopardi, 2018) about the privacy and security of data (conversations) associated with the use of voice assistants. However, not much has been said about whether the perceived value of voice assistants supersede individuals' privacy risk concerns. Similarly, there has been no exploration of whether brand credibility reduces individuals' privacy risk concerning the VAs. In terms of theory, the present study makes three key contributions:

- **Perceived features of VAs supersede individuals' privacy risk concerns -** Although for intelligent devices like voice assistants, which do not have many precursors, the risk of privacy is a serious concern for consumers. Our study shows that consumers make a trade-off between privacy risk and the benefits of VAs based on the overall perceived value of VAs. We drew on Prospect theory and U&GT to posit that users perceive value (utility, hedonic, social presence) of VAs as gain. Our findings reveal that the utility aspects of VAs are favored over hedonic features, contributing to overall perceived value leading to continued usage.
- **Brand credibility contributes to the perception of the overall value of VAs -**We drew on signaling theory to depict that technology products from recognizable brands have a better value perception, as their brand credibility can lower consumers' information search cost, decrease perceived risk (Erdem & Swait, 1998, 2004; Mitra et al., 1999), and enhance expected utility (value) of voice assistants. Our study results show that brand credibility significantly moderates the relationship between the features of VAs and their overall

perceived value. Therefore, if the brand perception is high, the perception of utility value of the artifact will improve, which in turn will lead to continuous usage.

- **Brand credibility assuages individuals' perceived privacy risk concerns –** Prior research has established that brands can be used to reduce risk perception (Peter & Ryan, 1976), build trust, and improve comfort (Davis et al., 2000). The positioning of brand credibility as a moderator in our study shows that privacy risks dropped when brand credibility was high. Our results establish the importance of brand credibility on lessening consumers' risk perception, thereby also suggesting that brand signaling of voice-based devices can elicit trust about the overall value of the device.

6.3 Practical implications

Although brand credibility has been discussed widely in the marketing literature, little is known about the effect of brand credibility on individuals' overall perceived value and continued usage decision of intelligent technologies like voice assistants. The findings of the present study reveal the key attributes of VAs (utility, hedonic, and social presence) to influence users' engagement with the device. It further reveals that women prefer to use VAs for intrinsic benefits (such as fun and enjoyment, social presence, etc.) than extrinsic (utility/functional) features. Given the VA market is evolving rapidly, it would serve existing VA brands (e.g. Amazon, Apple, Google) and the emerging ones to be mindful of the soaring customer expectations. The firms should keep in mind that:

a. Improving the technical capabilities of VAs will win consumers whereas a poor technology interface can erode brand credibility.
b. The functionality of the applications should be mapped to the customer journey. This constitutes the possible experiences users might have while interacting with the application

from the start to continuing with the usage. Also, if customers are not aware of the range of features of VAs, it will lead to a lack of optimal utilization of these devices. Therefore, organizations should pitch diverse applications of voice assistants in their marketing communications while approaching different user groups. The promotions can be customized (age and genderwise) to highlight specific applications and their usage.

c. As voice assistants are faceless presences, the tone of voice, therefore, becomes a very important medium of exchange. A robotic voice or an unrelated expression may lead to creating an incoherent and uncomfortable customer experience (e.g. the voice tone may be subtle and serious for medical appointment booking, and could be cheerful for restaurant booking).

d. For VA makers and app integrators, diversity should be a key consideration. A 2019 study by UNESCO revealed that gender bias and stereotypes were engineered into AI-powered VA applications (UNESCO, 2019). The marketers can improve their image as conscious, unbiased, and caring brands to further improve their credibility among diverse user groups.

Our findings reveal that brand credibility is indeed providing a cushioning effect for privacy concerns, and users feel confident about the continuance of usage, based upon the perception, 'my brand won't let me down.' This research can be used to evaluate users' perceptions of a brand.

6.4 Limitations and future research

This study offers significant insights into the effect of brand credibility on consumers' perception of the overall value of voice assistants and their continuance of usage decisions. However, the study has focused mainly on understanding the value enhancers for consumers, and the research did not explicitly extend to understanding the value reducers for VAs. As our qualitative analysis of user-generated sentiments revealed, that users expressed frustration and irritation with the voice assistants (e.g. VAs not able to process or respond to queries with alacrity). Future research can look into these areas.

The majority of respondents in our study were from an age group ranging up to 35 years. But it has been observed that voice assistants are also becoming popular among middle-aged citizen groups. The 25-49 age group has been found by the PWC (2018) report to be using VAs most frequently. Therefore, future research may examine the individual differences among various age groups to refine the present study findings further.

Finally, this study looked into the overall credibility of the brand, while future research may unlock this construct further and explore how the antecedents (trustworthiness and expertise) of brand credibility may impact the users' loyalty or switching propensity to other brands.

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Tables

Table 1: Users' Adoption of Intelligent Devices: Select Review

Study	**Context**	**Key Findings**
Alepis & Patsakis (2017)	Analysed five VAs: Google Assistant, S. Voice, Cortana, Alexa, and Siri	The IPAs can be exploited from applications or nearby devices leading to malicious attacks and privacy risks
Castelo et al. (2019)	4 Online Lab Studies with over 1,400 participants and two online field studies with over 56,000 participants	Increasing VA devices' algorithms' perceived affective human-likeness is effective at increasing the use of such algorithms for subjective tasks
Fernandes & Oliveira (2020)	Survey of 238 young consumers	Customer-robot rapport building - Extends the service robot acceptance model by Wirtz (2018) to show that Customers increasingly organize their everyday activities with the support of technology.
McLean & Osei-Frimpong (2019)	Survey of 724 in-home VA users	The utilitarian benefits, symbolic benefits, and social benefits provided by VAs are significant. Hedonic benefits only motivate the use of in-home VAs in smaller households
Han & Yang (2018)	304 survey samples	Interpersonal attraction (task attraction, social attraction, and physical attraction) and security/privacy risk are affecting the adoption of IPAs
Moriuchi (2019)	368 respondents aged between 25-28years surveyed from Amazon's Mechanical Turk (mTurk)	User's subjective norms in using the internet impact perceived usefulness and perceived ease of use of VA
Vimalkumar et al. (2021)	252 Indian respondents using virtual-based digital assistants	Perceived privacy risk has a strong negative and significant influence on perceived trust. To increase trust, one has to address the risk perception towards technology
Guzman (2019)	Responses of 28 participants of different races and ethnicities (Latino, self-identified white, Black, Asian, Middle-Eastern) from field sites	Voice-based, mobile virtual assistants such as Siri, Google have complex designs. Some users perceive the conversational agent's voice as representing the phone, while other users perceive the conversational agent's voice as the assistant in the phone
Nasirian et al. (2017)	Offline survey of 104 students from a University in the US	Interaction quality, trust, and personal innovativeness are significant motivators for using VAs
Hasan et al. (2020)	Data was collected from a sample of 675 Apple iPhone	Perceived risk has a significant negative influence on brand loyalty. The influence of novelty value of

	using respondents from the MTurk platform	using Siri was found to be moderated by brand involvement and consumer innovativeness
Cowan et al. (2017)	20 participants were recruited from a University community (14 students, 6 non-students) for semi-structured focus groups	Infrequent users are uncomfortable in using IPAs in public because of social embarrassment concerns, hence, limits their usage. Users find the lack of integration of third-party apps with IPAs frustrating. Concerns over data privacy, ownership, and use of user data for commercial benefits
Moorthy & Vu (2014)	120 smartphone users From U.S. recruited from Amazon Mechanical Turk (AMT)	Participants preferred using the VAPA in a private location (e.g. home), and even in that environment, they were hesitant about using it to input private or personally identifying information in comparison to more general, non-private information
Dubiel et al. (2018)	An online survey of 118 VPA users	Compared with infrequent users, frequent users of VPAs are more satisfied with their VPAs, more eager to use them in a variety of settings, but equally concerned about their privacy
Present study	An empirical survey of 1820 VA users, and qualitative analysis of user-generated content	Brand credibility significantly moderates the relationship between VA features and the overall perceived value of VAs – higher brand credibility reduces users' perception of privacy risks

Table 2: Demographics of Respondents

Demographics	Frequency	Percentage(%)
Gender		
Men	1058	58.1
Women	762	41.9
Age Range		
<20	58	3.2
20-25	932	51.2
25-30	462	25.4
30-35	142	7.8
>35	226	12.4
Profession		
Student	245	13.5
Working Professional	1345	73.9
Business	173	9.5
Housewife	57	3.1

Table 3: Descriptive Statistics Analysis

Variables/ Scale adapted from	Final Survey Questionnaire	Mean	Std. Deviation	Cronbach alpha
While answering the following questions, please recall the brand of your voice assistant and your experience with it.				
Utility Features (Davis, 1989; Venkatesh, 2000)	In my opinion, using the voice assistant increased my task effectiveness	3.798	.8728	0.773
	Using the voice assistant enabled me to navigate (browse) quickly.	3.776	.9081	
	In my opinion, using the voice assistant increased my overall efficiency	3.930	.8596	
Hedonic Features (Al-Natour et al., 2011)	I consider that my interaction with the voice assistant is exciting	3.495	.9653	0.783
	I consider that my interaction with the voice assistant is pleasant	3.615	.8875	
	I consider that my interaction with the voice assistant is interesting	3.652	.9120	
Social Presence (Al-Natour et al., 2011; Gefen & Straub, 2003a)	There is a sense of human contact when interacting with the voice assistant	3.428	1.0625	0.847
	There is a sense of personal touch when interacting with the voice assistant	3.348	1.0212	
	There is a sense of sociability when interacting with the voice assistant	3.287	1.0312	
	There is a sense of human warmth when interacting with the voice assistant	3.079	1.1067	
Perceived Privacy Risk (Yang et al., 2017)	In general, it would be risky to give personal information to the voice assistant	3.511	1.0409	0.872
	There would be a high potential for privacy loss associated with giving personal information to the voice assistant.	3.537	1.0429	
	Personal information could be inappropriately used by the manufacturers of the voice assistant	3.528	1.0165	
	Providing my personal information to the voice assistant would involve unexpected problems	3.441	1.0010	
Brand Credibility (Erdem & Swait, 1998)	This brand delivers what it promises	3.99	.800	0.813
	This brand product claims are believable	3.903	.8418	
	The voice assistant services offered by the brand lives up to their promise	3.891	.8416	
	This brand is at the forefront of using voice assistance technology to deliver a better service	3.900	.8747	

Overall Perceived Value (OPV) (Cronin et al., 2000)	I find it easy to get the voice assistant to do what I want it to do.	3.790	.9384	0.819
	The experience with voice assistant has satisfied my needs and wants	3.660	.9513	
	Overall, the value of experience with the voice assistant is very high	3.548	.9428	
Voice Assistant Continued Usage Intention (VACUI) **(**Bhattacherjee 2001)	I intend to continue using voice assistant rather than use any alternative means	3.861	.8608	0.847
	I would like to continue my use of voice assistant	3.773	.8802	
	I intend to continue using the voice assistant rather than discontinue its use.	3.868	.9432	

Table 4: Factor Correlation Matrix

	Utility Features	Hedonic Features	Social Presence	Privacy Risk (PPR)	Brand Credibility	OPV	VACUI	AVE
Utility Features	**0.656**							0.510
Hedonic Features	0.643	**0.723**						0.523
Social Presence	0.382	0.585	**0.764**					0.583
Privacy Risk (PPR)	0.115	0.028	-0.088	**0.795**				0.631
Brand Credibility	-0.699	-0.542	-0.416	-0.051	**0.726**			0.527
OPV	0.733	0.627	0.463	0.002	-0.561	**0.783**		0.612
VACUI	0.810	0.654	0.382	0.128	-0.627	0.744	**0.656**	0.501

Table 5: Confirmatory Factor Analysis (Model Fit)

Parameters (Threshold Value)	**Model Values**
chi-square (χ^2) value	4.757
Degree of freedom (df)	8, p<0.0001
CFI[2] (>0.90)	0.9926
GFI[3] (>0.90)	0.993
AGFI[4] (>0.90)	0.0.964
RMSEA[5] (<0.05)	0.045

[2] CFI – comparative fit index
[3] GFI – goodness of fit index
[4] AGFI – adjusted goodness of fit index
[5] RMSEA – root mean square error of approximation

Table 6: Full Model Hypotheses Analysis with Path Estimates

Hypothesis	Relationship	Bootstrap Sample	Path Coefficients	Supported/Not Supported	Effects
H1	Utility→OPV	5000	0.61**	Supported	Strong
H2	Hedonic→OPV	5000	0.21**	Supported	Medium
H3	Social Presence→OPV	5000	0.12**	Supported	Medium
H4	Privacy Risk→OPV	5000	-0.01*	Supported	Low
H7	OPV→VACUI	5000	0.80**	Supported	Strong

Note: **p<0.001, *p<0.01
OPV is the abbreviation of overall perceived value and VACUI is the abbreviation of voice assistant continued usage intentions.

Table 7: Hypotheses Results for Brand Credibility as a Moderator

		Low Brand Credibility (BC)	High Brand Credibility (BC)	Supported/Not Supported	Effect
H5a(+)	Utility→OPV	0.518**	0.697**	Supported	Strong
H5b(+)	Hedonic→OPV	0.179**	0.253**	Supported	Medium
H5c(+)	Social Presence→OPV	0.129**	-0.03*	Not Supported	Low
H5d(-)	Privacy Risk→OPV	-0.11*	-0.01*	Supported	Low

Note: **p<0.001, *p<0.01
OPV is the abbreviation of overall perceived value and VACUI is the abbreviation of voice assistant continued usage intentions.

Table 8: Hypotheses Results for Gender as a Moderator

		Men	Women	Supported/Not Supported	Effect
H6a(+)	Utility→OPV	0.748**	0.748**	Not Supported	Strong
H6b(+)	Hedonic→OPV	0.162**	0.139**	Supported	Medium
H6c(+)	Social Presence→OPV	0.129**	0.08*	Not Supported	Low
H6d(-)	Privacy Risk→OPV	-0.03*	-0.03*	Supported	Low

Note: **p<0.001, *p<0.01
OPV is the abbreviation of overall perceived value and VACUI is the abbreviation of voice assistant continued usage intentions.

Table 9: Rating based Breakup of Number of Reviews

Review Rating	1	2	3	4	5
OKGoogle (7654)	1832	1319	1273	1576	1660
Alexa (5861)	892	756	1861	1235	1117

Figures

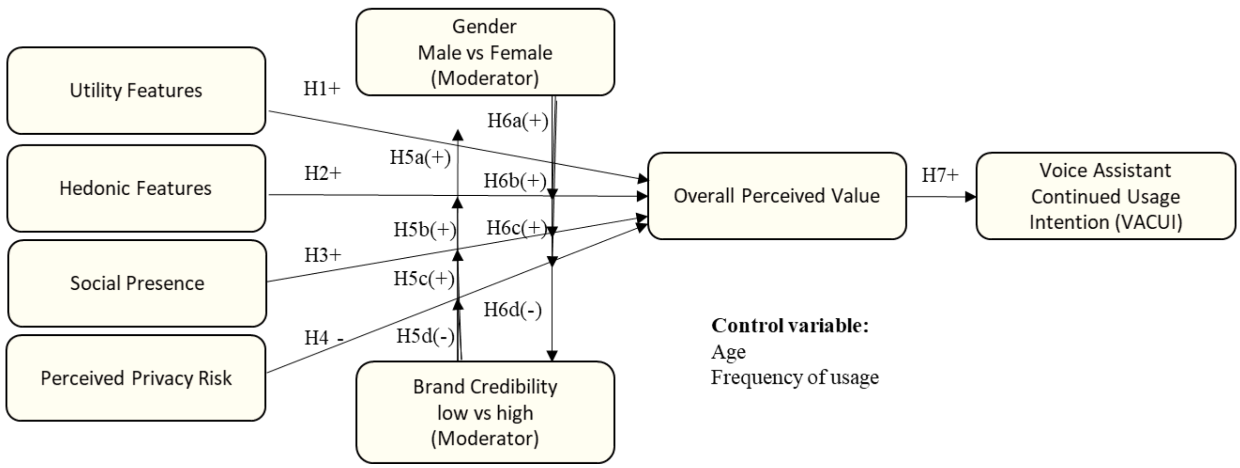

Fig. 1. Conceptual Model

Note: For moderating effects, + (-) indicates stronger(weaker) associations of the two moderators' brand credibility and gender.

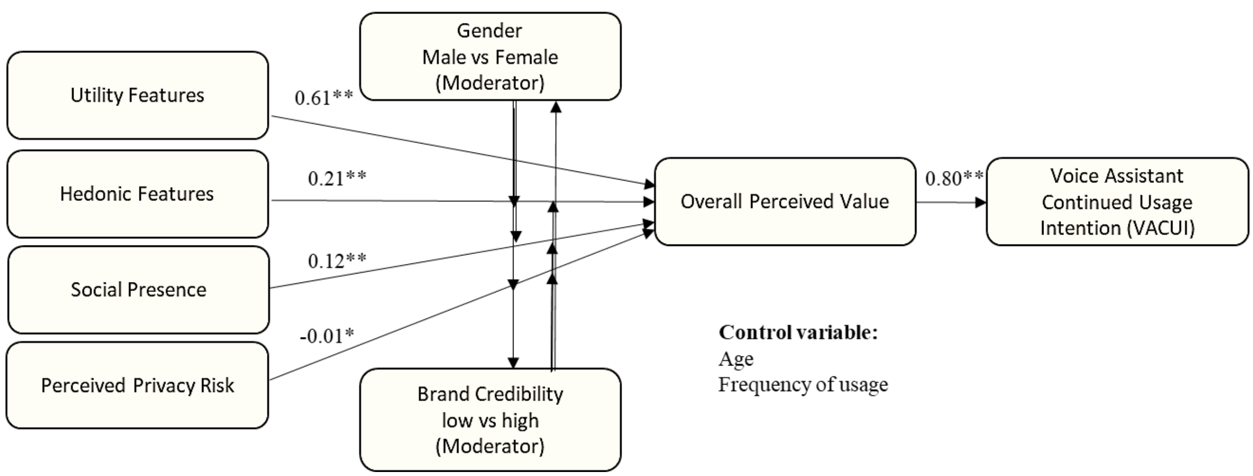

Fig. 4. Full Model Analysis (without moderators)

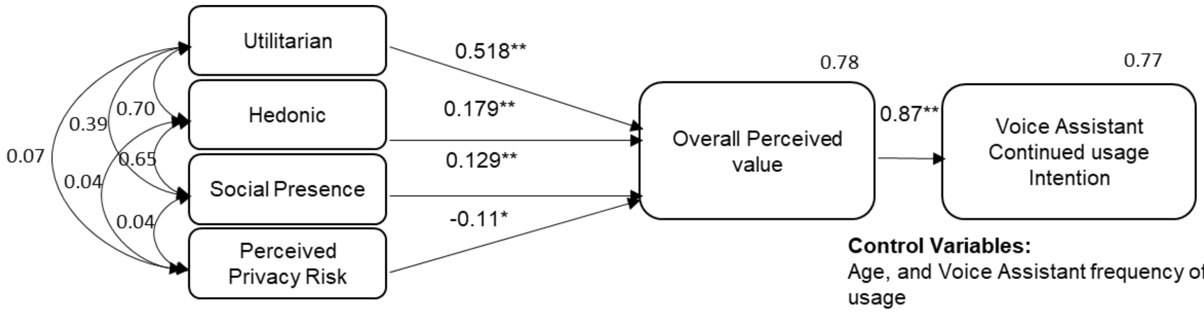

Fig. 5. Amos Results for the Structural Model with Low Brand Credibility (n=1111)

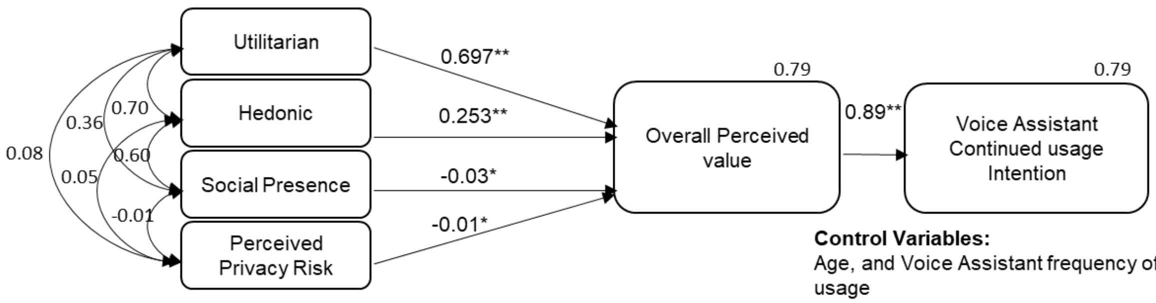

Fig. 6. Amos Results for the Structural Model with High Brand Credibility (n=709)

Fig. 5. Word Cloud of OKGoogle Reviews

Fig. 6. Word Cloud of Alexa Reviews

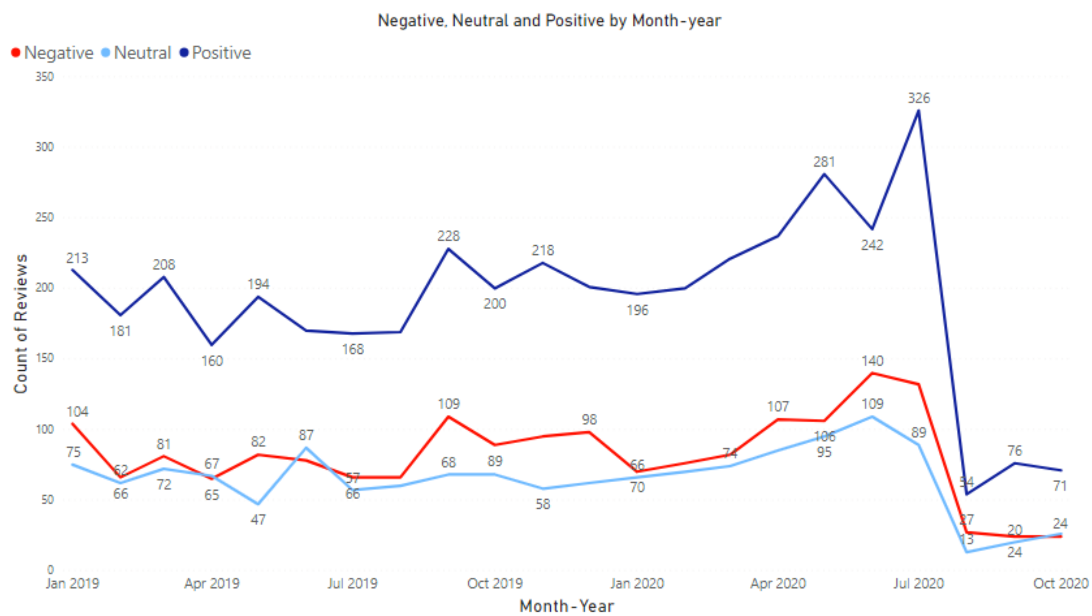

Fig. 7. Sentiment Analysis for OKGoogle Reviews

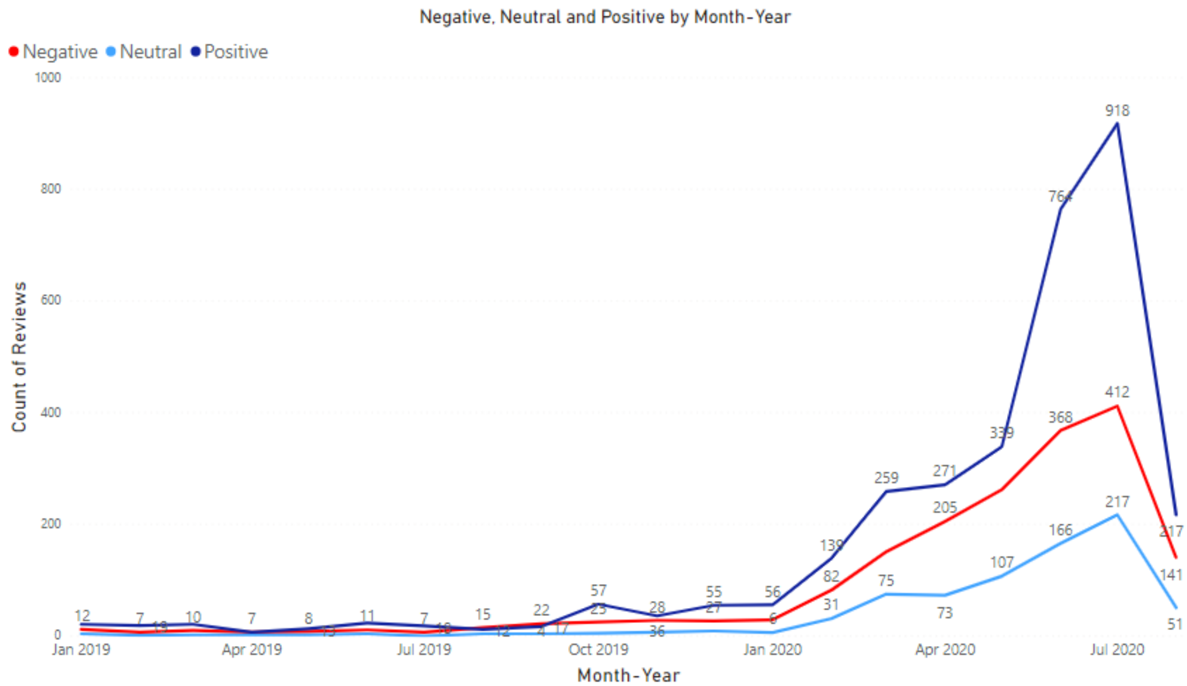

Fig. 8. Sentiment Analysis of Alexa Reviews