

Speak, Assist, Purchase: Exploring the Impact of Voice Assistants on Consumer Purchase Intention

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Abstract

Artificial intelligence has the power to influence and transform consumer behaviour as well as marketing tactics. Although billions of people use smart devices daily, consumer acceptance of AI-enabled Voice Assistants (VA) like Google Assistant, Siri, and Alexa still needs to be higher. The study explores the role of anthropomorphism in impacting VA acceptance through two intervening variables, i.e., perceived usefulness and perceived ease of use. In addition, the research explores the effect of VA Acceptance on purchase intention. Data from 648 VA users in India was gathered using purposive sampling. The findings showed that anthropomorphism positively and moderately influences perceived usefulness and perceived ease of use. In addition, the two intervening variables were found to have a significantly positive impact on VA Acceptance. Further, consumers VA acceptance determines their intention to purchase using VA in the future. Based on these findings, the study concludes with the theoretical and managerial implications.

Keywords: Anthropomorphism; Acceptance; Perceived Usefulness; Perceived Ease of Use; Voice Assistants.

1. Introduction

Research in Business and Marketing reveals that today's consumers are driven by the need for time-saving, convenience and enjoyment (Morganosky, 1986; Roy et al., 2017). The analysis by PwC (2018) reveals that approximately 93% of consumers are delighted with automatic VA features or facilities. VA serve this need as they enable consumers to have a quick hands-free experience and perform tasks repetitively without getting annoyed (Arnold et al., 2019; Foehr & Germelmann, 2021; Pitardi & Marriott, 2021; Sundar, 2020). Moreover, VA saves consumers from the affective and cognitive fatigue entailed in decision-making (Yoon et al., 2013; Hoyer et al., 2020). Consumers are getting dependent on VA, especially for daily routine and repetitive tasks like making a call, setting reminders and alarms, listening to songs, and asking for weather forecasts. Moreover, checking bank account balances, making payments, and using transaction history as a key search indication are all components of VA's job as a customer engagement tool.

Besides, VA also helps consumers to interact with brands. As Klaus and Zaichkowsky (2021) remarked, in the future, brands will similarly talk with us as Alexa and Google Assistant interact in the present. It is being researched that unique congenial voices can challenge visual online shopping and help differentiate a brand, like logos, taglines, and colours. It is even argued that users shall value recommendations by VA more in the future than the brands (Klaus & Zaichkowsky, 2020). Thus, VA is becoming the new touchpoint for brands to interact with consumers (Smith, 2018) and help create positive psychological notions and increase convenience. Forecasts by Statista (2021) and Juniper Research (2020) show that by 2024 consumer interaction with digital VA will overtake the world population, reaching 8.4 billion smart devices. The analysis by PwC (2018) says that approximately 93% of customers are highly satisfied with automatic VA features. Google (2019) mentions that India has 400 million active internet users and is witnessing a 270% Year-on-Year (YoY) growth in voice searches, making it mainstream. In the crowd of digital requirements, VA found a highly effective and exceptional remedy that offers personalized recommendations, by which marketers make more effective marketing strategies like cross-selling and up-selling through voice (Rzepka et al., 2022). Yet consumer intention to purchase using VA needs exploration and understanding.

The necessity to understand VA as a major interaction tool is a significant future research area (Klaus & Zaichkowsky, 2021; Verhoef et al., 2017). Customer-Technology interface focusing on VA is considered a research priority topic as per Marketing Science Institute (MSI) 2020-2022. In the same vein, scholars, including Rzepka and Berger (2018) and Poushneh (2021), have advised the need to explore the personality traits of VA. Scholars, namely Hermann (2021), Moriuchi (2019) and Sundar (2020), underline the need to understand the outcomes of artificially intelligent technology. Fernandes and Oliveira (2021) have specified the need to understand the VA acceptance from the current usage perspective. This study will contribute to the VA literature and provide new insights by (i) exploring the role of Anthropomorphism (ANTHRO) as a driver of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (ii) shedding light on the impact of PU and PEOU on VA Acceptance (iii) measuring the impact of the current VA Acceptance on Purchase Intention.

2. Literature Review

2.1 AI to respond to the human voice

With the aid of Artificial Intelligence (AI), the global population can now efficiently use Amazon's Alexa, Google's Google Assistant and Apple's Siri. As per this evidence, it can be stated that such advanced technology (AI) effectively gained prominence with the rise of VAs. Users with special needs use machine learning and AI in speech recognition in case of taking the privilege of VA (Sherif, 2018). This indicates that in the case of speech recognition services, neural networks and deep learning increase the quality and maintain the standard of VA responses. In this modern era, people have experienced voice AI to use voice commands to interpret and receive directives. This is solid evidence in the real-time world that voice AI can respond and interact with human questions based on natural languages.

2.2 Natural language processing

In this present modern era, natural language processing has made it possible for people to communicate with computers by using their languages and it helps in scaling other language-oriented tasks. This means the natural language process is highly conjugated in VA (AI-specialised) for reading books, interpreting data or information and hearing speech (Cherif & Lemoine, 2019). People regularly use natural language processing technology to check word spelling.

2.3 VA and Voice recognition technology

VA carry out predetermined activities by reacting to commands utilizing the information they collect and communicating with consumers in a human-like voice. For VA to function, internet-connected hardware (e.g., Amazon Echo Dot, Google Home, etc.) or software (e.g., Google Assistant and Apple's Siri) is required. It mainly consists of VA provided by the major voice ecosystem participants, such as Amazon's Alexa, Apple's Siri, and Google's Google Assistant (Koetsier, 2021). It has been noted that voice recognition technology is used effectively in VA devices and applications, which is crucial for making the VA facility for customers user-friendly and simple to use when needed. According to the study's conclusions by PwC (2018), speech recognition technology, which can decipher human voice, is thought to be a software application or integrated hardware component. The world's population currently uses speech recognition technology since it allows users to perform various tasks by speaking directly to Google Home and Amazon Alexa. According to this information, voice recognition technology has been praised for its ability to accurately convert human speech into printed words due to its advanced algorithms.

2.4 Consumers interested in purchasing high-tech products

Nowadays, people tend to find ways to get their demands fulfilled at their doorsteps. People often look forward to using shortcuts and saving time and cost daily. VAs have become an essential tool in human life due to their advanced features and easy use. In the crowd of digital requirements, VA found a highly effective and exceptional remedy that offers personalized recommendations, by which marketers make more effective marketing strategies like cross-selling and up-selling through voice (Rzepka et al., 2022). The young population is the main target for tech companies, as the adult generation deals with confusion about using cutting-edge technology and usually carry on traditionally followed habits like typing and searching (Rzepka et al., 2022). However, high-tech products (VA) are leading the race as they are highly cost

effective and readily available at our doorsteps. For instance, tech giants have started the facility of VAs in mobile phones and smart speakers (e.g., Google Home and Amazon Alexa).

2.5 Kano model

Kano model is essential to assess the impact of products and service features based on consumer satisfaction. This means the Kano model helps provide a detailed account based on consumer satisfaction and helps brands customize products and services accordingly. Key features of the Kano model are performance features, excitement features, basic features and downloads to prioritize the road map to customers. As per this understanding, the Kano model is instrumental in supporting producer discussion and specification through better development of consumer understanding. **[Referred to appendix: 1]**

2.4 Improvements in AI technology are increasing the compatibility and accessibility of VA.

Recent changes in information and communication technology are enabling new opportunities for companies to improve the quality of smart devices. For example, Amazon has increased their Echo dot device's compatibility, forcing the organization to introduce a switch to stop the information-sharing phase. Recent problems associated with data miss management forced Amazon to introduce the feature of stopping the information-sharing process from incorporating a sustainable environment for their customers. Pawlasczyk et al. (2019) suggested that the instant disabling of the recording feature associated with the Amazon Echo Dot creates a suitable environment for consumers to avail the products. Amazon cloud technology is included in the safe management of VA devices (Pawlasczyk et al., 2019). The changes in the network artefacts are enabling Amazon to make positive changes in their device architecture as well **[Referred to appendix: 2]**.

3. Hypothesis Development

3.1 Anthropomorphism (ANTHRO)

ANTHRO assigns human or individual traits to objects, people, animals, events, or even abstract notions that are not human (Epley et al., 2008). The fundamental idea behind ANTHRO is attributing human traits to inanimate objects. Consumers develop attachments to anthropomorphic figures early on, such as Mickey Mouse and in the modern world, to smart devices. It is not surprising that market analysts believe that these features of non-human creatures resembling humans drive technology-oriented interactions (Wirtz et al., 2018). Experts in human-computer interaction, such as Nass and Moon (2000), Nass et al. (1997), and Nass et al. (1994), have demonstrated the potency of humanistic cues in speech. Consumers' increased usage intention is a result of their perception of technology's expressive voice as being more socially savvy (Heerink et al., 2008). According to Klaus and Zaichowsky (2021), VA resemble a real discussion and help consumers transition from the conventional visual experience to a complete voice-based experience. In other words, the humanness that VA portrays impacts cognition. Accordingly, the study hypothesizes that:

H1: ANTHRO positively impacts Perceived Usefulness (PU).

H2: ANTHRO positively impacts Perceived Ease of Use (PEOU).

3.2 Perceived Usefulness (PU)

PU is one of the fundamental determinants of consumer acceptance of technology (Davis, 1989). AI technology's perceived utility significantly impacts consumer acceptance of the latest technological advancements (Gursoy et al., 2019; Lin et al., 2019). Consumers can control home automation smart devices like television and lights, play music and podcasts, and set alarms and reminders (Ammari et al., 2019; Hoy, 2018). Given the ability mentioned above of VA to be useful, the following hypothesis is proposed:

H3: PU has a positive impact on VA Acceptance.

3.3 Perceived Ease of Use (PEOU)

PEOU measures how much an individual believes a specific technology demands little physical or mental effort (Davis, 1989). The effort necessary to utilize a specific technology has also been described by researchers using a related term called

effort expectancy (Venkatesh et al., 2003). Researchers in the context of smartphones (Belanche et al., 2019; Go et al., 2020) and mobile payment have investigated this construct as a fundamental driver of technology acceptance and usage behaviour (Patil et al., 2020). Based on the above discussion, in the context of VA, the study hypothesizes that:

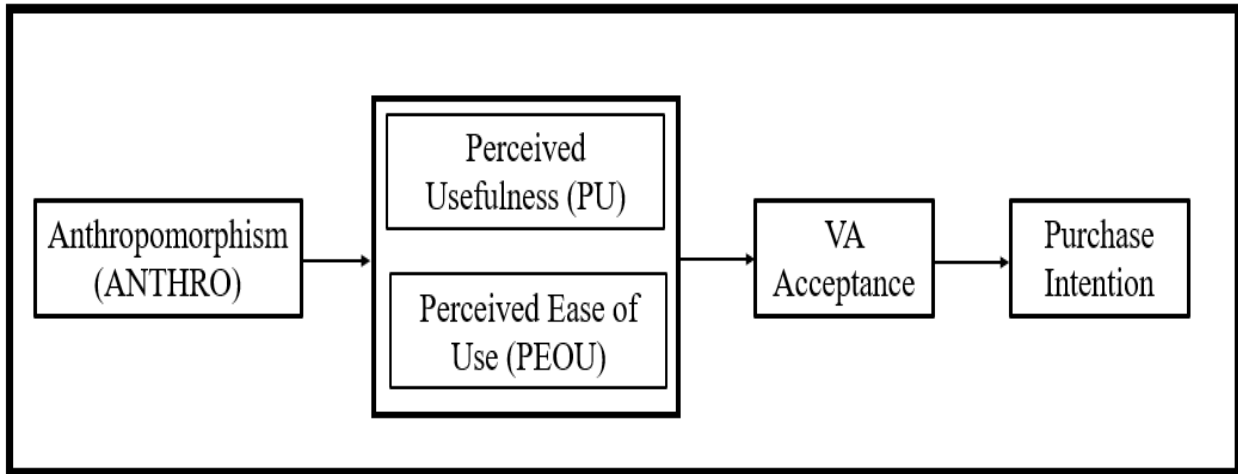
H4: PEOU has a positive impact on VA Acceptance.

3.4 Purchase Intention

Purchase Intention depicts consumers' likelihood or willingness to purchase a product or avail service. Nowadays, consumers want to discover means of meeting their needs at their doorsteps. Consumers frequently look forward to using shortcuts every day to save time and money. VA have emerged as a vital tool in modern living because of its cutting-edge functionality and simplicity of use. Consumers use VA technology by just speaking near VA, streamlining and expediting daily tasks. In the past, VA were mainly used for searching for any terms. Now, VA signs have been put near the phrase search on Flipkart, Amazon, and other food chains. Since elders struggle with deciding whether to use modern technology or stick with more established practices like typing and searching, tech businesses primarily target the younger demographic (Rzepka et al., 2022). Individuals worldwide are shocked by the rapid adoption of new technologies and their outcomes, and employing high-tech items makes it simple for people to discover simple answers. Individuals are receiving assistance from advanced technology to offer appropriate reactions by integrating with digital or advanced technology, which has become extremely valuable for content producers, web analytics, and web developers (Ewers et al., 2020). Based on the above discussion, the study hypothesizes that:

H5: VA Acceptance has a positive impact on Purchase Intention.

Figure 1: Research Model



4. Methodology

4.1 Questionnaire and Measures

The questionnaire has 28 items on a five-point Likert scale ranging from 1 to 5, where 1 represents strongly disagree and 5 means strongly agree. Table 1 shows the items for each construct. For measuring ANTHRO, nine items were adopted from Lu et al. (2019) and Moriuchi (2020). Constructs PU and PEOU were assessed using six-item scales adapted from Davis (1989). Five item scale was adopted for VA Acceptance (Venkatesh et al., 2003; Venkatesh et al., 2012). To measure Purchase Intention, three items were adapted from Lu et al. (2010). The construct scales were modified to fit into the context of the study.

Table 1. Scale Items

Construct	Indicators	Items
Anthropomorphism (ANTHRO) (Lu et al., 2019; Moriuchi, 2020)	ANTHRO1 ANTHRO2 ANTHRO3 ANTHRO4 ANTHRO5 ANTHRO6 ANTHRO7 ANTHRO8 ANTHRO9	VA has a mind of its own. VA is aware and responsive to the surroundings. VA has free will. VA is sociable. VA experiences emotions. When I interact with VA, it feels like someone is in the room. VA seems like a real person to me. I feel a sense of human warmth in the interaction with VA. I feel a sense of human contact in the interaction with VA.
Perceived Usefulness (PU) (Davis, 1989)	PU1 PU2 PU3 PU4 PU5 PU6	VA enables me to accomplish tasks more quickly. Using VA increases my productivity. VA enhances my overall (work/learning/life) performance. VA enhances my overall (work/learning/ life) effectiveness. Using VA to complete tasks makes my life easier. Overall, I find VA useful.
Perceived Ease of Use (PEOU) (Davis, 1989)	PEOU1 PEOU2 PEOU3 PEOU4 PEOU5 PEOU6	VA is easy to use. Learning to use VA is easy. My interaction with the VA is clear and understandable. VA is flexible to use. I find it easy to get the VA to do what I want. It is easy for me to become skilful at using VA.
VA Acceptance (Venkatesh et al., 2003; Venkatesh et al., 2012)	ACC1 ACC2 ACC3 ACC4 ACC5	Using VA is a good idea. I like using VA. I intend to continue using VA in the future. I plan to use VA frequently. I will always try to use VA in my daily life.
Purchase Intention (Lu et al., 2010)	PI1 PI2 PI3	I would consider purchasing using VA in the future. I will purchase using VA in the future. I intend to purchase using VA.

4.2 Data Collection

An online questionnaire using Google Forms was used to collect the data from individuals who reside in India and currently use VA. Social media was used to contact VA users aged 18 years and above. Scholars like Balakrishnan and Dwivedi (2021) and Dogra and Kaushal (2021) employ this well-accepted online data-gathering approach in marketing research. With more than 1700 message receivers, the study discovered 677 people who freely completed the questionnaire. Finally, 648 valid replies were taken into account for the study sample. Based on the boxplot, 29 responses were detected as outliers. Table 2 shows the demographic profile of the respondents.

Table 2: Demographic Profile of Respondents (sample size = 648)

Variables	Classification	Frequency	Percentage (%)
Gender	Male	332	51.2
	Female	315	48.4
	Other	1	0.4
Year of Birth	1946-1964	25	3.9
	1965-1980	37	5.7
	1981-1996	177	27.4
	1997-2004	409	63

Qualification	High School (12 th pass)	168	26
	Bachelor's degree	193	29.9
	Master's degree	215	33.1
	M.Phil	13	2
	Ph.D or higher	71	11
	Other	13	2

The responses indicated that consumers' usage of VA was concentrated on four brands, including Google's Google Assistant (78.3%), Apple's Siri (10.3%), Amazon's Alexa (8.9%) and Samsung's Bixby (2.5%). The sample characteristics are shown in Table 3.

5. Data Analysis and Results

5.1 Common Method Bias (CMB) Test

Harman's single-factor test was used to determine whether CMB would impact our findings by determining whether a single factor would emerge from the factor analysis and explain most of the variance (Podsakoff et al., 2003). The results revealed that the first significant factor only explained 43% of the overall variation, which is below the suggested cutoff point (<50%). The current study also tested CMB using the Common Latent Factor (CLF). The two models' regression weight differences with and without CLF were within the 0.2 criteria. Constructs are free of CMB, according to the findings of the CLF estimate and the Harman one-factor model.

Table 3: Sample Characteristics (sample size = 648)

Variables	Description	Frequency	Percentage (%)
Device	Mobile Phone	591	90.7
	Laptop	7	1.1
	Smart Speaker	39	6
	Television	5	0.7
	Others	6	1
Language	English only	285	44.1
	Hindi only	16	2.6
	English and Hindi	345	53
	Others (Bengali, Tamil, Urdu)	2	0.3
Experience	Less than 6 months	92	14.2
	6 months-1 year	78	12.1
	1-2 years	190	29.2
	2-3 years	120	18.5
	3-4 years	75	11.7
	4-5 years	61	9.3
	More than 6 years	32	5
Habit	More than 3 times a day	157	24.2
	2-3 times a day	166	25.6
	Once a day	91	14.2
	2-3 times a week	74	11.4
	Once a week or less frequently	160	24.6
Gender of VA	Male	562	86.8
	Female	86	13.2

5.2 Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA)

Using SPSS 26, EFA was used to determine the factors influencing each component, and CFA was used to determine the model's fitness. EFA forms two dimensions of ANTHRO: humanoid (items 1 to 5) and parasocial relationship (items 6 to 9). The fit indices of each construct in Table 4 show that the model reflects a good fit.

Table 4: Model Fit Indices of Each Construct

	CMIN/DF	GFI	AGFI	CFI	RMR	RMSEA
ANTHRO	2.618	0.958	0.918	0.98	0.76	0.076
PU	2.527	0.977	0.941	0.989	0.022	0.074
PEOU	1.223	0.990	0.969	0.998	0.013	0.028
VA Acceptance	1.962	0.989	0.958	0.995	0.14	0.059
Purchase Intention	1.698	0.990	0.963	0.998	0.08	0.048

5.3 Reliability and Validity

Table 5 shows each construct's values of Cronbach alpha, Average Variance Extracted (AVE), and Composite Reliability (CR). The Cronbach alpha and CR values are greater than 0.70 (Hair, 1997; Hair et al., 2012), and AVE is higher than 0.50 (Fornell and Larcker, 1981), indicating that the measurement model is reliable. Table 6 represents the inter-correlation values between each construct, with the squared root of AVE values represented in the diagonals. The values show that the discriminant validity of the model lies in the acceptable range.

Table 5: Cronbach Alpha, AVE and CR

Construct	Factors	Cronbach Alpha	AVE	CR
ANTHRO	Humanoid	0.886	0.613	0.888
	Parasocial Relationship	0.933	0.763	0.928
		0.924	0.678	0.95
PU		0.914	0.637	0.913
PEOU		0.886	0.545	0.878
VA Acceptance		0.894	0.624	0.892
Purchase Intention		0.901	0.654	0.932

Table 6: Discriminant Validity

	ANTHRO	PU	PEOU	VA Acceptance	Purchase Intention
ANTHRO	.824				
PU	.503**	.799			
PEOU	.352**	.699**	.739		
VA Acceptance	.439**	.439**	.680**	.79	
Purchase Intention	.350**	.421**	.662**	.594**	.78

The squared root of AVE's is presented in the diagonal for each construct in bold and italic format. **p<0.5

5.4 Hypothesis Testing: Using Structural Equation Modelling (SEM)

The model fit indicators for each hypothesis test are shown in Table 5. SEM is done using IBM AMOS Version 23. The study provides insights into the role of ANTHRO in impacting the consumers' acceptance of VA. The findings show that the first dimension of ANTHRO, i.e., humanoid (SRW= 0.182), has a low influence, and the other dimension, i.e., parasocial relationship (SRW=0.419), has a moderate effect on consumers' perception of VA usefulness. Hence, ANTHRO facilitates

PU, supporting H1. In addition, the results show that ANTHRO has a positive and significant impact on PEOU, supporting H2. The dimensions of ANTHRO, humanoid (SRW=.179) and parasocial relationship (SRW=.255) have a low influence on PEOU. Moreover, the results also prove that both PU (SRW=0.681) and PEOU (SRW=.688) facilitate VA Acceptance, supporting H3 and H4. Finally, the analysis revealed that consumers' current VA Acceptance significantly impacts Purchase Intention (SRW=0.691), supporting H5. Hence, all hypotheses are supported.

Table 7: Hypotheses Testing

Hypotheses	Relationship	CMIN/DF	GFI	AGFI	CFI	RMR	RMSEA
H1	ANTHRO → PU	2.503	.909	.872	.959	.072	.074
H2	ANTHRO → PEOU	2.642	.911	.872	.951	.084	.077
H3	PU → VA Acceptance	2.356	.936	.901	.972	.035	.070
H4	PEOU → VA Acceptance	2.522	.941	.906	.965	.030	.074
H5	VA Acceptance → Purchase Intention	2.452	.938	.902	.970	.032	.071

The study also performs mediation analysis to explore the mediating effect of VA Acceptance between PU and PEOU, and purchase intention. Preacher and Hayes (2004) methodology has been used to check the mediating effect VA Acceptance between PU and Purchase Intention. The result revealed that the indirect effect of PU on purchase intention through VA Acceptance is significant ($\beta = .157$, $p < 0.05$). In addition, the non-zero values in lower and upper bound limits at a 95% confidence interval also confirm the same (see Table 5). Further, the Sobel Test (Sobel, 1982) also supported the significance of the indirect effect of PU on purchase intention through VA Acceptance (Sobel statistics = 2.42, $p < 0.05$).

In the same vein, the analysis revealed that the indirect effect of PEOU on purchase intention through VA Acceptance is also significant ($\beta = .145$, $p < 0.05$). Further, the non-zero values in the lower and upper bound limits also support the same (Table 8). The values of Sobel statistics are significant for the indirect effect of PEOU and purchase intention through VA Acceptance (Sobel statistics = 2.18, $p < 0.05$).

Table 8: Mediation Analysis

Hypothesis	Direct beta without the mediator	Direct beta with the mediator	Indirect effect	LL95-UL95	Mediation type
PU→Acc→PI	.313**	.216	.157**	.064-.300	Full mediation
PEOU→Acc→PI	.355**	.190	.145*	.041-.284	Full mediation

PU = Perceived Usefulness; Acc = VA Acceptance; PI = Purchase Intention

6. Conclusion and Implications

VA are revolutionizing consumers' interaction with smart objects. Although VA have been accepted by consumers, our understanding of consumer behaviour towards this anthropomorphic technology remains somewhat limited. The objective of the study is to examine the role of ANTHRO in VA Acceptance. In addition, to understand the effect of current VA Acceptance on Purchase Intention.

The study has both theoretical and practical implications. The study contributes to the literature on VA acceptance, which is still in its infancy stage and largely theoretical. The findings offer a perspective regarding consumers' understanding of the role of human elements of technology (ANTHRO). The study establishes ANTHRO (humanoid and parasocial relationship) as a bi-dimensional construct, an important antecedent of PU and PEOU. Moreover, the role of ANTHRO in the context of Indian VA users has not been explored much. The results show that the voice cue of VA is equally essential in impacting consumers' perception of VA usefulness and ease of use. In addition, the study's findings highlight the equivalent weight given to PU and PEOU in VA acceptance, which is a crucial finding for marketers and technology developers. Therefore, regular software upgrades that include anthropomorphic features might aid in giving the key participants in the speech ecosystem a competitive edge. For instance, the VA's emotional component has to be strengthened to make the interactions more cordial. The tone and pitch of a VA voice may be programmed to change to convey different emotions. There should be an effort to personalize the process; for example, the VA should have a name, age, and general

demeanour. Additionally, marketers need to consistently work to inform current and potential users of VA of the countless advantages of doing so. Hence, if a service provider aims to increase consumers' acceptance of VA, including anthropomorphic traits might be an effective solution.

7. Future Research Directions

The study makes contributions to research VA-related consumer behaviour. However, the paper has certain shortcomings that future researchers may address. Firstly, the study obtained data from respondents located in India. A comparative analysis of data from developed and developing countries should be done to understand the varying degrees of acceptance among individuals of different cultural backgrounds. Academicians can also make comparisons between metropolitan with non-metropolitan. Secondly, the model can be tested in different industries (e.g., education, banking and finance). Third, potential moderators, including demographic, age, gender, education, income, and occupation, can be considered. Behavioural moderating variables like habit, experience, and type of device can also be used to understand VA acceptance. Fourth, future research should also work towards developing a broader framework by identifying more potential drivers like the brand of VA, etc. Lastly, research to explore the impact of VA gender on the attitude and degree of acceptance should also be conducted.

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Appendix 1: Kano Model

The Kano Model



Source: <https://www.prodify.group/blog/a-product-managers-guide-to-the-kano-model>

Appendix 2: Significant Factors Associated with Amazon Alexa

