EXPLORING THE CRITICAL SUCCESS FACTORS OF AI-BASED VOICE ASSISTANTS: A TEXT MINING AND STRUCTURAL TOPIC MODELLING APPROACH

Surbhi Choudhary
Research Scholar, Department of Business Administration, National Institute of Technology, Kurukshetra- 136119, Haryana (India).
Email id: surbhi_62000010@nitkkr.ac.in

Dr. Neeraj Kaushik
Associate Professor, Department of Business Administration, National Institute of Technology, Kurukshetra- 136119 Haryana (India).
Email id: neeraj.kaushik@nitkkr.ac.in

Dr. Brijesh Sivathanu
Associate Professor, Department of Management, COEP Technological University, Formerly College of Engineering Pune (COEP), Pune- 411005 (India).
Email id: brij.jesh2002@gmail.com

ABSTRACT

Owing to the increased consumption of voice-controlled technology, there has been a mounting demand for AI-based voice assistants by consumers. Regardless of the growing fascination among the users, there exists a certain knowledge gap that needs an in-depth exploration and scholarly attention. Specifically, the dynamics of post-purchase experience and cognitive dissonance towards the usage of voice assistants remain unexplored in the innovation consumption literature. To address this gap, this study investigates the critical success factors associated with the usage of AI-based voice assistants using machine learning algorithms. The study employs a novel application of topic modelling wherein the user-generated content (consumer reviews = 20,336) is summarized, and an assessment of the optimal number of latent themes are developed. The results reveal the underlying topics generated from the summarization of consumer reviews that encompass media richness, interactivity, facilitating conditions, and consumer perception. These latent themes outline the cogent factors that can act as cognitive and social drivers to improve human-computer communication. Since the findings unravel the cognition process of users' post-purchase involvement, it dispels a myriad of supplements to automation engineers and product designers.

Keywords: AI-based Voice assistants, Human-computer communication, User-generated content, Structural Topic Modelling, Text Mining

1. Introduction

The emergence of Industry 4.0 has led to advancements in artificial intelligence-based infrastructure at different operational levels and business cycles, which have rendered improved services to consumer's lives (Balakrishnan et al., 2021). The rapid assimilation of artificial intelligence-integrated products and the advancements in information communication-related technology have encouraged contemporary research in emerging markets (Dwivedi et al., 2023). Subsequently, the deployment of artificial intelligence-enabled products in the lives of consumers has paved the way for business transformation and shifted the focus of marketers to decision support systems, which enable information-driven decision-making (Plant, 1993).

Since the past decade, the emergence and functionality of voice technology have been ubiquitous, resulting in it's wide integration with devices (Malodia et al., 2023). Given the popularity of voice technology and the paucity of research using large quantum of data, it has become imperative to establish motivating factors which precisely contribute to enhance user experience and usage. Voice assistants are equipped with intelligence which renders consumers with utilitarian and hedonic dimensions, and this, in turn, helps them to accomplish symbolic and value figurative benefits (Frank et al., 2021).

The measurement of internal beliefs and analysis of post-purchase involvement during purchase decisions can be a challenge for marketers (Hinojosa et al., 2017). Arguably, the extant literature on cognitive dissonance illustrates the significance of anatomising post-purchase communication and its fallouts on repurchase intention and satisfaction (Chou, 2012; Festinger, 1968). Therefore, this study reinforces the utility of the publicly available artefacts and exercises them to generate the latent dimensions of consumer purchase of voice assistants. Consequently, this will dispel several improvements in automation and propose more AI-empowered tangible products for consumers (Frank et al., 2021).

The term user-generated content encompasses the data that individuals produce on electronic commerce platforms, such as online reviews (Mumuni et al., 2020), ratings (Ghasemaghaei et al., 2018), question and answers (Banerjee et al., 2021), tweets (Grover et al., 2019). Intriguingly, in the literature on consumer-to-consumer communication, user-generated content is pre-dominantly acknowledged to be electronic word of mouth (eWOM) (Chatterjee, 2001). User-generated content is one form of data which dispels consumers' observations and navigation across channels, facilitates decision making and mitigate the pre-purchase misfit uncertainties (Banerjee et al., 2021). Lately, the research on consumer product reviews has gained traction as consumers highly embrace it (Khern-am-nuai et al., 2016) and also directly function as a serviceable instrument for retailers (Kwark et al., 2014). Zhang et al. (2010) explicitly mention how consumer reviews can redeem upsides like an increase in customer loyalty and new product introductions that distinguish the versatility among existing line products. This corresponds to increase attention from the virtual audience, which affects product sales (Chevalier & Mayzlin, 2006) and amplifies the bottom line of the businesses and retailers (Ghasemaghaei et al., 2018).

The existing literature records a comprehensive work to empirically test the adoption, behavioural pattern and usage factors of voice assistants (Dogra & Kaushal, 2021; Pillai & Sivathanu, 2020; Vimalkumar et al., 2021). Most of the research work stands upon theoretical bases like Theory of Reasoned Action (Fishbein & Ajzen, 1975), Theory of Planned Behavior (Ajzen, 1991), Technology Acceptance Model (Davis, 1989), and Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). However, the growing research in the field of artificial intelligence-enabled products demands explorations of contemporary factors that can aid in value fusion, value co-creation and user motivations (Pal et al., 2023). The prior research work accessible in the area of diffusion of innovative technology essentially pivots towards an explanatory foundation rather than an exploratory premise (Kasilingam, 2020; Pitardi et al., 2022). Consequently, an in-depth analysis specific to the usage of AI-based voice assistants remains limited. Thus, to diverge through the chasm, a deeper exploration and mining of extrinsic factors become essential (Johnson et al., 2018). The study also recognises the methodological gap that exists in the prior research work. Predominantly, the previous research has mainly relied upon a survey-based approach, and this can be validated by a plethora of extant literature available on the user experience of voice assistants (Balakrishnan et al., 2021; Pillai & Sivathanu, 2020; Vimalkumar et al., 2021). However, these empirical researches, using a survey-based approach, either suffer from social desirability biases or find it difficult to generalise the findings to a broader population (Grover & Kar, 2020). Thus, to cater to the aforesaid gaps, this study instrumentalises machine learning algorithm by harnessing user-generated content, which enables investigation of the exploratory factors and identifies the overlooked considerations of voice assistants. To cater to the aforesaid gaps, the current research focuses on the following research question pertaining to framing a logical structure of the user-generated context of AI-based voice assistants.

RQ: What meaningful themes are generated by extracting the hidden semantic structure in customer reviews of voice assistants?

The study documents academic and practical significance by attempting to provide exploratory evidence by deeply examining customer reviews and skimming out the potential concerns and strategic factors (Shankar et al., 2022; Bai et al., 2023). By a thorough examination of the semantic structure arising from the consumer review, the internal thoughts and expressions can be examined, which serve as strategic tools to unravel the subliminal stimuli of users (Chou, 2012; Shankar et al., 2022).

The rest of the paper is organised as follows. The second section discusses the background of the existing studies. Next, the third section talks about the design and methodology adopted for the same. The fourth section dispel results, and discussion of the study. Next section provides the fundamental implications for academia and practitioners. The last section defines the limitations of the study, which shows the direction for future research work.

2. Theoretical background and literature review

2.1 AI-based voice assistants

AI-based voice assistants are one of the new forms of cost-effective and advanced technological products which have improved service quality and increased user engagement (Chung et al., 2018). Past studies have widely explained the utility (McLean & Osei-Frimpong, 2019), social consequences (Cambre & Kulkarni, 2019), perceptions and concerns (Moorthy et al., 2015), and multiplicity of usage of voice assistants across industries (Biduski et al., 2020; Kerly et al., 2007; Liu & Sundar, 2018). Accompanying this, voice assistants are utilized across different age groups and play a significant role in the domestic environment by offering companionship and social support (Brause & Blank, 2020; Ramadan et al., 2021).

The digital transformation is driving the growth of global voice assistant applications, and it is anticipated that the e-commerce purchases executed using digital assistants is estimated to increase from 4.6 billion US dollars in 2021 to 19.4 billion US dollars in 2023 (Statista, 2023). This is an increase of more than 400 percent in only two years. Furthermore, the ability of voice assistants to provide flexibility, the ability of self-learning and personalization gives a pathway to improve interactions and helps in generating gains for technological investments by businesses (Bavaresco et al., 2019).

2.2 User-generated content

The rapid growth of e-commerce has made it pertinent for retailers to assess user experience, post-purchase dissonance and future motivations. Since consumer voice plays an instrumental role in providing insights about the purchase journey and helps obtain credible particulars about future anticipations, it becomes imperative to evaluate online consumer reviews, feedback, and experience over digital platforms. Extant literature is available on the examination of consumer reviews and how it impacts organization performance, customer satisfaction and repurchase intention (Chatterjee, 2001; Mumuni et al., 2020; Shaker et al., 2021).

Accounting for the number of advantages, the user-generated content does not compose of non-response biases (Michie & Marteau, 1999), consistency motif, acquiescence biases and the number of other prejudices that the sample survey holds (Podsakoff et al., 2003). Therefore, the study used a text-mining approach to probe consumer perception of voice assistants (Yang et al., 2021). Table 1 displays the prime studies in the area of AI-based voice assistants by consumers. It is evident that the substantial work in past literature has mainly centered around the empirical testing of antecedents and captured pre-purchase cognition.

Table 1: Major prior studies on voice assistants

Author (Year)	Dimensions examined	Methodology adopted	Findings
Nasirian et al., (2017)	Interaction quality, individual's trust	PLS-SEM	• AI-based technologies have complicated features that can affect their adoption. • Interaction quality greatly impacts users trust and technology adoption.

Author (Year)	Dimensions examined	Methodology adopted	Findings
McLean & Osei-Frimpong (2019)	utilitarian benefits, symbolic benefits, and social benefits	PLS-SEM	• The usage of in-home voice assistants is driven by utilitarian, symbolic, and social benefits. • The adoption of in-home voice assistants is only driven by hedonic benefits in small households. • Perceived privacy risks have a detrimental impact on usage of in-home voice assistants.
Fernandes & Oliveira (2021)	Functional, social, and relational elements	PLS-SEM	• The use of digital voice assistants in customer service interactions is driven by functional, social, and relational factors. • These factors' impacts are moderated by experience and the requirement for interpersonal contact. • While anthropomorphism is not always favourable, developing a rapport with customers and robots is crucial.
Hsieh & Lee (2021)	Media richness and parasocial interactions, trust, perceived usefulness, and perceived ease of use.	PLS-SEM	• Media richness and parasocial interactions are important variables influencing the development of trust, perceived usefulness, and perceived ease of use. • These factors influence attitude, continued usage intentions and e-commerce purchase intentions via digital assistants.
Lee et al. (2021)	Personal innovativeness, intention to recommend	Partial least square using ADANCO	• Personal innovativeness has associations with a higher inclination to suggest AIVAS to others. • Confirmation is related to all four ex-ante instrumentality opinions (hedonic motivation, compatibility, pricing value, and perceived security). • Technology anxiety does not directly correlates with the intention to recommend.
Poushneh (2021)	Functional intelligence, sincerity	PLS-SEM	• Voice assistant personality traits (VAP) have an impact on consumer experience. • VAPs that incorporate functional intelligence, sincerity, and creativity empower users to handle their verbal communications with the VA, streamline their voice engagement, and indulge in exploratory behaviour.
Balakrishnan et al. (2021)	Perceived value, resistance to AIVA.	PLS-SEM	• The research discovered an insignificant association between inertia and AIVA resistance. • It was discovered that perceived value had a negative but significant association with AIVA resistance. • Inertia was found to significantly differ across gender groups.

Author (Year)	Dimensions examined	Methodology adopted	Findings
Malodia et al. (2021)	Social identity, personification, information search, task function.	Interviews and PLS-SEM	• Social identity and personification are strongly related to usefulness and playfulness. • Usefulness and playfulness are related to information search and task function. • Trust and frequency of use considerably affect the relationship between the usefulness and utilisation of voice assistants.

3. Methodology

Customer reviews possess huge amounts of information and are considered a great source of valuable information (Chatterjee, 2001). To improvise the extrinsic factors of voice assistants and to compound the voluntary usage among consumers, the current study uses consumer review data and utilises unstructured data to develop novel insights. Through the text mining approach, the study extracts relevant, valuable, and non-trivial information from non-structured data to surmount information overload (Netzer et al., 2012). In the current research, Structural Topic Modelling is utilised to generate output that directs towards topic estimation (Sánchez-Franco et al., 2021; Fresneda et al., 2021).

Foremost, the study assembled the consumer review data of those specific voice assistants, which are widely embraced and utilized by consumers in India. According to Statista (2023), Amazon Echo Dot has accustomed high concentration among users, followed by Amazon Alexa and Google Home Mini. The consumer reviews of these products were collected from two major online retail websites, i.e., Amazon.in and Flipkart.in, which are the largest e-commerce platforms in India (Forrester, 2022). The study dataset contains more than 20,000 user-generated reviews belonging to three Amazon Echo and two Google Home products. The descriptions about the products are outlined in Table 2.

The initial raw review data were found to be unstructured, thus, further refinement was done through the text cleaning process. To be specific, the user's written reviews in non-English language were discarded from the original dataset. Additionally, the non-textual inputs such as numbers, symbols, and emojis were also removed from the data. Once the data cleaning was completed, then the study employed a range of machine learning algorithms to perform text mining of review contents (Dwivedi et al., 2023).

More importantly, this study used Structure Topic Modelling (STM) (Roberts et al., 2014), which is a semi-automated approach designed to extract and summaries open-ended and qualitative responses to provide the emerging themes (Dwivedi et al., 2023). It belongs to the category of the Mixed Membership model of the unsupervised method as they 'infer' rather

Table 2. Distribution of sample (Online reviews)

S.no	Product	
1	Echo Dot (4th Gen, 2020 release) with clock. Next generation smart speaker with powerful bass, LED display and Alexa (Blue)	1,162
2	Echo (4th Gen, 2020 release). Premium sound powered by Dolby and Alexa (Black)	1,026
3	Echo Dot (3rd Gen) – New and improved smart speaker with Alexa (Black)	9,766
4	Google Home Mini with Google Assistant Smart Speaker (Chalk)	7448
5	Google Home with Google Assistant Smart Speaker (White)	934
	Total	20,336

than 'assume' the contents of the topic (Wang & Blei, 2011). The STM algorithm yields the keynote themes, which are enveloped as latent topics and further can also aid to ascertain the correlation that exists between them (Sánchez-Franco et al., 2021). Withal, Structure Topic Modelling (STM) differs from another popular mixed membership model Latent Dirichlet Allocation (LDA), in the following aspects: (a) here the topics can be correlated, hence it provides an improved fit with the data (Ryoo et al., 2021) (b) word-usage within a topic can vary by covariate (c) every document has its own distribution over topics (Roberts et al., 2014).

Coherence scores (He et al., 2008) were employed to determine the optimal number of topics. A topic is considered coherent, provided the words within a topic are semantically identical to one another (Shetty & Ramesh, 2021). The highest coherent score indicates the optimal topics.

4. Results and Discussion

The study investigates the consumer data to identify emergent themes, which provide both beliefs and concerns relating to consumer experience by using voice assistants. For this purpose, the study employs Structure Topic Modelling over user-generated reviews and the overview of the estimated coherence score are presented in Fig 1.

This study attempts to decipher and validate the user's expression through feedback in the form of reviews given on public platforms of e-commerce websites like Amazon and Flipkart.

4.1 Amazon products

4.1.1 Product-related characteristics

The first factor includes the top unique words like bass, gen, super, well, wifi, easy, assistant, battery, superb, loved, item, product, best, buy, working, and value, indicating the product-related characteristics. The first thing consumers look for is the ability of the voice assistant to deliver the promised services like portability, automation, and visual attractiveness (Yang & Lee, 2019). The reflection of same can be seen in the review of the user:

"The setup was nice and easy with Alexa app on mobile. The sound quality is good but not as good of the likes of Bose sound link plus. Buy this if you are looking for a nice speaker for music, else Echo dot does the job."

Therefore, in the case of AI-based voice assistants, product-related characteristics are defined as the significant product design aspects that consumers believe will fulfil the transactional assigned task (Lobato et al., 2021). Through the review, the consumer highlights the aspects like quality parameters and also conveys the effort required for the configuration setup of voice assistants.

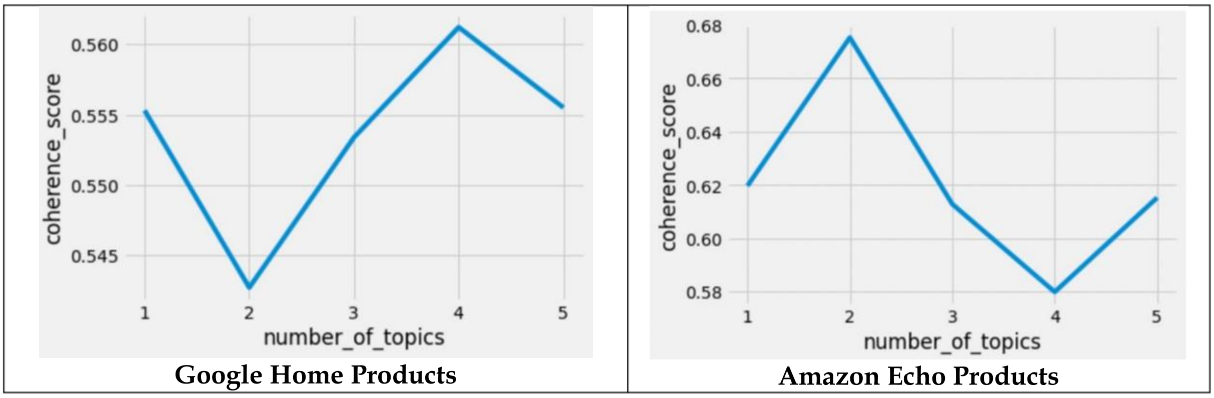

Fig 1: Coherence score graph

From the given charts, we considered four topics for Google products and two topics for Amazon products. The latent topics, along with their label and High Loading unique terms, are reported in Table 3 (Amazon products) and Table 4 (Google products).

4.1.2 Perceived media richness

The second factor includes the words like work, bulb, price, want, Bluetooth, song, works, playing, volume, times, voice speaker, awesome, dot, amazing, songs, product, and need, which denotes the core function of amazon product Alexa, i.e., voice assistant.

Here the top words are related to the sound and responsiveness aspect. The consumer expression is presented below:

"Alexa is just awesome. It has all answers ready all the time."

Perceived media richness indicates the degree to which a communication medium has the ability to deliver rich and complex information (Lei et al., 2021). This involves aspects such as the presence of nonverbal cues, being able to offer immediate feedback, and the ability to use natural and expressive language (Chaves & Gerosa, 2021).

Table 3: Latent topics of Amazon products

Factors	Label	High Loading unique terms
Amazon Factor-1	Product related characteristics	bass, gen, super, well, Wi-Fi, assistant, battery, superb, loved, item, product, best, buy, working, value
Amazon Factor-2	Perceived media richness	work, price, answer, Bluetooth, song, playing, volume, times, voice, response speaker, awesome, dot, amazing, songs, product, need
Common words in both themes	sound, echo, recognition, much, play, product, Alexa, quality, smart, nice, voice, device, buy, great, awesome, amazon, best, music, dot, working, songs, amazing, use, speaker, really, worth, better, time, home, bass, excellent, using, work, price.	

4.2 Google products

4.2.1 Facilitating Conditions

The top words in the first theme of Google product reviews include words like India, echo, support, command, products, say, songs, features, needs, phone, listen, service, want, and thing. Interestingly, some of these words refer to the system infrastructure like support, phone, command, say etc., and the rest of the words include product features. The example of the same is expressed below:

"Google home mini is very good device and a smart speaker. It works tremendously well in USA, Canada but in India it's kinda disappointing. Problem arises with its mic itself we can't control home mini when it plays a song command "hey Google" it just can't recognize you need to scream louder and it then recognizes sometimes not even when I scream. Then I use my home app and change the music but Alexa is far better and has a good mic recognition."

As per the review provided by the consumer, the voice assistants are no doubt considered a modern and functional device, yet there is a lack of efficient infrastructure that could provide a seamless communication system in India (Dogra & Kaushal, 2021). Additionally, the review dispels concerns conferring to voice recognition, which needs to be augmented for superior functionality.

4.2.2 Customer Perception

All media communication is directed to create a favourable impression of the product in the customer's mind. Hence, it is pertinent to seek how the customer perceives the product. Google product second theme includes the unique top words- terrific, wonderful, wow, classy, simply, recommended, market, fabulous, perfect, highly, brilliant, every, penny, fair, choice, disappointed, okay, pretty, waste, delightful, decent, job, poor, slightly, absolute, useless, rubbish, horrible, terrible, expectations, expected, utterly, meet. All of these words indicate the customer experience of using the device. One of the specific illustration of customer perception is in the following review:

"Google Home mini is good so for. The main reason I bought is for Google's magnificent recommendation engine for Music, it's so awesome and queues amazing songs once it learns you. The assistance response more human than Alexa (I have gen2 dot), I like contextual conversation with home where Alexa needs more time to figure it out, and she speaks Hindi to which is amazing, where in Alexa I had to thought her thorough. So far so good."

Based on the analysed review, the perceptivity of the consumer towards the google product indicate how well the expectations of the user are being fulfilled. It can be derived from the comments that consumers pose a mixed viewpoint regarding the operation and usage of voice assistants. Thus, it becomes imperative for marketers to address the dual conception and also bring in a scope to amplify the degree of satisfaction (Buhalis & Moldavska, 2021).

4.2.3 Interaction

The daily usage of the product creates an impression of either delight or frustration on the part of the consumer. The top unique words in the third theme of Google products include like, much, working, well, used, power, bought, speakers, works, recognition, response, compared, available, internet, and playing. These words provide various dimensions of user interaction with voice assistants. The user describes their intercommunication experience as follows:

"Amazing Product in just one word! Apart from playing Music and Radio. The product basically makes the work of Google Search much easier. Just say the search words and Assistant speaks up beautifully. No more typing! Beautifully crafted. Simple Design with Classy look. Audio quality absolutely perfect with Bass and Treble option. Thanx Flipkart for next day delivery and for the Freebie...."

As per the user expression, the product addresses convenience, uniqueness and also signifies the effortless fulfilment of emotional stimulations of the user. Thus, it signifies that the loyalty quotient of the user can be developed by reaffirming the improved interaction quality (Lee et al., 2021).

4.2.4 Product-related characteristics

Just like in the case of Amazon products, one of the themes which emerged in Google product is product-related characteristics. The top unique words here are battery, bass, work, connectivity, YouTube, useful, get, play, premium, and mic. These functional and design attributes play a significant role in acceptance among the masses and can also serve as a basis of product differentiation (Banerjee et al., 2021). The following comment by the user relates to the characteristics that the product possesses:

"Google mini home smart speaker has decent quality audio but bass quality is less compared to other smart speakers. Also, it has kind of reception problem if you play music at full volume than most of the time it didn't catch your voice or respond to ok Google. Also, it didn't have battery do have to connect it to power all time to make it work. PS - You can also connect powerbank with this speaker to make it work on the go."

In the case of voice assistants, product traits are an indispensable requirement for consumer engagement. Improved attributes and seamless functionality are crucial accessories for amplifying the user's trust (Malodia et al., 2021). Thus, concluding this, it is evident that consumer are inclined majorly towards upgraded and multipurpose devices.

Table 4: Latent topics of Google products

Factors	Label	High Loading unique terms
Google Factor-1	Facilitating Conditions	India, echo, support, command, products, say, songs, features, needs, phone, listen, service
Google Factor-2	Customer Perception	purchase, terrific, wonderful, wow, classy, simply, recommended, market, fabulous, perfect, highly, brilliant, every, penny, fair, choice, disappointed, okay, pretty, waste, delightful, decent, job, poor, slightly, absolute, useless, rubbish, horrible, terrible, expectations, expected, utterly, meet
Google Factor-3	Interaction	like, much, working, well, used, power, bought, speakers, works, many, recognition, response, compared, available, internet, playing
Google Factor-4	Product related characteristics	battery, bass, work, connectivity, YouTube, useful, get, play, premium, mic
Common words in all themes	amazing, assistant, awesome, battery, best, better, Bluetooth, buy, connect, device, excellent, flipkart, good, google, great, home, like, love, mini, money, much, music, need, nice, one, play, price, product, purchase, quality, really, smart, sound, speaker, super, time, use, voice, waste, wifi, working, works, worth	

5. Implications

5.1 Theoretical implications

The current study provides manifold implications for literature and practitioners. Theoretically, the current study contributes to service delivery literature by evaluating big data processing in the context of voice assistants. To be specific, the research provides critical success factors for AI-based voice assistants that are directly stemming from consumers' experience. This brings forth a credible expression of users which renders exploratory payoff to the researchers. In particular, Structural Topic Modelling enables researchers to examine how user-generated evaluations evolve and change over time. This long-term perspective aids in identifying developing trends, evolving user preferences, and areas that require enhancements or modifications. It contributes to a better understanding of the changing nature of user views and expectations of voice assistants.

The study also confers to the literature on eWOM, which bestows an instrumental role in influencing consumer decision-making. Whilst such kinds of studies are more exploratory in nature, they possess the attribute of being "data-rich" and "theory skeletal" due to their administration of big data analytics (Sánchez-Franco et al., 2021). Furthermore, the outcomes showcased in this study shed light on the profound importance of pertinent technological characteristics in shaping consumers' adoption of innovative products. More precisely, the present study provides the user's narrative, which can be embraced as a heuristic for theory creation, leveraging on inductive parlance of reasoning, which offers signals that may propel future academicians and marketing professionals.

5.2 Practical Implications

Along with the academic contribution, the study provides a plethora of inputs to automation engineers, product designers, and marketers. To elaborate, the findings of the research unravel the experience of user's post-purchase involvement, which serves as a useful piece of information for product designers and automation engineers in this industry. The observations reveal that although the utilitarian benefits (McLean & Osei-Frimpong, 2019) enchant a crucial part in the successful operation of voice assistants nevertheless, hedonic gains too hold a significant role in attracting consumer's attention. The topic that accounts for both Amazon products and Google products is "Product characteristics", which suggests that it is paramount for consumers to have competent and highly configured products that provide them with premium connectivity and dotting experience (Tables 3 & 4). Besides this, the Topic "Interaction" exhibits the argument that peculiar differences in cultures and languages among the masses of India necessitate strategic advertising of the usability and efficacy of the products with distinctive functionality. Hitherto, the suggestions were primarily endorsed towards product designers and automation engineers. Subsequently, by deducing the highly positive and negative reviews from user content, marketers can evaluate the presence or absence of fundamental features which govern the user's overall assessment in a conducive manner. Furthermore, it boards upon the marketers to fulfil the uncatered communication gap between the users and the purveyors to enlarge social promotions, and this will subsequently lead to better returns on investments.

6. Limitations and Future research directions

The current research possesses some limitations that can be catered for future research work. Firstly, the study evaluates consumer post-purchase experience via online reviews from e-commerce platforms. In future, the question-and-answer section can be analysed in order to gauge consumer predicament while operating AI-based voice assistants. Along with this, tweets of users can be analysed to comprehend the state of the art of AI-based voice assistants. Further, the current study put forward consumer expression through structural topic modelling. However, further examination of consumer's voice can be performed through latent semantic analysis, capturing sentiment analysis and other methods of text mining. Lastly, the study did not consider the demographic differences among the users who engage with voice assistants. Hence, it will be valuable to cross-validate the results with demographic characteristics.

References

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes*, *50*, 179–211. https://doi.org/10.47985/dcidj.475

Bai, S., He, H., Han, C., Yang, M., Yu, D., Bi, X., Gupta, B. B., Fan, W., & Panigrahi, P. K. (2023). Exploring thematic influences on theme park visitors' satisfaction: An empirical study on Disneyland China.

Journal of Consumer Behaviour, November 2022, 1–17. https://doi.org/10.1002/cb.2157

Balakrishnan, J., Dwivedi, Y. K., Hughes, L., & Boy, F. (2021). Enablers and Inhibitors of AI-Powered Voice Assistants: A Dual-Factor Approach by Integrating the Status Quo Bias and Technology Acceptance Model. *Information Systems Frontiers*. https://doi.org/10.1007/s10796-021-10203-y

Banerjee, S., Dellarocas, C., & Zervas, G. (2021). Interacting User-Generated Content Technologies: How Questions and Answers Affect Consumer Reviews. *Journal of Marketing Research*, *58*(4), 742–761. https://doi.org/10.1177/00222437211020274

Bavaresco, M. V., D'Oca, S., Ghisi, E., & Lamberts, R. (2019). Technological innovations to assess and include the human dimension in the building-performance loop: A review. *Energy and Buildings*, *202*. https://doi.org/10.1016/j.enbuild.2019.109365

Biduski, D., Bellei, E. A., Rodriguez, J. P. M., Zaina, L. A. M., & De Marchi, A. C. B. (2020). Assessing long-term user experience on a mobile health application through an in-app embedded conversation-based questionnaire. *Computers in Human Behavior*, *104*. https://doi.org/10.1016/j.chb.2019.106169

Brause, S. R., & Blank, G. (2020). Externalized domestication: smart speaker assistants, networks and domestication theory. *Information Communication and Society*, *23*(5), 751–763. https://doi.org/10.1080/1369118X.2020.1713845

Buhalis, D., & Moldavska, I. (2021). Voice assistants in hospitality: using artificial intelligence for customer service. *Journal of Hospitality and Tourism Technology*, *13*(3), 386–403. https://doi.org/10.1108/JHTT-03-2021-0104

Cambre, J., & Kulkarni, C. (2019). One voice fits all? Social implications and research challenges of designing voices for smart devices. *Proceedings of the ACM on Human-Computer Interaction*, *3*(CSCW). https://doi.org/10.1145/3359325

Chatterjee. (2001). Online Reviews: Do Consumers Use Them? *ACR 2001 Proceedings*, *18*(2), 129–134.

Chaves, A. P., & Gerosa, M. A. (2021). How Should My Chatbot Interact? A Survey on Social Characteristics in Human–Chatbot Interaction Design. *International Journal of Human-Computer Interaction*, *37*(8), 729–758. https://doi.org/10.1080/10447318.2020.1841438

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, *43*(3), 345–354. https://doi.org/10.1509/jmkr.43.3.345

Chou, S. Y. (2012). Online Reviews and Pre-Purchase Cognitive Dissonance : A Theoretical Framework and Research Propositions. *Journal of Emerging Trends in Computing and Information Sciences*, *3*(2), 199–204.

Chung, A. E., Griffin, A. C., Selezneva, D., & Gotz, D. (2018). Health and fitness apps for hands-free voice-activated assistants: Content analysis. *JMIR MHealth and UHealth*, *6*(9), 1–13. https://doi.org/10.2196/mhealth.9705

Lee, O.K., Ayyagari, R., Nasirian, F., & Ahmadian, M. (2021). Role of interaction quality and trust in use of AI-based voice-assistant systems: *Journal of Systems and Information Technology*, *23*(2), 154–170. https://doi.org/10.1108/JSIT-07-2020-0132

Davis, F. D. (1989). Perceived Usefulness , Perceived Ease of Use , and User Acceptance of. *MIS Quarterly*, *13*(3), 319–340.

Dogra, P., & Kaushal, A. (2021). An Investigation of Indian Generation Z Adoption of the Voice-Based Assistants (VBA). *Journal of Promotion Management*, *27*(5), 673–696. https://doi.org/10.1080/10496491.2021.1880519

Dwivedi, Y. K., Sharma, A., Rana, N. P., Giannakis, M., Goel, P., & Dutot, V. (2023). Evolution of artificial intelligence research in Technological Forecasting and Social Change: Research topics, trends, and future directions. *Technological Forecasting and Social Change*, *192*(December 2022), 122579. https://doi.org/10.1016/j.techfore.2023.122579

Fernandes, T., & Oliveira, E. (2021). Understanding consumers' acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption. *Journal of Business Research*, *122*(January 2020), 180–191. https://doi.org/10.1016/j.jbusres.2020.08.058

Festinger, L. (1968). *Theory Cognitive Dissonance*. Stanford University Press, 1–291.

Fishbein, M., & Ajzen, I. (1975). Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research. *Addison-Wesley*. https://doi.org/10.2307/2065853

Forrester. (2022). *2022 Online Marketplace Tracker, Global.*

Frank, B., Herbas-Torrico, B., & Schvaneveldt, S. J. (2021). The AI-extended consumer: Technology, consumer, country differences in the formation of demand for AI-empowered consumer products. *Technological Forecasting and Social Change*, *172*(July). https://doi.org/10.1016/j.techfore.2021.121018

Fresneda, J. E., Burnham, T. A., & Hill, C. H. (2021). Structural topic modelling segmentation: a segmentation method combining latent content and customer context. *Journal of Marketing Management*, 37(7–8), 792–812. https://doi.org/10.1080/0267257X.2021.1880464

Ghasemaghaei, M., Eslami, S. P., Deal, K., & Hassanein, K. (2018). Reviews' length and sentiment as correlates of online reviews' ratings. *Internet Research*, *28*(3), 544–563. https://doi.org/10.1108/IntR-12-2016-0394

Grover, P., & Kar, A. K. (2020). User engagement for mobile payment service providers – introducing the social media engagement model. *Journal of Retailing and Consumer Services*, *53*(December 2018), 101718. https://doi.org/10.1016/j.jretconser.2018.12.002

Grover, P., Kar, A. K., & Ilavarasan, P. V. (2019). Impact of corporate social responsibility on reputation—Insights from tweets on sustainable development goals by CEOs. *International Journal of Information Management*, *48*(January), 39–52. https://doi.org/10.1016/j.ijinfomgt.2019.01.009

He, J., Larson, M., & de Rijke, M. (2008). *Advances in Information Retrieval , 30th European Conference on {IR} Research, {ECIR} 2008, Glasgow, UK, March 30-April 3, 2008. Proceedings*. *4956*(March 2008). https://doi.org/10.1007/978-3-540-78646-7

Hinojosa, A. S., Gardner, W. L., Walker, H. J., Cogliser, C., & Gullifor, D. (2017). A Review of Cognitive Dissonance Theory in Management Research: Opportunities for Further Development. *Journal of Management*, *43*(1), 170–199. https://doi.org/10.1177/0149206316668236

Hsieh, S. H., & Lee, C. T. (2021). Hey Alexa: examining the effect of perceived socialness in usage intentions of AI assistant-enabled smart speaker. *Journal of Research in Interactive Marketing*, *15*(2), 267–294. https://doi.org/10.1108/JRIM-11-2019-0179

Johnson, V. L., Kiser, A., Washington, R., & Torres, R. (2018). Limitations to the rapid adoption of M-payment services: Understanding the impact of privacy risk on M-Payment services. *Computers in Human Behavior*, *79*, 111–122. https://doi.org/10.1016/j.chb.2017.10.035

Kasilingam, D. L. (2020). Technology in Society Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society*, *62*(February), 101280. https://doi.org/10.1016/j.techsoc.2020.101280

Kerly, A., Hall, P., & Bull, S. (2007). Bringing chatbots into education: Towards natural language negotiation of open learner models. *Knowledge-Based Systems*, *20*(2), 177–185. https://doi.org/10.1016/j.knosys.2006.11.014

Khern-am-nuai, W., Ghasemkhani, H., & Kannan, K. N. (2016). The Impact of Online Q&As on Product Sales: The Case of Amazon Answer. *Ssrn*. https://doi.org/10.2139/ssrn.2794149

Kwark, Y., Jianqing, C., & Raghunathan, S. (2014). Online product reviews: Implications for retailers and competing manufacturers. *Information Systems Research*, *25*(1), 93–110. https://doi.org/10.1287/isre.2013.0511

Lee, K. Y., Sheehan, L., & Lee, K. (2021). *The continuation and recommendation intention of artificial intelligence-based voice assistant systems (AIVAS): the influence of personal traits*. https://doi.org/10.1108/INTR-06-2020-0327

Lei, S. I., Shen, H., & Ye, S. (2021). A comparison between chatbot and human service: customer perception and reuse intention. *International Journal of Contemporary Hospitality Management*, *33*(11), 3977–3995. https://doi.org/10.1108/IJCHM-12-2020-1399

Liu, B., & Sundar, S. S. (2018). Should Machines Express Sympathy and Empathy? Experiments with a Health Advice Chatbot. *Cyberpsychology, Behavior, and Social Networking*, *21*(10), 625–636. https://doi.org/10.1089/cyber.2018.0110

Lobato, A. I., Palacios, L. L., & López, R. P. (2021). What characteristics of smart home speakers should companies invest in? Differences between actual and potential users. *UCJC Business and Society Review*, *18*(1), 128–165. https://doi.org/10.3232/UBR.2021.V18.N1.04

Malodia, S., Ferraris, A., Sakashita, M., Dhir, A., & Gavurova, B. (2023). Can Alexa serve customers better? AI-driven voice assistant service interactions. *Journal of Services Marketing*, *37*(1), 25–39. https://doi.org/10.1108/JSM-12-2021-0488

Malodia, S., Islam, N., Kaur, P., Dhir, A., Islam, N., Kaur, P., & Dhir, A. (2021). Why Do People Use Artificial Intelligence (AI)-Enabled Voice Assistants? *IEEE Transactions on Engineering Management*, *PP*, 1–15. https://doi.org/10.1109/TEM.2021.3117884

McLean, G., & Osei-Frimpong, K. (2019). Hey Alexa … examine the variables influencing the use of artificial intelligent in-home voice assistants. *Computers in Human Behavior*, *99*(January), 28–37. https://doi.org/10.1016/j.chb.2019.05.009

Michie, S., & Marteau, T. (1999). Non-response bias in prospective studies of patients and health care professionals. *International Journal of Social Research Methodology*, *2*(3), 203–212. https://doi.org/10.1080/136455799295014

Moorthy, A. E., Vu, K. L., Moorthy, A. E., & Vu, K. L. (2015). Privacy Concerns for Use of Voice Activated Personal Assistant in the Public Space. *International Journal of Human-Computer Interaction*, *31*(4), 307–335. https://doi.org/10.1080/10447318.2014.986642

Mumuni, A. G., O'Reilly, K., MacMillan, A., Cowley, S., & Kelley, B. (2020). Online Product Review Impact: The Relative Effects of Review Credibility and Review Relevance. *Journal of Internet Commerce*, *19*(2), 153–191. https://doi.org/10.1080/15332861.2019.1700740

Nasirian, F., Ahmadian, M., & Lee, O. K. D. (2017). AI-based voice assistant systems: Evaluating from the interaction and trust perspectives. *AMCIS 2017 - America's Conference on Information Systems: A Tradition of Innovation*, *2017-Augus*(May).

Netzer, O., Feldman, R., Goldenberg, J., & Fresko, M. (2012). Mine your own business: Market-structure surveillance through text mining. *Marketing Science*, *31*(3), 521–543. https://doi.org/10.1287/mksc.1120.0713

Pal, S., Biswas, B., Gupta, R., Kumar, A., & Gupta, S. (2023). Exploring the factors that affect user experience in mobile-health applications: A text-mining and machine-learning approach. *Journal of Business Research*, *156*(December 2022), 113484. https://doi.org/10.1016/j.jbusres.2022.113484

Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. *International Journal of Contemporary Hospitality Management*, *32*(10), 3199–3226. https://doi.org/10.1108/IJCHM-04-2020-0259

Pitardi, V., Wirtz, J., Paluch, S., & Kunz, W. H. (2022). Service robots, agency and embarrassing service encounters. *Journal of Service Management*, *33*(2), 389–414. https://doi.org/10.1108/JOSM-12-2020-0435

Plant, R. E. (1993). Expert systems in agriculture and resource management. *Technological Forecasting and Social Change*, *43*(3–4), 241–257. https://doi.org/10.1016/0040-1625(93)90054-B

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Poushneh, A. (2021). Humanizing voice assistant: The impact of voice assistant personality on consumers' attitudes and behaviors. *Journal of Retailing and Consumer Services*, *58*, 102283. https://doi.org/10.1016/j.jretconser.2020.102283

Ramadan, Z., F. Farah, M., & El Essrawi, L. (2021). From Amazon.com to Amazon.love: How Alexa is redefining companionship and interdependence for people with special needs. *Psychology and Marketing*, *38*(4), 596–609. https://doi.org/10.1002/mar.21441

Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., Albertson, B., & Rand, D. G. (2014). Structural topic models for open-ended survey responses. *American Journal of Political Science*, *58*(4), 1064–1082. https://doi.org/10.1111/ajps.12103

Ryoo, J. H., Wang, X., & Lu, S. (2021). Do Spoilers Really Spoil? Using Topic Modeling to Measure the Effect of Spoiler Reviews on Box Office Revenue. *Journal of Marketing*, *85*(2), 70–88. https://doi.org/10.1177/0022242920937703

Sánchez-Franco, M. J., Arenas-Márquez, F. J., & Alonso-Dos-Santos, M. (2021). Using structural topic modelling to predict users' sentiment towards intelligent personal agents. An application for Amazon's echo and Google Home. *Journal of Retailing and Consumer Services*, *63*(June). https://doi.org/10.1016/j.jretconser.2021.102658

Shaker, A. K., Mostafa, R. H. A., & Elseidi, R. I. (2021). Predicting intention to follow online restaurant community advice : a trust-integrated technology acceptance model. *European Journal of Management and Business Economics*. https://doi.org/10.1108/EJMBE-01-2021-0036

Shankar, A., Tiwari, A. K., & Gupta, M. (2022). Sustainable mobile banking application: a text mining approach to explore critical success factors. *Journal of Enterprise Information Management*, *35*(2), 414–428. https://doi.org/10.1108/JEIM-10-2020-0426

Shetty, S. J., & Ramesh, V. (2021). pyResearchInsights—An open-source Python package for scientific text analysis. *Ecology and Evolution*, *11*(20), 13920–13929. https://doi.org/10.1002/ece3.8098

Statista. (2023). *Voice assistant e-commerce transaction value worldwide 2021-2023*.

Statista. (2023). *Global smart speaker market share 2016-2024*.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478.

Vimalkumar, M., Sharma, S. K., Singh, J. B., & Dwivedi, Y. K. (2021). 'Okay google, what about my privacy?': User's privacy perceptions and acceptance of voice based digital assistants. *Computers in Human Behavior*, *120*(October 2020). https://doi.org/10.1016/j.chb.2021.106763

Wang, C., & Blei, D. M. (2011). Collaborative topic modeling for recommending scientific articles. *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 448–456. https://doi.org/10.1145/2020408.2020480

Yang, H., & Lee, H. (2019). Understanding user behavior of virtual personal assistant devices. *Information Systems and E-Business Management*, *17*(1), 65–87. https://doi.org/10.1007/s10257-018-0375-1

Yang, M., & Han, C. (2020). Revealing industry challenge and business response to Covid-19: a text mining approach. *International Journal of Contemporary Hospitality Management*, 33(4), 1230–1248. https://doi.org/10.1108/IJCHM-08-2020-0920

Zhang, J. Q., Craciun, G., & Shin, D. (2010). When does electronic word-of-mouth matter? A study of consumer product reviews. *Journal of Business Research*, *63*(12), 1336–1341. https://doi.org/10.1016/j.jbusres.2009.12.011

***