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# Alexa Buy It for Me: Exploring the Impact of Voice Assistants on Consumer Purchase Intention

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M30, M31, M39, O30

**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 intention to use Voice Assistants (VA) like Google Assistant, Siri, and Alexa still needs to be higher. The study explores the role of anthropomorphism in impacting behavioural intention to use VA through two intervening variables, i.e., perceived usefulness and perceived ease of use. In addition, the research explores the effect of behavioural intention 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 behavioural intention. Further, consumers' behavioural intention determines their intention to purchase using VA in the future. Based on these findings, the study concludes with the theoretical and managerial implications.

## 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) exposes 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 (Pitardi and Marriott, 2021; Sundar, 2020). Moreover, VA save 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). The analysis by PwC (2018) says that approximately 93% of consumers 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 and 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 Behavioural Intention (iii) measuring the impact of the current Behavioural Intention on Purchase Intention.

## 2. Literature Review

### *2.1. AI (Artificial Intelligence) 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. Consumers with special needs use machine learning and AI including speech recognition in case of taking the privilege of VA (Agrwal *et al.*, 2023; Sherif, 2018). Consumers 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.

In this present modern era, natural language processing has made it possible for consumers 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 and Lemoine, 2019). People regularly use natural language processing technology to check word spelling.

### *2.2. 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 consumers 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.

### 2.3. Consumers Interest 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 carries 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).

### 2.4. 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 consumers. 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]*

### 2.5. 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 mismanagement forced Amazon to introduce the feature of stopping the information-sharing process from incorporating a sustainable environment for their consumers. Pawlascyzyk *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 (Pawlascyzyk *et al.*, 2019). The changes in the network artefacts are enabling Amazon to make positive changes in their device architecture as well .

## 3. Hypotheses 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 behavioural intention to use technology (Davis, 1989). AI technology's perceived utility significantly impacts consumer behavioural intention towards the latest technological advancements (Gursoy *et al.*, 2019; Lin *et al.*, 2019). Consumers can control home automation smart devices like televisions and lights, play music and podcasts, and s*et al*arms 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 Behavioural Intention.

### *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 Behavioural Intention.

### *3.4. Purchase Intention*

Purchase Intention depicts consumers' likelihood or willingness to purchase a product or avail service (Abdul and Soundararajan, 2022; Banerjee and Padhi, 2023). In the past, VA were mainly used for searching for the meaning of words, but presently VA signs have been put near the phrase search on Flipkart, Amazon, and other food chains. 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 has 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 the VA, thereby streamlining and expediting daily tasks. Based on the above discussion, the study hypothesizes that:

H5: Behavioural Intention has a positive impact on Purchase Intention.

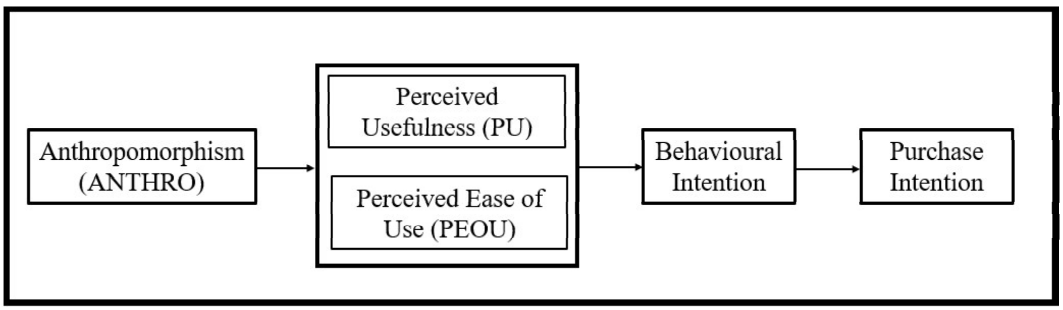


**Figure 1: Research Model**

## 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). A three-item scale was adopted for Behavioural Intention (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.

### *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) & 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.

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.

**Table 1: Scale Items**

| *Construct* | *Indicators* | *Items* |
|---|---|---|
| Anthropomorphism (ANTHRO) (Lu *et al.*, 2019; Moriuchi, 2020) | ANTHRO1 | VA has a mind of its own. |
| | ANTHRO2 | VA is aware and responsive to the surroundings. |
| | ANTHRO3 | VA has free will. |
| | ANTHRO4 | VA is sociable. |
| | ANTHRO5 | VA experiences emotions. |
| | ANTHRO6 | When I interact with VA, it feels like someone is in the room. |
| | ANTHRO7 | VA seems like a real person to me. |
| | ANTHRO8 | I feel a sense of human warmth in the interaction with VA. |
| | ANTHRO9 | I feel a sense of human contact in the interaction with VA. |
| Perceived Usefulness (PU) (Davis, 1989) | PU1 | VA enables me to accomplish tasks more quickly. |
| | PU2 | Using VA increases my productivity. |
| | PU3 | VA enhances my overall (work/learning/life) performance. |
| | PU4 | VA enhances my overall (work/learning/ life) effectiveness. |
| | PU5 | Using VA to complete tasks makes my life easier. |
| | PU6 | Overall, I find VA useful. |
| Perceived Ease of Use (PEOU) (Davis, 1989) | PEOU1 | VA is easy to use. |
| | PEOU2 | Learning to use VA is easy. |
| | PEOU3 | My interaction with the VA is clear and understandable. |
| | PEOU4 | VA is flexible to use. |
| | PEOU5 | I find it easy to get the VA to do what I want. |
| | PEOU6 | It is easy for me to become skilful at using VA. |
| Behavioural Intention (Venkatesh *et al.*, 2012) | BI1 | I intend to continue using VA in the future. |
| | BI2 | I plan to use VA frequently. |
| | BI3 | I will always try to use VA in my daily life. |
| Purchase Intention (Lu *et al.*, 2010) | PI1 | I would consider purchasing using VA in the future. |
| | PI2 | I will purchase using VA in the future. |
| | PI3 | I intend to purchase using VA. |

**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 |

*Source:* Author's Own Compilation

## 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.

### *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.

### *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

**Table 3: Sample Characteristics (Sample Size = 648)**

| *Variables* | *Description* | *Frequency* | *Percentage (%)* |
|---|---|---|---|
| Device | Mobile Phone | 591 | 91.2 |
| | Laptop | 7 | 1.08 |
| | Smart Speaker | 39 | 6.01 |
| | Television | 5 | 0.8 |
| | Others | 6 | 0.9 |
| Language | English only | 285 | 43.9 |
| | Hindi only | 16 | 2.5 |
| | English and Hindi | 345 | 53.2 |
| | Others (Bengali, Tamil, Urdu) | 2 | 0.3 |
| Experience | Less than 6 months | 92 | 14.2 |
| | 6 months-1 year | 78 | 12.04 |
| | 1-2 years | 190 | 29.3 |
| | 2-3 years | 120 | 18.5 |
| | 3-4 years | 75 | 11.6 |
| | 4-5 years | 61 | 9.4 |
| | More than 6 years | 32 | 4.9 |
| Habit | More than 3 times a day | 157 | 24.2 |
| | 2-3 times a day | 166 | 25.6 |
| | Once a day | 91 | 14.04 |
| | 2-3 times a week | 74 | 11.4 |
| | Once a week or less frequently | 160 | 24.7 |
| Gender of VA | Male | 562 | 86.8 |
| | Female | 86 | 13.2 |

*Source:* Author's Own Compilation

**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 |
| Behavioural Intention | 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 |

*Note:* ANTHRO=Anthropomorphism, PU=Perceived Usefulness, PEOU=Perceived Ease of Use

*Source:* Author's Own Compilation

*et al.*, 2012), and AVE is higher than 0.50 (Fornell & Larcker, 1981), indicating a reliable measurement model. 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 |
| Behavioural Intention | | 0.894 | 0.624 | 0.892 |
| Purchase Intention | | 0.901 | 0.654 | 0.932 |

*Note:* ANTHRO=Anthropomorphism, PU=Perceived Usefulness, PEOU=Perceived Ease of Use
*Source:* Author's Own Compilation

**Table 6: Discriminant Validity**

| | *Anthro* | *PU* | *PEOU* | *Behavioural Intention* | *Purchase Intention* |
|---|---|---|---|---|---|
| ANTHRO | .824 | | | | |
| PU | .503** | .799 | | | |
| PEOU | .352** | .699** | .739 | | |
| Behavioural Intention | .439** | .439** | .680** | .79 | |
| Purchase Intention | .350** | .421** | .662** | .594** | .78 |

*Note:* The squared root of AVE's is presented in bold and italic format in the diagonal for each construct. **p<0.5. ANTHRO=Anthropomorphism, PU=Perceived Usefulness, PEOU=Perceived Ease of Use
*Source:* Author's Own Compilation

### *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 behavioural intention towards 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 prove that both PU (SRW=0.681) and PEOU (SRW=.688) facilitate Behavioural Intention, supporting H3 and H4. Finally, the analysis revealed that consumers' current Behavioural Intention 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 > Behavioural Intention | 2.356 | .936 | .901 | .972 | .035 | .070 |
| H4 | PEOU > Behavioural Intention | 2.522 | .941 | .906 | .965 | .030 | .074 |
| H5 | Behavioural Intention > Purchase Intention | 2.452 | .938 | .902 | .970 | .032 | .071 |

*Note:* ANTHRO=Anthropomorphism, PU=Perceived Usefulness, PEOU=Perceived Ease of Use
*Source:* Author's Own Compilation

The study also performs mediation analysis to explore the mediating effect of Behavioural Intention between PU and PEOU, and purchase intention. Preacher and Hayes (2004) methodology has been used to check the mediating effect Behavioural Intention between PU and Purchase Intention. The result revealed that the indirect effect of PU on Purchase Intention through Behavioural Intention 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 Behavioural Intention (Sobel statistics = 2.42, $p < 0.05$).

In the same vein, the analysis revealed that the indirect effect of PEOU on purchase intention through Behavioural Intention 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 Behavioural Intention (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→BI→PI | .313** | .216 | .157** | .064-.300 | Full mediation |
| PEOU→BI→PI | .355** | .190 | .145* | .041-.284 | Full mediation |

*Note:* PU=Perceived Usefulness, BI=Behavioural Intention, PI=Purchase Intention
*Source:* Author's Own Compilation

## 6. Conclusion and Implications

VA is 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 Behavioural Intention. In addition, to understand the effect of intention to use VA on Purchase Intention.

The study has both theoretical and practical implications. The study contributes to the literature on VA related consumer behaviour, 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 Behavioural Intention to use VA, which is a crucial finding for marketers and technology developers. Therefore, striking a balance between creating a relatable, human-like interaction and maintaining an easy and clear understanding of the assistant's capabilities is crucial. For instance, a better understanding of the different tones and slang of consumers by the VA would aid in decreasing the consumers' frustration caused by the repetition of voice commands. In addition, there should be an effort to personalize the human-VA interaction process; for example, the VA should have a name, age, and general demeanour to provide consumers with an amiable feeling.

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' usage intention towards VA, including anthropomorphic traits might be an effective solution to give the key participants in the speech ecosystem a competitive edge. Balancing human-like qualities with clear communication of the assistant's capabilities is key to creating a successful and user-friendly interaction.

## 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 behavioural intention. 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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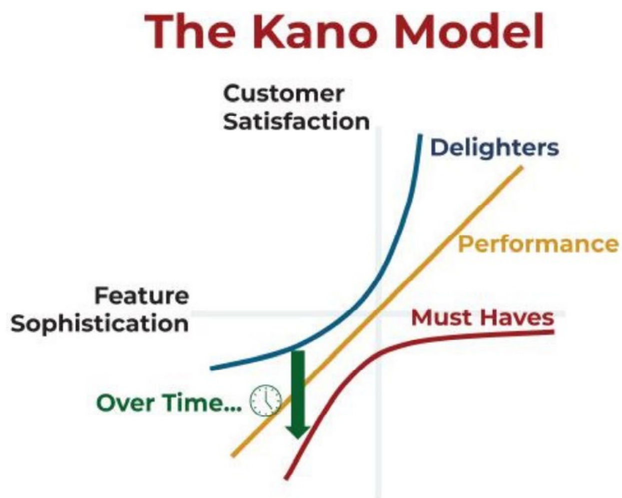
## Appendix 1: Kano Model

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




## Appendix 2: Significant Factors Associated with Amazon Alexa