

Impact of Digital Assistant Attributes on Millennials' Purchasing Intentions: A Multi-Group Analysis using PLS-SEM, Artificial Neural Network and fsQCA

Abstract: The rising population of millennials, coupled with Digital Assistants (DA) and online purchasing trends among consumers have gained increasing attention by global marketers. The study evaluates the influence of DA attributes on the purchasing intention (PUI) of millennials. A combined approach of PLS-SEM, Artificial Neural Network (ANN) and Fuzzy-set Qualitative Comparative Analysis (fsQCA) is used to predict the PUI of 345 millennials. Also, multi-group analysis is employed to uncover the influence of gender on the relationship between PUI and DA attributes. The findings suggest that DA attributes may amplify purchasing intention among millennials, especially through perceived interactivity and anthropomorphism. Further, the moderating role of gender was found significant on the inter-relationship of perceived interactivity and PUI. This research is a pioneer study in the area of artificial intelligence, conversational commerce, DA and AI-powered chatbots. This study will help marketers and practitioners to predict millennial purchasing intentions. An evaluation of this paper may help them to foster immersive and effective engagement through DA.

Keywords: Artificial intelligence; Conversational commerce; Chatbots; Millennials; Customer purchase; Interactivity; Artificial neural network

1. Introduction

Conversational commerce (CC) is emerging as a strong communication method to enhance online purchasing. It is a concept that describes how customers move through the purchase process using natural language (Mayer and Harrison, 2019; Balakrishnan and Dwivedi, 2021). This can be through web-based chatbots, voice assistants or artificial intelligence (AI) empowered chatbots. The term CC was introduced in 2016 and is recognised throughout the digital sector (Messina, 2016). The introduction of the Amazon Echo smart speaker in 2014 and Alexa has revolutionised the retail industry and unlocked the potential of natural language

processing. Since then, the industry has conducted a range of experiments that have opened up opportunities for new markets (McLean, et al., 2021).

Through time, customers have become more comfortable with the digital assistant (DA) and now expect more personalised content and offers for their online purchases (Canziani and MacSween, 2021). The term DA is used interchangeably with voice assistant, AI enabled chatbot and chatbot assistant. However, “Digital Assistant (DA)” is an umbrella term that includes voice assistant, AI enabled chatbot and chatbot assistant (Pantano and Pizzi, 2020; Ramadan, 2021). DAs primarily integrate AI-enabled chatbots that interact with customers using natural language processing and are much more than AI pilots; they are developing and improving considerably year by year. The main strength of the DA is the AI application without human interference that can reduce the churn rate of customers (Wilson and Daughy, 2018). Due to its enhanced acceptability and potential, marketers use DA to augment customer journeys and engagements. With the use of DA, consumers buy FMCG (fast moving consumer goods), make travel bookings, purchase books etc.; examples include Oyo Rooms who use a chat enabled interface to search and book hotels; HDFC Bank has an insurance chatbot to provide financial advice while Domino’s has an intelligent chatbot on Facebook Messenger for ordering pizza (Huang and Rust, 2021).

The contribution of DA and conversational commerce is evident in the current scenario but studies are rare in exploring its potential conceptually and empirically (Balakrishnan and Dwivedi, 2021). AI and data analytics are now an essential part of human lifestyle that cannot be ignored (Porra et al., 2020). Based on AI algorithms, DAs are deployed to optimise performance output. Currently, the presence of DA becomes significant in the digital environment where customers can access products via multiple touch points and expect a seamless experience. Based on customer preference, content personalisation is also provided through DA (McLean et al., 2021).

Throughout the last two years, COVID-19 has impacted markets and driven drastic changes in consumer behaviour. With less manpower, flexible hours and higher usage of the online marketplace, organisations have shifted their focus on DAs to fulfil order management, inquiry handling, personalised content, omni channels and technical assistance. Therefore, organisations

are now more inclined towards DA enabled customer support services where customers tend to make online purchases based on the recommendations and advice offered (Shankar et al., 2021). With AI enabled technological support, customer purchase intention can be predicted with appropriate recommendations made, based on the past activities of a consumer using machine learning and AI algorithms (Choudrie et al., 2021). This increases the probability of a customer making a purchase. However, current literature is limited to examining the customer's outlook towards DAs. Many studies have looked at only the technological adoption of the DA. The adoption of DA on its own does not offer the answer; rather, we need to explore what traits of DA drive an individual to initiate a purchase intention (Zhong et al., 2021).

The educated, younger and healthier populations (millennials) of emerging economies are acting as fuel for a substantial increase in goods and services consumption and consequently, expenditure on online purchasing (Patwa et al., 2021). Spending by consumers (millennials) in these economies is projected to be higher than in developed nations. The role of the internet and e-commerce platforms is very significant in millennials' attitudes towards purchasing. It has been found that 43% of urban internet users in emerging economies use information that they collect online to guide their buying (Kendall et al., 2020). The millennials of emerging economies are not just chatting, posting, using social networking or downloading videos, they are exploring and buying products online. The rising numbers of smartphones available and the increase in omni channel marketing have contributed greatly to online purchase actions. E-commerce through smartphones is highly significant in these markets. It accounts for more than 70% of online retail purchases in China (Cheong et al., 2020). Therefore, the DA becomes vitally important for organisations to grab the target market of millennials (Cui et al., 2021).

Among the BRIC (Brazil, Russia, India and China) economies, India has a higher number of internet users, mainly consisting of millennials. In terms of growth perspective, millennials in emerging economies represent an enormous opportunity (Cheong et al., 2020). With the change in buying patterns, customers now expect marketers and retailers to switch to more advanced and efficient media to facilitate their purchasing actions. Therefore, millennials and their purchase intentions require to be analysed so that the DA can serve them more effectively. To achieve this, the millennials' choices, perception towards DA and their purchase intentions need to be linked

and thoroughly investigated. The current study has developed from the gap stated above, explaining the need to understand the millennial purchase intention based on DA characteristics. There is momentum in exploring DA and its contribution to customer purchase decisions, yet no research has investigated it empirically or conceptually. Moreover, the future research directions suggested by Moriuchi (2019) support the need for further investigation into customer engagement through DAs from a commercial viewpoint.

The present study extends empirical research through Uncanny Valley Theory (UVT), social presence and Theory of Planned Behavior (TPB) integrating the DAs and their consequence on customer (millennials) buying intention. With the UVT contribution, this study provides an understanding of DAs and customer (millennial) intention towards them. Besides using this theory, this study identifies the three main functions of DAs - perceived anthropomorphism, social presence and perceived interactivity. These three functions are the building blocks of DAs. Further, the TPB theory extends the research and identifies the purchase intention of the customer and its relationship with DAs. Based on the gap discussed above, the current study raises the following questions.

RQ1: How do DA attributes influence the purchase intention (PUI) of customers (millennials)?

RQ2: Does gender moderate the inter-relationship between the DAs and purchase intention (PUI) of customers (millennials)?

The study will impart significant inputs into conversational commerce, DA and purchase intention by answering the above-mentioned research questions. The results of the study enrich existing literature on the purchase intention and role of human-like machines. The study will also provide insights to improve performance of companies as well as future strategies to engage customers more appropriately. Besides the theoretical framework, the study proposes a hypothetical model based on UVT, social presence theory and Theory of Planned Behavior (TPB). Besides theoretic implications, this study is useful for decision makers to develop strategic plans for influencing millennial purchasing intentions.

The present study has collected data from 345 millennials, all with experience of purchasing using DAs. This research is a pioneer in the area of artificial intelligence, conversational

commerce, DA, AI-powered chatbots and presents a novel model to measure the impact using PLS-SEM, Artificial Neural Network (ANN) and Fuzzy-set Qualitative Comparative Analysis (fsQCA) methods. These are the most appropriate methods for predicting the model. The PLS-SEM achieves greater statistical power at all sample sizes, but particularly smaller sample sizes, compared to CB-SEM (Hair et al. 2019). The PLS-SEM characteristic of higher statistical is useful for exploratory research that examines less developed or developing theory (Hair et al. 2019). The linear and non-linear relationships can be captured by ANN. While PLS-SEM offers the evaluation of pre-determined relationships that are anticipated to explain the dependent variable of interest, the fsQCA methodology permits assessment of several alternative causal recipes concurrently (Ragin, 2006). fsQCA examines how causal conditions (independent variables) combine into several configurations entailing equifinality, thus conducting to the same outcome (dependent variable) (Pappas et al., 2017). To a certain extent, it complements PLS-SEM results (Gelhard et al., 2016; Woodside, 2013). Lee et al. (2020) proposed that single-stage PLS-SEM application might only capture the linear relationship within a research framework, and might be insufficient to predict complex decision-making processes. The other researchers have attempted to mitigate this constraint by performing a second-stage data analysis using fuzzy-set qualitative comparative analysis (fsQCA) and artificial neural network (ANN) (Hasan et al., 2022). Therefore, the current study has implemented a multi-stage PLS-SEM-ANN-fsQCA approach that enhances the accuracy of a non-linear and asymmetric relationship. Moreover, the role of gender through multi-group analysis is identified and its moderating effect on DAs and PUI is explored.

The organisation of the study is as follows:

Section 2 elaborates the theoretic background of the research study and hypothesis development. Section 3 explicates the methods undertaken in detail. Section 4 discusses the results of the study. The research contributions and implications are presented in Section 5. Finally, Section 6 states conclusions and suggests directions for future researches.

2. Theoretical Background

The foremost theory grounded on human responses to human-like machines is Uncanny Valley Theory (UVT), proposed by Mori (1970). This theory proposed that initially, humans react

positively to a human-like machine to a certain extent but subsequently, these positive reactions turn into negative responses when the machine comes with imperfect human looks and behaviours (Ciechanowski et al. 2019; Li et al., 2021). The negative response generated can again become positive when human likeness becomes perfect, forming the valley-like chart of human response against human-like machines (Mori, 1970; Urgan et al., 2018). Past research has empirically proved that UVT confirms the positive-negative-positive sequence relationship among the human response and human-like machines (Kätsyri et al., 2015). Ciechanowski et al. 2019 concluded that people prefer simpler text-based chatbots compared to animated avatars.

Previous studies on ‘technology humanness’ have investigated the association between the user’s understanding and the machine (Kamide et al., 2014). The user’s response varies based on their view of social presence imparted by the machine (Lankton et al., 2015). A significant association is found between the perceived humanness of the device and the user’s trust and emotional reaction to the device that leads to its adoption. (Lankton et al., 2015). The other theory in context to a relationship with technology humanness includes the theory of social presence (Chattaraman et al., 2019). This theory suggested that a user’s perception of the machine is formed built on human warmth attributes of DA (Lankton et al., 2015). Another viewpoint lies with the human perceived personification of machines. In the past, human predisposition has been explored to personify acceptance, for instance, digital assistants including chatbots, voice-based chatbots and AI-based chatbots (Lee et al., 2019). These devices are sometimes treated as a human companion, although the users actually know that the humanoid of the device are 100% realised through AI and NLP technologies (Mir et al., 2021). Previous literature suggests that humans are more comfortable in interacting with intelligent agents that are able to mimic what humans do; the degree of personification is directly correlated to the level of satisfaction towards the machine (Purinton et al., 2017).

Other research has utilized the TPB model for predicting the behaviour or intention towards purchase. Few studies have shown the combination of other models with TPB, whereas others have incorporated critical factors into it (Ajzen, 1991).

The use of DAs provides appropriate information to customers that is likely to influence their purchase (Lu et al., 2014). Consumer attitude has been assessed using TAM and TPB models towards online platforms (Dedeke, 2016); an online travel provider website was also evaluated (Ayeh et al., 2013). The current study extends UVT, TPB and social presence theory to explore the purchase intention towards DA.

2.1 Digital Assistant Attributes

DAs have several attributes, such as human-like interaction and rich quality of information. Their four main attributes are perceived anthropomorphism, perceived social presence, perceived interactivity and information quality (Bartneck et al., 2009; Balakrishnan and Dwivedi, 2021). The current study utilises these four functions of DAs in developing the research framework.

2.1.1 Perceived Anthropomorphism

The best way to influence social cues is by offering an anthropomorphic interface. With DAs, human-like attributes such as gestures, facial expressions, voice/speech can be achieved (Qiu and Benbasat, 2010). Previous research studies have utilised transformation in anthropomorphic interfaces to develop intelligent agent appearance and behaviour such as 2D or 3D, avatars or modulations in communications. E-commerce firms need to know how to use DAs that can influence customer perception through anthropomorphism (Araujo, 2018). The objective of DAs is viewed as social actors with the capability of processing attitudes similar to humans (Qiu and Benbasat, 2009). It has been recognised that users perceive DAs as human-like personalities that utilise characteristics such as politeness in their interactions. The usage of DAs is not limited to human-like attributes, it can also predict a user's loyalty (Sundar, 2004). Brahnam (2009) concluded that social acceptance is received from anthropomorphic attributes' application as cues in DAs. DAs utilise voice and chat both to enhance the acceptability and likeability of anthropomorphic attributes. The trust generated in DAs due to anthropomorphism has been assessed in a research study conducted by Nordheim (2018).

A research survey performed by Sheehan et al. (2020) assesses anthropomorphism the chatbots to explain the inter-relationship between perceived humanness and adoption scores. Further, it suggests that unresolved errors were enough to decrease anthropomorphism and the acceptance

intent. [Moussawi et al. \(2020\)](#) showed that perceived anthropomorphism is the degree to which an agent is perceived as human-like. Their findings reveal that anthropomorphism is the substantial antecedent of DA adoption. Also, anthropomorphism enhances the enjoyment of using a personal intelligent assistant without the lack in initial trust. [Jang et al. \(2021\)](#) investigated chatbot services from a managerial perspective to enhance the adoption of chatbots at organisational level. Based on the social response theory ([Nass et al., 1994](#)), several studies have shown how humans deploy social rules to DA designed on anthropomorphism characteristics. This study also regards anthropomorphism as a human like characteristic, behavioral pattern and showing emotions towards non-human agents ([Epley et al., 2007](#)). However, limited studies are available on DAs' anthropomorphic attributes, especially in the commercial context. Thus, the impact of anthropomorphism on PUI is measured in the current study.

2.1.2 Perceived Social Presence

Based on the communication theory, social presence states a degree of salience felt by an individual during an interaction with machines ([Short et al., 1976](#)). This function has been extensively used in the area of information system research to examine computer-mediated communication ([Venkatesh and Johnson, 2002](#); [Cyr et al., 2009](#)). Social presence is a psychosomatic link to a user one who visualises DAs as warm, personal and sociable ([Srivastava and Chandra, 2018](#)). From a social media perspective, social presence outcomes are positive as there is a sense of warmth in social networking sites that attracts and influences an individual ([Algharabat and Rana, 2020](#)). Also, this function signifies a sense of sociability which enhances trust, loyalty and usage intention in the environment of e-commerce ([Leong et al., 2020](#)). Based on social presence theory, while interacting to an anthropomorphized agent, humans may perceive a social presence. This concept is useful in assessing users' perceptions of individual contact with other users in a technology-mediated interaction ([Qiu and Benbasat, 2009](#)). According to this theory, perception of a user towards the machine is shaped on the human warmth attributes of DA ([Lankton et al., 2015](#)). Past studies have considered virtual agents and acknowledged social presence as an important concept that describes the feeling of being prominent. This is employed to define the quasi-social relationship between the DA and users. Also, it can evaluate user perceptions in relation to social traits ([Qiu and Benbasat, 2009](#)). This

function is essential for enhancing those social interactions that may develop a connection and influence intention (Poncin et al., 2017). Li et al. (2021) showed a positive impact of social presence through virtual agents on the consumer's intention to use.

2.1.3 Perceived Interactivity

Some studies have shown that interactivity has been a major attribute in influencing interpersonal attraction and satisfaction (Oh and Sundar, 2015; Lew et al., 2018) with engagement; behaviour and attitude formation in relation to healthcare has also been noted (Bellur and Sundar, 2017). A study conducted by Yang and Shen (2018) identified that perceived interactivity affected the user response in the form of attitude formation and behavioural intentions. Perceived interactivity is expressed as the view of reciprocal communication and perceived active control. It includes the ability to manage and control communication through a medium (Ischen et al., 2020).

Previous studies show that the existence of perceived interactivity results into positive attitude formation (Ischen et al., 2020; Go and Sundar, 2021). Based on these research conclusions, we conclude that DAs possess interactivity attributes that may influence the customer's intention to purchase. Thus, we propose that higher interactivity of DAs will lead to an influence on PUI. The impact of perceived interactivity on PUI will therefore be measured in the current study.

2.1.4 Information Quality

DAs need to have a strong information database that will generate appropriate responses to users. Also, natural language processing needs to convert human language to appropriate information while interacting with the user (Li et al., 2021). A study conducted by Kuligowska (2015) highlighted a chatbot's ability to understand a human conversation as one of the most important parameters for evaluation. If the user feels that the information provided by the DA is understandable and appropriate, then the perception or intentions towards the purchase can be influenced. Lee et al. (2021) established the effect of the quality dimensions of chatbots: understandability, reliability, responsiveness, assurance and interactivity are important to the user's post-use conformation.

The example of Alexa is well known for its capabilities that showcase human-like attributes and deliver human experience rather than merely acting as a machine (Ramadan, 2021). In the current study, the research model postulates the inter-relationships among the DA attributes and the customer presence. Based on this, conceptual framework is developed as exhibited in Figure 1.

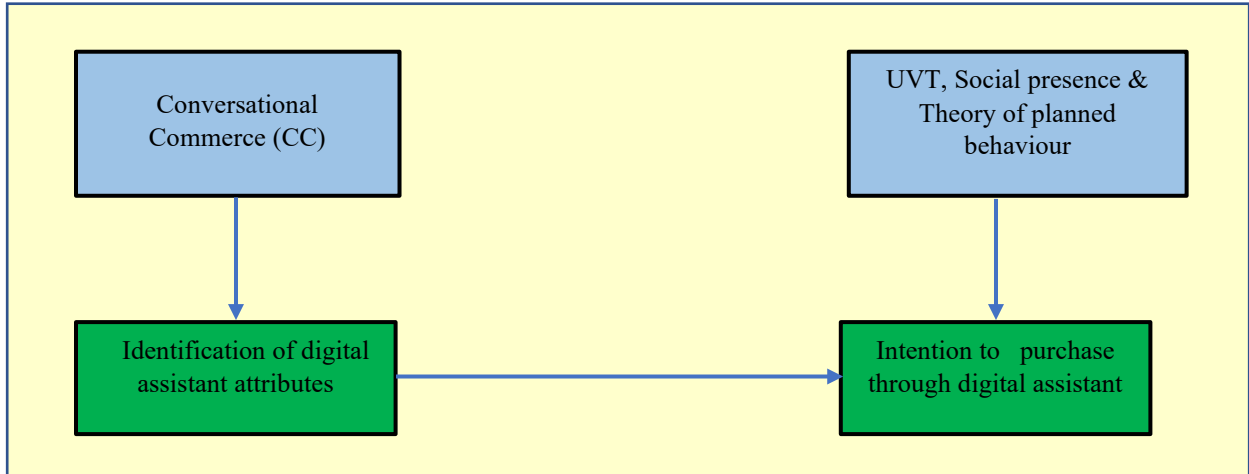


Figure 1: Conceptual model

2.2 Hypotheses' Development

Perceived anthropomorphism is the most widely investigated construct in artificial intelligence and intelligent agents (Ho and Mac-Dorman, 2017). Past studies have deliberated about anthropomorphism based on UVT and suggested that human attributes could increase the user's level of comfort in accessing and using it (Mori et al., 2012; Broadbent, 2017). Research has also formulated that attitude formation might happen but there was no such evidence for this predisposition. Studies have also found that human-like attributes tend to stimulate technology-oriented interactions and develop intentions (Fan et al., 2016). Human-like assistance can lead to inducing customers into purchasing or booking a service (Labroo et al., 2008). This impersonation also affects purchase intention. Payne et al. (2013) showed the influence of brand anthropomorphic personality on intention towards purchase. Some studies have shown that anthropomorphism can be stimulated by cues on web portals and chatbots (Araujo, 2018). The chatbot has an additional benefit of anthropomorphism compared to a website because of its intelligent interaction (Chong et al., 2021). TPB specified that a positive attitude develops the behavioral intention (Ajzen, 1991). Studies conducted on e-commerce have shown support to

TPB. Up to the present day, there are no studies that explain the role of DA attributes on the intention to purchase, especially in the context of millennial customers. The above research findings fall into line with the propositions from UVT that human-like attributes can enhance millennials' intention to purchase a product using online platform through DAs. To measure the influence of PA, the following hypothesis is proposed.

H1(a): Perceived Anthropomorphism (PA) of DA positively affects the customer's (millennials) Intention to Purchase (PUI).

It has to be noted that social presence and anthropomorphism are distinct attributes. The concept of anthropomorphism refers to human-like attributes whereas social presence (SP) infers that a medium is perceived as a real social interaction partner with low prominence on the technological contribution (Araujo, 2018; Ischen et al., 2020). In DAs, the social presence will be higher compared to websites due to the actual interaction. From the social presence theory perspective, the construct of social presence that provides a sense of warmth and sociability that leads the customer to being influenced (Gefen and Straub, 2004). Previous studies on technology adoption have examined the relationship between the user's comfortability with technology and the humanness of it (Brown, 2008; Carter and Liu, 2018). A few studies have also assessed the perception of an individual based on the social presence of the device used. The theory of social presence is related to the sociable attribute of the device (Lankton et al., 2015). Findings from previous studies are related to the present study by proposing that customers are more influenced by human-like partner/conversations, warmth and sociability of the machines i.e. DAs. Thus, this study aims to identify the impact of SP on PUI through the following proposed hypothesis.

H1(b): Social Presence (SP) of digital assistants positively affects the customer's (millennials) Intention to Purchase (PUI).

Some evidence supports interactivity as an important construct in measuring user response to smart or intelligent agents. The interactivity of smart devices develops the user's positive attitude towards the device (Shin et al., 2019) DAs are known to be error-free and provide seamless interaction and conversation just like human agents. This perceived interactivity has also shown positive responses such as satisfaction, engagement and behavioral intentions (Ischen et al.,

2020). Based on the TPB, positive attitude may lead to behavioral intention, and hence this characteristic of DAs may create a positive response towards purchase intention among millennials. Based on the theoretical explanation of message interactivity, DAs' attributes may influence perceived interactivity; thus, a proposed hypothesis is

H1(c): Perceived Interactivity (PI) of DAs positively affects the millennials' Intention to Purchase (PUI).

A noteworthy relationship between information system quality and user positive response has been identified. A DA needs to have a strong information system or database that will allow it to generate the most suitable responses to users. The conversion of the human language to providing relevant information and query solving needs a strong, reliable information system. Thus, the quality of the DA needs to be measured. Several studies conducted on chatbots have shown a significant link between the user's understandability and his reactions (Sugumaran et al., 2017). A study by Kuligowska (2015) has shown the understandability of human conversation to be one of the most important constructs to evaluate the DA. In the case when the information given by the DA to the user is understandable, the performance outcome can be positive. Li et al. (2021) measured the effect of quality dimensions of chatbots, also showing that users are satisfied with the quality of DAs. These findings have supported the current study towards a theoretical relationship among the variables undertaken in the context of millennials' purchase intention. The following hypothesis is made to measure the effect of information quality on PUI.

H1(d): Information Quality (IQ) positively affects the customer's (millennials) Intention to Purchase (PUI).

2.2.1 The moderating effect of gender on digital assistants and customer's (millennials) intention to purchase.

There is an effect of gender in decision making processes proven by the study conducted by He and Freeman (2010) in the field of psychology where it was demonstrated as a cognitive filter. Based on the study conducted by Tobias-Mamina et al. (2021), gender has an influence on

trustworthiness and attitude; they found behavioural intent to be stronger in female users, whereas PUI was stronger for male users. The study conducted by Balakrishnan and Dwivedi (2021) concluded that age and gender act as the confounding variables in conversational commerce; they also observed the insignificant relationship between age and gender with PUI through DA. Previous studies have shown the moderating effect of gender on perceived risk and continuance intention where males had a higher value than females (Martin and Phillips, 2017). Büyükdag et al. (2020) disclosed that there is a significant role of gender and PUI in the context of price discounts. Park et al. (2021) showed the moderating effect of gender, age and income on the perception of luxury in explaining online consumer engagement and purchase intention. As can be seen, previous studies have shown different results for moderating variables including gender.

Therefore, the current study has conducted multi-group analysis to observe the effect of gender on PUI through the following hypotheses.

H2(a): Gender moderates the Perceived Anthropomorphism (PA) and customer's (millennials) Intention to Purchase (PUI) inter-relationship.

H2(b): Gender moderates the Perceived Interactivity (PI) and customer's (millennials) Intention to Purchase (PUI) inter-relationship.

H2(c): Gender moderates the Social Presence (SP) and customer's (millennials) Intention to Purchase (PUI) inter-relationship.

H2(d): Gender moderates the Information Quality (IQ) and customer's (millennials) Intention to Purchase (PUI) inter-relationship.

On the basis of above discussion, the proposed model is shown in Figure 2.

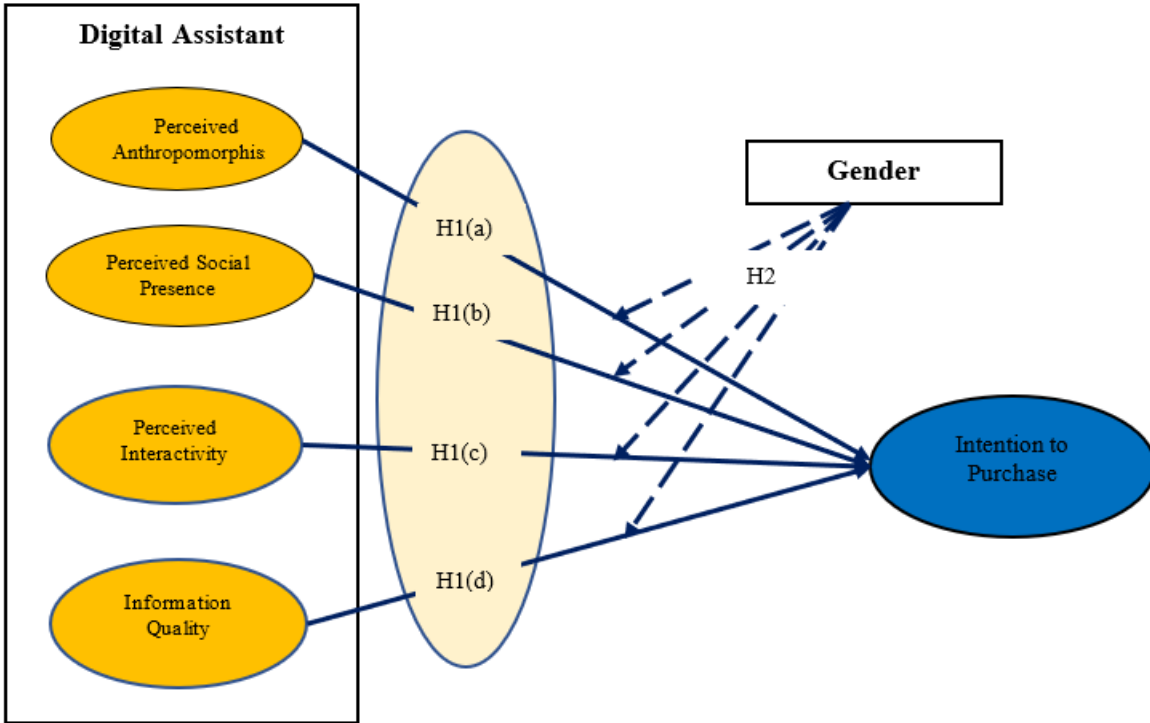


Figure 2: Proposed research model

3. Methodology

The selection of methodology depends on the nature of data collection and research objectives. The method should be undertaken after considering the sample size, outliers and multivariate assumptions, normality, multi-collinearity etc. The current study has employed Partial Least Square (PLS-SEM) and ANN to predict the purchase intention of millennials. PLS-SEM is employed in the study as the sample size satisfies the 1:10 ratio (Hair et al., 2011). It is the most appropriate method for prediction purposes; it is not sensitive to sample size as compared to CB-SEM. All 20 items are selected in the study due to factor loading values more than 0.70 (Hair et al., 2011). Following the research questions, for detection of both linear and non-linear relationships to uncover the predictive capacity of exogenous variables, ANN is used as this is the most suitable method (Hew et al., 2019). ANN employs artificial intelligence for generation of the solution based on the principle of the human brain. PLS is conducted using SMART PLS 3.0 with ANN analysis conducted using SPSS 25.0. fsQCA is applied to validate the results of PLS-SEM and ANN. The current study has undertaken the fsQCA method as it considers the outcome and predictor variables on a fuzzy scale rather than a dichotomous scale (Ragin, 2009).

3.1 Data Collection

A survey-based approach was utilised for data collection. An e-discussion among academia (marketing) experts and data scientists was conducted in phase one to assess the relevance of measures undertaken. A panel of nine experts was convened including two senior professors of the marketing domain, three professionals from data science (all with experience of five+ years) and four professionals from operations management. This phase was followed by a pilot study on 20 respondents in the second phase; all respondents had long experience working with digital assistants. The Cronbach's alpha values were calculated and two items with low values were modified to enhance clarity and appropriateness. A final questionnaire was prepared and shared with respondents in the English language; this included measurement scales and demographic questions such as education, gender, age and exposure to DAs etc. The constructs were undertaken from previous studies. The items of perceived anthropomorphism have been adapted (Qiu and Benbasat, 2009); perceived interactivity (Ischen et al., 2020) and purchase intention through DAs (Pantano and Viassone, 2015).

The questionnaire was developed on an established scale undertaken in previous studies (Qiu and Benbasat, 2009; Bartneck et al., 2009; Pantano and Viassone, 2015) although items had been slightly changed to align with the research study. The items were measured on a Likert scale of 1-5. The questionnaire included two sections. In the first section, the research construct information was shared followed by a demographic description of respondents in the second section. The current study involved millennials with prior experience of online purchasing through DA. These millennials were aware of DAs and the different categories available on e-commerce platforms. The sample was collected from India as it is one of the emerging economies to be expanded and boosted by a well-educated, younger and healthier population with rising incomes and acting as fuel for a substantial increase in goods and services consumption. The spending by consumers (millennials) in these economies is projected to be more than in developed nations. India has a greater number of internet users among the 15-35 years of age group and thus a sample from this country is a good representation of emerging economies. Details of the respondents are presented in Table 1.

Table 1: Demographic profile of the sample

	Categories	Frequency	Percentage
Gender	Male	232	67.3
	Female	113	32.7
Age group	18 to 24 yrs.	213	61.7
	25 to 30 yrs.	96	27.8
	30 to yrs.	36	10.4
Education	Undergraduate	44	12.8
	Graduate	105	30.4
	Postgraduate	98	28.4
	Professional	98	28.4
	Undergraduate	44	12.8
Purchase through e-commerce	Once in 15 days	55	15.9
	Twice in 15 days	54	15.7
	Once in a month	66	19.1
	Twice a month	96	27.8
	Once a week	74	21.4
Exposure to digital assistant	High	45	13.0
	Medium	194	56.2
	Low	106	30.7

3.2 Artificial Neural Network (ANN)

ANN utilises AI to generate a solution; it is appropriate for determining the predictive power of any bias. ANN employs neurons that are dispersed in multiple layers, gathered as input, output or hidden. Several types of ANN are present, but in feed forward, a back-propagation multilayer perceptron (MLP) method has been applied in the current study (Negnevitsky, 2011). A typical neural network has several hierarchical layers including on input, one or more hidden and one output layer. With one hidden layer, any continuous function can be represented whereas with two hidden layers, discontinuous functions can also be modelled (Negnevitsky, 2011). Each layer comprises of neurons which are connected to other neurons of the following layer and each connection is represented by synaptic weight.

The current study has utilised ANN to determine the predictive power of bias in the context of DA and intention to purchase among millennials. ANN has the advantage of capturing non-linear relationships to address the quality parameters and multivariate assumptions. SEM analysis oversimplifies the intricacies of the decision-making process while ANN is not recommended for hypotheses that test causal relationships. However, in terms of prediction accuracy, ANN

provides better results. The importance of each exogenous construct was assessed using sensitivity analysis and further expressed as a percentage of the relative importance. The ANN model comprises of three layers: the input layer, the hidden layer and the output layer. The current study uses MLP-ANN using SPSS v.25 and includes three input variables and one output variable. The independent variables of PLS-SEM - IQ (Information Quality), PA (Perceived anthropomorphism), PI (Perceived interactivity) and SP (Perceived Social presence) are introduced as input neurons; Intention to Purchase (PUI) is regarded as an output neuron. The automated generation of hidden neurons (nodes) takes place and an activation function is used for both hidden and output layers. In addition, ten-fold cross-validations are used for prediction accuracy of the trained network. Previous studies have looked at the application of ANN models to resolve complex problems in the area of marketing (Liebana-Cabanillas et al., 2017; Sharma and Sharma, 2019).

3.3 Fuzzy Set Qualitative Comparative Analysis (fsQCA)

fsQCA explains each combination of causal conditions and outcomes (Ragin, 2009; Pappas, 2018; Pappas and Woodside, 2021; Mattke et al., 2022). This method has been applied successfully in several contexts including information systems and marketing (Pappas, 2018; Pappas and Woodside, 2021). According to user's guide of fsQCA (Ragin, 2017), data calibration, construction of truth table, and analysis of causal conditions are necessary steps in data analysis procedure. The fsQCA starts with calibration of causal factors and outcome variables into fuzzy sets with a range of 0 and 1; 0 denotes non-membership and 1 denotes full membership. fsQCA undertakes metric scale data, although the causal conditions and outcomes could be represented as a single item. Hence, each construct is embodied by a single item which was computed by the arithmetic mean. The calibration of variables was conducted into sets using fsQCA software recommended by Ragin (2009) and Pappas and Woodside (2021). According to Ragin (2009), variables need to be transformed into calibrated sets using three substantively meaningful thresholds: full membership, full non-membership and a crossover point. This crossover point embodies the point of maximum ambiguity. Based on these breakpoints, all the remaining scores were calculated. The thresholds were taken as 5,3,1

The truth table calculated all the possible configurations that might occur, providing 2^k rows, with k represents the number of outcome predictors, and each row represented every possible

combination. While computation of all possible configurations, the frequency was also presented, while several lines had a frequency of zero indicating that none of the cases in the sample were explained by them. As the number of variables in an analysis increase, the number of possible configurations increases exponentially (2^k), thus the more variables the more combinations are likely to have a frequency of zero (Pappas and Woodside, 2021). In the next step, the truth table sorting by frequency and consistency was conducted. The threshold frequency was set to 1 and all combinations with smaller frequency are removed from further analysis. Once removing configurations with low frequency, the truth table was sorted by “raw consistency”. At this point a consistency threshold was set to 0.75. The lowest consistency values were 0.854436, 0.742686, 0.670488. Proportional Reduction in Inconsistency (PRI) consistency scores should be high and close to raw consistency scores (e.g., 0.7), while configurations with PRI scores below 0.5 indicate significant inconsistency (Greckhamer et al., 2018). PRI consistency is used to avoid simultaneous subset relations of configurations in both the outcome and the absence of the outcome (i.e., negation). Symmetric (SYM) consistency was used to examine the presence and negation of the outcome and same consistency standard for both analyses (i.e., presence and its negation) (Pappas and Woodside, 2021). fsQCA computed three solutions namely, complex, parsimonious and intermediate. The truth tables are presented in Appendix (Figure A1 and A2).

4. Results

In Figure 3, the relationships among the perceived anthropomorphism, perceived interactivity, social presence, information quality and intention to purchase are investigated using PLS-SEM through SmartPLS3.0 software.

4.1 Measurement Model

With SMART PLS 3.0, the measurement model is developed and exhibited in Figure 3. The Cronbach’s alpha, reliability, validity and fit indices are shown in the subsequent sections.

4.1.1 Reliability

The values obtained in the model are shown in Table 2. The reliability has been examined through Composite Reliability (CR) and Cronbach’s alpha. From Table 2, the values of

Cronbach's alpha for the constructs are IQ = 0.849; PA = 0.834; 0.706; SP = 0.822; PUI = 0.855. For CR, the values are IQ = 0.899; PA = 0.900; PI=0.8371; SP= 0.894; PUI = 0.896. The values of each construct have a value greater than 0.70 (Nunnally and Bernstein, 1994) showing that the model is reliable.

4.1.2 Convergent Validity

This validity could be achieved when all the items load significantly on their denominated latent variables (Hair et al., 2012). This has been measured through factor loading and average variance extracted (AVE). Table 2 presents the values of factor loadings and AVE.

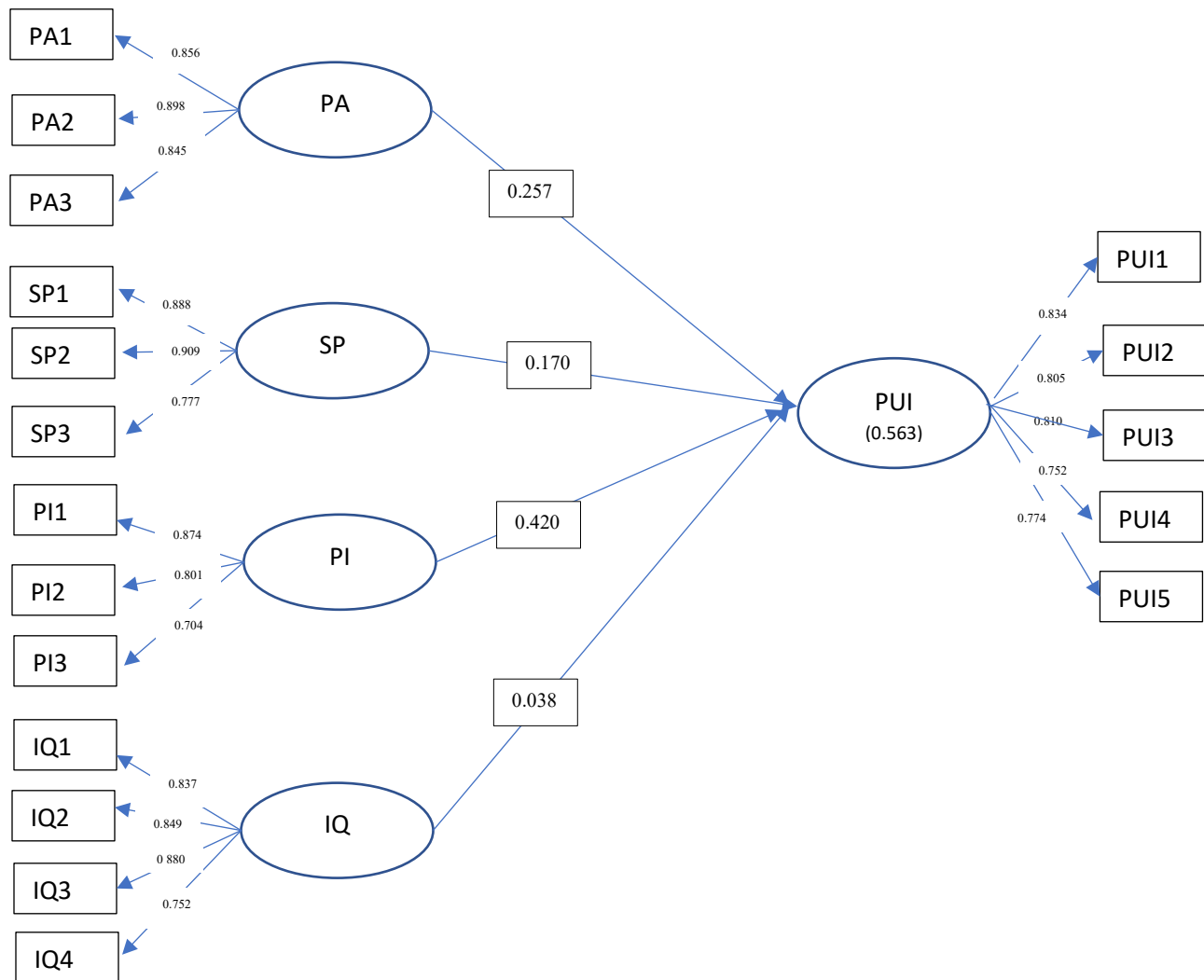


Figure 3: Measurement model

Table 2: Cronbach's Alpha, CR and AVE

	Cronbach's Alpha	rho A	CR	AVE
IQ	0.849	0.852	0.899	0.690
PA	0.834	0.836	0.900	0.751
PI	0.706	0.722	0.837	0.634
SP	0.822	0.836	0.894	0.739
PUI	0.855	0.860	0.896	0.633

Note: IQ= Information Quality, PA= perceived Anthropomorphism, PI= Perceived Interactivity, SP =Social presence, PUI= Purchase intention

The CR values indicate that the objective has been achieved as it exceeds the threshold values. CR > 0.60 and values of AVE > 0.50 respectively (Fornell and Larcker, 1981).

4.1.3 Discriminant Validity

Discriminant validity signifies the degree to which the latent variables are distinct from each other. This validity is obtained when the square root of AVE for each construct is greater than the correlations of all the other constructs (Fornell and Larcker, 1981). Table 3 shows the values obtained for discriminant validity.

Table 3: Discriminant validity

	IQ	PA	PI	PUI	SP
IQ	0.831				
PA	0.227	0.867			
PI	0.302	0.574	0.796		
SP	0.252	0.623	0.687	0.796	
PUI	0.171	0.687	0.637	0.62	0.86

Table 3 indicates that validity is achieved when the non-diagonal values (square root of AVE) are higher than the off-diagonal values. Further, the Heterotrait monotrait (HTMT) ratio was also computed to confirm the discriminant validity issues and results indicating the fulfilment of the criteria; this satisfies the condition as the values are less than 0.90 (Henseler et al., 2015) (Table 4).

Table 4: HTMT Ratio

	IQ	PA	PI	PUI	SP
IQ					
PA	0.271				
PI	0.394	0.738			
PUI	0.291	0.728	0.879		
SP	0.201	0.816	0.836	0.733	

4.1.4 Non-Response and Common Method Bias (CMB)

Non-response bias test was conducted and showed no significant difference between respondents and non-respondents. Two groups were formed; the first group was comprised of respondents who responded in the first two weeks with the second group comprised of respondents who responded in the last two weeks. For each construct, t-test comparisons were computed between group means; results indicated that no significant differences exist. Further, to control for CMB, the Harman single factor test was used and found that the majority of variance was not attributed to one factor. CMB arises due to a single source of data (Avolio et al., 1991). It undermines validity (MacKenzie and Podsakoff, 2012) and also has an effect on structural relationship (Kline, 2015). The two ways to minimise CMB are by procedural design and statistical control (Reio, 2010). The current study has employed the statistical control method using Harman's one factor test to verify CMB issue. Based on the results, it is observed that 40.1 percent of the total variance was the largest variance explained. The results fulfil the condition as it shows less than 50 percent threshold (Fuller et al., 2016; Podsakoff et al., 2012). Also, the full-collinearity test was conducted; results obtained show values less than 3.3 (Kock, 2015), indicating the absence of CMB.

Table 5: Collinearity stats

Outer	VIF
IQ1	2.126
IQ2	2.401
IQ3	2.517
IQ4	1.431
PA1	2.091
PA2	2.468
PA3	1.699
PI1	1.763
PI2	1.612
PI3	1.214
PU1	2.101

PU2	1.901
PU3	2.023
PU4	1.784
PU5	1.690
SP1	2.335
SP2	2.525
SP3	1.499

Table 5 presents VIF values; all are less than the threshold value of 3.3 that indicates the absence of CMB in the model.

4.2 Structural Model

Table 6 presents the hypotheses results, showing that PA, PI and SP have a significant effect on PUI of millennials; PA →PUI (P -value <0.05); SP →PUI (P -value <0.05); PI →PUI (P -value <0.05).

Table 6: Bootstrapping results for structural model

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t -Statistics (O/STDEV)	P Values	Significance
H1: PA →PUI	0.257	0.257	0.055	4.705	0.000	***
H2: SP → PUI	0.170	0.171	0.052	3.234	0.000	***
H3: PI → PUI	0.420	0.420	0.049	8.495	0.000	***
H4: IQ → PUI	0.038	0.041	0.037	1.025	0.306	Insignificant

*** indicates $p < 0.05$; significant; IQ= Information Quality, PA= perceived Anthropomorphism, PI= Perceived Interactivity, SP =Social presence, PUI= Purchase intention

The results shows that IQ does not have a significant effect on PUI (P -value >0.05). The cut-off value is 5 % to determine the statistical significance.

4.3. Multi-Group Analysis (MGA)

MGA using PLS is used to test a structural relationship. It evaluates the moderation effect on relationships. With multi-group analysis, sub-samples within the total population are made. Two groups are made based on gender - female and male. Moderation is run in PLS-SEM using multi-group analysis with the effect measured on the inter-relationships between the DA attributes and millennials' purchasing intention (see Table 7).

Table 7: A multi-group analysis

	Path Coefficients-diff (female - male)	p-Value original 1-tailed (female vs male)	p-Value new (female vs male)	Significance
PA -> PUI	-0.028	0.605	0.790	<i>Insignificant</i>
PI -> PUI	0.0207	0.017	0.034	***
SP -> PUI	-0.095	0.813	0.374	<i>Insignificant</i>
IQ -> PUI	0.007	0.462	0.923	<i>Insignificant</i>

*** indicates $p < 0.05$; significant; IQ= Information Quality, PA= perceived Anthropomorphism, PI= Perceived Interactivity, SP =Social presence, PUI= Purchase intention

The results show that the hypotheses IQ -> PUI; PA -> PUI; SP -> PUI are found to be insignificant whereas PI -> PUI is significant. This proves that gender moderates the inter-relationship between PI and PUI as the p -value is significant.

4.4 Artificial Neural Network Validation

ANN was conducted to complement the PLS-SEM investigation as discussed in section 3.2. ANN was conducted using MLP (multi-layer perceptron) in SPSS v. 25. In the current study, a Multilayer Perceptron (MLP) feed-forward back propagation multilayer training algorithm with a hyperbolic tangent activation is employed. The study has utilised a six-fold cross-validation process where data was segmented into training and test data to avoid the issue of overfitting; data was divided into two parts (80% for training and 20% for testing) (Liebana-Cabanillas et al., 2017). This study has only one model in ANN. The significant reflective independent variables are undertaken as input neurons for the output neuron (dependent variable) in the ANN analysis. Figure 4 shows the developed model. Also, the prediction results from ANN are more precise in comparison to the PLS-SEM method. Therefore, an integrated PLS-SEM-ANN approach explains the prediction model in a better way, consequently enhancing the robustness of the results. To validate the ANN findings, an accuracy measure, Root Mean Square Error (RMSE), has been used (Yadav et al., 2016). From equations 1 and 2, RMSEA is calculated where SSE indicates the sum of squared error; MSE is the mean squared prediction error.

$$MSE = [1/n] \times SSE \dots\dots\dots (1)$$

$$RMSEA = \sqrt{MSE} \dots\dots\dots (2)$$

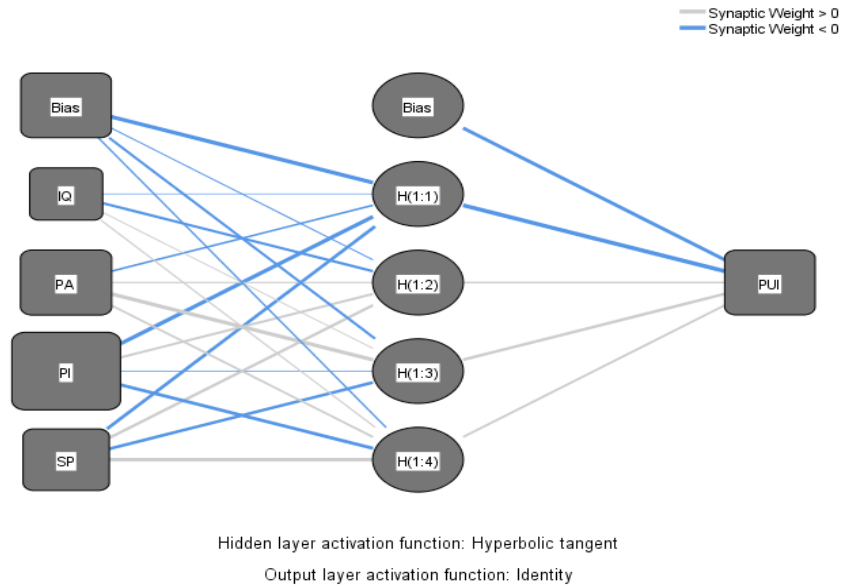


Figure 4: ANN model

The values of average RMSE lie between 0.4 to 0.5 for both the training and testing sets as shown in Figure 5. The values of RMSE are lower than 0.5; hence it can be interpreted that ANN models are accurate, reliable and capture the relationships between predictors and outputs (Chong, 2013). The RMSEA values for training and test data confirm that all the predictor variables have a significant effect on PUI. All values are less than 0.50 and near to each other; this shows that the model fit is accurate and reliable.

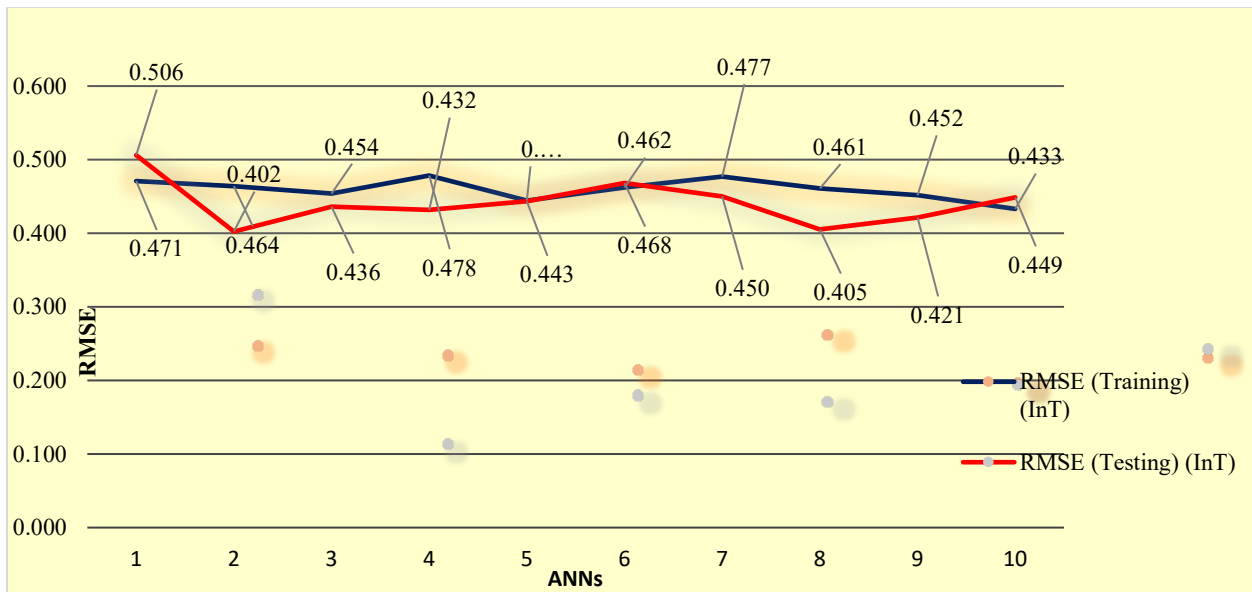


Figure 5: RMSE values (training and test data)

4.4.1 Sensitivity analysis

Sensitivity analysis helps to compute normalised importance using the ratio of the relative importance of each input and expressed as a percentage (Ooi and Tan, 2016). This study determines the variations in the dependent variable with a change in independent variables. The computation is carried out by undertaking the average of importance of IQ, PA, PI and SP as independent variables and PUI as a dependent variable. The results obtained through sensitivity analysis are shown in Table 8.

Table 8: ANN model results

ANN models	IQ	PA	PI	SP
ANN1	0.00	0.44	1.00	0.41
ANN2	0.08	0.20	1.00	0.17
ANN3	0.08	0.44	1.00	0.21
ANN4	0.09	0.20	1.00	0.35
ANN5	0.01	0.34	1.00	0.30
ANN6	0.21	0.65	1.00	0.53
ANN7	0.01	0.33	1.00	0.20
ANN8	0.05	0.33	1.00	0.56
ANN9	0.10	0.36	1.00	0.15
ANN10	0.13	0.42	1.00	0.29
Mean	0.08	0.37	1.00	0.32
Normalized	8%	37%	100%	32%

Note: IQ= Information Quality, PA= Perceived Anthropomorphism, PI= Perceived Interactivity, SP =Social presence, PUI= Purchase intention

Results are based on the normalised relative importance (%) and shown as above in Table 8. Based on these results, PI is the most significant predictor of PUI (with 100% normalised relative importance) followed by PA, SP and IQ with 37%, 32% and 8% normalised relative importance respectively. The results of PLS, SEM and ANN are matched and support each other. With ANN analysis, it is validated that PI is the most influential variable as it has obtained the highest normalised importance ratio in comparison to others. The results of ANN match with PLS-SEM. The construct has a similar influence as seen in PLS-SEM. Thus, the model predicted in the study is reliable.

The study has employed fsQCA to measure the synergistic impact of the multiple factors on an outcome. The steps of fsQCA have been applied including calibration, truth table construction and analysis of necessary conditions.

4.5 fsQCA results

The fsQCA application has offered three solutions; complex solution, parsimonious and intermediate solution. The complex solution presented all the possible combinations of conditions when traditional logical operations are applied (Appendix, Figure A3). The parsimonious solution presented the most important conditions which cannot be left out from any solution (Appendix, Figure A4). Finally, the intermediate solution is obtained when performing counterfactual analysis on the complex and parsimonious solutions including only theoretically plausible counterfactuals. The intermediate solution has a higher consistency than the parsimonious (Appendix, Figure A5) According to the findings of parsimonious solutions, PI, PA and SP are the core conditions for influencing PUI of the millennials. To clearly demonstrate the findings obtained from complex, intermediate and parsimonious solutions, the results are summarised in Table 9.

Table 9: fsQCA Results

	Solution		
Configuration	1	2	3
Information Quality	●		⊗
Perceived Anthropomorphism	●	⊗	●
Perceived Interactivity		●	
Social presence		⊗	●
Consistency	0.887519	0.823859	0.928026
raw coverage	0.750329	0.238064	0.340561
unique coverage	0.451905	0.0103811	0.100131
Overall solution coverage:	0.877179		
Overall solution consistency:	0.870052		

Note: black circle (●) indicates the presence of a condition; crossed-out circle (⊗) indicates the absence/negation whereas blank space denotes “do not care” condition.

Three causal configurations that lead to PUI have consistency more than 0.82, coverage values between 0.237 to 0.748 and overall solution coverage more than 0.90. This shows that the model is informative. Path 1 suggests that when IQ is less, PUI can be influenced through PI. Path 2 suggests that in the absence of SP, PUI can be influenced by PA and PI. Path 3 indicates that PA and SP can lead to influence on PUI in the absence of IQ. In the presentation of findings shown in Table 9,

5. Discussion of Findings

The study has observed the effect of DA attributes on the PUI of millennials through a hypothesised model. The investigation included a purposive survey among 345 millennials. A total of four hypotheses were formulated for model 1 without any moderation effect and one hypothesis for model 2 with gender moderation effect. Table 6 shows that apart from IQ, other attributes including PA, SP and PI have a significant effect on PUI. This study is novel in exploring the impact of PA on the PUI of millennials. The first hypothesis (*H1: PA -> PUI; $\beta = 0.275; p < 0.05; significant$*) indicates the positive influence of PA on the PUI of millennials. The study on millennial PUI is also dependent on the time spent on the internet and the acceptability of smart devices. In the past few years, the average time spent among Indian users has grown and due to the disruptive environment, there has been an increase in the usage of machines. The human-machine ratio has previously been a concern, but currently it is becoming a survival strategy for organisations. Intelligent agents have become an integral part of human lives. Thus, human-like attributes influence humans towards their attitude formation and intention for purchase actions.

The above research findings are in line with the UVT propositions that human-like attributes can enhance millennials' PUI on e-commerce sites through DAs. The second hypothesis (*H2: SP-> PUI; $\beta = 0.17; p < 0.05; significant$*) indicates the significant effect of SP on the PUI of millennials. SP is higher compared to website activity due to the actual interaction. A sense of warmth and sociability is generated, leading to influence on the customer. This is supported by the social presence theory that suggests the relationship of SP to services based on technology, including social media and chatbots (Poncin et al., 2017). Key findings from past studies suggest

that a customer is highly influenced by the human-like partner/conversations, warmth and sociability of machines. Li et al. (2021) also showed a positive impact of social presence through virtual agents on the consumer's intention to use. Social presence is essential for making a connection with the user to develop attitude formation and intention. The study aligns with other research (Eple et al., 2007; Balakrishnan et al., 2021) that supports the opinion that humans have an inclination to become associated with anthropomorphic agents.

Other findings from the study show the positive relationship between the DA and interactivity, demonstrating the significant effect of PI on the PUI of millennials ($H3:PI \rightarrow PUI; \beta = 0.420; p < 0.05; significant$). This supports hypothesis 3. This aligns with previous studies that have highlighted the positive impact of the level of interactivity of smart devices on attitude towards the device (Shin et al., 2016). This construct has maximum effect on the PUI, showing that millennials perceive that DAs are efficient in interaction and can guide users in their purchase actions. The effect of PI has also shown a positive response on behavioural intentions in a past study conducted by Ischen et al. (2020). The findings of this study are supported by Yang and Shen (2018) who identified the perceived interactivity effect on the user response in the form of behavioural intentions. The effect of IQ on PUI is found to be insignificant ($H4:IQ \rightarrow PUI; \beta = 0.038; p > 0.05; insignificant$), thus rejecting the hypothesis. This shows a non-significance of information quality on the purchasing intention of millennials. As the information provided to the user is sometimes not appropriate or not relevant, there is no trigger to purchase. Information quality also has a problem of responsiveness and is low compared to human interaction. This finding is supported by Li et al. (2021). The users may believe that DAs are not able to understand the problem in the appropriate way.

With multi-group analysis, the moderation effects of gender, shown in Table 7, show that, except for perceived interactivity, all other attributes are insignificant. The values of perceived anthropomorphism, perceived social presence and information quality are found to be non-significant, implying that all three attributes are not affected by gender. The results from PLS-SEM were validated by ANN; the results are shown in Table 7. Perceived interactivity, with a value of 100%, shows highest influence. This shows that millennials have an inclination towards interactivity involving DA; in addition, males have higher influence than females. The findings

suggest that millennials perceive DA to be sensitive and interact like humans. This is because millennials belong to the more educated, tech-savvy members of society, spending more time on machines; they also appreciate innovative features with a human-like touch. This generation wants to save time and have experiences of shopping with high engagement.

Three solutions, complex, intermediate and parsimonious, are obtained from fsQCA analysis. The intermediate solution comprises of both core and peripheral conditions, there is a need to make the distinction to enhance an explanation of the interpretation. Through combined parsimonious and intermediate solutions, an elaborated and aggregated view of the findings may be presented. Based on the parsimonious and intermediate solutions in the current study, it can be seen that the presence of PI, SP and PA are core conditions for PUI whereas absence of IQ indicates it as the weak predicting variable. Moreover, to achieve higher purchase intention among millennials, the attributes of DAs can be combined with either (i) PI and IQ (model 1) (ii) PI, absence of PA and absence of SP (model 2) (iii) PA, SP with absence of IQ (iv) SP, PA and PI. This leads to an intermediate solution which has highlighted the core conditions, clearly presenting all core and peripheral conditions, to allow for a better interpretation of the findings.

These fsQCA results support the results obtained from PLS-SEM and ANN model applications. Table 10 presents in detail the findings from PLS-SEM analysis; this indicates the strongest effect of perceived interactivity (PI) on the PUI of millennials, also supported by the ANN method. The multi-method approach has similar findings that suggest to marketers that they should consider the combination of PI, PA and SP in AI powered chatbots or DAs when they are targeting millennials in an emerging economy like India. The results from fsQCA indicate that in the presence of PI, PA and SP can lead to high PUI but the negation or absence of the same characteristics of DA can lead to the desired outcome, depending on how they combine with other characteristics. For a clear presentation of the findings, Table 10 is formed.

Table 10: Comparative results of PLS-SEM, ANN and fsQCA

PLS SEM findings	ANN findings	fsQCA findings
PA attribute of AI powered digital assistants has a significant effect on the PUI of the millennials	PA has a 37 % relative importance and second highest for PUI of millennials	PA is present in one conditions out of three conditions that explains the PUI of the millennials
<i>Or it can be interpreted as: PA is</i>	<i>Or it can be interpreted as: PA has</i>	<i>Or it can be interpreted as</i>

<i>a significant predictor of PUI for the millennials</i>	<i>a significant relative importance in the PUI of the millennials</i>	<i>PA explains the high PUI of the millennials in 1 out of 3 solutions</i>
SP attribute of AI powered digital assistants has a significant effect on the PUI of the millennials	SP has a 32 % relative importance and second highest for PUI of millennials	SP is present in one condition out of three conditions that explains the PUI of the millennials.
<i>Or it can be interpreted as: SP is a significant predictor of PUI for the millennials</i>	<i>Or it can be interpreted as: SP has a significant relative importance in the PUI of the millennials</i>	<i>Or it can be interpreted as SP explains the high PUI of the millennials in 1 out of 3 solutions</i>
PI attribute of AI powered digital assistants has a significant effect on the PUI of the millennials	PI has a 100 % relative importance and second highest for PUI of millennials	PI is present in two conditions out of three conditions that explain the PUI of the millennials.
<i>Or it can be interpreted as: PI is a most significant predictor of PUI for the millennials</i>	<i>Or it can be interpreted as: PI has a highest significant relative importance in the PUI of the millennials</i>	<i>Or it can be interpreted as: PI explains high PUI of the millennials in 2 out of 3 solutions</i>
IQ attribute of AI powered digital assistants has an insignificant effect on the PUI of the millennials	IQ has only 8 % relative importance and least rated for PUI of millennials	IQ is present in one condition out of three conditions that explain the PUI of the millennials. Also, IQ is absent in the core conditions.
<i>Or it can be interpreted as: IQ is a non-significant predictor of PUI for the millennials</i>	<i>Or it can be interpreted as: PI has the least significant relative importance in the PUI of the millennials</i>	<i>Or it can be interpreted as: IQ can be either present or negated for the PUI of the millennials</i>
The single solution obtained is the best solution	<i>significant relative importance of the variables for PUI are calculated</i>	Multiple solutions are possible and may refer to different types of users
<i>The results indicate an R^2 of 0.56.3, that justifies that 56.3% of the variance of intention</i>	<i>PI is the most significant predictor of PUI (with 100% normalised relative importance)</i>	<i>The results indicate an overall solution coverage of .87, suggesting 3 solutions cover the substantial proportion of PUI</i>

Millennials are outward-looking, an aspirational population who want to have ease of shopping, immediate access to brands and high comfortability. Millennials prefer texting compared to talking and prefer a casual interaction with chatbots. The results from multi-methods are significant for marketers and businesses aiming to develop a strategy to deliver a satisfying, contextual, interactive and memorable experience to millennials.

5.1 Theoretical and practical implications

The present study extends the empirical research through Uncanny Valley Theory (UVT), social presence and Theory of Planned Behavior (TPB), integrating the DA attributes effect on customer (millennials) purchase intention. This study extends the research on UVT and social presence theory to identify the effects of PA, SP and PI. These theories have contributed to exploring human responses towards machines as examined in past studies. With this study, the contribution is extended to explore the effect of PA, SP and PT of DA on millennials' PUI. Further, TPB theory extends the research and identifies the purchase intention of the customer and the relationship with DA.

Based on these findings, the theoretical contributions are presented. Primarily, this research has extended the knowledge base on DA, CC and UVT. The study has enriched the body of literature relevant to DA, chatbots and AI chatbots (Balakrishnan and Dwivedi, 2021; Fernandes and Oliveira, 2021). The study contributes to developing an association between DA attributes and the purchase intention of millennials. The results also enhance many implications in the area of marketing and operations where the attributes of DA may augment the purchase actions among millennials. This study offers insight to researchers to extend their work in AI, DA and marketing functions. Malik et al. (2021) have suggested that AI may bring integration in organisational functions. In line with this, the current study provides a strong base for future marketing and business operations.

Besides the primary contribution, the current study provides the following contributions based on the hypotheses: 1) The study extends knowledge related to anthropomorphism and UVT on DA attributes; 2) The current study has extended the knowledge of SP by showing the effect of humanness towards purchase intention among millennials. This is also supported by the theory of SP that proposes the relationship of social presence with services based on technology including social media and chatbots (Lankton et al., 2015). Emerging from UVT, social presence theory and TPB models are important for predicting the behaviour or intention towards purchase. Only a few studies have shown the combination of other models with TPB, whereas others have incorporated critical factors into it (Ajzen, 1991). The current study has extended the TPB model to predict the customer intention based on DA attributes.

Based on these findings, it is clear that PUI has been influenced more by PI than SP and PA. As millennials are the most targeted users, marketers and technology developers need to improvise on the weak DA attributes. The initial stages of DA were focused on information, query handling and attractive features. But with recent advancement, AI-enabled chatbots are more inclined towards delivering the interactive environment, engagement and social presence to provide a human-like experience to users. The same is reflected through the results; marketers and technology developers need to integrate the customer journey with maximised functions. Examples such as the chat enabled interface of Oyo Rooms to search and book hotels, HDFC Life insurance chatbot, Domino's and the intelligent chatbot on Facebook Messenger for ordering pizza show the strength of DA and its effect on purchase intention (Huang and Rust, 2021).

The new breed of online shopping experiences has multiple touch points for users; it is therefore desirable to have AI-enabled chatbots to engage customers appropriately. This has a significant implication. With the advancement of technology and increasing usage of humanness, online purchases can be easily influenced for those users who can move from engagement with human agents into chatbot users. This will help firms to save costs while enhancing service satisfaction. Emerging technologies in the area of augmented reality provide opportunities to enhance the level of engagement among the users. Therefore, this study offers insights on how to incorporate augmented reality in interactivity and social presence.

During the recent disruptive environment, the relevance of machines has emerged more prominently. With smaller workforces, many working from home and safety guidelines in place, our focus has shifted to online shopping. Customers nowadays spend more time on the internet and purchase products through e-commerce sites. This change in customer behaviour is a thought-provoking process for organisations, marketers and developers to utilise machines optimally and depend less on humans. The pandemic has become a catalyst to transform the marketplace. The conversational AI market will reach \$77.6 billion by 2022, with a 37.3% growth rate (CAGR) (International Data Corporation). The study conducted by Tsai et al. (2021) examined which factors of chatbot communication and profile design may drive chatbot effectiveness and also the mechanism underlying the messaging and design effects on consumer

engagement. Shumanov and Johnson, (2021) has examined whether human-computer interactions can be more personalized by matching consumer personality with congruent machine personality using language. This study is useful for marketers and developers to draw up their future strategic plans for targeting customers. Also, the argument on firms saving costs, can be expanded as the deployment of chatbots can have a dual role, since they can be used both by consumers as well as employees and service agents whose job is to support consumers (Vassilakopoulou et al., 2022). There is major potential when humans and AI join forces (Raisch and Krakowski, 2021). With DA, marketers can reach the general public with less cost and perform their functions with more efficiency. As more marketers and customers use DA, the demand for the development of AI-enabled chatbots will rise.

6. Conclusion

The study examines the conversational commerce impact through DAs on millennial intention to purchase. The study has employed PLS-SEM, ANN and fsQCA to predict millennial purchase intention towards DA attributes. The results from PLS-SEM reveal that perceived interactivity has the highest significance in developing PUI followed by PA, SP and IQ among millennials. These findings were also tested through ANN and fsQCA, with results from all methods complementing each other. The findings suggest that millennials perceive DA to be sensitive, human-like, show empathy towards millennials' expectations and are highly influenced by the interactivity characteristics of DA. Millennials belong to the educated and tech-savvy category; they spend more time on their machines and need innovative features such as a human-like touch. This study offers valuable insights into the areas of marketing, technology and operations. These results are significant for marketers and developers to develop future strategies that will deliver an enjoyable, contextual, interactive and memorable experience to millennials. Marketers can use this model to enhance the reach to millennials with less cost and more efficiency. As the usage of DA increases, marketers and developers need to focus on DA attributes to develop their future strategic plans for targeting millennials appropriately.

The study has few limitations. Firstly, the study covers a sample from only one country (India); thus, the intention to purchase among millennials is limited in the geographical context. The results can only be generalised to those countries which have similar conditions and context.

However, this study can help researchers to understand and interpret the results through understanding the use and adoption of DA in India. Secondly, the study focused on the influence of DA attributes on millennial purchase intention using UVT theory. Although the current study investigates the key features of DA that should be focused on by marketers and developers, it is suggested to embrace more variables such as security and usefulness. Thirdly, there is a need to uncover other business models (B to B and B to G). Lastly, this study offers an initial insight into DA acceptance by millennials. Future work needs to incorporate studies for specific product categories and to develop strategies that are industry specific. The results can be extended to AI and machine learning approaches for identification of trends of customer purchases using DA. With the AI powered chatbots the information can be extracted from social media on how customers interact and engage with such technologies. Specifically, the study offers insight to examine the impact of PA, SP and PI independently on the PUI of the millennials.

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Appendix

Edit Truth Table
 File Edit

PA	SP	PI	IQ	number	PUI	raw consist.	PRI consist.	SYM consist
1	1	1	1	106 (58%)		0.941532	0.908141	0.971275
1	1	1	0	28 (74%)		0.952242	0.894955	0.954196
0	0	0	0	14 (81%)		0.670824	0.116841	0.11768
0	0	0	1	10 (87%)		0.74358	0.216982	0.218658
1	0	1	1	8 (91%)		0.959648	0.888018	0.900575
0	1	1	1	8 (96%)		0.935728	0.8125	0.824905
0	0	1	1	5 (98%)		0.854436	0.549836	0.549836
1	1	0	0	1 (99%)		0.941163	0.72747	0.727471
0	0	1	0	1 (100%)		0.868706	0.534614	0.534616
1	0	0	0	0 (100%)				
0	1	0	0	0 (100%)				
1	0	1	0	0 (100%)				
0	1	1	0	0 (100%)				
1	0	0	1	0 (100%)				
0	1	0	1	0 (100%)				
1	1	0	1	0 (100%)				

Figure A1: Truth Table

Edit Truth Table

File Edit

PA	SP	PI	IQ	number	PUI	raw consist.	PRi consist.	SYM consist
1	0	1	1	8	1	0.959648	0.888018	0.900575
1	1	1	0	28	1	0.952242	0.894955	0.954196
1	1	1	1	106	1	0.941532	0.908141	0.971275
1	1	0	0	1	1	0.941163	0.72747	0.727471
0	1	1	1	8	1	0.935728	0.8125	0.824905
0	0	1	0	1	1	0.868706	0.534614	0.534616
0	0	1	1	5	1	0.854436	0.549836	0.549836
0	0	0	1	10	0	0.74358	0.216982	0.218658
0	0	0	0	14	0	0.670824	0.116841	0.11768

Figure A2: A sorted truth table in fsQCA based on raw consistency after removing combinations with low frequency

```

--- COMPLEX SOLUTION ---
frequency cutoff: 1
consistency cutoff: 0.854436

          raw          unique
          coverage    coverage    consistency
          -----
PI*IQ      0.750329    0.451905    0.887519
~PA*~SP*PI 0.238064    0.0103811   0.823859
PA*SP*~IQ  0.340561    0.100131    0.928026
solution coverage: 0.877179
solution consistency: 0.870052

```

Note: IQ= Information Quality, PA= Perceived Anthropomorphism, PI= Perceived Interactivity, SP =Social presence, PUI= Purchase intention

Figure A3: COMPLEX SOLUTION

Model: $PUI = f(PA, SP, PI, IQ)$
 Algorithm: Quine-McCluskey
 --- PARSIMONIOUS SOLUTION ---
 frequency cutoff: 1
 consistency cutoff: 0.854436

	raw	unique	
	coverage	coverage	consistency
	-----	-----	-----
PI	0.932326	0.0461236	0.850414
PA	0.863863	0.0144106	0.880604
SP	0.841831	0.00481826	0.862884

solution coverage: 0.976829
 solution consistency: 0.809445

Note: *IQ*= Information Quality, *PA*= Perceived Anthropomorphism, *PI*= Perceived Interactivity, *SP* =Social presence, *PUI*= Purchase intention

Figure A4: PARSIMONIOUS SOLUTION

Model: $PUI = f(PA, SP, PI, IQ)$
 Algorithm: Quine-McCluskey
 --- INTERMEDIATE SOLUTION ---
 frequency cutoff: 1
 consistency cutoff: 0.854436

Assumptions:

	raw	unique	
	coverage	coverage	consistency
	-----	-----	-----
PI*IQ	0.750329	0.451905	0.887519
~PA*~SP*PI	0.238064	0.0103811	0.823859
PA*SP*~IQ	0.340561	0.100131	0.928026

solution coverage: 0.877179
 solution consistency: 0.870052 solution consistency: 0.809445

Note: IQ= Information Quality, PA= Perceived Anthropomorphism, PI= Perceived Interactivity, SP =Social presence, PUI= Purchase intention

Figure A5: INTERMEDIATE SOLUTION