

**A COMPARATIVE STUDY OF CUSTOMER
ENGAGEMENT THROUGH CHATBOTS AND
CUSTOMER EXECUTIVES**

Thesis Submitted for the Award of the Degree of

DOCTOR OF PHILOSOPHY

In

Management

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DECLARATION

I, hereby declared that the presented work in the thesis entitled “A comparative study of customer engagement through chatbots and customer executives” in fulfilment of degree of **Doctor of Philosophy (Ph. D.)** is outcome of research work carried out by me under the supervision Dr. Pinnika Syam Yadav, working as Assistant Professor in the Department of Management of Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.



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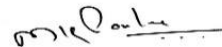
CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled “A comparative study of customer engagement through chatbots and customer executives” submitted in fulfillment of the requirement for the reward of degree of **Doctor of Philosophy (Ph.D.)** in the Department of Management is a research work carried out by Kuldeep Tickoo bearing registration number: 42000519 is bonafide record of his original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.



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Abstract:

In recent years studies related to customer engagement have gained attention from different parts of continents gaining attention in both scholar and marketing communities. Furthermore, the adoption of artificial intelligence-related technology to engage with consumers is still nascent. Using chatbots to engage with consumers has become a common practice these days to engage with customers. Through an initial literature review, the study has identified literature related to chatbots and customer engagement is still in the initial stage and the studies related to customer executive to customer engagement are abundant. Based on this, the study has further explored a comprehensive method of Chatbots and customer engagement. Despite extensive research, the study has found only conceptual models and literature suggestions from the articles, based on this exploration the study has identified its research gap and proceeded to draw a conceptual framework based on the study findings. The study has decided to relate the service attributes to customer engagement, for the customer engagement constructs are defined in past studies. The challenging part of the study is to identify common attributes of both chatbots and customer executives as the study is trying to relate service attributes to customer engagement for both (chatbots and customer executives). Through extensive research, the study has identified that Controllability, flexibility, conversation quality, and interaction are common attributes for both the chatbots and customer executives.

The service sector generally contributes two-thirds of all nations' GNP (Gross national product). And also the first-line warrior of product placement In today's competitive markets, where customer loyalty and retention are paramount, companies increasingly leverage chatbots for 24/7 support and instant responses. Understanding how artificial intelligence can complement human customer service is crucial to maximizing engagement and satisfaction. This study delves into four key attributes shaping customer perception: Controllability (user control during interaction), Flexibility (adapting to unique needs), Conversation Quality (richness and relevance), and Interaction (overall communication flow). While AI offers advantages, human empathy remains valued. Businesses must therefore create a harmonious blend of automation and personal touch. By aligning service attributes with emotional connection, cognitive

interest, and behavioural investment – key elements of customer engagement – companies can craft exceptional experiences. This synergy between chatbots and human executives has the potential to revolutionize customer service and set the benchmark for future research. As the industry innovates, this study aims to provide actionable guidelines to enhance both AI and human interactions.

The integration of chatbots with human customer service representatives has the potential to revolutionize the customer experience. By combining the efficiency and constant availability of AI with the empathy and personalized touch of human interaction, businesses can create exceptional interactions that cater to the ever-changing needs of their customers. However, to fully realize the benefits of this synergy, companies must strike a delicate balance between automation and personalized service. Finding the optimal mix of AI and human involvement is crucial for fostering meaningful and effective customer interactions. This study aims to provide actionable guidelines for businesses seeking to optimize their customer service strategies by harnessing both AI and human resources. Through an understanding of the key factors that influence customer perception and engagement, companies can develop a framework for integrating chatbots and human representatives in a way that maximizes customer satisfaction and loyalty. In today's rapidly evolving landscape, businesses must adapt and innovate to remain competitive. This study seeks to contribute to the ongoing conversation about customer service excellence, offering insights and best practices for leveraging AI and human interactions to create impactful and meaningful customer experiences.

Anthropomorphism is an attribute of human characteristics to non-human application. It is a common phenomenon observed in various fields such as literature, arts and technology. This study is trying to explore the role of anthropomorphism in understanding the customer's concerns and creation of an engaging environment. This study is trying to provide the importance of human behaviour and cognition to understand and resolve customer issues. The initial reason to interact with either a chatbot or a customer executive is due to info on product or service-related issues. The study has further utilised conversation quality, controllability, and flexibility as attributes to measure the service attributes to measure the impact of customer

executives and chatbots. The study of customer characteristics and Ease of Use as a mediator between service attributes to customer engagement has been considered due to their unique presence in the customer engagement process through TRA (Theory of reasoned action) and TPB (Theory of Planned Behaviour). Consumers usually follow these paths when they try to engage with a product. Based on this the study has developed the conceptual framework. To measure the conceptual model the study has utilised SmartPLS to analyse the sample of 722 respondents collected from Indian consumers through convenience sampling

The study results suggest that both customer executives and chatbots have a significant direct effect on all the preceding variables customer engagement, Ease of Use, and customer characteristics. Suggesting that consumers are accepting both customer executives and chatbots. When the study tried to analyse which service is more effective through the T-value and beta coefficient value, customer executives' results seemed more effective as all the factors of customer executives seem more effective and much higher than compared to that of chatbots. Later on, while evaluating the mediation effect the study came to find out that the study results seemed to be having a partial mediation effect on both the customer executives and chatbots out of them customer executives seemed to have a stronger mediation effect than compared to that of chatbots.

In the current study, customers engage with both customer executives seem and chatbots, however the construct of perceived anthropomorphism to customer engagement is supported only by customer executives and not by chatbots, thus indicating a clear need that chatbots can be technically programmed to integrate humor and human-like integration into their conversations. Therefore, managers are encouraged to positively balance the use of services to precisely engage with customers. Further the study underlines that Flexibility that flexibility of chatbots is appreciated by customer's and by leveraging it in business can lead to addressing customer questions fast, quicker and in a flexible manner. Service bots could help the companies to reduce the financial load and also increase the customer interaction rate.

To maintain positive service metrics from the Customer side, companies need to opt for both customer executives and chatbots.

Table of Contents

Chapter - 1.....	2
1. Introduction	2
Chapter - 2.....	10
2. Literature Review.....	10
2.1 Conversation Quality.....	12
2.2 Perceived Anthropomorphism	16
2.3 Flexibility	26
2.4 Controllability	29
2.5 Ease of Use.....	34
2.6 Customer Characteristics.....	38
2.7 Reason of Interaction	43
2.8 User Expertise	47
2.9 Conversation Duration	49
2.10 Customer Engagement	50
CHAPTER-3.....	64
3. Research Methodology	64
3.1 Research Objectives	64
3.2 Research Design.....	64
3.2.1 Sampling and the study population	67
3.2.1.1 Sampling.....	67
3.3 The study sample size	70
3.4 Measurement and Instrument.....	71
3.4.1 Reliability and Validity	79
3.4.2 Validity.....	82
3.4.3 Pre-testing: Pilot study	86

3.5 Hypothesis Formulation	87
3.6 Ethical Consideration	97
CHAPTER – 4	99
DATA ANALYSIS AND INTERPRETATION	99
4. Introduction	99
4.1 Preliminary Examination of the Data.....	99
4.2 Demographic Profile	100
4.3 Conceptual Model Analysis	105
4.3.1 Customer Executive:.....	106
4.3.1.2 Assessment of Construct Validity and Reliability:.....	108
4.3.1.3 Discriminant Validity	112
4.4 Assessment of the Hypothesis:.....	114
4.4.1 Hypothesis Assessment	115
4.4.1.1 Assessment of Mediation Effect:.....	119
4.4.1.2 Assessment of Moderation Effect:	122
4.3.2 Chatbot.....	135
4.3.2.1 Data Validation:.....	135
4.3.2.2 Assessment of Construct Validity and Reliability:.....	137
4.3.2.3 Discriminant Validity	139
4.3.2.4 Assessment of the Hypothesis:	141
4.3.2.5 Hypothesis Assessment	142
4.3.2.6 Assessment of Mediation Effect:.....	146
4.3.2.7 Assessment of Moderation Effect:	149
Chapter - 5.....	165
FINDINGS, CONCLUSION, STUDY IMPLICATIONS, LIMITATIONS AND RECOMMENDATIONS	165

5.1 Findings.....	165
5.2 CONCLUSION.....	207
5.3 Discussions:.....	209
5.4 Managerial Implications:.....	210
5.5 Limitations:	210
5.6 Recommendations for Future Studies:	212
6. References.....	214
7 Appendices.....	224

LIST OF TABLES

Sr. No.	Title no.	Page
3.1	Summary of Research Instrumentation	73
3.2	The measurement items and their sources	73-78
3.3a	Reliability Analysis of the Instrument (customer executives)	80-81
3.3b	Reliability Analysis of the Instrument (chatbots)	81-82
3.4	Validity Analysis	83-85
4.1	Details of customers of e-commerce websites Profile (N=722)	100-102
4.2	Customer executive Data Structure and distribution	106-108
4.3	Construct Validity and reliability	110-112
4.4	Results of Hetrotrait-Monotrait Ratio. Discriminant Validity	113
4.5	The findings of the Fornnel and Larcker criterion; Discriminant Validity	113-114
4.6	Model Fitness	115
4.7	Path Coefficient of Research Hypothesis; Direct effect of customer executive	116
4.8	Variables Heads Labels; Short Heading of Customer executive Data set	117
4.9	Assessment of Mediation	120
4.10	Customer executive data Moderation with respect to Ease of Use and Customer Characteristics	122-123
4.11	Customer executive (Moderation Table)	126-127
4.12	Chatbot Data structure and Distribution	135-137
4.13	Path Coefficient of Research Hypothesis Construct Validity and Reliability	139

4.14	HTMT (Hetrotrait-Monotrait Ratio)	140
4.15	Discriminant Validity	140-141
4.16	Model Fitness	141-142
4.17	Direct effect	143
4.18	Chatbot Data Variable Heads	143-144
4.19	Assessment of Mediation	147
4.20	Chatbot Moderation concerning Ease of Use and Customer Characteristics	149-150
4.21	Moderation Table	153
5.1	Comparison table (Direct Assessment)	173-196
5.2	Comparison table (Through Mediation Analysis)	197-205

LIST OF FIGURES

Sr. No.	Title	Page no.
1.1	AI is Key innovator Driver	6
1.2	Number of papers on AI in marketing between 1991-2000	6
1.3	Trend topics	7
2.1	Literature Review Timelines	10
2.2	Conceptual Framework	62
3.1	Research Design Process	67
4.1	Gender	102
4.2	Age	103
4.3	Education	103
4.4	Interaction with e-Commerce websites	104
4.5	Conversation Duration	104
4.6	Reason for interaction	105
4.7	Path Analysis Model	109
4.8	Analysis Model; Hypothesis Assessment model	115
4.9	Assessment of moderation analysis with respect to Customer executives	124

4.10	Anthropomorphism; Reason*Perceived Anthropomorphism	128
4.11	Reason*Conversation Quality	128
4.12	Reason*Flexibility	129
4.13	Reason*Controllability	130
4.14	Conversation Duration*Perceived Anthropomorphism	130
4.15	Conversation Duration*Conversation Quality	131
4.16	Conversation Duration*Flexibility	131
4.17	Conversation Duration*Controllability	132
4.18	Interaction*Perceived Anthropomorphism	133
4.19	Interaction*Conversation Quality	133
4.20	Interaction*Flexibility	134
4.21	Interaction*Controllability	135
4.22	Analysis model PLS-Model	138
4.23	Hypothesis Assessment Model	142
4.24	Assessment of moderation with respect to Chatbots	151
4.25	Reason*Perceived Anthropomorphism	154

4.26	Reason*Conversation Quality	155
4.27	Reason*Flexibility	156
4.28	Reason*Controllability	157
4.29	Conversation Duration*Perceived Anthropomorphism	158
4.30	Conversation Duration*Conversation Quality	158
4.31	Conversation Duration*Flexibility	159
4.32	Conversation Duration*Controllability	160
4.33	Interaction*Perceived Anthropomorphism	160
4.34	Interaction*Conversation Quality	161
4.35	Interaction*Flexibility	162
4.36	Interaction*Controllability	162

CHAPTER-1
INTRODUCTION

Chapter - 1

Introduction

1. Introduction

In the rapidly advancing landscape of technology, the realm of human-machine interaction has witnessed a paradigm shift, with one of the most significant contributors being chatbots. These intelligent conversational agents have emerged as transformative entities, altering how individuals engage with technology, businesses optimize their operations, and societies navigate the digital frontier.

The integration of chatbots into various facets of daily life has become palpable, transcending traditional boundaries and permeating industries such as customer service, healthcare, education, and beyond. As society embraces the era of Industry 4.0, where smart technologies redefine conventional practices, it becomes imperative to dissect the foundations and implications of chatbots. This thesis aims to provide an extensive examination of the historical antecedents that paved the way for the development of chatbots, tracing their roots from simple rule-based systems to the sophisticated, machine learning-driven conversational agents of today.

Within the broader context of artificial intelligence (AI), chatbots represent a noteworthy application of natural language processing (NLP) and machine learning algorithms. As the capabilities of chatbots continue to evolve, it is crucial to comprehend the theoretical foundations that underpin their functioning, enabling a deeper understanding of the mechanics behind these intelligent conversational agents.

In addition to their technical aspects, the sociocultural implications of chatbots warrant meticulous exploration. This thesis will investigate how these digital entities influence communication patterns and human behaviour. Understanding the ethical considerations surrounding chatbot interactions, including issues related to privacy,

bias, and accountability, will be crucial in assessing the broader impact of these technologies on individuals and communities.

Furthermore, the practical applications of chatbots across diverse sectors necessitate a detailed analysis of their effectiveness and limitations. Whether enhancing customer support, streamlining business processes, or augmenting educational experiences, chatbots have become integral components of contemporary systems. However, challenges such as the "uncanny valley" phenomenon and the potential for unintended consequences require a nuanced examination to formulate informed recommendations for their responsible deployment.

As we navigate this juncture where artificial intelligence intersects with human conversation, this thesis aspires to contribute to the academic discourse surrounding chatbots. By synthesizing historical perspectives, technical insights, and societal implications, it seeks to provide a holistic understanding of the multifaceted landscape of chatbots, offering a foundation for further research, policy development, and ethical considerations in the ever-evolving domain of human-machine interaction.

According to Kumar, Dwivedi & Anand (2021), the healthcare sector has been at the forefront of the adoption of Artificial intelligence (AI) technologies; they conducted a mixed-method study to identify the constituents of responsible AI in the healthcare sector and investigate its role in value formation and market performance. Data acquisition, fairness, assessment, and informed and explainable algorithms are key aspects of AI technology.

Artificial intelligence will likely substantially change marketing strategies and customer behaviours (Davenport et al., 2019), based on extensive interactions with practice, the authors propose a multidimensional framework for understanding the impact of AI involving intelligence levels, task types, and whether AI is embedded in the robot. In an analysis of more than 400 AI use cases across 19 industries and nine business functions, McKinsey & Co. indicates that the greatest potential value of AI pertains to domains related to marketing and sales (Chui et al., 2018). Marketers plan

to use AI in areas like segmentation and analytics (related to marketing strategy) and messaging, personalization and predictive behaviours (linked to customer behaviours) (Columbus, 2019). AI offers the potential to increase revenues and reduce costs. Revenues may increase through improved marketing decisions (e.g., pricing, promotions, product recommendations, enhanced customer engagement); costs may decline due to the automation of simple marketing tasks, customer services, and (structured) market transactions. Most AI is virtual in form. However, few studies have shown that customers' discomfort with AI is accentuated when the AI application is embedded in a robot. More research must be presented to provide in-depth insight into user experience and user motivation concerning chatbots for customer service (Folstad et al., 2019). Forrester (2017) surveyed more than 7000 individual users of customer service. He found that a larger proportion were satisfied with manual chat-based customer service (60%) than with customer service from what Forrester referred to as text-based virtual agents (50%). Forrester also identified key drivers of positive and negative user experience in interactions with such agents. Specifically, the agents' efficiency and availability were considered positive. However, their perceived inability to handle complex requests (47%) and a sense of being forced to interact with a virtual agent when this was not wanted (40%) were seen as negative. Nearly half the respondents (46%) reported wanting human-like virtual agents with human-like visual presentations for more personal experiences.

The authors (Huang, Rust, 2020) develop a three-stage framework for strategic marketing planning, incorporating multiple artificial intelligence (AI) benefits: mechanical AI for automating repetitive marketing functions and activities, thinking AI for processing data to arrive at decisions, feeling AI for analyzing interactions and human emotions. This framework lays out the ways that AI can be used for marketing research, strategy (segmentation, targeting, and positioning, STP), and actions. At the marketing research stage, mechanical AI can be used for data collection, thinking AI for market analysis, and feeling AI for customer understanding. The academic literature on AI in marketing may be sorted into four main types. These are (1) technical AI algorithms for solving specific marketing problems (e.g., Chung et al., 2009; Chung et al., 2016; Dzyabura and Hauser, 2011, 2019), (2) customers' psychological reactions

to AI (e.g., Luo et al. 2019; Mende et al. 2019), (3) effects of AI on jobs and society (e.g., Autor and Dorn, 2013; Frey & Osborne, 2017; Huang & Rust, 2018), and (4) AI-related managerial and strategic issues (e.g., Fountaine et al., 2019; Huang & Rust, 2020). Feeling AI can be used to enhance interaction and engagement. For example, service robots can easily do surface-acting (Wirtz et al. 2018), Moreover, "one-voice" AI can enhance customer engagement by integrating various interfaces into a customer's journey (Singh et al., 2020). At the feeling level, various embodied robots engage customers and optimize their experience. For example, Pepper robots are used by Marriott to greet and interact with customers. Hotels and travel typically involve more interactions and more emotions, and thus, feeling AI naturally suits. Nevertheless, marketers need to be cautious in that anthropomorphized robots are found to increase perceived warmth but decrease liking (Kim et al., 2019); thus, in the case of embodied frontline robots, marketers need to consider the appearance of robots. Customer understanding Current practice relies heavily on focus groups to gain qualitative insights about customers. Focus groups are time-consuming and labour-intensive, not to mention not representative. Marketers also observe customers' behaviours and choices, as well as their reactions to promotions, to understand their preferences and the underlying reasons. By contrast, data about customers' feelings, moods, and emotions can be obtained directly from customers' interaction with AI (e.g., conversational bots) rather than inferred from psychometrics, using conversational bots and analyzed using feeling analytics (e.g., posts on social media, voice recordings of customer interactions, and chat transcripts). Feeling analytics can identify customer insights with scale and cost-efficiently. Given that emotional data are personal and in context, understanding customers in context provides richer insights about who they are and what they like.

In 2017, Forrester summarized the most prominent technology trends over the next three years (see Figure 1). AI is a core new technology that will affect companies' adoption of other technologies at all phases of development. AI will also be a major factor that decides the impact of new technologies on companies. In this survey, 65% of respondents believe that AI will play a vital role in their digital transformation.

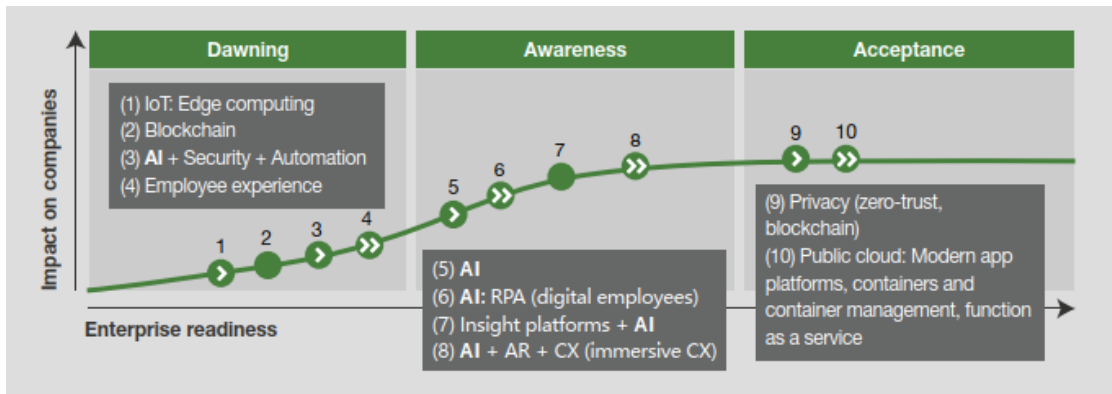


Figure 1.1: AI is A Key Innovator Driver
 (Source: Forrester Research, Inc, October 19, 2017)

The authors (Feng et al., 2020) provide a good insight into the evolution of AI topics with corresponding research papers.

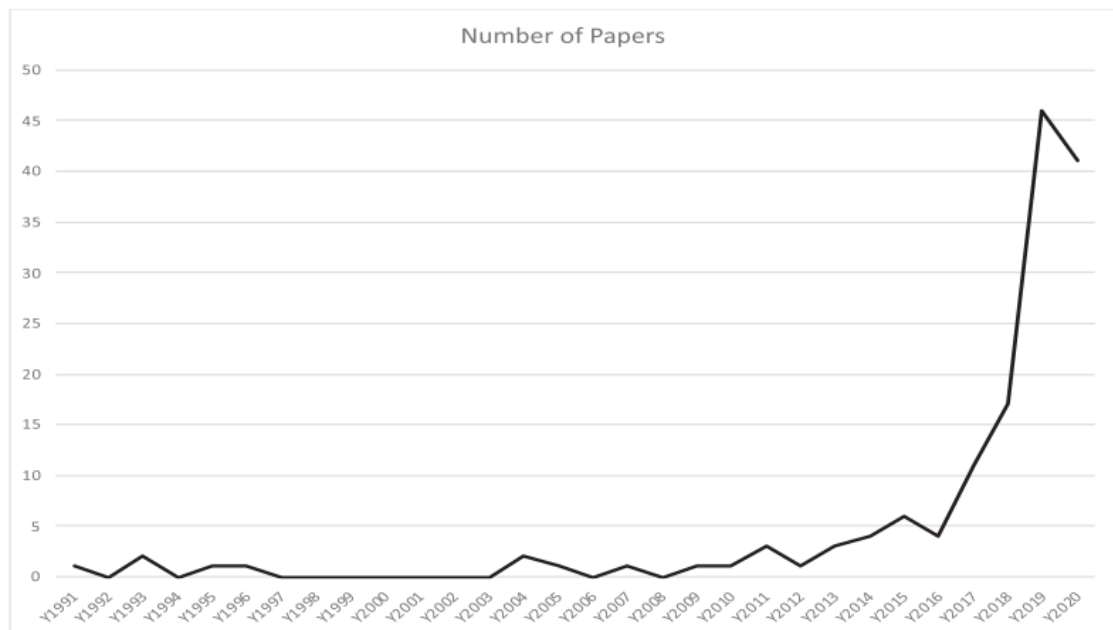


Figure 1.2: Number of papers on AI in marketing between 1991-2000 (Source: Feng et al., 2020)

Figure 3 presents a trend analysis depicting the overall changes in the research topic over time. If we divide the trend into three phases, the beginning phase shows a basic understanding of the research topic. The researchers were keen to draw the initial

picture with basic research understanding. The research topic evolved once it moved towards the middle phase of the trend. In the last phase, from 2017 to 2019, the researchers moved towards including emerging technologies, such as big data, neural networking, machine learning, and many more.

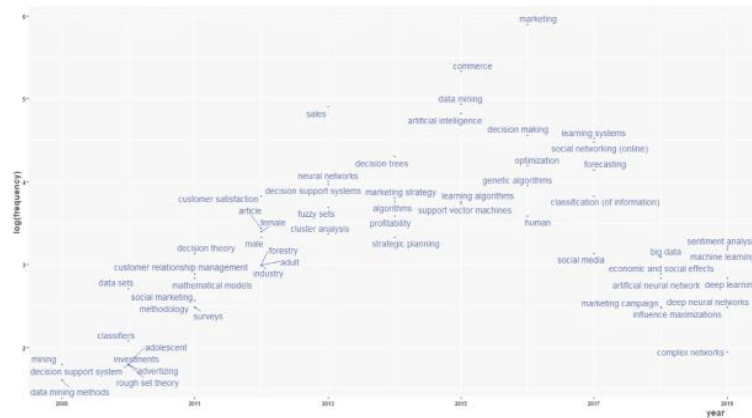


Figure 1.3: Trend topics (Source: Verma et al., 2020)

According to the report from July 2021, Feb 2023, Dec 2023 by the Indian Brand Equity Foundation (IBEF), a trust established by the Department of Commerce, Ministry of Commerce and Industry, Government of India, E-commerce users across India are increasing at a rate of ~ 6 million new entrants every month and e-commerce is expected to reach USD 163 billion by 2026, growth of 27% CAGR. Furthermore, India's digital sector is expected to increase multi-fold and reach USD 1 Trillion by 2030 from USD 85-90 billion in 2020.

One of the profound digitalization approaches companies, including e-commerce platforms, are exploring and investing in is the deployment of chatbots to enhance customer engagement around the clock. Communicating with customers through live chat interfaces has become an increasingly popular means of providing real-time customer service in e-commerce settings. Customers use these chat services to obtain information (e.g., product details) or assistance (e.g., solving technical problems). The real-time nature of chat services has transformed customer service into two-way communication with significant effects on trust, satisfaction, and repurchases (Adam et al., 2020). Human chat service agents are frequently replaced by conversational

software agents (CAs) such as chatbots, which are systems such as chatbots designed to communicate with human users using natural language (e.g., Gnewuch et al., 2017; Pavlikova et al., 2003; Pfeuffer et al., 2019). The chatbot market size is estimated at USD 5.1 Billion with a CAGR of 23.3% from 2023 to 2030 (Grand et al., Analysis Report By Application, By Type, By Vertical, By Region (North et al.), And Segment Forecasts, 2023 – 2030|| Report ID: GVR-1-68038-598-4; Number of Pages: 132). Major technology companies like IBM and Microsoft have invested substantially in chatbot platforms to power customer service.

The present study of customer engagement through chatbots and customer executives stems from the need to deepen businesses understanding of key factors influencing customer interaction. By examining the moderating effects of variables such as the "reason for interaction," "user expertise," and "conversation duration," companies can gain valuable insights into how these elements shape the ease of use and overall customer experience. This analysis will enable businesses to identify which engagement approach—chatbots or human executives—offers more effective support in different contexts. Furthermore, the study will illuminate critical aspects of both chatbots and human interactions that impact customer satisfaction, loyalty, and engagement. These insights will empower organizations to make informed decisions when designing sales and service strategies, allowing them to leverage the strengths of each medium and enhance engagement through the appropriate use of technology and human touchpoints. The comparative study of customer executive vs chatbot should address strategies businesses should deploy to effectively serve the customers. How can businesses determine whether customer executives or chatbots provide the most effective service? What strategies should they deploy to meet diverse customer needs? A comparative study between customer executives and chatbots seeks to answer these questions. Should chatbots handle routine inquiries, or do human executives offer a superior touch in complex situations? What factors, like customer expertise or interaction context, influence these decisions? Uncovering the answers will help businesses craft tailored, effective engagement strategies for better customer service.

CHAPTER-2
LITERATURE REVIEW

Chapter - 2

2. Literature Review

In the expansive realm of customer engagement, chatbots have emerged as pivotal tools reshaping the landscape of marketing and serviceability. To delve into this complex interplay, an exhaustive literature review was undertaken, focusing on the nuanced aspects of conversation quality, anthropomorphic design, flexibility, and controllability. The goal was to dissect their profound impact on mediators, such as ease of use and customer characteristics, ultimately influencing the overarching concept of customer engagement. Throughout this exploration, various moderators, including the reason for interaction, user expertise, and conversation duration, were identified as pivotal variables shaping the dynamics of this multifaceted relationship.

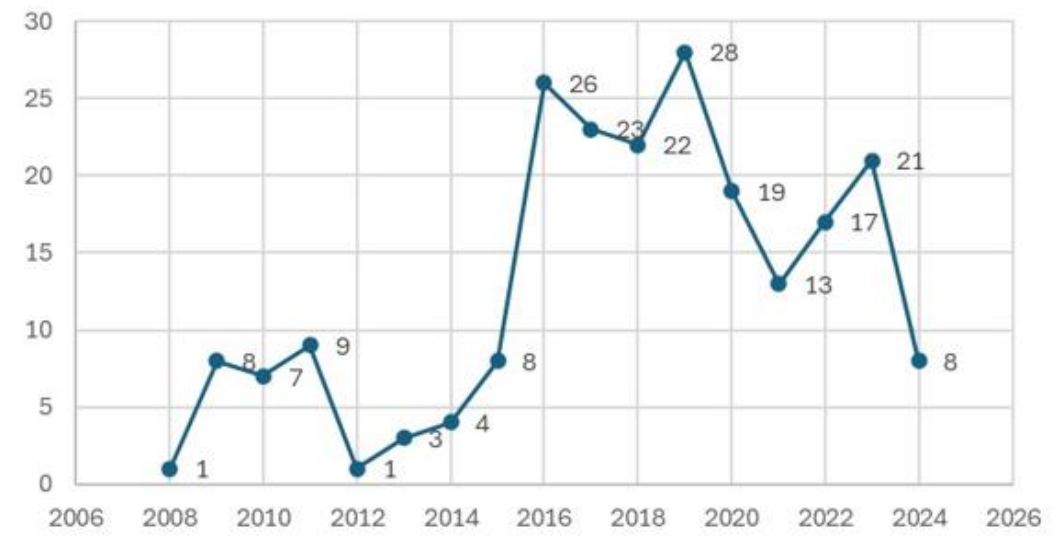


Figure 2.1 : Literature Review Timeline

As this study is based on novel topic of chatbots with limited available literature, we haven't explicitly outlined the exclusion criteria. However, we looked at Scopus based journals and the high-ranking journals. Database searched are Scopus indexed journals and Web of Science.

The first pillar under scrutiny in the literature review was conversation quality. Recognizing the significance of chatbot interactions in fostering meaningful engagement, researchers sought to understand how the quality of conversations could serve as a catalyst. The effectiveness of chatbots in enhancing customer engagement hinges on the ability to facilitate smooth, coherent, and relevant dialogues. Studies indicated that high conversation quality significantly contributed to positive customer experiences, influencing their perceptions and attitudes towards the brand or service.

Anthropomorphic design emerged as another critical element in the examination of chatbot dynamics. As users increasingly engage with technology, the human-like attributes of chatbots play a pivotal role in shaping their responses and interactions. The literature review unveiled that an anthropomorphic design, characterized by features mirroring human traits, could evoke a sense of familiarity and comfort, enhancing the overall user experience. Understanding the psychological impact of anthropomorphic design became instrumental in optimizing chatbot interfaces for improved engagement.

Flexibility and controllability emerged as dual factors shaping the user experience with chatbots. Flexibility, denoting the adaptability of chatbots in responding to diverse user queries and needs, proved to be a key determinant of satisfaction. Simultaneously, controllability, referring to users' perceived ability to guide and influence the Chatbots actions with a sense of security and confidentiality, played a crucial role in fostering a sense of empowerment and security. The literature review highlighted the delicate balance between flexibility and controllability, emphasizing the need for chatbots to offer adaptable responses while affording users a sense of control over the interaction.

The mediators in this intricate relationship included ease of use and customer characteristics. The ease with which users could navigate and interact with chatbots became a central theme in determining the success of these automated systems. Additionally, customer characteristics, including Customer Inertia, Satisfaction, Attitude and Motivation, were identified as influential factors in shaping the impact of chatbot interactions. The literature suggested that tailoring chatbot interactions to align with user characteristics could significantly enhance engagement and satisfaction.

However, the complex web of interactions in the chatbot-user dynamic was further influenced by moderators. These external factors acted as variables that could either amplify or mitigate the impact of mediators. The reason of interaction, such as seeking information, making a purchase, or addressing a query, played a crucial role in shaping user expectations and satisfaction levels. User expertise in utilizing chatbots and the duration of the conversation also emerged as moderators that influenced the overall dynamics of engagement.

In essence, the literature review provided a comprehensive framework for understanding the intricate interplay between customer engagement, chatbots, marketing, and serviceability. The findings underscored the pivotal role of conversation quality, anthropomorphic design, flexibility, and controllability in shaping user experiences. Furthermore, the identified mediators and moderators shed light on the contextual and user-specific variables that can either amplify or temper the impact of these design and interaction elements.

2.1 Conversation Quality

In the dynamic landscape of contemporary customer service, artificial intelligence (AI) chatbots have emerged as frontline champions, transforming the way organizations engage with their clientele. This transformative shift is underscored by a study by De Keyser et al. (2019), highlighting various organizations' growing adoption of AI chatbots. The momentum of this adoption is further exemplified by Gartner's projection that, by 2021, a staggering 15% of all global customer service interactions will be handled entirely by AI—a remarkable 400% increase from 2017.

Delving deeper into regional developments, the "2019 China Artificial Intelligence Industry Research Report," released by the China Economic and Information Research Center in December 2019, provides a glimpse into the flourishing AI chatbot business. The report indicates that the scale of AI chatbot operations surged to 2.72 billion yuan in 2018 and is poised to surpass 16 billion yuan in 2022. This exponential growth

underscores AI chatbots' significant role in the rapidly evolving Chinese market and beyond.

Armed with advanced technologies such as natural language processing (NLP), cloud computing, machine learning, and biometrics, AI chatbots have redefined customer service contours. Unlike human customer service representatives or traditional self-service technologies (SST), AI chatbots offer organizations immediate, consistent, and cost-effective services. The foundational shift lies in the fact that the quality dimensions used to assess human customer service, such as tangibles, reliability, responsiveness, assurance, and empathy, may need to catch up in capturing the innovative technical characteristics unique to AI chatbot services.

Moreover, the intelligence embedded in AI chatbots transcends that of websites or traditional information systems. Including human-like intelligence, encompassing language understanding and recognition capabilities, introduces a novel dimension that existing studies must address adequately. As customers increasingly spend time in digital environments, brands are capitalizing on this trend, moving towards digital services that leverage virtual service agents or "e-service agents".

This transition has given rise to Chatbot agents, an innovative and entertaining manifestation of e-service agents designed to satisfy clients like traditional offline service agents. Traditionally, offline service agents played a pivotal role in determining the success of service exchanges, representing the brand, enhancing customer/brand relationships, and providing engaging and enjoyable overall shopping experiences. Even in the digital era, these service agents continue to exert influence, with 87% of in-store purchase decisions still being impacted by their interactions.

The strategic adoption of digital services, particularly the incorporation of Chatbots offering 24-hour customer service, is gaining prominence in the luxury sector. This move aligns seamlessly with the values of luxury retail brands that prioritize superior service and cater to consumers willing to pay a premium for an enhanced experience.

The chatbot concept has become an essential tool for realizing these brand values in the digital realm.

Chatbots are machine agents designed to interact with users in natural language. The surge in text-based chatbots for customer service indicates their accessibility, ease of implementation, and cost-efficiency. A report by Gartner in 2019 revealed that 31% of customer communication managers had either implemented chatbots or had plans to do so shortly. Customer service chatbots' potential operational efficiency gains were estimated to be as high as 25% by 2025.

The narrative extends to the research endeavours of Balakrishnan et al. (2021), who delved into factors influencing resistance and attitude towards AI voice assistants (AIVA). By integrating the dual-factor framework and the Technology Acceptance Model (TAM), the study explored dimensions such as status quo bias factors and Ease of Use and usefulness. The research identified that perceived value exhibited a negative but significant relationship with resistance to AIVA, underlining the nuanced dynamics at play.

Feine et al. (2019) contributed to understanding customer chatbot interactions by exploring whether sentiment scores from textual input could serve as a proxy for measuring chatbot service encounter satisfaction (CSES). The study employed a three-step approach, comparing sentiment analysis methods, testing the correlation between sentiment scores and CSES values, and analyzing this correlation at the utterance level. The findings validated using sentiment scores as an automatic and objective proxy for measuring CSES in online service encounters.

Chen et al. (2022) added a multidimensional perspective to understanding AI chatbot service quality (AICSQ). Through a mixed-method approach, the researchers classified AICSQ dimensions through grounded theory analysis of semi-structured interviews. The resulting AICSQ scale exhibited good reliability and validity, with a nomological test confirming its positive influence on customers' satisfaction, perceived value, and intention to use AI chatbots continuously. In another vein, Schwede et al. (2022) delved into the design of recommendation messages and the communication style employed

by chatbots. The study revealed that a two-sided recommendation message increased purchase intention, but only when complemented by a warm or competent communication style. This highlights the importance of refining chatbot communication styles for effective persuasion in providing recommendations.

Moving on, Zhou et al. (2023) examined the impacts of the communicating agent (chatbot vs. human agent) on anticipated communication quality and its underlying mechanisms. Two experimental studies found that users anticipated lower communication quality with chatbots than human agents. Adopting a multiple-choice communication strategy for chatbots was identified as a means to enhance users' anticipated communication quality.

Park et al. (2023) applied the Communication Accommodation Theory to explore how robot employees' communication style can mitigate perceived intimacy, reducing customer anger and negative word-of-mouth, especially in service failures. The study advocated adaptive communication styles based on failure severity to effectively manage negative customer experiences.

Finally, Li et al. (2023) delved into the effect of chatbot language style on customers' continuance usage intention and attitude toward the brand. The study, conducted through scenario-based experiments, revealed that an informal language style increased continuance usage intention and brand attitude through the mediating role of parasocial interaction. The findings also highlighted the moderating role of brand affiliation, emphasizing the need for tailored language strategies based on existing brand relationships.

In conclusion, the narrative surrounding AI chatbots traverses the realms of technological advancement, customer service evolution, and nuanced interactions. From their surge in adoption to the exploration of customer perceptions and resistance factors, researchers and practitioners are actively engaging with the transformative potential of AI chatbots. The multidimensional analyses conducted by various studies contribute not only to academic discourse but also offer practical insights for businesses

seeking to harness the power of AI chatbots in enhancing customer experiences and shaping brand perceptions in the ever-evolving digital landscape.

2.2 Perceived Anthropomorphism

Chatbots for customer service are typically designed with efficiency and effectiveness in mind (Nordheim et al., 2019). However, perceived quality in customer service may depend not only on frictionless goal completion but also on the emotional quality of the service experience (Berry et al., 2002). From a user experience perspective (Hassenzahl, 2018), chatbots for customer service are designed to maximize pragmatic quality – that is, the character of the chatbot as valuable and usable, serving the instrumental needs of the user. However, to realize the service quality potential of such chatbots, it may also be beneficial to strengthen hedonic quality – that is, the Chatbots ability to benefit user's well-being through engagement and stimulation. Strengthening hedonic quality in chatbots for customer service may strengthen the overall user experience. Hedonic quality is an important aspect of the general chatbot user experience (Følstad & Brandtzaeg, 2020), and failures with chatbot applications have been attributed to a lack of engaging interactions (Jenkins et al., 2007; Schuetzler et al., 2014).

A promising approach for strengthening hedonic quality in chatbots, and thereby, overall user experience, has been to strengthen their human likeness (Smestad & Volden, 2018). That is, to leverage chatbot features that make its interactions resemble those expected from a human (Araujo, 2018), utilizing human conversation as a metaphor for conversational design (Moore & Arar, 2018). For example, strengthening human likeness in chatbots for customer service could imply designing chatbot interactions to mimic interactions between customers and skilled customer service personnel (Adam et al., 2020). Industry reports suggest that many users expect humanlike characteristics, such as friendliness, in chatbots for customer service (Drift, 2018). Previous studies on trust in chatbots for customer service have found human likeness important for user experience (Nordheim et al., 2019). Human likeness

in chatbots has been found to strengthen user perceptions of anthropomorphism and social presence; the former term refers to the chatbot being perceived as having humanlike traits (Araujo, 2018; Nass & Moon, 2000), the second refers to the chatbot being perceived as salient and immediate in its presentation and interactions (Go and Sundar, 2019).

Chatbot human likeness and corresponding user perceptions of anthropomorphism and social presence may depend on various interaction design decisions – from the chatbot persona and conversation style (Go and Sundar, 2019) to its conversational intelligence (Jain et al., 2018). Two aspects of interaction design currently understudied in this context are (a) the conversation types supported in the chatbot and (b) its interaction mechanisms.

A chatbot may support several conversation types, that is, forms of conversations with different styles and objectives. Roller et al., 2020b noted that chatbot conversations to communicate expertise and knowledge may span from goal-oriented task completion to in-depth discussions of specific topics. In the customer service context, conversations for goal-oriented task completion are critical (Xu et al., 2017). However, conversations that engagingly convey knowledge and information are also desirable to users (Chung et al., 2020). Shevat (2017) captures this variation in conversation, distinguishing between task-led and topic-led conversations. The former concern's narrow goal completion, and the latter concerns in-depth exploration and reflection on specific topics. Topic-led conversations, with exploratory and engaging exchanges between the user and chatbot, may contribute to a humanlike chatbot appearance as these more closely resemble informal human conversational interaction than do task-led conversations. As such, topic-led conversations may also add to the hedonic quality of chatbots for customer service.

The interaction mechanisms in a chatbot are how users can send messages and receive information and content. These typically consist of a blend of free text input fields and buttons with predefined answer alternatives (Li et al., 2020; Shevat, 2017; Valério et al., 2017). Free text input may enable interactions that

strengthen the human likeness in the chatbot, as these may resemble interactions with skilled customer service personnel. Button interaction, while facilitating efficient interaction, may reduce users' perceptions of interacting with a humanlike entity (Jain et al., 2018; Valério et al., 2020). Hence, it is of high interest to know how increased use of free text interaction in customer service chatbots may strengthen their humanlike appearance and hedonic quality without the support of button interaction. While conversation types and interaction mechanisms in chatbots for customer service arguably may impact human likeness and user experience, there is a lack of empirical knowledge.

Sheehan et al. (2020) investigated the relationship between miscommunication and adopting customer service chatbots. Anthropomorphism is tested as an account of the relationship. Two experiments compare the perceived humanness and adoption scores for

- (a) an error-free chatbot,
- (b) a chatbot seeking clarification regarding consumer input and
- (c) a chatbot that fails to discern context.

The results suggest that unresolved errors are sufficient to reduce anthropomorphism and adoption intent. However, there is no perceptual difference between an error-free chatbot and one that seeks clarification. The ability to resolve miscommunication (clarification) appears as effective as avoiding it (error-free). Furthermore, the higher a consumer's need for human interaction, the stronger the anthropomorphism-adoption relationship. Thus, anthropomorphic chatbots may satisfy the social desires of consumers who need human interaction.

Kim et al. (2012) empirically explored anthropomorphism, dissecting the intricate interplay between mindful and mindless considerations. The crux of their investigation lay in discerning whether users consciously recognized and treated computers as human entities (mindful) or if these interactions were occurring at a non-conscious level (mindless). To untangle this web of cognitive processes, the researchers manipulated two pivotal variables—namely, the presence or absence of a humanlike agent and the degree of interactivity—within the context of a health website. Through meticulous

experimental design, they endeavoured to ascertain whether these variables functioned as anthropomorphic cues, capable of eliciting either a mindful appreciation of humanness attributed to the website, or a mindless evaluation of the site framed in human terms. Their endeavours yielded compelling evidence supporting mindless anthropomorphism, prompting contemplation on its potential repercussions for user assessments of the credibility of information disseminated on the website.

Fast-forwarding, Haugeland et al. (2022) embarked on a distinct yet equally intriguing exploration. Their primary objective was to design chatbot interactions that more closely mirrored the nuanced exchanges observed in interactions with skilled customer service personnel. In the landscape of evolving technology, the study sought to bridge the gap between artificial intelligence and human-like engagement. In a carefully orchestrated randomized experiment involving 35 participants, the research team meticulously dissected two critical chatbot interaction design features. First on the examination table were topic-led conversations, strategically engineered to encourage customer reflection, as opposed to the more task-oriented and efficiency-focused task-led conversations. Secondly, the researchers delved into interaction modalities, comparing free text interaction—where users predominantly communicated in their own words—with button interaction, where interactions predominantly occurred through predefined answer alternatives.

Within the framework of this experiment, the researchers designated key dependent variables: participant perceptions of anthropomorphism and social presence—crucial metrics tied to the human likeness of chatbot interactions—alongside pragmatic and hedonic quality. The study also integrated semi-structured interviews to glean deeper insights into the user experience. Results from this comprehensive analysis unveiled a nuanced tapestry of findings. Topic-led conversations emerged as potent catalysts, amplifying both anthropomorphism and hedonic quality. However, the same robust effect was not replicated for free text interaction, a divergence attributed to perceived shortcomings in chatbot flexibility and adaptivity, as communicated through user feedback. This intricate exploration into the realms of human-computer interaction not only shed light on the mechanisms underlying anthropomorphism but

also provided valuable insights for the ongoing development and refinement of interactive technologies.

Blanche et al. (2020) embarked on a mission to enrich the field of research on the human likeness of robots by extending their focus to the essential considerations for service managers in selecting and implementing service robots. Their study introduces a comprehensive three-part framework that intricately examines the factors crucial for optimal adaptation in different service components. The framework, consisting of robot design, customer features, and service encounter characteristics, is a robust guide for service managers, providing a holistic approach to decision-making in service robots.

Blanche et al. (2020) diligently clarifies definitions and address overlapping concepts within robot design, customer features, and service encounter characteristics to augment their framework. This meticulous effort aims to synthesize existing knowledge on each variable, enabling a more nuanced understanding of the intricate interplay between these factors. Additionally, the researchers identify research gaps that warrant further exploration, thereby contributing to the current body of knowledge and setting the stage for future investigations in the dynamic field of service robots.

The proposed framework and the articulated research questions serve as a beacon, guiding scholars and practitioners in navigating the complex landscape of service robot implementation. Blanche et al. (2020) provide a structured research agenda that fosters academic inquiry and offers practical insights for those engaged in the practical application of service robots.

In a parallel thread of inquiry, Bartneck et al. (2009) focus on the critical need for standardized measurement tools in the human-robot interaction (HRI) domain. Conducting an exhaustive literature review, they distill five key concepts in HRI: anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety. Transforming these concepts into five consistent questionnaires, the researchers create the "God-speed" series. This innovative tool quantitatively measures users' perceptions of robots, facilitating a more systematic and standardized approach to evaluating human-robot interactions. The "God-speed" series not only provides a valuable

resource for researchers but also underscores the commitment of Bartneck et al. (2009) to advancing the field of HRI. By establishing standardized measurement tools, the researchers contribute to establishing a common language and methodology, fostering greater coherence and comparability across studies in the multifaceted realm of human-robot interaction.

Duffy et al. (2003) enter the discourse by exploring the nuances of meaningful social interaction between robots and humans, particularly through the lens of anthropomorphism. Their study posits that as robots become integral parts of our social space, humans will inevitably project their interpretations onto these machines, akin to how we interpret the behaviour of pets. Contrary to viewing anthropomorphism as a hindrance to social robot development, Duffy et al. (2003) propose that it serves as a valuable mechanism that demands careful examination and application in social robot research.

The researchers delve into the strategic use of anthropomorphic paradigms to enhance robots' functionality and behavioural characteristics in anticipation and actual human interaction. The study posits that social interaction is fundamentally observer-dependent by explicitly designing anthropomorphic features, such as a head with eyes and a mouth. This acknowledgement underscores the importance of exploring the mechanisms underlying anthropomorphism to unlock the key to developing socially engaging machines.

Epley et al. (2007) contribute a theoretical framework to explain when and why people are likely to anthropomorphize. Focusing on three psychological determinants—accessibility and applicability of anthropocentric knowledge, motivation for understanding the behaviour of other agents (affecting motivation), and the desire for social contact and affiliation (sociality motivation)—the researchers propose a comprehensive theory. This theory predicts that anthropomorphism is more likely to occur under specific conditions, providing insights into the variability of anthropomorphism and offering testable predictions about its dispositional, situational, developmental, and cultural influences.

The proposed theory by Epley et al. (2007) contributes to understanding the varied nature of anthropomorphism and organizes diverse research findings in the field. It lays the groundwork for exploring psychological processes underlying anthropomorphism, with potential applications in robotics and human-computer interaction. The insights offered by this theoretical framework extend into the inverse process of dehumanization, offering a more nuanced understanding of the complex dynamics between humans and human and nonhuman agents.

Building on this foundation, Waytz et al. (2010) further explore the implications of perceiving an agent as humanlike. Their study posits that this perception has significant consequences for social influence, accountability, and the moral consideration of the agent. Waytz et al. (2010) identify three primary factors—elicited agent knowledge, sociality motivation, and reflectance motivation—that account for substantial variability in anthropomorphism. Understanding these factors sheds light on the process of anthropomorphism and illuminates the inverse process of dehumanization, wherein humans treat other humans as animals or objects.

This expanded perspective on anthropomorphism, encompassing both human and nonhuman agents, contributes to a broader view of social cognition. Waytz et al. (2010) bridge the gap between social psychological theory and its application to various agents, paving the way for a more inclusive understanding of social interactions.

In a parallel exploration, Bartz et al. (2016) delve into the intricate relationship between loneliness and anthropomorphism. Replicating the association in a larger sample, the study reveals that reminders of close, supportive relationships reduce the tendency to anthropomorphize. This finding aligns with the idea that the need for belonging plays a causal role in anthropomorphism. Notably, the study distinguishes attachment anxiety as a stronger predictor than loneliness, shedding light on the underlying mechanisms and reinforcing the notion that anthropomorphism is a motivated process, reflecting an active search for potential sources of connection.

Bartz et al. (2016) contribute to the evolving narrative by illuminating the interplay

between psychological states and anthropomorphism. Their findings enrich the understanding of the factors influencing anthropomorphism and provide practical implications for mitigating its effects. The acknowledgement of loneliness and attachment anxiety as significant contributors adds depth to the discourse, emphasizing the multifaceted nature of the relationship between humans and anthropomorphized entities.

In conclusion, the collective efforts of Blanche et al. (2020), Bartneck et al. (2009), Duffy et al. (2003), Epley et al. (2007), Waytz et al. (2010), and Bartz et al. (2016) contribute to a nuanced understanding of the complexities surrounding the human-robot interaction spectrum. From frameworks guiding the selection and implementation of service robots to standardized measurement tools, explorations of anthropomorphism, and examinations of the psychological determinants shaping these interactions, each study adds a layer of insight to the multifaceted landscape of human-robot dynamics. The ongoing dialogue in this field fosters a more holistic comprehension of the intricate relationship between humans and robots, paving the way for future advancements and applications in this rapidly evolving domain.

Within the expansive landscape of anthropomorphism, Bruni et al. (2018) contribute a multifaceted elucidation that transcends conventional boundaries, extending beyond the robotics domain. Their work ventures into diverse realms, exploring the term in the context of common-sense knowledge and probing its implications for animal rights and its role in using humans as models for scientific explanations. The researchers posit the notion of "constructive anthropomorphism," arguing that attributing human psychological features to other entities, irrespective of their rational agency, represents an inherent and natural inclination deeply rooted in human cognition.

Diving deeper into the intricate interplay of anthropomorphism and emotion, Lee et al. (2018) embark on a study centered around the anthropomorphism of flexible displays. In a meticulously designed experiment, 281 participants are presented with 101 unique 3D images featuring objects bent at various axes. Their task involves reporting the strength of emotions evoked by these objects, ranging from happiness and disgust to anger, fear, and sadness, all within the confines of an online survey. Crucially,

participants are required to categorize the object's shape based on three emotional dimensions: happiness, disgust-anger, and sadness-fear. The study unfolds a complex tapestry where the combination of the bending axis (horizontal or diagonal) and convexity (bending convex or concave) emerges as a significant predictor of emotional valence. This empirical evidence underscores the pivotal role of anthropomorphic design in flexible displays, influencing emotional interactions and triggering a spectrum of emotions in users.

Shifting gears to the dynamic realm of human-machine interaction, Dwivedi et al. (2023) focus their lens on chatbots, exploring how these digital entities incorporate various behavioural and psychological marketing elements to enhance customer satisfaction across different stages of the purchase journey. Grounded in the Elaboration Likelihood Model (ELM), their research delves into how cognitive and peripheral cues impact experiential dimensions, ultimately shaping chatbot user recommendation intentions. The study introduces the mediating variables of warmth and competence strategically positioned in both the purchase and post-purchase stages. Employing a robust explanatory sequential mixed-method research design, the researchers validate their proposed conceptual model through a 3x3 factorial design, amassing a substantial dataset comprising 354 responses in the purchase stage and 286 responses in the post-purchase stage. In the second stage, they conduct in-depth qualitative interviews (Study 2) to gain further insights into the validity of the experimental research (Study 1).

The outcomes from Study 1 bring forth significant findings, indicating that "cognitive cues" and "competence" play pivotal roles in influencing recommendation intentions among chatbot users. In contrast, "peripheral cues" and warmth significantly contribute to positive experiences during the purchase stage. Moreover, the researchers meticulously identified and articulated 69 thematic codes through exploratory research, providing a deeper and more nuanced understanding of the variables at play. Theoretically, this study extends the ELM, introducing novel dimensions to human-machine interactions, which is particularly crucial in the age of digital transformation. From a managerial standpoint, the study underscores the importance of incorporating a "humanness" element in chatbot development, actively contributing to more engaging

and positive customer experiences.

Shifting the focus to artificial intelligence in the tourism industry, Zhang et al. (2023) highlight the pervasive infiltration of AI chatbots, driven by their cost-effectiveness and efficiency. Despite their ubiquity, the impact of emotional expressions of chatbots on service outcomes has been a relatively unexplored terrain in research. Drawing upon the expectancy violations theory, the authors embark on a journey to unravel how emotional expressions of chatbots affect customer satisfaction through three meticulously designed experiments within the context of tourist attraction recommendations.

The study unveils noteworthy findings, indicating that chatbots' expressions of concern for customers can significantly enhance customer satisfaction by mitigating expectancy violations. Importantly, the study identifies moderating factors such as the customer's goal orientation, the human likeness of chatbot avatars, and the relationship between customers and chatbots. These factors, in turn, moderate the negative relationship between emotional expression and expectancy violation. These novel insights not only propel the field of research on the emotional expressions of chatbots forward but also provide critical considerations for the strategic deployment of chatbots in customer service within the tourism industry.

In a final revisitation of Lee et al. (2018) study on anthropomorphism and emotion, the findings underscore the importance of the axis of bending and convexity as crucial antecedents in emotional interactions with flexible objects. This provides empirical evidence supporting the anthropomorphic design of flexible displays and emphasizes the significant role these design elements play in triggering at least three types of emotions in users. Collectively, these studies weave a rich tapestry in the expansive landscape of anthropomorphism, spanning diverse domains from common sense knowledge to emotional interactions with technology. The research sheds light on the multifaceted dimensions of human-machine interactions in the digital era and prompts further exploration into the intricate and evolving dynamics of these relationships.

2.3 Flexibility

In the frontline service context, "efficiency–flexibility ambidexterity" refers to the ability to provide frontline service that is simultaneously efficient and flexible (Yu et al., 2020). Modern companies increasingly rely on artificial intelligence (AI) based chatbots for frontline efficiency–flexibility, and ambidexterity (Silva & Bonetti, 2021). Equipped with sophisticated speech recognition and natural language-processing tools, AI chatbots can efficiently address complex service requests (Pantano & Pizzi, 2020). Examples include Amazon's Alexa, Google's Assistant, and Apple's Siri (Ramadan, 2021). The algorithms embedded in chatbots can also suggest products that might interest a customer, thus helping the chatbots flexibly cater to different needs (Chinchanachokchai et al., 2021). Brick-and-mortar stores, such as Hilton Worldwide, Suning, Auchan, and Aditya Birla Retail, have adopted embodied chatbots to take orders and recommend products (Pillai et al., 2020; Prentice and Nguyen, 2020, 2021). Chatbots have been deployed in various industries (e.g., retail, travel planning, airports, restaurants, and hotels) because they provide companies with an effective and flexible approach to performing service tasks (Hughes & Ogilvie, 2020).

Although AI chatbots are an advanced tool for implementing frontline services, there are still gaps in research on frontline efficiency–flexibility and ambidexterity. First, although human employees' efficiency and flexibility have been addressed in the literature (e.g., Adler et al., 1999; Eisenhardt et al., 2010; Kao & Chen, 2016; Yu et al., 2020), little research has shed light on the efficiency–flexibility ambidexterity of virtual frontline employees (Research Gap 1). Second, customer orientation has emerged as a pivotal marketing strategy for establishing efficiency–flexibility ambidexterity, as it makes it possible to fine-tune offerings to ensure efficient and flexible frontline services (Miao & Wang, 2016; Liu & et al., 2019). Although much attention has been paid to the antecedents of efficiency–flexibility ambidexterity (see Yu et al., 2020), little is known about its relationship with customer-oriented behaviours (Research Gap 2). Third, while it is generally assumed that frontline service needs to be adapted to interaction contexts for maximal effectiveness (Mullins et al., 2020; Panagopoulos et al., 2020), only a handful of studies have investigated the contingency of efficiency–flexibility ambidexterity. Without exception, studies have examined contingent factors

from the service provider side, such as work unit-level leadership (Yu et al., 2020) and service employees' traits (Kao & Chen, 2016). Although a given customer may have specific concerns, such as privacy threats, switching costs, and personalization benefits, when interacting with a chatbot (Bashir et al., 2021; Pizzi & Scarpi, 2020), studies have not recognized customer-side factors as potential contingencies.

Chatbot offers a new layer of support to the service quality dimension by assuring personalized service is available to meet customer needs anytime and anywhere. In addition, Chatbot is designed to drive future luxury brand/consumer relationships. For example, Louis Vuitton offers a Chatbot service that provides information about global offline stores, access to personal service agents regarding product care, and conversational interfaces that show the craftsmanship behind the products (Forbes, 2017a; Forbes, 2017b; Forbes, 2017c).

In the fast-paced and ever-evolving landscape of customer relations, Vishnoi & et al. (2018) provide invaluable insights into the shifting dynamics of customer expectations, elucidating the defining variables of loyalty in an era dominated by digital experiences. Customers, as they argue, have become increasingly discerning, seeking convenience, quality, product features, and value for money, forming the pillars of their loyalty quotients. In this digital age, the essence of loyalty transcends the mere placement of products in customers' minds; it extends to cultivating a deep connection in their hearts and souls. Amidst a vast product ecosystem offering myriad options and brand choices, customers can easily be swayed by alternative brands, changing lifestyles, and evolving trends.

Marketers, recognizing the pivotal touchpoints influencing customer behaviour, are navigating a landscape transformed by technological innovations and abundant consumer data. This surge in information encompasses insights into buying behaviour, purchase cycles, key target attributes, technology and product preferences, payment modes, consumption patterns, favourable digital platforms, delivery methods, and more. Leveraging artificial intelligence (AI) tools, this wealth of consumer data can be

transformed into meaningful insights, empowering decision-makers in the increasingly complex marketing world.

Building upon this foundation, Klaus and Zaichkowsky (2021) delve into the transformative impact of AI on consumer decision-making and its implications for services marketing, research, and management. Their exploration revolves around the primary reasons consumers delegate their shopping decisions to AI-powered bots: convenience and ease of use with voice commands, feelings of control, and the positive emotions associated with voice interactions. Recognizing that consumers value convenience and find joy in spending money on time-saving services, the authors stress the importance of understanding and catering to these consumer preferences.

Providing enjoyable experiences while mitigating perceptions of security or privacy risks should be a focal point for firms leveraging AI technologies in their services. As consumers increasingly embrace the ease and efficiency of AI-driven services, firms prioritizing creating positive, enjoyable interactions stand to gain a competitive edge in the market.

In the realm of customer service quality and performance, Rossmann et al. (2020) contribute a research model focused on chatbots. Their conceptual model explores the intricate dynamics of customer service quality and performance within chatbots, assessing the impact of various service dimensions on customer relationship metrics across different service channels and comparing hotlines to chatbots. The findings from six independent studies underscore a robust main effect of the conceptualized service dimensions on critical metrics such as customer satisfaction, service costs, and intention to reuse services, word-of-mouth recommendations, and customer loyalty. Importantly, the research identifies that distinct service dimensions are relevant for chatbots compared to traditional service hotlines, emphasizing the nuanced nature of customer interactions in the digital age. As businesses increasingly turn to chatbots to enhance customer service, understanding these nuanced dimensions becomes crucial for optimizing customer satisfaction and building lasting loyalty.

Collectively, these studies illuminate the evolving landscape of customer relations in the digital era, emphasizing the role of AI, the importance of understanding consumer preferences, and the need for tailored approaches to enhance customer satisfaction and loyalty across various service channels. The interplay of convenience, positive emotions, and service quality dimensions is a testament to the contemporary marketplace's intricate dance between technology and human experience. As businesses navigate this complex terrain, a nuanced understanding of consumer behaviour and the strategic integration of AI emerges as a key determinant of success in cultivating lasting customer loyalty and satisfaction. The ability to harness consumer data, transform it into actionable insights, and deliver seamless, enjoyable experiences positions forward-thinking firms at the forefront of the evolving customer-centric landscape.

2.4 Controllability

The success of integrating AI into business and customers critically depends on workers' trust in AI technology (Glikson et al., 2020). Transparency, reliability and anthropomorphism play a role in trust (both cognitive and emotional). Trust is a dynamic concept that is prone to changes based on the behaviour of the trusted agent (Crisp & Jarvenpaa, 2013; Schoorman et al., 2007). Hoff and Bashir (2015) posited that the way trust in technology unfolds differs from how it develops in humans due to the common positivity bias toward new technologies (Parasuraman & Manzey, 2010). In contrast to the initial low trust in unfamiliar humans, new technologies may produce unrealistically optimistic beliefs regarding their abilities and functionality (Dzindolet et al., 2003). Thus, while trust in humans generally increases through frequent interactions, trust in technology decreases with time, based on encounters with errors and malfunctions (Madhavan & Wiegmann, 2007). However, the opposite also could be true when it comes to AI.

Swaminathan et al. (2019) conducted a comprehensive study to unravel the intricate web of factors influencing e-loyalty in e-commerce. Their research delves into business and customer factors, shedding light on the dynamics contributing to customer loyalty in the digital landscape. The multifaceted nature of e-loyalty is dissected through the

lenses of credibility, e-satisfaction, site knowledge, inertia, innovativeness, and aggressiveness.

In e-commerce, business credibility emerges as a pivotal factor influencing customer loyalty. The study identifies that the reputation of the e-business and its alignment with the customer's self-image significantly impact business credibility. The trustworthiness and authenticity of the e-business play a crucial role in shaping customer loyalty. This finding emphasizes the importance of cultivating a positive brand image and maintaining transparency to foster a sense of credibility among customers.

E-satisfaction, a key component in the study, is the customer's contentment with their prior purchasing experience with a given e-commerce firm. The research underscores that e-satisfaction is intricately linked to the customer's value perception, care, and choice. A satisfied customer is likely to remain loyal, while a dissatisfied customer is prone to explore alternatives and resist efforts to develop a closer relationship with the current retailer. The level of satisfaction emerges as a critical determinant in fostering loyalty, highlighting the need for e-commerce retailers to prioritize customer satisfaction as a cornerstone of their strategy.

Site knowledge, another facet explored in the study, is shaped by the customer's experience, involvement, and expertise. The findings suggest that a well-informed customer who is actively engaged with the website and possesses expertise contributes to enhanced site knowledge. This, in turn, plays a significant role in influencing e-loyalty. E-commerce retailers, therefore, need to focus not only on the user-friendliness of their websites but also on providing informative content and engaging experiences to enhance site knowledge.

The study introduces customer factors such as inertia, innovativeness, and aggressiveness. Inertia, where repeat purchases occur based on situational cues rather than strong partner commitment, is a key customer factor influencing loyalty. Out of habit, many customers continue to patronize the same e-commerce platforms.

Understanding and addressing customer inertia becomes crucial for businesses seeking to retain their customer base.

In customer factors, innovativeness and aggressiveness are identified as contributors to e-loyalty. Innovative and aggressive customers, open to new experiences and assertive in their decision-making, are more likely to exhibit loyalty in e-commerce. This highlights the need for e-commerce retailers to cater to their customer base's diverse needs and preferences, recognizing that different segments may respond differently to marketing strategies.

Transitioning to the study by Dabholkar et al. (2012), the focus shifts to the role of recommendation agents (RAs) in shaping customer satisfaction, trust, and purchase intentions. The research reveals that greater consumer participation in using RAs leads to heightened satisfaction, increased trust, and higher purchase intentions related to the RA and its recommendations. This underscores the importance of involving customers in decision-making, leveraging RAs as tools to enhance their overall experience.

However, the study also notes the impact of financial risk on the product under consideration. Financial risk emerges as a moderating factor, reducing satisfaction, trust, and purchase intentions. This finding underscores the need for businesses to address and mitigate financial risks to enhance customer satisfaction and trust, thereby increasing the likelihood of purchase intentions.

The dynamic nature of customer motivations is explored by Ameen et al. (2021), who emphasizes that customers are motivated by hedonism and a need for autonomy. This insight holds profound implications for marketing strategies, suggesting that customers may be willing to sacrifice hedonic utility for stronger self-relevant values. The decision to accept sacrifices is contingent on situational factors, emphasizing the importance of understanding the context in which customer decisions are made.

Furthermore, the research suggests that customers are willing to sacrifice elements they cannot control, such as power over choices and privacy, particularly in AI-driven technologies. Automated systems' increasing prevalence and complexity raises

questions about the trade-offs customers are willing to make for convenience, personalization, and service quality. This willingness to sacrifice what cannot be controlled has implications for trust and perceived sacrifice in AI-enabled customer service and experience.

As the research landscape evolves, Andre et al. (2018) pose a critical question: When do consumers sacrifice preferred choice options to assert their autonomy, and when does the quest for pleasure, comfort, and convenience dominate their choices? The intricate interplay between convenience, personalization, and service quality, mediated by trust and perceived sacrifice, shapes the relationships in the era of AI-enabled customer service and experience.

In conclusion, the amalgamation of findings from these studies underscores the complexity of factors influencing e-loyalty and customer behaviours in the digital age. E-commerce retailers must be attuned to the multifaceted nature of customer motivations, satisfaction, and trust. Fostering credibility, ensuring customer satisfaction, addressing financial risks, and navigating the intricate dance of autonomy and sacrifice are crucial to developing effective marketing strategies. As the digital landscape evolves, businesses that understand and adapt to these nuanced dynamics will be well-positioned to cultivate lasting customer loyalty and drive success in the competitive e-commerce arena.

In the ever-evolving landscape of digital interactions, Rese et al. (2020) embarked on a study that delves into the acceptance of the text-based "Emma" chatbot. To unravel the complexities of user acceptance, the study contrasts the widely recognized Technology Acceptance Model (TAM) with the lesser-known Uses and Gratifications (U&G) theory. "Emma" was conceived for the pre-purchase phase of online fashion retailing, seamlessly integrated into Facebook Messenger by the German online retail giant Zalando. The study, anchored in usability, gathered data from 205 German Millennials, providing a rich dataset for analysis.

Rese et al. (2020) findings shed light on the multifaceted nature of user acceptance. Both utilitarian factors, encompassing the "authenticity of conversation" and "perceived usefulness," and hedonic factors, such as "perceived enjoyment," emerged as influential in shaping the acceptance of "Emma." However, the study unveiled potential hurdles to widespread adoption. Privacy concerns, a perennial issue in the digital realm, and the perceived immaturity of the technology exerted negative influences on usage intention and frequency. The models employed, TAM and U&G, demonstrated similar predictive power. However, the U&G theory offered unique insights into customers' motivations to engage with "Emma", providing a more nuanced understanding beyond the traditional TAM framework.

Switching gears, Lee et al. (2017) embarked on a fascinating exploration of human-computer interaction, specifically focusing on the dynamics of self-disclosure and reciprocity in an interactive movie recommendation system facilitated by a conversation agent (CA). Grounded in the Computers-Are-Social-Actors (CASA) paradigm and uncertainty reduction theory, the study aimed to unravel the intricacies of user satisfaction and intention to use the conversation agent (CA).

By employing a two-way ANOVA test, the researchers sought to unravel the effects of self-disclosure and reciprocity on user satisfaction. While the interactional effect of these variables on user satisfaction proved insignificant, the main effects were highly significant. PLS analysis further illuminated the intricate dynamics, highlighting perceived trust and interactional enjoyment as significant mediators in the relationship between communication variables and user satisfaction. Notably, the study revealed that reciprocity played a more substantial role than self-disclosure in predicting relationship building between the CA and the user.

Furthermore, the study underlined the pivotal role of user satisfaction as a key influencer of the intention to use the interactive movie recommendation system. These practical and theoretical findings contribute valuable insights into the nuanced world of human-computer interaction, where trust, enjoyment, and reciprocity emerge as critical elements shaping user satisfaction and, consequently, the intention to use.

Shifting the focus to the concerns of the contemporary digital landscape, Choi et al. (2023) addressed the escalating apprehensions among consumers regarding sharing personal information. In an era where data privacy is paramount, the study navigated the intersection of AI agents, specifically chatbots, and consumers' willingness to disclose personal information. Grounded in the Stereotype Content Model (SCM) and Regulatory Focus Theory, the study examined the interplay between chatbot interaction styles, individual regulatory focus, and consumers' willingness to self-disclose.

The results, gleaned from four studies encompassing a substantial sample size (N = 1075), unfolded intriguing dynamics. Chatbots adorned with warm interaction styles elicit a more robust willingness to self-disclose among promotion-focused consumers than their prevention-focused counterparts. Conversely, chatbots projecting a competent interaction style were more effective in encouraging self-disclosure among prevention-focused consumers. The intricate dance of consumer trust acted as a psychological mechanism in the disclosure induction process, emphasizing the delicate balance between technology and human concerns.

The study by Choi et al. (2023) contributes to the burgeoning field of AI agent-related research by uncovering the factors influencing consumers' willingness to self-disclose and providing actionable insights for refining the positive impact of consumer chatbot interactions. While grounded in contemporary concerns over data privacy, the study charts a path for future research endeavours in the ever-evolving landscape of AI-enabled consumer interactions.

2.5 Ease of Use

In the ever-evolving landscape of luxury fashion retail, Chung et al. (2020) embarked on a comprehensive exploration in 2020, challenging the narrative surrounding personalized care in the digital age. Their inquiry sought to unravel the complex question of whether luxury brands could maintain their essence of providing personalized care through the emerging avenue of e-services, specifically leveraging Chatbots. These digital tools had rapidly gained prominence, promising both

convenience and the delivery of highly personalized and unique customer assistance, disrupting the conventional paradigm of face-to-face interactions.

Chung et al. (2020) investigation delved deep into the intricate dynamics of luxury fashion retail, aiming to dissect the potential of e-services to integrate seamlessly with the established ethos of personalized care. The advent of Chatbots, with their ability to engage customers in real-time conversations, represented a paradigm shift in how luxury brands could extend their bespoke services to a broader digital audience. The study meticulously examined the efficacy of this transition, aiming to ascertain whether the core values of luxury, often associated with exclusivity and personalized attention, could transcend the physical realm and find resonance in the digital domain.

In parallel, Guemues et al. (2021) embarked on a distinct yet complementary exploration, shedding light on the widespread adoption of Chatbots as a pivotal component of customer service strategies. In a world increasingly characterized by a 24/7 digital presence, brands sought to leverage this emerging technology to cater to the evolving needs of their customer base. However, a notable challenge surfaced - the lingering reservations of some customers who preferred the familiarity of human interactions over potential uncertainties associated with technology-driven engagements.

Recognizing the imperative for brands to address these concerns and refine their Chatbot interfaces to align more closely with customer expectations, Guemues et al. (2021) laid the groundwork for an in-depth investigation into the factors influencing customer experience and behavioural intentions regarding Chatbots. The research team constructed a robust study, enlisting 211 Turkish Chatbot users through non-probability convenience sampling, to unravel the intricate interplay of Ease of Use, usefulness, enjoyment, and risk factors in shaping the landscape of digital customer interactions.

Chung et al. (2020) study challenged the narrative surrounding luxury brands and personalized care in the digital era. As the luxury landscape continues to evolve, the study asked critical questions about the adaptability of these brands in the face of emerging digital tools. The exploration into Chatbots as facilitators of personalized care

demonstrated a forward-thinking approach, questioning whether the essence of luxury could be extended beyond traditional face-to-face interactions.

Guemues et al. (2021) explored the broader adoption of Chatbots across industries, acknowledging the evolving nature of customer interactions in an increasingly digitalized world. The focus on addressing customer reservations underscored the importance of aligning technological innovations with human expectations, recognizing that the success of digital tools hinges on mitigating uncertainties and providing a seamless experience.

Building upon these insights, the studies underscore the nuanced relationship between technology and customer expectations. Chung et al. (2020) examination of luxury brands provides a glimpse into the evolving definition of luxury in the digital age. As traditional notions of exclusivity contend with the accessibility facilitated by Chatbots, luxury brands face the challenge of balancing heritage with innovation.

Guemues et al. (2021) investigation further deepens our understanding of customer attitudes towards chatbots. The meticulous examination of factors influencing user experience, such as Ease of Use, usefulness, enjoyment, and risk, sheds light on the intricacies of digital interactions. The emphasis on perceived trust and interactional enjoyment as mediators highlights the multifaceted nature of customer relationships with Chatbots.

Together, these studies contribute valuable insights into the intersection of luxury, technology, and customer expectations, highlighting the transformative potential of Chatbots in reshaping the landscape of personalized care and digital customer service. As the luxury and retail industries continue to navigate the complexities of the digital age, these studies offer a foundation for understanding the delicate balance between tradition and innovation in pursuing customer-centric experiences. The evolving narrative of luxury and digital interactions underscores the need for brands to continually adapt and redefine their strategies to meet the evolving demands of a tech-savvy and discerning customer base.

The methodological backbone of the study lay in the sophisticated analysis tools, employing the Statistical Package for Social Sciences (SPSS) and SmartPLS3. Through meticulous scrutiny, the research team unearthed significant revelations. Ease of Use and usefulness emerged as linchpin factors, wielding considerable influence over behavioural intentions, highlighting the pivotal role of seamless interactions and practical utility in shaping user behaviour in the digital realm.

Conversely, the study challenged conventional wisdom by revealing that perceived risk had no discernible impact on customer experience and subsequent behavioural intentions. This departure from anticipated outcomes underscored the resilient adaptability of users and challenged preconceived notions about potential barriers to the acceptance of technology-driven interfaces.

Adding another layer to the narrative, the study underscored the significance of perceived enjoyment as a distinct factor influencing customer experience. The emotional dimension of engaging with chatbots played a pivotal role, suggesting that the user experience is not solely shaped by functional aspects but also by the emotional resonance of the interactions.

The research illuminated a direct link between customer experience and behavioural intention. The positive correlation emphasized that the quality of interactions within the digital space directly impacted users' intentions to engage further. This insight served as a clarion call for brands to prioritize user-centric design and craft positive, enjoyable interactions to foster sustained engagement and build enduring relationships with their tech-savvy clientele.

In conclusion, Chung et al. (2020) and Guemues et al. (2021), through their respective explorations, not only dissected the intricacies of customer dynamics in the realms of luxury fashion and digital customer service but also provided a roadmap for brands navigating these evolving landscapes. The narrative evolved from questioning the feasibility of maintaining personalized care in luxury e-services to dissecting the intricate factors shaping user experiences and behavioural intentions in the era of Chatbots. The amalgamation of these studies provided a comprehensive understanding,

urging brands to not only embrace technology but to humanize it, ensuring that the transition to digital interfaces retains the essence of personalization, a hallmark of luxury in the ever-changing tapestry of consumer interactions.

2.6 Customer Characteristics

In the dynamic landscape of customer service interactions, Kvale et al. (2021) conducted an extensive investigation into the realm of customer satisfaction surveys as a means to delve deeper into user experiences, particularly those involving interactions with a customer service chatbot. Their research, encompassing a comprehensive analysis of 5,687 customer satisfaction reports, aimed to shed light on the intricate relationship between these reports and the successful resolution of issues prompting users to engage with the chatbot.

The findings of the Kvale et al. (2021) study underscored the pivotal role of customer satisfaction reports in gauging the effectiveness of chatbot interactions. A key revelation from their analysis was the direct correlation between the satisfaction of users and the extent to which the issues prompting chatbot interactions were successfully addressed. This linkage between customer satisfaction and problem resolution is a critical benchmark for evaluating the efficacy of chatbot-driven customer service.

Delving deeper into the nuances of their research, Kvale et al. (2021) uncovered significant variations in the performance of different chatbot intents concerning customer satisfaction and problem resolution. This revelation suggests that the user experience is far from uniform and is intricately tied to the nature of the problems driving users to engage with the chatbot. The diversity in chatbot intents highlights the need for a nuanced approach to improving user experience, considering the specific challenges associated with each intent.

Furthermore, Kvale et al. (2021) identified key characteristics associated with particularly high or low customer experiences. These characteristics provide valuable insights for optimizing chatbot performance, offering a roadmap for efficient enhancements in user experience. The nuanced understanding of different intents and their corresponding impact on customer satisfaction opens avenues for targeted improvements, steering chatbot development towards enhanced functionality and user-centric design.

In light of their findings, Kvale et al. (2021) pointed to several implications for both theoretical understanding and practical implementation. Recognizing the close link between customer satisfaction and problem resolution not only contributes to the theoretical understanding of user experience but also provides a tangible metric for assessing the success of customer service chatbots. This insight is crucial for businesses aiming to enhance their customer service strategies through intelligent automation.

Moreover, the study's identification of key characteristics influencing customer experience is a practical guide for businesses seeking to optimize their chatbot interactions. By homing in on these characteristics, companies can tailor their chatbot development and deployment strategies, addressing specific pain points and ensuring a more satisfactory user experience. Kvale et al.'s research, therefore, bridges the gap between academic insights and real-world applications, fostering a more holistic approach to the evolution of chatbot technology in customer service.

Building upon the foundation laid by Kvale et al., Nicolescu and Tudorache (2022) embarked on an analysis to unravel the intricacies of overall customer experience with customer service chatbots. Their systematic literature review (SLR) method, drawing insights from 40 empirical studies, sought to distill the main influencing factors shaping customer experience and delineate resulting dimensions, encompassing perceptions, attitudes, feelings, responses, and behaviours.

The multifaceted nature of customer experience emerged as a central theme in Nicolescu and Tudorache's analysis. They categorized the influencing factors into three

broad categories: chatbot-related, customer-related, and context-related factors. Further distinctions were made within the chatbot-related category, encompassing functional, system, and anthropomorphic features. This comprehensive categorization laid the groundwork for understanding the intricate web of elements shaping user interactions with chatbots.

The diversity of factors identified by Nicolescu and Tudorache (2022) converged to yield positive or negative customer perceptions, attitudes, and feelings. This nuanced understanding of the emotional and cognitive aspects of customer experience is instrumental in crafting strategies beyond mere functionality, acknowledging the holistic impact of chatbot interactions on user sentiment.

Central to their findings were the influential factors that determined customer satisfaction and subsequent behaviours. Response relevance and problem resolution emerged as the linchpin factors, substantially impacting customer satisfaction, continued usage of chatbots, product purchases, and recommendations. This empirical evidence reinforces the significance of addressing fundamental aspects of chatbot functionality to ensure positive outcomes for users and businesses.

Nicolescu and Tudorache's research provide a comprehensive framework for businesses to navigate the complex landscape of customer service chatbots. By understanding the multifaceted dimensions of customer experience and honing in on key influencing factors, companies can refine their strategies to enhance user satisfaction and drive positive customer behaviours.

In conclusion, the studies conducted by Kvale et al. (2021) and Nicolescu and Tudorache (2022) contribute significantly to the evolving field of customer service chatbots. Kvale et al. (2021) focus on customer satisfaction reports and shed light on the nuanced relationship between user satisfaction and problem resolution, offering a tangible metric for assessing the success of chatbot interactions. On the other hand, Nicolescu and Tudorache's (2022) comprehensive analysis delves into the diverse factors shaping the overall customer experience, providing a holistic framework for

businesses to optimize their chatbot strategies. Together, these studies pave the way for a more nuanced and effective approach to leveraging chatbots in customer service, with implications extending to both theoretical understanding and practical implementation. The combined insights point towards a future where chatbots not only fulfill functional roles but also contribute positively to the broader spectrum of customer emotions, attitudes, and behaviours.

In the ever-evolving landscape of human-computer interactions, Shumanov and Johnson (2023) embarked on a pioneering exploration to unravel the potential for personalization in these interactions by aligning consumer personality with a congruent machine personality through language. The study, framed by similarity attraction theory and the five factors of the personality model, sought to answer three pivotal research questions: Can chatbots be moulded to adopt a personality through response language? Does aligning consumer personality with a congruent chatbot personality enhance consumer engagement? Moreover, finally, does this alignment lead to improved financial returns for organizations? The investigation delved into uncharted territory, shedding light on the intricate dynamics of personality-driven interactions in human-machine interfaces.

The first research question set the stage for understanding the malleability of chatbots in assuming a personality through the use of response language. Drawing from a substantial sample of over 57,000 chatbot interactions, Shumanov & Johnson's (2023) study demonstrated that chatbots can be manipulated to adopt distinct personalities through the language employed in their responses. This revelation is a pivotal breakthrough, as it opens the door to the deliberate crafting of chatbot personalities, allowing organizations to tailor their virtual agents to resonate with specific consumer demographics or preferences.

Moving to the second research question, the study explored whether aligning consumer personality with a congruent chatbot personality could enhance consumer engagement. The research findings provided compelling evidence that such alignment has a positive impact on consumer engagement with chatbots. By leveraging the principles of

similarity attraction theory and the established five factors of the personality model, Shumanov and Johnson (2023) unveiled a mechanism through which personalized interactions in the virtual realm can be enhanced, creating a more engaging and resonant experience for consumers.

The third research question delved into the impact of aligning consumer chatbot personalities on organizational financial returns. In a business landscape where customer satisfaction and engagement often correlate with financial success, this aspect of the study is particularly pertinent. Shumanov & Johnson's (2023) findings illuminated a direct link between personality congruence and improved organizational financial outcomes. This correlation implies that investing in the alignment of chatbot personalities with those of consumers can be a strategic move for companies seeking to enhance customer experience and boost their bottom line.

The study's alignment with similarity attraction theory and the five factors of the personality model adds a robust theoretical underpinning to the findings, grounding them in well-established psychological frameworks. Acknowledging personality as a mechanism for enhancing human-machine interactions represents a significant theoretical advancement, bridging the gap between established personality theories and their application in the dynamic context of virtual interactions.

While the concept that personality is conveyed through language and that individuals are more responsive to those with similar personalities is not new in human interactions, Shumanov and Johnson's (2023) study brings a fresh perspective by applying these principles to human-computer interactions. The scarcity of research in this domain makes their contribution particularly noteworthy. The study addresses a critical gap in the literature and pioneers a new avenue for exploring the nuanced interplay between personality, language, and technology.

Furthermore, the study's emphasis on the positive impact of personality congruence on consumer engagement and purchasing outcomes aligns with a broader trend in emerging research. The recognition of words and language as potent factors influencing

customer satisfaction and purchasing behaviour, as highlighted by McFerran, Moore, and Packard (2019), underscores the significance of Shumanov and Johnson's (2023) findings in the context of a rapidly evolving digital marketplace.

In conclusion, Shumanov & Johnson's (2023) groundbreaking study marks a significant leap forward in understanding the intricacies of human-computer interactions. By demonstrating the manipulability of chatbots in assuming distinct personalities through response language and highlighting the positive impact of aligning Customer-chatbot personalities on engagement and financial returns, the study opens new avenues for strategic interventions in developing and deploying virtual agents. The integration of well-established psychological theories adds depth to the findings, cementing the study's contribution to theoretical understanding and practical implications in personalized human-computer interactions. As organizations navigate the landscape of AI-driven customer interactions, Shumanov & Johnson's (2023) research provides valuable insights into the untapped potential of leveraging personality to enhance the virtual user experience and drive business success.

2.7 Reason of Interaction

Brandtzaeg et al. (2017) embarked on a quest to decipher the motives propelling individuals to engage with chatbots in the ever-expanding realm of human interaction with digital technologies. Through an online questionnaire administered to 146 chatbot users in the United States (aged 16–55 years), the study aimed to unravel the multifaceted reasons behind the adoption of chatbot technology. The results shed light on critical motivational factors that drive users to interact with automated agents, offering valuable insights into the intricate dynamics of human chatbot engagement.

Productivity emerged as the foremost motivational factor, with users seeking timely and efficient assistance or information. In this context, chatbots were perceived as facilitators of productivity, aligning with users' expectations of seamless and swift interactions. Beyond productivity, the study uncovered additional motivational factors

related to entertainment, social and relational aspects, and curiosity about the novel phenomenon of interacting with chatbots. The findings were contextualized through the lens of the uses and gratifications theory, providing a theoretical framework to understand why individuals actively choose to engage with automated agents online.

In a parallel exploration, Lee and Hwang (2008) delved into the intricate realm of human-robot interaction, employing a game-theoretic approach to elucidate cooperative decision-making models. Their focus extended beyond the development of standalone artificial systems to creating cooperative systems interacting with human users. The study proposed a model integrating the robot's knowledge and human users' cues, fostering cooperative decision-making processes. By adopting a game-theoretic perspective, the research provided a formal and plausible account of human-robot interaction, offering valuable insights into the dynamics of cooperative decision-making in this context.

Meanwhile, Fernandes et al. (2021) made significant contributions to the nascent field of automated technologies, addressing gaps in the literature and offering empirical validation of the conceptual framework known as the Service Robot Acceptance Model (SRAM). This pioneering study focused on Digital Voice Assistants (DVAs) and the Millennial cohort. The sRAM, conceived by Wirtz et al. (2018), incorporates both social and relational features of service robots, aligning with the evolving landscape of technology-mediated interactions. The study empirically validated the sRAM and extended it by exploring mediating and crossover effects while incorporating the moderating role of experience and preference for human interactions.

The empirical investigation involved 238 young Customers, and the data analysis, conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), provided insights into users' motivations to adopt intelligent digital voice assistants in service encounters. The findings highlighted the driving forces behind adoption, unravelling the interplay of functional, social, and relational elements. Additionally, the study revealed the moderating role of experience and the need for human interaction, further enriching our understanding of technology acceptance dynamics.

One noteworthy revelation from the study challenged the universal positivity attributed to anthropomorphism, suggesting that it is not universally positive in the context of digital voice assistants. The research also highlighted the underexplored realm of customer-robot rapport building, contributing to a more holistic understanding of digital voice assistants' adoption.

In conclusion, these studies by Brandtzaeg et al. (2017), Lee and Hwang (2008), and Fernandes et al. (2021) collectively contribute to the evolving discourse on human interaction with automated technologies. They unravel the intricacies of motivation, cooperative decision-making, and acceptance dynamics, providing valuable insights for researchers, practitioners, and policymakers navigating the complex landscape of human-technology interactions. As technology advances, these studies serve as foundational pillars, shaping our understanding of the multifaceted relationship between humans and intelligent automated systems.

In the ever-expanding landscape of human-technology interactions, studies by Kim et al. (2022), Zhang et al. (2023), and Gatzidoufa et al. (2022) provide valuable insights into the nuanced dynamics of human-robot interaction, the relationship between loneliness and mobile phone addiction, and the adoption intention toward chatbots, respectively. Kim et al. (2022) explore the realm of human-robot interaction through social exchange theory, delving into the relational and psychological states underpinning users' interactions with service robots in hotel settings. Leveraging empirical studies with the robots Pepper and Connie, the researchers unearthed key trust and usage intentions determinants. Perceived intelligence, social presence, and social interactivity emerged as influential factors shaping users' trust. At the same time, social presence and interactivity also played pivotal roles in fostering rapport, ultimately driving usage intentions. The study unravelled the intricate mediating roles of rapport, trust, and uniqueness neglect in the complex web of human-robot attributes and usage intentions. These findings contribute substantially to our understanding of the multifaceted nature of human-robot interactions and provide actionable insights for designing and implementing service robots in diverse settings.

Shifting the focus to psychology and technology, Zhang et al. (2023) investigate the intricate relationship between loneliness and mobile phone addiction. In an era dominated by digital connectivity, understanding the underlying mechanisms between these variables becomes imperative. The study contributes to the growing body of knowledge by unravelling the impact of loneliness on mobile phone addiction and the pathways through which this association unfolds. The findings enhance our comprehension of the psychological factors influencing mobile phone use and offer valuable guidance for parents and constructive suggestions for rationalizing college students' mobile phone use in the mobile Internet era. By addressing the complex interplay of emotions and technology use, the study bridges critical gaps in our understanding of the psychological aspects of mobile phone addiction.

In a parallel exploration of the burgeoning field of chatbots, Gatzidoufa et al. (2022) undertake a comprehensive literature review, meticulously examining empirical studies focused on individuals' adoption intentions toward chatbots. Employing the PRISMA methodology, the researchers unveil a rich landscape of 39 empirical studies spanning diverse research fields, theoretical models, methods, and factors influencing adoption intentions. The study provides a systematic categorization of existing literature and identifies critical research gaps, paving the way for future investigations in this promising realm of information technology. By synthesizing and categorizing extant knowledge, the paper serves as a valuable resource for scholars, practitioners, and policymakers involved in understanding and shaping the trajectory of chatbot adoption.

In conclusion, these three studies collectively contribute to the evolving discourse on human-technology interactions, shedding light on the intricacies of human-robot dynamics, the psychological underpinnings of mobile phone addiction, and the adoption intentions toward chatbots. As technology continues to play an increasingly central role in our lives, these studies provide a roadmap for understanding, navigating, and harnessing the potential of emerging technologies to enhance human well-being and societal progress.

2.8 User Expertise

In the ever-evolving landscape of human-computer interaction, the seminal work of Hill et al. (2015) delved into an insightful analysis, unravelling the intricacies that underpin conversations with intelligent agents, particularly the widely used chatbot Cleverbot. This study aimed to provide a nuanced comparison between 100 instant messaging conversations and 100 interactions with Cleverbot across seven dimensions, including metrics such as words per message, words per conversation, messages per conversation, word uniqueness, and the utilization of profanity, shorthand, and emoticons.

The results of their exhaustive analysis, conducted through a Multivariate Analysis of Variance (MANOVA), painted a fascinating picture of human-chatbot communication dynamics. Notably, individuals engaged with the chatbot for prolonged durations, even though the messages exchanged were comparatively shorter than those in human-to-human interactions. Furthermore, conversations with Cleverbot exhibited a discernible reduction in the richness of vocabulary often observed in human discourse, coupled with an increased deployment of profanity. These findings suggested that while basic language skills translated seamlessly to interactions with chatbots, significant differences existed in the content and quality of these digital conversations.

Building upon this exploration, Fan et al. (2022) undertook a commendable effort to contribute to the expanding literature on AI chatbots, delving into efficiency-flexibility and ambidextrous performance in customer-oriented behaviours. Their research made pivotal contributions across three dimensions. It broadened the horizons of ambidexterity research by extending its purview to the context of AI chatbots, addressing the imperative to understand how artificial intelligence can support frontline service. The study broke new ground by investigating the impact of customer-oriented behaviours on the ambidexterity of AI chatbots, aligning with the proposition that sales strategy may play a crucial role in fostering frontline ambidexterity. It brought insights into rational choice theory, unveiling the moderating role of customers' rational choices in shaping the efficiency-flexibility performance of chatbots.

Leveraging a substantial dataset comprising over 130,000 man-machine dialogues from an e-bike sharing platform, the study unravelled a nuanced relationship between chatbots' customer-oriented behaviours and their efficiency-flexibility ambidexterity. A delicate equilibrium between functional and relational customer-oriented behaviours resulted in higher levels of ambidexterity, both when balanced and at an elevated level. The study incorporated a follow-up experiment and online survey to bolster their findings, revealing that the negative imbalance effect was more pronounced with decreased perceptions of non-personalization costs and increased privacy concerns. Conversely, the positive balance effect was more pronounced with increased non-personalization costs, decreased privacy concerns, and decreased opportunity costs.

Consistent with the stimulus-organism-response framework, the study demonstrated that efficiency-flexibility ambidexterity partially mediated the relationship between chatbots' (im)balanced customer-oriented behaviours and subsequent customer patronage. This study significantly enriched the existing literature in this domain by introducing an AI application context and providing a more nuanced, nonlinear perspective on the antecedents and consequences of frontline ambidexterity.

In conclusion, the collaborative works of Hill et al. (2015) and Fan et al. (2022) stand as pillars of insight into the evolving landscape of human-computer interaction. Hill et al. (2015) meticulous analysis uncovered the subtleties of language use and content quality in human-chatbot communication, while Fan et al.'s exploration of AI chatbots' ambidextrous performance offered a comprehensive understanding of the intricate interplay between customer-oriented behaviours, rational choices, and efficiency-flexibility dynamics. Together, these studies propel our comprehension of the evolving dynamics between humans and intelligent agents, providing a robust foundation for future research and practical implementations in the burgeoning field of artificial intelligence.

2.9 Conversation Duration

Borsci et al. (2022) unfolded as a multidimensional exploration into the intricacies of human interaction with chatbots. This comprehensive study aimed to contribute to the existing body of knowledge and to bridge the gap between theoretical understanding and practical applications in the rapidly evolving realm of artificial intelligence.

The initial phase of the investigation involved a meticulous, systematic literature review, drawing insights from a diverse pool of 141 participants. This heterogeneous group comprises experts and novices who are well-versed in the intricacies of chatbot interactions, providing a comprehensive spectrum of perspectives. Through a combination of survey responses, focus group sessions, and hands-on testing of chatbots, the research team curated a rich dataset that laid the foundation for subsequent analyses.

Central to the research objectives were two key mandates. Firstly, the researchers aimed to distill the defining attributes critical for evaluating the quality of interactions with chatbots. This aspect of the study sought to unravel the intricacies of user experiences, identifying factors that transcend the conventional metrics often used in assessing satisfaction. Secondly, the team aspired to innovate by conceptualizing and piloting a novel scale specifically tailored to measure user satisfaction post-chatbot interaction. This dual-pronged approach underscored the ambition of the study to not only understand existing dynamics but also to contribute novel tools for future research and design considerations.

The fruition of these ambitious goals materialized in the form of two distinct yet synergistic instruments. The BOT-Checklist, a diagnostic tool in the form of a comprehensive checklist, was a testament to the evolution of prior research. This tool emerged as a reliable mechanism capable of systematically assessing and benchmarking the quality of a Chatbots user experience. Grounded in established principles, the BOT-Check provided a standardized approach, offering researchers and practitioners a valuable instrument for ensuring the efficacy of chatbot interactions.

Complementing the BOT Checklist was developing the BOT Usability Scale (BUS-15), a 15-item questionnaire meticulously crafted to capture the nuances of user satisfaction. The estimated reliability of the BUS-15, ranging between .76 and .87, testified to its robustness as a metric. What set this scale apart was its organization into five distinct factors, each addressing a specific facet of user experience. This facilitated a more granular analysis and broadened the evaluation scope beyond traditional satisfaction tools.

One noteworthy aspect of the BUS-15 was its ability to correlate strongly with the widely used UMUX-LITE. This correlation was pivotal, highlighting the BUS-15's capacity to complement existing tools. Designers and researchers could now leverage this correlation to understand user experiences with chatbots better. The BUS-15, by incorporating elements such as conversational efficiency, accessibility, and the overall quality of the Chatbots functionality, transcended the limitations of conventional satisfaction tools. This breakthrough allowed for a more nuanced exploration of user sentiments, enriching the field and paving the way for future advancements in human-chatbot interaction studies.

In essence, this paper not only undertook a study but orchestrated a paradigm shift in how researchers and designers evaluated chatbot interactions. The holistic approach, anchored in empirical evidence and propelled by innovative instrument development, positioned this study as a cornerstone in the evolving landscape of human-AI interaction research. The legacy of their work echoed in the corridors of academia, influencing subsequent endeavours and setting a benchmark for the dynamic fusion of theory and practical application in the realm of artificial intelligence studies.

2.10 Customer Engagement

In a comprehensive exploration of customer engagement (CE) measurement scales, Hollebeek et al. (2023) embarked on a systematic review to take stock of major scales assessing a customer's engagement with a brand or specific brand elements. The study used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach to scrutinize CE scale development articles from 2005 to January

2023). The evaluation encompassed the conceptualization, dimensionality, itemization, and underlying theoretical perspective of these scales, aiming to identify potential risks and pitfalls in their application.

The review's findings underscored the existence of theoretical contamination within specific CE measures, raising concerns about the inclusion of related concepts in the proposed CE definitions. This revelation compromised the theoretical rigour of these measures, emphasizing the imperative for scholars to scrutinize the theoretical underpinnings of their adopted CE scales. To further contribute to the discourse, the authors used customer data to test a five-dimension model measuring Chatbot for customer perceptions of interaction, entertainment, trendiness, customization, and problem-solving. The results shed light on the interactive and engaging nature of Chatbot e-service in brand/customer service encounters, providing marketers and managers in the luxury context with a valuable instrument for assessing the effectiveness of e-service agents.

In a parallel endeavour, Ferreira et al. (2020) crafted a procedure for comparing scales and applied it to evaluate brand engagement measures in social media. The study introduced a systematic approach for selecting, standardizing, and comparing scales, incorporating classical test theory (CTT) and item response theory (IRT). This procedure was then applied to a survey of 233 respondents, comparing three scales designed to measure Customer engagement with brands on social media platforms.

The results illuminated similar characteristics among the three scales, but distinct recommendations emerged based on specific requirements. Vivek et al. (2014) scale advocated for enhanced discrimination between construct dimensions, Hollebeek et al. (2014) scale demonstrated suitability as a one-dimensional scale, and Dessart et al. (2016) reduced scale exhibited a superior ability to capture information for affective and cognitive dimensions. However, the study highlighted that the scales could have proved more efficient in discriminating between weakly and strongly engaged individuals.

Both studies contribute significantly to customer engagement measurement, offering insights into the strengths and weaknesses of existing scales. Hollebeek et al. (2023)

systematic review identified potential pitfalls in CE scales and provided a practical application in the assessment of Chatbot e-service. On the other hand, Ferreira et al. (2020) work focused on comparing brand engagement scales in social media, providing a valuable guide for researchers and practitioners seeking the most appropriate tools for their specific contexts. Together, these studies underscore the evolving nature of customer engagement measurement and the need for ongoing refinement and adaptation to ensure the relevance and accuracy of assessments in the dynamic landscape of Customer-brand interactions.

In an in-depth exploration of the theoretical underpinnings of Customer Engagement (CE), Brodie et al. (2011) navigate the realms of relationship marketing theory and the service-dominant (S-D) logic to elucidate the conceptual foundations of CE. This comprehensive analysis extends beyond marketing and delves into the social science, management, and marketing academic literature while considering its practical business applications. The study formulates five fundamental propositions (FPs) to construct a definitive definition of CE, differentiating it from other relational concepts such as "participation" and "involvement".

The first proposition posits that CE is grounded in interactive experiences, emphasizing the relational aspect of customer-brand interactions. The second proposition asserts that CE is characterized by value co-creation, reflecting a shift from a transactional to a relational paradigm. The third proposition distinguishes CE from participation, highlighting the active involvement of customers in the former compared to the passive involvement in the latter. The fourth proposition differentiates CE from involvement, emphasizing the depth and intensity of the emotional and cognitive connection in CE. Finally, the fifth proposition elucidates the essence of CE by emphasizing its dynamic and evolving nature, driven by ongoing interactions and experiences.

This analysis culminates in developing a framework for future research, laying the groundwork for refining the conceptual domain of CE. The framework provides a roadmap for scholars to explore the various dimensions of CE, fostering a deeper understanding of its relational foundations. Overall, Brodie et al. (2011) study

establishes CE as a crucial concept for marketing and service management research, offering a nuanced perspective that transcends transactional approaches.

Building on the foundational understanding of CE, Hollebeek et al. (2023) delve into the intricate landscape of customer journeys (CJ) and the concept of investments within this journey, introducing the concept of 'customer journey value (CJV). Defined as the perceived value of a customer's journey to the customer and the firm, CJV introduces accountability. The study develops a social exchange theory-informed framework for CJV, where customer- and firm-based customer engagement value (CEV) are posited as core antecedents.

The framework predicts that CJV yields customer-based consequences, such as attitudinal and behavioural brand loyalty, and firm-based consequences, including enhanced customer lifetime value. The propositions laid out in this framework set the stage for empirical testing and validation, offering future research opportunities to explore the practical implications of CJV. While Brodie et al. (2011) focused on customer perspectives, Hollebeek et al. (2023) presented an opportunity for scholars to examine CJV from a multi-stakeholder perspective. This expansion could broaden the scope of studied stakeholders, aligning with the concept of stakeholder theory and facilitating a more comprehensive understanding of the value generated through customer journeys.

In conclusion, with their theoretical foundations and frameworks, these studies contribute significantly to the evolving landscape of customer engagement and customer journeys. They provide a robust foundation for future empirical investigations, offering scholars and practitioners valuable insights into customer-brand interactions' dynamic and multifaceted nature.

Conceptual Framework

The conceptual framework outlines the interplay between chatbots, human customer executives, ease of use, customer characteristics, and engagement. Chatbots, automated conversational agents, compete with human representatives for customer interactions.

Ease of use, influenced by interface simplicity and clarity, impacts customer perception and interaction. Customer characteristics, including demographics and preferences, affect their choice between chatbots and human assistance. Engagement, measured by interaction frequency and emotional response, reflects the connection between customers and service providers. Overall, user-friendly interfaces and personalized interactions drive higher engagement, while customer characteristics shape preferences for chatbots or human representatives in customer service interactions.

Conversation Quality and Ease of Use

User experience is greatly impacted by conversation quality and ease of use in human-computer interaction, especially in chatbots and virtual assistants (de Sá Siqueira et al., 2023). Conversation quality, ease of use, and Customer engagement affect the customer experience. High-quality interactions and user-friendly interfaces boost customer satisfaction and engagement (Rane et al., 2023). Companies that emphasize these qualities and react to changing customer desires and preferences in the competitive market can create strong customer relationships (Joel et al., 2024).

Controllability and Ease of use

The interplay between controllability and ease of use is dynamic and substantially influences the effectiveness of technological systems and the level of user satisfaction (Keiningham et al., 2017). Although increased controllability may improve adaptability and user satisfaction, it may also introduce difficulty that diminishes the simplicity of operation (Jin et al., 2020). By implementing purposeful design methods and comprehending user requirements, designers can create systems that harmonize these two pivotal elements, yielding robust yet user-friendly products that accommodate a broad range of individuals (Meyer-Waarden et al., 2023).

Perceived Anthropomorphism and Ease of Use

Perceived anthropomorphism and ease of use contribute more to the ever-changing human-computer interaction environment (Ferrari, A. 2021). User engagement and satisfaction may be significantly improved by combining perceived anthropomorphism with simplicity of usage (Xing & Jiang, 2024). Anamorphic characteristics may

increase system involvement and intuitiveness but can bring challenges (Zafar, & Ben Slama, 2022). Marketers may use intelligent design to develop systems that use anthropomorphism to improve accessibility and user experience by understanding this relationship. Marketers attempt to create practical, intuitive, and engaging solutions as technology becomes increasingly integrated.

Flexibility and ease of use

Flexibility and ease of use in technology and system design are difficult to balance. A flexible system can adapt to user needs and conditions (Meyer-Waarden et al., 2023; Zafar & Ben Slama, 2022). A system's intuitive and simple nature is often called ease of use. Both are essential for building successful, user-friendly products, but they sometimes need revision. Flexibility lets customize and adjust to changes. Ease of use makes products and processes accessible to a broader audience, reducing learning curves and improving user satisfaction (Lee & Yew, 2022). They are essential in building and executing solutions across fields to fulfill people's unique needs and preferences. The study discusses flexibility and ease of use's useful interactions, inherent tensions, and ways to balance them.

Ease of use and Customer engagement

Digital products and services must be simple and engaging to succeed in today's competitive market (Babatunde et al., 2024). When a simple product is simple, customers are happier, use it again, and engage more. User-centered design, iterative testing, easy on boarding, consistent experiences, and accessible design may help balance simplicity, customization, and usefulness (Molina-Recio et al., 2020). Companies may create products that meet customer needs and build lasting relationships by stressing these strategies. In contrast, customer engagement involves personal conversations and brand interactions, resulting in brand loyalty and lasting relationships (Kaur, H et al., 2020). According to research on ease of use and customer engagement, an intuitive user experience may increase customer satisfaction and engagement.

Conversation Quality, Customer Inertia customer engagement

Customers' engagement, and inertia must interact crucially if businesses want to retain loyal customers and build long-term relationships (Rane et al., 2023). Businesses may create successful plans to improve customer retention and satisfaction by understanding how controllability impacts Customer inertia and engagement (Magatef et al., 2023). Companies strategically managing controllable elements of their operations and customer contacts may effectively increase Customer inertia and engagement.

Controllability, Satisfaction, customer engagement

For brands that seek to establish relationships that last while developing a Customer base that is loyal to them, it is essential to understand the relationship between controllability, customer satisfaction, and customer engagement (Ting et al., 2021). By proactively controlling the areas of their operations and interactions with customers that are within their control, businesses can drastically improve Customer satisfaction and engagement measurements (Han, & Anderson 2022). By using a comprehensive strategy, businesses can keep their Customers, cultivate stronger relationships, and inspire brand loyalty, ultimately leading to long-term success.

Controllability, Attitude, Customer engagement

In today's highly competitive business marketplace, it is essential to have a comprehensive understanding of the complex relationship between controllability, customer attitude, and customer engagement to achieve sustainable growth and customer loyalty (Keiningham et al., 2017; Ting et al., 2021). There is a close relationship between all components, and efficient management can dramatically improve a company's capacity to attract, retain, and satisfy its Customers (Yapanto et al., 2021). To build loyalty, businesses must understand the relationship between controllability, customer attitude, and customer engagement. Each principle affects the others, and when together, they provide the framework for effective customer relationship management. Businesses may dramatically impact Customer opinions and engagement by carefully managing their operations and customer interactions (Rane et al., 2023). This study examines how controllability influences Customer perceptions, drives customer engagement, and provides strategic insights into utilizing these dynamics for a company's success.

Controllability, Motivation, Customer engagement

The controllability, customer motivation, and engagement relationship shape customer loyalty and sustainable growth in today's competitive corporate environment (Kee et al., 2024; Ting et al., 2021). Understanding and controlling these components helps improve a company's customer acquisition, retention, and satisfaction (Halkiopouloset al., 2022; Sağlam & Montaser, 2021). This work investigates how controllability affects Customer motivation and engagement, offering business strategies for success. Strong Customer motivation leads to engagement. Engaged Customers are more loyal, purchase more, and share ideas, creating an environment of continual development and loyalty (Sajjad & Zaman, 2020). The strength of controllability, customer motivation, and engagement drive business success. Strategically managing controllable activities and customer interactions may boost Customer motivation and engagement (Rane et al., 2023). A comprehensive strategy boosts customer satisfaction and loyalty and provides a strong platform for development (Rane, 2023). Mastering controllability in service quality, customization, communication, and consistency can help organizations succeed in a competitive market.

Anthropomorphism, Customer Inertia and customer engagement

Effective current marketing strategies include understanding Customer decision-making psychology and behavior (Halkiopouloset al., 2022). When handled well, anthropomorphism, customer inertia, and Customer engagement may boost customer loyalty and company performance (Stocchi et al., 2022). This psychological phenomenon may greatly affect customers' brand perceptions and interactions. Humanizing a brand may generate feelings that increase customer inertia and engagement. Using these dynamics to turn passive Customers into committed advocates helps ensure long-term growth and market competitiveness (Ahmad et al., 2024; Halkiopouloset al., 2022). This study examines how anthropomorphism affects Customer engagement and how organizations may use it. Understanding the relationship between anthropomorphism, Customer inertia, and engagement may boost customer loyalty and company performance.

Anthropomorphism, Customer Satisfaction and Customer engagement

A fascinating shift exists in anthropomorphism, satisfaction, and customer engagement within marketing and customer relations (Chi & Hoang, 2023; Maduku et al., 2024). This complicated framework can infuse brands with a human touch, resulting in increased satisfaction and lasting relationships. This study investigates the importance of anthropomorphism in business, its influence on customer satisfaction, and its contribution to fostering customer engagement. Using anthropomorphism can be a valuable strategy for making brands more approachable, enhancing customer satisfaction, and increasing engagement (Tsai & Chuan, 2021). Like a market research analyst, businesses can establish emotional connections with customers by infusing brands with human-like traits and values. This approach enhances customer satisfaction, loyalty, and advocacy. Businesses can foster strong connections with customers by focusing on product quality, responsive service, and interactive experiences, turning them into optimistic brand advocates (Haryono et al., 2023). In today's competitive marketplace, businesses prioritizing satisfaction and engagement through anthropomorphism will thrive and build strong and enduring connections with their customers.

Anthropomorphism, Attitude and Customer Engagement

In dynamic marketing and brand management, anthropomorphism is being used to strengthen Customer-brand relationships (Haryono et al., 2023; Han et al., 2021). Humanizing products, services, or whole companies may elicit emotions, influence customer perceptions, and increase engagement (Han et al., 2021; Schanke et al., 2021). This study shows how anthropomorphism shapes opinions among customers and fosters customer engagement. Brand humanization, customer perceptions, and engagement depend on anthropomorphism (Wu et al., 2023). Companies may connect with customers by giving brands human-like traits and values, like market research analysts. This strategy improves customer involvement and attitudes. Companies may convert passive purchasers into brand supporters by creating customized experiences, compelling storytelling, and encouraging customer engagement (Calder et al., 2018).

Anthropomorphism, Motivation, and Customer Engagement

In today's dynamic marketing environment, companies constantly search for new ways to build deeper customer relationships. Anthropomorphism, motivation, and customer engagement have become essential elements of these strategies (Tsai et al., 2021). Brands can establish robust and enduring Customer relationships by incorporating anthropomorphism, motivation, and customer engagement (Wu et al., 2023). Businesses can create meaningful connections that drive loyalty and advocacy by humanizing brands, understanding motivational drivers, and fostering deep engagement (Shamdasani, 2021). By incorporating anthropomorphism, motivation, and customer engagement, brands can establish robust and enduring connections with Customers (Wu et al., 2023). Businesses can create meaningful relationships that drive loyalty and advocacy by understanding what motivates Customers and fostering deep engagement.

Flexibility, Customer Inertia and Customer Engagement

Understanding flexibility, customer inertia, and customer engagement is essential for efficient marketing and retention of customers in the ever-changing business environment (Kolasani, 2023). These three interrelated aspects influence Customer behaviour and opinions. This work investigated how flexibility affects Customer inertia and engagement and how to use it for company success (Shamdasani, 2021). Flexibility, inertia, and engagement boost Customer loyalty and company performance. Businesses may proactively meet Customer requirements by strategically managing flexibility in product offers, customer service, and operational processes, reducing inertia and increasing engagement (Yang et al., 2020). A comprehensive strategy boosts customer satisfaction and loyalty and provides a solid platform for development.

Flexibility, Satisfaction, and Customer Engagement

Today's fast-paced market is continuously evolving; therefore, businesses must adapt. Flexibility and demands from customers are key to long-term customer relationships (Joel et al., 2024). According to the study, businesses may improve Customer satisfaction and engagement via operational flexibility (Alzoubi et al., 2022). This results in brand loyalty and success, it shows. Building long-term relationships with customers needs flexibility, satisfaction, and engagement. Flexible business techniques

that match customers' evolving needs may boost Customer satisfaction and engagement (Joel, et al., 2024).

Flexibility, Attitude, and Customer Engagement

Marketers must continually adapt their strategy to meet Customers' shifting needs in today's competitive business environment. Building long-term brand-Customer relationships requires flexibility, Customer satisfaction, and engagement (Rane, 2023). The study explores how adaptation in corporate operations enhances Customer satisfaction, strengthens connections, and promotes long-term brand loyalty and success. Building and sustaining customer relationships requires understanding flexibility, customer satisfaction, and engagement (Joel, et al., 2024). Companies may meet changing customer expectations with adaptive business strategies, improving customer satisfaction and perception (Alzoubi et al., (2022). Positive attitudes enhance engagement, brand loyalty, and success. Precision in applying these techniques may lead to sustainable growth and loyal Customers in the present company market (Shamdasani, 2021).

Flexibility, Motivation, and Customer Engagement

In today's changing business environment, marked by constant shifts and evolving tastes of Customers, it has become crucial for companies to incorporate adaptability, motivation, and customer engagement to succeed in highly competitive markets (Tsai et al., 2021). This study investigates the strategies that businesses can employ to achieve long-term success. It examines the importance of operational flexibility, Customer motivation, and meaningful engagement in creating a sustainable pathway to success (Alzoubi et al., 2022). The symbiotic relationship between flexibility, motivation, and customer engagement is crucial for business success in today's fast-paced and competitive environment (Alzoubi et al., 2022). With a keen focus on adaptability in operations, a deep understanding of what motivates individuals, and a commitment to building genuine connections with customers, businesses can pave the way for long-term growth and financial success (Rane, 2023). In order to thrive in the ever-changing marketplace, companies must prioritize these aspects and be able to adapt to evolving Customer needs quickly.

Controllability, Customer Inertia, and Customer Engagement

In today's challenging business environment, sustainable development and success need to understand the complex interaction between controllability, customer inertia, and customer engagement (Han et al., 2021). Every component affects Customer behaviour and brand loyalty in its way. Controllability, customer inertia, and customer engagement are examined in this research to help firms build strong relationships and loyalty (Stocchi et al., 2022). To build long-term customer relationships, firms must understand the complicated relationship between controllability, customer inertia, and customer engagement (Ahmad et al., 2024; Alzoubi et al., 2022). Businesses may enhance customer experience by controlling several areas, minimizing Customer inertia and increasing engagement and loyalty (Henderson et al., 2021). Businesses may build loyalty and brand advocates by customizing Customer experiences, communicating openly, and offering targeted incentives (Rane et al., 2023).

Controllability, Customer satisfaction, and Customer Engagement

In a modern company where customer-centricity prevails, controllability, satisfaction, and engagement are key to effective customer relationships (Tsai et al., 2021). This study highlights how controllability enables Customers, affects satisfaction, and encourages engagement, building loyalty. A successful customer-centric approach requires control, satisfaction, and engagement (Rane et al., 2023). Businesses can generate loyalty, advocacy, and sustainable growth by giving Customers authority, meeting their needs, and encouraging meaningful participation (Alzoubi et al., 2022).

Controllability, Attitude, and Customer Engagement

Controllability, attitude, and customer engagement are essential to company success in the complex customer-business relationship (Arslan, 2020). This study examines how controllability empowers Customers, how attitude shapes their perceptions and behaviors', and how customer engagement builds long-lasting relationships. Successful customer-centric strategies need control, attitude, and engagement. Enabling Customers, creating favorable opinions, and encouraging meaningful interaction may help businesses establish loyal, valued, and durable relationships (Rane et al., 2023;

Wibowo et al., 2020). Prioritizing these characteristics and adapting to changing Customer requirements and preferences can help companies succeed in the competitive market and retain customers' confidence.

Controllability, Motivation, and Customer Engagement

The relationship of controllability, motivation, and Customer engagement creates customer-brand relationships and creates long-lasting relationships (Zhang et al., 2024). This study examines how controllability empowers Customers, motivation motivates their behaviour, and meaningful engagement leads to mutually beneficial business-customer relationships. Successful customer-brand relationships need controllability, motivation, and engagement. Empowering Customers, tapping into motivating factors, and creating meaningful engagement may help businesses generate loyalty, advocacy, and sustainable growth (Rane et al., 2023). Companies that highlight these factors and react to changing customer needs and preferences will succeed in the competitive market and become valued partners.

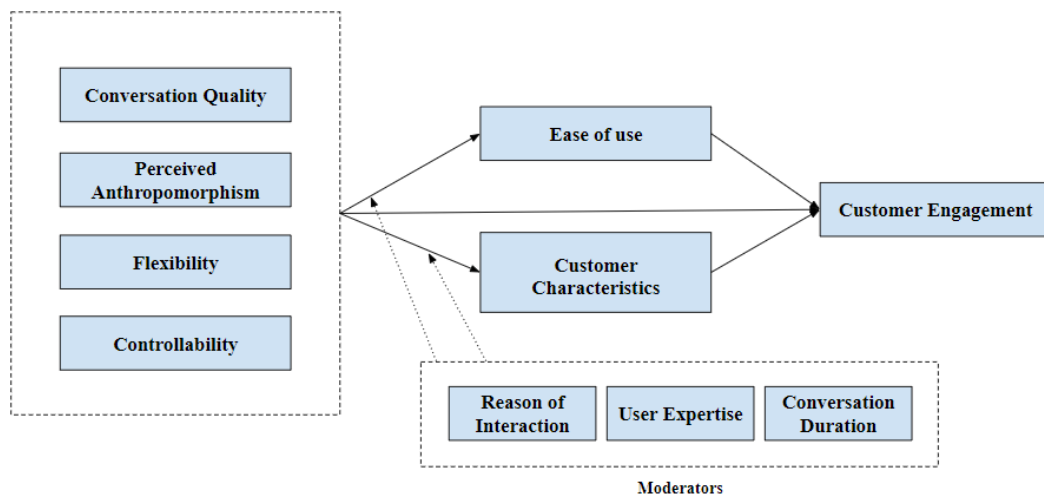


Figure 2.2 : Conceptual Framework

CHAPTER - 3

RESEARCH

METHODOLOGY

CHAPTER-3

3. Research Methodology

Research methodology is a systematic approach to identifying problems, collecting data, analyzing that data, and arriving at conclusions is essential. It is important to consider all available alternatives before making any decisions, as there are many different aspects to consider. Ultimately, the goal is to arrive at conclusions that can solve the problem or contribute to theoretical formulations.

This chapter will discuss the appropriate methods that can be selected by analyzing objectives and comparing various alternatives. The research methodology followed in detail elaborates the research objectives and procedure, including the overall research design, sampling procedure, data collection and analysis methods, and statistical techniques employed for data analysis. Additionally, the chapter discusses the study's assumptions and research methodology.

3.1 Research Objectives

- To examine the role of Ease of Use & Customer characteristics between service attributes and customer engagement.
- To study the effect of Reason of Interaction, user expertise and Conversation Duration between service attributes and Ease of Use & Customer characteristics.
- To compare the effectiveness of chatbots and customer executives for customer engagement.

3.2 Research Design

A research design is a logical and systematic plan for directing a research study. Moreover, it is a process that guides a researcher in collecting, analyzing, and interpreting observations.

For the study, research will be conducted by using a Descriptive design. The reason for using this design is to compare customer engagement between chatbots and customer executives and also measure the impact of ease of use and customer characteristics on Customer engagement. With this approach, the researcher will gain insights into how

different types of customer support affect engagement levels and identify any factors affecting customer engagement.

Descriptive research is a valuable scientific method that involves observing and describing the behaviour of a subject without any influence, as explained by Chaubey (2016). A Descriptive Study on Saving and Investment Behaviour of Investors: Evidence from Uttarakhand Rishabh Dev. It is also known as statistical research. Statistical research is a useful technique that helps to describe various phenomena as they exist. It is particularly helpful in identifying and obtaining information on the characteristics of a particular issue, such as a community, group, or people. This type of research is primarily concerned with describing social events, social structure, social situations, and other related topics. It is an essential tool for anyone looking to better understand the world around them.

The researcher carefully observes and describes their findings through descriptive research. This research helps them answer important questions about what, who, where, how, and when. By providing a detailed and comprehensive description of their observations, the researchers will gain a deeper understanding of the situation and draw meaningful conclusions from their research.

Descriptive research is a valuable tool for understanding the current situation. It is used in various fields, including physical and natural science, but it is especially useful in the social sciences. These fields are commonly used to conduct socioeconomic surveys and analyze jobs and activities. Descriptive research aims to depict the characteristics of a specific group or situation accurately. This can include studying the attitudes and views of individuals towards a particular group. Descriptive research is an effective method for obtaining an in-depth understanding of various phenomena across a variety of areas of study. It provides in-depth descriptions and information, the foundation for further study, and the formulation of hypotheses for conducting analytical or experimental studies.

The study will be conducted using a questionnaire to gather data from users of e-commerce sites who interact with customer executives. We will analyze the conversation quality, Visualization, Anthropomorphic design, Flexibility and Controllability and their impact on the Ease of use on one side, Customer characteristics on the other, and overall impact on Customer engagement. The research methodology about the respondents has been further reviewed, and it has been clarified that each respondent will be asked to provide feedback twice on the same questionnaire, one for experience with customer executives and the second for experience with chatbots. Most of the previous literature is available in the academics and financial industries, where few studies have been done by measuring the impact of interaction with chatbots. In those, there is a prototype and a very controlled group. There have been four primary steps involved in the process of developing the research for this study. These steps include the research design, the collecting of data, the analysis of the data, and the outcomes (results).

A pilot study was conducted with 100 participants representing more than ten percent of the sample size. The completion of the questionnaire was an expectation that was placed on every responder. In addition, the participants were asked to provide input about the arrangement and flow of the questionnaire and evaluations concerning the readability and correctness of the questions. Consequently, the study got valuable information from the respondents who participated in the pilot study and subsequently the questionnaire was revised to include input. After completing the final questionnaire, it was distributed for collection of the primary data-gathering process. PLS-SEM was then used to analyze the data, and the results were used to draw implications.

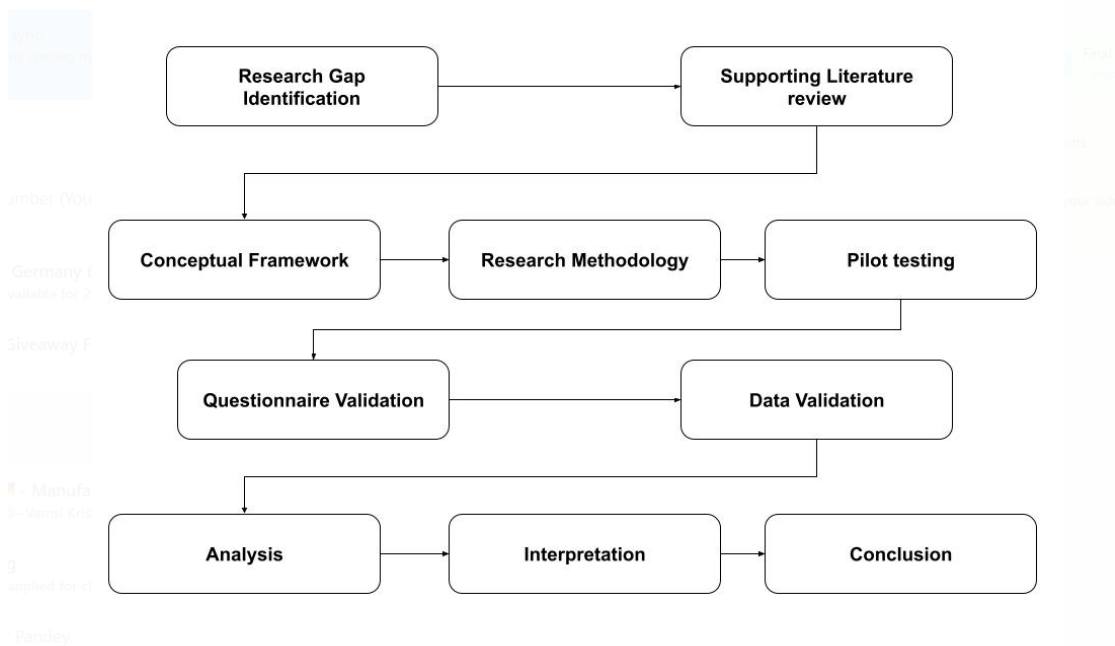


Figure 3.1: Research Design Process

3.2.1 Sampling and the study population

It is not easy to thoroughly investigate and study the universe. It is thus necessary to go to the sampling procedure as an alternative. That is how exact this research is. Similarly, this study is exact. As per Manheim (1977), "a sample is a part of the population studied to make inferences about the whole population."

3.2.1.1 Sampling

The foundation of research methodology is sampling, essential to obtaining significant and broadly applicable results. The sampling process is choosing a subset from a larger population; its skill is striking a careful balance between representation, efficiency, and reliability. One of the primary objectives of sampling is to produce a group representative of the total population being investigated, which reflects that population's features. In order to draw reliable conclusions about the broader group, it is essential to achieve representativeness.

For this study, a technique a non-random sampling technique was used. A kind of sampling known as non-probability sampling is used when selecting the sample. This method involves selecting the sample based on criteria that are not chosen at random. In other words, this indicates that only a select few individuals from a population can be included in the sample. Convenience sampling was utilized as part of the non-probability sampling methods that were used in this research study (R. K. Singh et al., 2021). Because the individual researcher has limited resources regarding money and time, these sample strategies suit them. It is common practice to refer to the complete group of persons from whom the researcher gathers data to conduct research as the target population. For example, the research's target population consists of users who use chatbots on e-commerce websites and interact in conversation with customer executives in India. Therefore, the studies emphasized those users who use chatbots on e-commerce websites converse with customer executives in India. The researchers select participants for the convenience sampling method, a non-probability sample method, based on how easy it is for them to obtain and how readily available they are. Researchers must carefully consider its inherent limits despite its practical benefits, such as simplicity and efficiency. The convenience sampling method strongly focuses on accessibility, one of the distinctive characteristics of this sample method. When the convenience of collecting individuals is greater than the need for a representative sample, researchers use this approach to collect data. People who are readily available and willing to participate in the study or easily accessible to the researcher are often selected as part of the process. For the most part, the ease and cost-effectiveness of convenience sampling are its key advantages. When time, money, or resources are limited, this kind of data collection is especially attractive since it is an easy and speedy approach to data collection. Researchers who may not have the resources to carry out more thorough and resource-intensive sample techniques might participate in this approach since it is accessible.

Population is "all of the units that make up the population from which a representative sample is drawn." According to Bryman (2012), the term "sample units" refers to the individuals of the population through whom measurements are taken as part of the sampling procedure. This occurs because the sample units themselves consist of

individuals from the population. Participants in the research sample for this study were chosen from among those who use chatbots on e-commerce websites to converse with customer executives in India. It is not feasible to research the complete population since there are restrictions on the amount of money and time that may be spent on the population. Because of this, when researchers carry out studies, they try to choose samples that are considered representative of the whole population.

According to Bell et al. (2018), a sample is a subset of the individuals who have been selected to represent a feature of the population that is being researched. This subset is used while researching the whole population because the sample is representative of the whole research population, so selecting who and what to examine is possible. The term "sample" refers to this particular segment of the population. It is one of the most essential aspects in deciding how accurate the results will be when performing quantitative research (Bajpai, N. 2011). When conducting this research, selecting the sample that will be analysed is one of the most crucial factors. A good sample should represent the whole population being investigated, which is the reason for this. Before beginning a survey, it is important to ensure the approach is clear for the above reasons.

Most of the previous literature is available in the academics, financial industries where few studies have been done by measuring impact of interaction with chatbots. In those there is a prototype and very controlled group and as a pilot study. However, with the growth of E-commerce in India, the number of users have been growing at rate of 6 million new entrants per month (source: Dec 2023, Feb 2023 and July 2021 report by Indian Brand Equity Foundation (IBEF), a trust established by Department of Commerce, Ministry of Commerce and Industry, Government of India), Further from this report, Indian e-commerce will reach USD 99 billion by 2024, growth of 27% over 2019-24 this is expected to result in growth of the Indian digital sector by multifold touching USD 1 Trillion by 20230 from USD 85-90 billion in 2020.

With this phenomenal growth in the e-commerce sector and users in India, we consider this as a good source for our research and adopt users of e-commerce websites in India who are also users of chatbots and interact with customer executives have been selected

as the sample for this research. The study is centered on customer interaction via chatbots and customer executives.

3.3 The study sample size

Both the sample's design and the sample's size are essential elements for determining the population's level of representativeness. Even though a larger sample size gives reliable findings, it is optional to consider the complete population being studied to get the best possible outcomes. For this research, a sample size of seven hundred and twenty two respondents has been selected to ensure that all necessary information is thoroughly represented.

One of the most difficult problems in statistical analysis is figuring out the sample size that will provide the most reliable findings. Imagine for a moment that the research project requires a bigger number of participants. Under such circumstances, the results will not be trustworthy and will not accurately represent the characteristics of the population as a whole (Collis & Hussey, 2013). A sample size that is too large, on the other hand, may result in a significant increase in the amount of money needed to carry out the research and the length of time required to complete it. Consequently, it is necessary to take into account both of these aspects.

With larger sample sizes, on the other hand, error margins were lowered, and results were achieved. Collecting data from a larger percentage of the population would result in achieving these advantages. It is optional to take into consideration every single person being targeted to get the best possible outcome, despite the fact that the study was conducted using a large sample size. This study aimed to collect data from a sample of all users of e-commerce websites in India who also communicate with customer executives. The sample consisted of users who utilize chatbots and interact with customer executives. Establishing the population's representativeness requires careful consideration of both the sample design and the sample size.

There are several different approaches to determining the appropriate sample size in research. The following will find a formula often used to calculate sample size.

It is equal to $N = (Z^2 * p * q) / S.E^2$

The number z represents the z value for the relevant confidence interval, the letter P stands for the probability that the event will occur, the letter Q stands for the chance that the event will not occur ($q=1-p$), and the letter SE stands for the margin of error that is wanted. It is recommended that a confidence interval of 95% be used for this study. That confidence interval has a z-value of 1.96, which corresponds to it. When the probability of the event occurring is unknown, it is considered to be half of what it would be otherwise. This is a conservative assumption in which we assume that the probability of an event occurring is 50 per cent, and the margin of error is to be limited to a maximum of 5 percent of the number that was initially calculated., then the sample size is calculated as-

$$N = (1.96 * 1.96 * 0.5 * 0.5) / (0.05 * 0.05)$$

$$N = 384.16.$$

Hence, this research's desired sample size should be at least 385.

However considering the previous studies and to have better representation of the population, out of the 900 samples collected for this research, the qualified sample size of N= 722 samples are used.

3.4 Measurement and Instrument

The collection of primary data was accomplished via the use of a questionnaire that was both well-structured and closed-ended. Conversation quality, Perceived Anthropomorphism, flexibility, controllability, Ease of Use, customer characteristics, and customer engagement are the questions that are included in the questionnaire.

On a Likert scale that ranges from one (1) to five (5), with one (1) representing "strongly disagree" and five (5) representing "strongly agree," the respondents were asked to rate the statements. This scale is intended to be described as an interval scale

Questionnaire Design: -

A list of questions that the researcher has developed has been included in a questionnaire. These questions are based on the objectives of the study. In order to collect the information that was looked for in line with the objectives of the study, a structured questionnaire was developed. The questions that were included in the questionnaire were formulated concerning the existing study that related to the study (Seymour Sudman, 1998). Specifically, the questionnaire has been divided into three sections. According to Malhotra (2007), the Likert scale as a rating scale may be conceptualized as "the widely used rating scale that requires the respondents to indicate the degree of agreement with each of the series of statements about the particular variable."

Marketing and business research are two areas that use the Likert scale, a five-point scale with a range of 1 (strongly disagree) to 5 (strongly agree). Thus, the questionnaire used by the study is divided into three parts, shown in Table 3.1.

Table 3.1: Summary of Research Instrumentation

	Part A	Part B
	Demographic Profile	Antecedents of customer engagement
Total No. of Questions	10	31
Scale of Measurement	Nominal	Interval Scale
Scale Type	Multiple Choice Questions	Likert

The measurement items/scales are adopted from the existing scales as mentioned in table 3.2.

Table 3.2: The measurement items and their sources

Construct	Measurement items	Source
Conversation quality	The Chatbot/ Customer executive provided good-quality information.	(Hsieh & Lee, 2021; Borsci et al., 2022)
	The information provided by the Chatbot/ Customer executive was helpful regarding my questions/problems	
	The Chatbot/ Customer executive provided responses to queries as I asked	
	The Chatbot/ Customer executive gave me the appropriate amount of information.	
	The Chatbot/ Customer executive responses were accurate.	
Perceived Anthropomorphism	I experienced a feeling of warmth with Chatbot/ Customer executive.	(Moriuchi, 2020; Klein & Martinez, 2022)
	I experienced friendliness with Chatbot/ Customer executive.	

	Interaction with Chatbot/ Customer executive gave me a feeling of personal communication	
	Chatbot/ Customer executive was logical towards me during the interactions.	
	Chatbot/ Customer executive behaved emotionally during the interactions.	
Flexibility	I feel that Chatbot/ Customer executive were adaptable to the situation.	(Cheng & Jiang, 2022; Borsci et al. 2022)
	It was easy to explain the Chatbot/ Customer executive what I wanted.	
	I found it easy to start a conversation with the Chatbot/ Customer executive.	
	Chatbot/ Customer executive were available every time to solve my queries.	
Controllability	I felt secured while communication with Chatbot/ Customer executive.	(Mostafa&Kasamani,2022; Cheng & Jiang, 2022)
	The Chatbot/ Customer executive were dependable.	

	The Chatbot/ Customer executive were trustworthy.	
	The Chatbot/ Customer executive was honest	
	The Chatbot/ Customer executive was user-friendly	
Ease of Use	My interaction with Chatbot/ Customer executive was understandable.	(Mostafa & Kasamani, 2022; Pillai & Sivathanu, 2020)
	I find interacting with Chatbot/ Customer executive was user-friendly.	
	It was easy to gain expertise in interacting with Chatbot/ Customer executive.	
	The process of interacting with Chatbot/ Customer executive was effortless.	
	Chatbot/ Customer executive was efficient.	
Customer Characteristics		
Customer inertia	I intend to use Chatbot/ Customer executive services the next time for my queries.	Mostafa & Kasamani, (2022)

	I consider Chatbot/ Customer executive to be a single point of contact for my queries.	
	Chatbot/ Customer executive are important to me for my queries.	
Satisfaction	I am satisfied with Chatbot/ Customer executive services.	Klein et al. (2022)
	The Chatbot/ Customer executive performed as expected.	
	The Chatbot/ Customer executive made me happy when I interacted with them.	
Attitude	It was fun to interact with Chatbot/ Customer executive.	Klein et al., (2022)
	The Chatbot/ Customer executive gave me an impression of friendliness.	
	The experience of interacting with the Chatbot/ Customer executive was positive.	
Motivation	I can enrich my knowledge through Chatbot/ Customer executive.	(Teng, C. I. 2018; Mohd Rahim et al. 2022)

	Interacting with Chatbot/ Customer executive gave me pleasure	
	Interacting with Chatbot/ Customer executive was exciting.	
Customer engagement	I encourage friends and relatives to buy from an e-commerce site's that employs a Chatbot/ Customer executive.	(Mostafa & Kasamani, 2022; Rather & Sharma, 2016)
	An e-commerce sites that employs Chatbot/ Customer executive is my first choice when buying.	
	I am likely to revisit the e-commerce sites that have Chatbot/ Customer executive.	
	If they employ Chatbot/ Customer executive, I would say positive things about those e-commerce sites to others.	
	I will maintain my relationship with those e-commerce sites that employ Chatbot/ Customer executive.	

Source: Adapted by researcher

3.4.1 Reliability and Validity

Reliability is a word used to characterize the consistency, stability, and dependability of an instrument used for measuring or evaluating something. To put it another way, it is the assessment of whether or not the results of a test are trustworthy and can be replicated under various conditions.

Cronbach's alpha (α) is a measurement of reliability that may be defined as the average of all possible split-half coefficients that result from various splitting of scale items. This is accomplished via the use of advanced software.

Cronbach's alpha, more often known as simply alpha, is a statistic generally used to determine the internal consistency reliability of a scale or test. This particular coefficient was developed by Lee Cronbach in 1951. Its purpose is to evaluate the degree to which a group of questions in a scale or test accurately reflect a single conceptual construct. According to George and Mallery (2011), Cronbach's alpha values are greater than 0.70 ($\alpha > 0.70$) and values greater than 0.70 are considered an appropriate match for the reliability of the construct. Moreover, it is important to note that Cronbach's alpha (α) value measures the internal consistency for different instrument constructions, calculated using the statistical applications SPSS 21.0.

The range of Cronbach's alpha (α) values for all the constructions includes values ranging from 0.70 to 0.90. Consequently, the reliability of the questionnaire has been checked out, and it is now suitable for further research. In order to guarantee that measuring scales are accurate, a comprehensive compilation of all types of reliability and validity has been carried out. Questionnaire structures have been subjected to extensive testing and validation to ensure reliability, and they have been applied in future studies. All possible forms of validity and reliability have been considered to guarantee that the measuring scales are accurate.

The following measures were used to establish validity and reliability.

- “Composite Reliability (CR)”
- “rho_A”

- “Cronbach’s alpha”
- “Average Variance Extracted (AVE)”
- “Heterotrait-monotrait (HTMT) ratio”

Table 3.3a: Reliability Analysis of the Instrument (for customer executives)

Construct	Item	Outer loading	AVE	CR	Cronbach's alpha	rho_A
Controllability	C1	0.777	0.672	0.891	0.837	0.84
	C2	0.827				
	C3	0.843				
	C4	0.831				
Customer engagement	CE1	0.836	0.702	0.904	0.859	0.864
	CE2	0.811				
	CE3	0.892				
Conversation Quality	CQ1	0.792	0.675	0.912	0.879	0.88
	CQ2	0.857				
	CQ3	0.81				
Flexibility	F1	0.773	0.539	0.778	0.731	0.742
	F2	0.717				
	F3	0.711				
Perceived anthropomorphism	PA1	0.876	0.688	0.868	0.773	0.793
	PA2	0.84				
	PA3	0.769				
Ease of Use	PEU1	0.769	0.622	0.868	0.796	0.803
	PEU2	0.866				
	PEU3	0.764				
Customer Characteristics	CCA1	0.832	0.692	0.871	0.777	0.778
	CCA2	0.837				
	CCA3	0.826				
	CCC1	0.826	0.681	0.865	0.766	0.767
	CCC2	0.815				
	CCC3	0.836				
	CCM1	0.79	0.702	0.876	0.787	0.786
	CCM2	0.873				
	CCM3	0.849				
	CCS1	0.861	0.717	0.884	0.803	0.804
	CCS2	0.846				
CCS3	0.833					

Table 3.3b: Reliability Analysis of the Instrument (for chatbots)

Construct	Item	Outer loading	AVE	CR	Cronbach's alpha	rho_A
Controllability	C1	0.771	0.595	0.815	0.742	0.743
	C2	0.74				
	C3	0.802				
Customer engagement	CE1	0.802	0.628	0.835	0.704	0.709
	CE2	0.825				
	CE3	0.749				
Conversation Quality	CQ1	0.8	0.624	0.869	0.799	0.802
	CQ2	0.824				
	CQ3	0.78				
Flexibility	F1	0.755	0.568	0.797	0.751	0.752
	F2	0.808				
	F3	0.694				
Perceived Anthropomorphism	PA1	0.829	0.686	0.868	0.771	0.773
	PA2	0.852				
	PA3	0.804				
Ease of Use	PEU1	0.79	0.639	0.898	0.86	0.871
	PEU2	0.768				
	PEU3	0.798				
Customer Characteristics	CCA1	0.834	0.669	0.858	0.752	0.752
	CCA2	0.833				
	CCA3	0.8				
	CCC1	0.819	0.644	0.844	0.722	0.728
	CCC2	0.749				
	CCC3	0.837				
	CCM1	0.751	0.649	0.847	0.728	0.732
	CCM2	0.804				
	CCM3	0.859				
	CCS1	0.868	0.687	0.868	0.772	0.777
CCS2	0.781					
CCS3	0.835					

3.4.2 Validity

The evaluation of the validity of a questionnaire is one of the most important processes that come into play while doing research (Malhotra & Dash, 2011). At this step, it is ensured that the instrument is measuring the construct or variable being studied correctly. The questionnaires were evaluated by academicians and marketing professionals with extensive knowledge and experience in this study area. Furthermore,

to get more reliable findings, suggestions are given based on the development of a scale. In addition to these recommendations, the scale should be increased, guidance should be provided for selecting the parameters, and suggestions should be made to maintain the language as easily as possible. In addition, repeated questions and grammatical errors are recommended to be eliminated from the questionnaire to make it simpler for respondents to understand and meet their requirements.

Table 3.4: Validity analysis

S. No	Name of the Respondent	Affiliation	Remarks
1	Dr Deepak Pandey	Professor, IILM University, School of Management, Gurugram.	<ul style="list-style-type: none"> ● It was suggested removing the repeated questions ● The Second part of the Questionnaire seems reasonable.
2	Dr. Amit Kakkar	Professor, Mittal School of Business, Lovely Professional University, Punjab.	<ul style="list-style-type: none"> ● It was suggested to rephrase certain questions. ● To correct few statements with tense and rewording for clarity.
3	Dr. Gautam Bhat	Associate Professor, Dr. Vishwanath Karad MIT World Peace University, Pune.	<ul style="list-style-type: none"> ● It was suggested to modify the questions, ● Few questions were repeated and changed.
4	Dr. Priyanka Nema	Associate Professor, Faculty of Management and Commerce Jagran Lakecity University, Bhopal	<ul style="list-style-type: none"> ● Some statements provide similar meanings. See the possibility of reducing the repetitions.

5	Dr. Shabnam Narula Gulati	Associate Professor, Mittal School of Business, Lovely Professional University, Punjab.	<ul style="list-style-type: none"> ● Remove unnecessary (, and.) ● Add they are in the question sentence ● Give numbering to all options for every question
6	Dr Rajashekarreddy P	Assistant Professor, Department of Marketing and Strategy, ICFAI Business School	<ul style="list-style-type: none"> ● Too many categories in Q.No.-5 ● Remove those statements that are repeated and convey the same meaning.
7	Dr. Nagraja P	Principal, Professor, Dr. B R Ambhedkar MBA College, Hyderabad.	<ul style="list-style-type: none"> ● Remove those statements that are repeated and convey the same meaning. ● Correct grammatical errors.
8	Ms. Vibha Gupta	General Manager, Power Automation, Siemens India.	<ul style="list-style-type: none"> ● Remove repetitions and add a few questions.
9	Mr. CBM Bhooshan	Executive Director, Acharya Institutes, Bangalore	<ul style="list-style-type: none"> ● Remove those statements that are repeated and convey the same meaning. ● Correct grammatical errors.
10	Mr. Deepak Pandey	Senior Director, Digital Grid, GE India.	<ul style="list-style-type: none"> ● Some statements provide similar meanings. See the possibility of reducing the repetitions. ● Correct grammatical errors

3.4.3 Pre-testing: Pilot study

An assessment and evaluation of the validity of each question is carried out throughout the pilot testing stage. It is essential to determine whether or not the question correctly measures the information it seeks to investigate in this context. As a result, in addition to achieving the objectives and goals outlined for the research study, it is essential to analyze the many components composing the questionnaire. Examining the flow of the questions is one of these distinctive characteristics. (Blumberg et al., 2014) Before the researchers can use the questionnaire in the process of data collecting, they need to conduct pilot studies using the questionnaire.

In order to successfully carry out a pilot study, it is necessary to choose a small number of participants that are representative of the total population under study (Bryman, 2012).

According to Kristin and Silverstein (2015), the purpose of the pilot testing is to find challenges associated with reading the content in question, locate unclear instructions, and inquire about questions that cause difficulty for the participants.

Along the same lines, before developing the final questionnaire for the respondents, during the pilot testing stage, any possible flaws in the original draft of the questionnaire should be detected and addressed, and the measures should be fine-tuned and improved. This takes place before the final questionnaire is developed. This will ensure that the questionnaire is as accurate as possible. Consequently, the researchers conducted a pilot study with one hundred participants, representing more than ten per cent of the sample size. The completion of the questionnaire was an expectation that was placed on every responder. In addition, they provide input about the arrangement and flow of the questionnaire and evaluations concerning the readability and correctness of the questions. Consequently, the study got valuable information from the respondents who participated in the pilot study and later revised the questionnaire to include input.

The study has modified and removed a few questions. The suggestions that helped the researcher to clear the different kinds of doubts are as follows:

- Identification of uncertain questions.
- Identification of the difficulty level of the questionnaire.
- Identification of objections to any particular question.
- Recognition to add something to the questionnaire.

3.5 Hypothesis Formulation

In the context of a study, the word "hypothesis" refers to a particular assertion or prediction that may be tested about the connection between two or more variables (Kistin & Silverstein, 2015). Considering the experiment, one may argue that this is either a claim or an assumption. When formulating a hypothesis, it is important to ensure that one's claims are clear and accurate. The hypothesis not only provides the specifications for the information that must be gathered and the questions that must be answered in the questionnaire but also outlines the scope of the research.

The hypothesis is an untested suggestion for a decision problem that may be empirically explored based on facts gathered throughout the research (Singh, 2006). This can be done based on the findings that were obtained.

The research hypotheses were informed by the conceptual framework, literature study, conversations on past work, and field experience. By participating in the study, users contributed ideas, theories, concepts, results, and conclusions from various studies and experiments to the hypothesis being tested.

The following is a list of the hypotheses that were developed for the investigation to conclude the population that was being researched:

Customer Engagement

Direct Assessment

H.1a.1: "There is a significant relationship between Controllability to customer engagement"

H.1a.2: "There is a significant relationship between Conversation Quality to customer engagement"

H.1a.3: "There is a significant relationship between Flexibility to customer engagement"

H.1a.4: "There is a significant relationship between Perceived anthropomorphism to customer engagement"

H.1a.5: "There is a significant relationship between Controllability to Ease of Use"

H.1a.6: “There is a significant relationship between Conversation Quality to Ease of Use”

H.1a.7: “There is a significant relationship between Flexibility to Ease of Use”

H.1a.8: “There is a significant relationship between Perceived anthropomorphism to Ease of Use”

H.1a.9: There is a significant relationship between Controllability to Customer Characteristics

H.1a.10: “There is a significant relationship between Conversation Quality to Customer Characteristics”

H.1a.11: “There is a significant relationship between Flexibility to Customer Characteristics”

H.1a.12: “There is a significant relationship between Perceived anthropomorphism to Customer Characteristics”

H.1a.13: “There is a significant relationship between Customer characteristics to Customer engagement.”

H.1a.14: “There is a significant relationship between Ease of Use to customer engagement”

H.1a.15: “There is a significant relationship between Customer characteristics to Attitude”

H.1a.16: “There is a significant relationship between Customer characteristics to Customer inertia.”

H.1a.17: “There is a significant relationship between Customer characteristics to motivation.”

H.1a.18: “There is a significant relationship between Customer characteristics to Satisfaction.”

Indirect Assessment

H.2a.1: “There is a significant mediation relationship between Ease of Use in Conversation quality to customer engagement”

H.2a.2: “There is a significant mediation relationship between Ease of Use in Flexibility to customer engagement”

H.2a.3: “There is a significant mediation relationship between Ease of Use in Perceived Anthropomorphism to customer engagement”

H.2a.4: “There is a significant mediation relationship between Ease of Use in Controllability to customer engagement”

H.2a.5: “There is a significant mediation relationship between Customer characteristics in Conversation quality to customer engagement”

H.2a.6: “There is a significant mediation relationship between Customer characteristics in Flexibility to customer engagement”

H.2a.7: “There is a significant mediation relationship between Customer characteristics in Perceived Anthropomorphism to customer engagement”

H.2a.8: “There is a significant mediation relationship between Customer characteristics in Controllability to customer engagement”

Moderation Hypothesis

H.3a.1: “There is a significant moderating role of Reason in between the Perceived Anthropomorphism to Ease of Use.”

H.3a.2: “There is a significant moderating role of Reason in between the Conversation Quality to Ease of Use.”

H.3a.3 : “There is a significant moderating role of Reason in between the Flexibility to Ease of Use.”

H.3a.4: “There is a significant moderating role of Reason in between the Controllability to Ease of Use.”

H.3a.5; “There is a significant moderating role of Conversation Duration in between the Perceived Anthropomorphism to Ease of Use.”

H.3a.6: “There is a significant moderating role of Conversation Duration in between the Conversation Quality to Ease of Use.”

H.3a.7: “There is a significant moderating role of Conversation Duration in between the Flexibility to Ease of Use.”

H.3a.8: “There is a significant moderating role of Conversation Duration in between the Controllability to Ease of Use.”

H.3a.9: “There is a significant moderating role of User Expertise in between the Perceived Anthropomorphism to Ease of Use.”

H.3a.10: “There is a significant moderating role of User Expertise in between the Conversation Quality to Ease of Use.”

H.3a.11: “There is a significant moderating role of User Expertise in between the Flexibility to Ease of Use.”

H.3a.12: “There is a significant moderating role of User Expertise in between the Controllability to Ease of Use.”

H.3a.13: “There is a significant moderating role of Reason in between the Perceived Anthropomorphism to Customer characteristics.”

H.3a.14: “There is a significant moderating role of Reason in between the Conversation Quality to Customer characteristics.”

H.3a.15: “There is a significant moderating role of Reason in between the Flexibility to Customer characteristics.”

H.3a.16: “There is a significant moderating role of Reason in between the Controllability to Customer characteristics.”

H.3a.17: “There is a significant moderating role of Conversation Duration in between the Perceived Anthropomorphism to Customer characteristics.”

H.3a.18: “There is a significant moderating role of Conversation Duration in between the Conversation Quality to Customer characteristics.”

H.3a.19: “There is a significant moderating role of Conversation Duration in between the Flexibility to Customer characteristics.”

H.3a.20: “There is a significant moderating role of Conversation Duration in between the Controllability to Customer characteristics.”

H.3a.21: “There is a significant moderating role of User Expertise in between the Perceived Anthropomorphism to Customer characteristics.”

H.3a.22: “There is a significant moderating role of User Expertise in between the Conversation Quality to Customer characteristics.”

H.3a.23: “There is a significant moderating role of User Expertise in between the Flexibility to Customer characteristics.”

H.3a.24: “There is a significant moderating role of User Expertise in between the Controllability to Customer characteristics.”

Additional Hypothesis for Assessment of moderation on customer engagement with respect to Customer Executives

H.3a.1.1: “There is a significant moderating role of Reason in between the Perceived Anthropomorphism to customer engagement”

H.3a.1.2: “There is a significant moderating role of Reason in between the Conversation Quality to customer engagement”

H.3a.1.3 : “There is a significant moderating role of Reason in between the Flexibility to customer engagement”

H.3a.1.4: “There is a significant moderating role of Reason in between the Controllability to customer engagement”

H.3a.1.5; “There is a significant moderating role of Conversation Duration in between the Perceived Anthropomorphism to customer engagement”

H.3a.1.6: “There is a significant moderating role of Conversation Duration in between the Conversation Quality to customer engagement”

H.3a.1.7: “There is a significant moderating role of Conversation Duration in between the Flexibility to customer engagement”

H.3a.1.8: “There is a significant moderating role of Conversation Duration in between the Controllability to customer engagement”

H.3a.1.9: “There is a significant moderating role of User Expertise in between the Perceived Anthropomorphism to customer engagement”

H.3a.1.10: “There is a significant moderating role of User Expertise in between the Conversation Quality to customer engagement”

H.3a.1.11: “There is a significant moderating role of User Expertise in between the Flexibility to customer engagement”

H.3a.1.12: “There is a significant moderating role of User Expertise in between the Controllability to customer engagement”

Chatbots

Direct Assessment

H.1b.1: “There is a significant relationship between Controllability to customer engagement”

H.1b.2: “There is a significant relationship between Conversation Quality to customer engagement”

H.1b.3: “There is a significant relationship between Flexibility to customer engagement”

H.1b.4: “There is a significant relationship between Perceived anthropomorphism to customer engagement”

H.1b.5: “There is a significant relationship between Controllability to Ease of Use”

H.1b.6: “There is a significant relationship between Conversation Quality to Ease of Use”

H.1b.7: “There is a significant relationship between Flexibility to Ease of Use”

H.1b.8: “There is a significant relationship between Perceived anthropomorphism to Ease of Use”

H.1b.9: “There is a significant relationship between Controllability to Customer Characteristics”

H.1b.10: “There is a significant relationship between Conversation Quality to Customer Characteristics”

H.1b.11: “There is a significant relationship between Flexibility to Customer Characteristics”

H.1b.12: “There is a significant relationship between Perceived anthropomorphism to Customer Characteristics”

H.1b.13: “There is a significant relationship between Customer characteristics to Customer engagement.”

H.1b.14: “There is a significant relationship between Ease of Use to customer engagement”

H.1b.15: “There is a significant relationship between Customer characteristics to Attitude”

H.1b.16: “There is a significant relationship between Customer characteristics to Customer inertia.”

H.1b.17: “There is a significant relationship between Customer characteristics to motivation.”

H.1b.18: “There is a significant relationship between Customer characteristics to Satisfaction.”

Indirect Assessment

H.2b.1: “There is a significant mediation relationship between Ease of Use in Conversation quality to customer engagement”

H.2b.2: “There is a significant mediation relationship between Ease of Use in Flexibility to customer engagement”

H.2b.3: “There is a significant mediation relationship between Ease of Use in Perceived Anthropomorphism to customer engagement”

H.2b.4: “There is a significant mediation relationship between Ease of Use in Controllability to customer engagement”

H.2b.5: “There is a significant mediation relationship between Customer characteristics in Conversation quality to customer engagement”

H.2b.6: “There is a significant mediation relationship between Customer characteristics in Flexibility to customer engagement”

H.2b.7: “There is a significant mediation relationship between Customer characteristics in Perceived Anthropomorphism to customer engagement”

H.2b.8: “There is a significant mediation relationship between Customer characteristics in Controllability to customer engagement”

Moderation Hypothesis

H.3b.1: “There is a significant moderating role of Reason in between the Perceived Anthropomorphism to Ease of Use.”

H.3b.2: “There is a significant moderating role of Reason in between the Conversation Quality to Ease of Use.”

H.3b.3 : “There is a significant moderating role of Reason in between the Flexibility to Ease of Use.”

H.3b.4: “There is a significant moderating role of Reason in between the Controllability to Ease of Use.”

H.3b.5: “There is a significant moderating role of Conversation Duration in between the Perceived Anthropomorphism to Ease of Use.”

H.3b.6: “There is a significant moderating role of Conversation Duration in between the Conversation Quality to Ease of Use.”

H.3b.7: “There is a significant moderating role of Conversation Duration in between the Flexibility to Ease of Use.”

H.3b.8: “There is a significant moderating role of Conversation Duration in between the Controllability to Ease of Use.”

H.3b.9: “There is a significant moderating role of User Expertise in between the Perceived Anthropomorphism to Ease of Use.”

H.3b.10: “There is a significant moderating role of User Expertise in between the Conversation Quality to Ease of Use.”

H.3b.11: “There is a significant moderating role of User Expertise in between the Flexibility to Ease of Use.”

H.3b.12: “There is a significant moderating role of User Expertise in between the Controllability to Ease of Use.”

H.3b.13: “There is a significant moderating role of Reason in between the Perceived Anthropomorphism to Customer characteristics.”

H.3b.14: “There is a significant moderating role of Reason in between the Conversation Quality to Customer characteristics.”

H.3b.15: “There is a significant moderating role of Reason in between the Flexibility to Customer characteristics.”

H.3b.16: “There is a significant moderating role of Reason in between the Controllability to Customer characteristics.”

H.3b.17: “There is a significant moderating role of Conversation Duration in between the Perceived Anthropomorphism to Customer characteristics.”

H.3b.18: “There is a significant moderating role of Conversation Duration in between the Conversation Quality to Customer characteristics.”

H.3b.19: “There is a significant moderating role of Conversation Duration in between the Flexibility to Customer characteristics.”

H.3b.20: “There is a significant moderating role of Conversation Duration in between the Controllability to Customer characteristics.”

H.3b.21: “There is a significant moderating role of User Expertise in between the Perceived Anthropomorphism to Customer characteristics.”

H.3b.22: “There is a significant moderating role of User Expertise in between the Conversation Quality to Customer characteristics.”

H.3b.23: “There is a significant moderating role of User Expertise in between the Flexibility to Customer characteristics.”

H.3b.24: “There is a significant moderating role of User Expertise in between the Controllability to Customer characteristics.”

Additional Hypothesis for Assessment of moderation on customer engagement with respect to Chatbots

H.3b.1.1: “There is a significant moderating role of Reason in between the Perceived Anthropomorphism to customer engagement

H.3b.1.2: “There is a significant moderating role of Reason in between the Conversation Quality to customer engagement”

H.3b.1.3: “There is a significant moderating role of Reason in between the Flexibility to customer engagement”

H.3b.1.4: “There is a significant moderating role of Reason in between the Controllability to customer engagement”

H.3b.1.5: “There is a significant moderating role of Conversation Duration in between the Perceived Anthropomorphism to customer engagement”

H.3b.1.6: “There is a significant moderating role of Conversation Duration in between the Conversation Quality to customer engagement”

H.3b.1.7: “There is a significant moderating role of Conversation Duration in between the Flexibility to customer engagement”

H.3b.1.8: “There is a significant moderating role of Conversation Duration in between the Controllability to customer engagement”

H.3b.1.9: “There is a significant moderating role of User Expertise in between the Perceived Anthropomorphism to customer engagement”

H.3b.1.10: “There is a significant moderating role of User Expertise in between the Conversation Quality to customer engagement”

H.3b.1.11: “There is a significant moderating role of User Expertise in between the Flexibility to customer engagement”

H.3b.1.12: “There is a significant moderating role of User Expertise in between the Controllability to customer engagement”

3.6 Ethical Consideration

None of the participants were forced to participate in the questionnaire filing process; instead, they consented to answer questions. They felt secure knowing their private information would not be revealed. Before the survey, the participants were informed about the study's objective and potential benefits. This made the reported findings more accurate.

CHAPTER - 4
DATA ANALYSIS

CHAPTER – 4

DATA ANALYSIS AND INTERPRETATION

4. Introduction

The analysis of the data collected, the outcome, and the conclusion established due to the interpretation of the data examined are the essential core of the research process.

After collecting primary data relevant to the study, the researcher used software such as SPSS 21 to analyze and interpret the findings. In this chapter, which focuses on the analytical aspect of the research carried out, the primary emphasis is on doing a comparative analysis of customer interaction via chatbots and customer executives. The data analysis has been done using appropriate statistical tests with the help of statistical tools such as Smart PLS 4.0 to validate the theoretical model.

The first part of this chapter is dedicated to doing an initial data analysis, explicitly identifying outliers and assessing normality. Afterwards, an investigation into the validity and precision of the measuring scale is presented, followed by the demographic details of the study's participants. Therefore, using appropriate statistical techniques ensures substantial support for all the proposed hypotheses. Finally, data analysis is conducted to assess the extent to which the study objectives have been achieved. Nevertheless, this chapter focuses primarily on verifying the model using advanced statistical techniques and instruments such as Smart PLS 4.0.

4.1 Preliminary Examination of the Data

In order to collect the necessary information for this research, a questionnaire in the form of a survey was sent to the participants. Despite this, Howell (2008) states that when survey approaches are used, it is common to have unanswered questions, leading to a lack of data. This scenario may play out if a respondent does not answer at least one of the questions on the questionnaire. As a direct result, the questionnaire's results cannot be examined.

Banerjee and Chaudhury (2010), on the other hand, indicated that the challenge may be overcome if the researcher collects a more significant number of genuine questionnaires than the permissible number of respondents in order to get survey information that is

accurate and reliable. Because of this, the researcher can get more information on the population that is the focus of the particular study. As a result, statistical analysis can achieve a higher accuracy level. The analysis, on the other hand, only used 722 of the 900 questionnaires used in this study. The total number of participants in this research are 722. The questionnaire had missing responses, and invalid responses were henceforth not considered. As a result, the number of collected questionnaires was sufficient to finish all the work required to achieve the study's objectives.

This data was examined to see normal distribution and to identify any outlier. This was done to prepare the data that was suitable for study.

4.2 Demographic Profile

In addition, frequency distribution analysis is used based on the demographic profile of customers of e-commerce websites who interact with chatbots and customer executives. This profile includes information such as the distribution of ages, genders, levels of education, the duration of conversations, and the purposes of the interactions.

The respondents were asked multiple-choice questions, which researcher designed to acquire background information from them. The demographics of the respondents are shown in Table 4.1. According to the findings of this research, data was obtained from 722 people in India between January 2024 and April 2024. This study includes demographic profiles, which may be seen in Table 4.1.

Table 4.1: Details of customers of e-commerce websites Profile (N=722)

	Items'	Frequency	Percentage (%)
Gender	Male	457	63.3
	Female	265	36.7
	Total	722	100.0
Age	18-25	481	66.6
	26-35	109	15.1
	36-45	106	14.7
	Above 45	26	3.6
	Total	722	100.0
Education	High school or below	28	3.9
	Intermediate	9	1.2
	Bachelor	570	78.9
	Master's & Above	115	15.9
	Total	722	100.0
User Expertise	Low	173	24.0
	Medium	473	65.5
	High	76	10.5
	Total	722	100.0
Conversation Duration	Short	259	35.9
	Average	421	58.3
	Long	42	5.8
	Total	722	100.0
Reason	Information	206	28.5
	Complaint	439	60.8
	Feedback	77	10.7

	Total	722	100.0
UCT	Pre-purchase/Information stage	155	21.5
	Purchase Stage	126	17.5
	Post Purchase stage	441	61.1
	Total	722	100.0

From January 2024 to April 2024, this study gathered responses (data) from 722 respondents who were customers of e-commerce websites in India. The complete demographic details of the respondents are presented in Figure 4.1, which is explored further in this section. The descriptive data revealed more male respondents (63.3%) than female respondents (36.7%). According to this survey, male and female customers differ slightly.

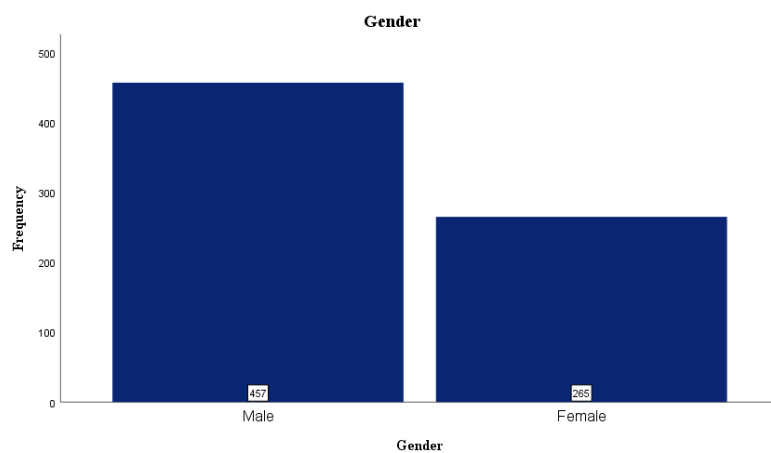


Figure 4.1: Gender

In addition, Figure 4.2 presents the Age of the respondents. According to the above characteristics, 66.6% comprises members aged 18-25. In comparison, 15.1 % of the population comprises members between the ages of 26 and 35. Therefore, the number of e-commerce users aged 18-25 is significantly higher than that of 26-35 and 36-45.

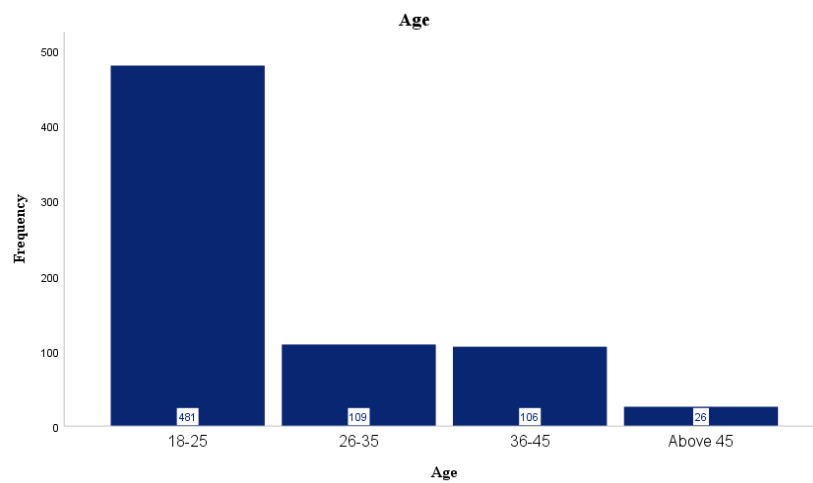


Figure 4.2: Age

Figure 4.3 illustrates the statistics that relate to the respondents' levels of education as a whole. Again, most respondents indicated that they had a Bachelor's degree which was 78.9%, followed by a master's degree, which was 15.9%, and then a High school or below, which was 3.9%.

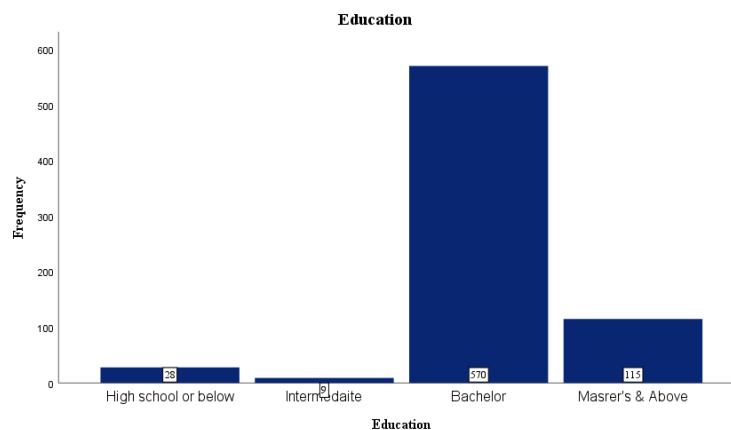


Figure 4.3: Education

In Figure 4.4, the data that pertain to the levels of interaction that the respondents had with e-commerce websites are shown. Once again, most respondents (65.5%) reported having a medium interaction, followed by a low interaction (24.0%), and then 10.5% of the respondents reported having a high interaction.

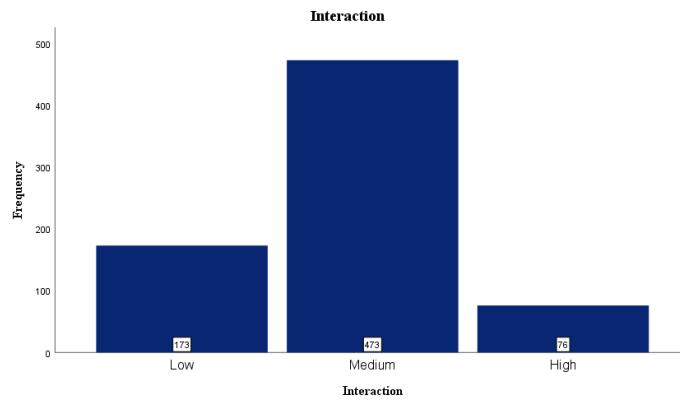


Figure 4.4: Interaction with e-Commerce websites

The information shown in Table 4.5 makes it clear that out of 722 respondents, 421 (58.3 per cent) said they had spent an average duration, while the remaining 259 (35.9 per cent) had a short duration.

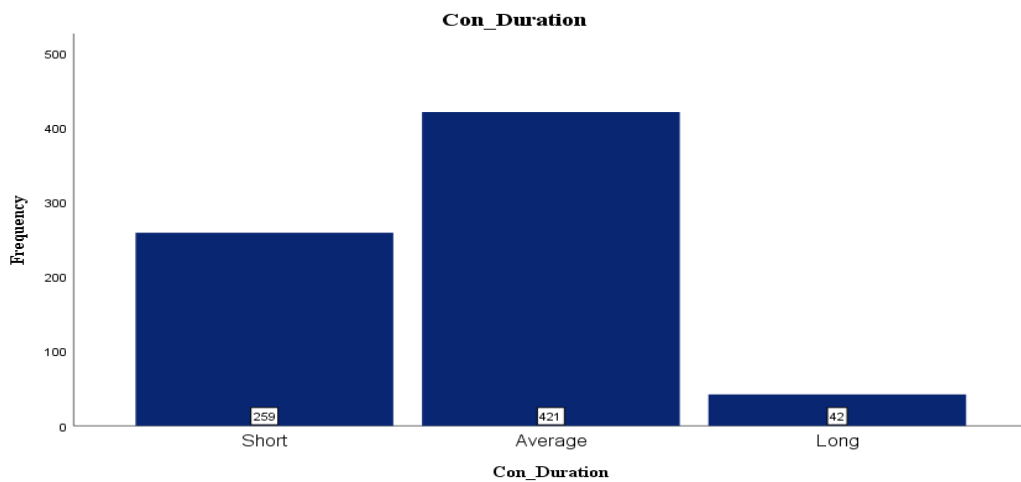


Figure 4.5: conversation duration

An illustration of the data related to the respondents' reasons for interacting is shown in Figure 4.6. Most respondents, 60.80%, said they had connected to complain. In comparison, 28.5% stated that they had done so to get information, and 10.7% claimed that they had interacted to provide feedback.

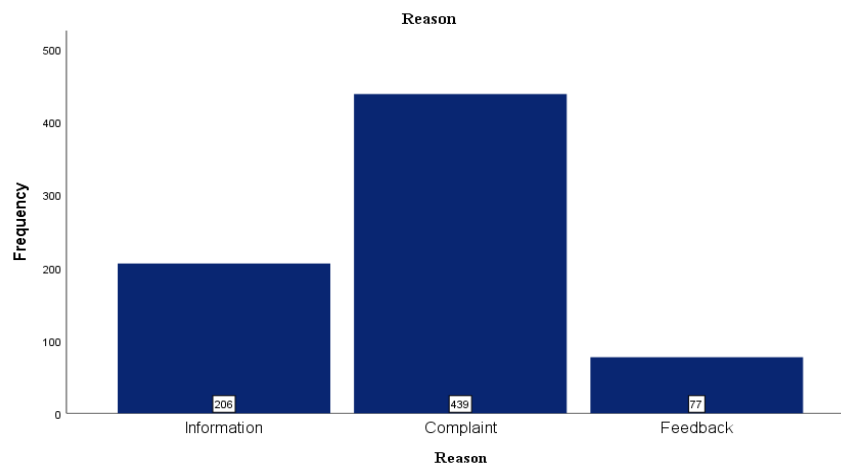


Figure 4.6: Reason for interaction

4.3 Conceptual Model Analysis

SmartPLS has been utilized to construct the model to validate and test the hypothesis. It allows users to easily conduct PLS-SEM (partial least square Structural equation modelling) with a user-friendly design interface. It also runs on the most advanced and powerful algorithms, allowing researchers to run complex models with multivariate data. Conducting data analysis using multivariate gives the researchers huge disadvantages, but SmartPLS runs on both the Variance and Covariance SEM approach. This gives researchers a huge advantage in conducting studies in multiple fields.

Furthermore, it is a step for the researchers to quality, construct, validate, and hypothesize, such as bootstrap, PLS_predict, mediation and moderation analysis, even the Multigroup analysis and much more with the help of SmartPLS. The main advantage of using SmartPLS is its GUI, which allows users to understand, create, and estimate path models easily. The current study has collected data from 722 respondents where the same participant has filled the data for both Customer executive and Chatbot. The data analysis was conducted in two parts. The researcher conducted the test run in two parts: constructing the model, validating it, and conducting reliability analysis and hypothesis testing separately for these two data sets.

4.3.1 Customer Executive:

4.3.1.1 Data Validation:

We are utilizing the Smart-PLS to test the normality of the data to understand and construct a model to predict accurately. Most of the values of Kurtosis and Skewness lie in between the range of -1 to +1. However, some parts of the data exhibit abnormal behaviour as kurtosis is on the positive side; meanwhile, all the Cramér-von Mises p-values have also shown significance, which does not suggest that the data is normal or non-normal. The study has utilised a web-based calculator (Zhang & Yuan, 2018) to test the Multivariate normality by using Mardia's (1970) test, which shows the data has outcome Mardia's Skewness (Beta = 10.56, $p < 0.05$) and Kurtosis (beta = 98.27, $P < 0.05$) suggest that data as non-normality. To predict the constructed model more accurately, a study has adopted SmartPLS, which handles non-normal data very well Hair et al., (2019).

Table 4.2: Customer executive Data Structure and distribution

Name	Mean	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
User Expertise	1.866	0.572	-0.099	-0.001	0
Con_Duration	1.699	0.571	-0.585	0.113	0
Reason	1.821	0.6	-0.4	0.093	0
UCT	2.396	0.818	-0.982	-0.844	0
CQ1	3.446	0.912	0.834	-0.8	0
CQ2	3.474	0.913	0.956	-0.956	0
CQ3	3.706	0.798	1.756	-0.996	0
PA1	3.179	0.949	-0.022	-0.305	0
PA2	3.425	0.862	0.167	-0.379	0
PA3	3.043	0.976	-0.439	-0.283	0
F1	3.382	0.942	0.155	-0.689	0
F2	3.679	0.851	0.25	-0.561	0
F3	3.648	0.876	1.328	-1.008	0
C1	3.432	0.811	0.515	-0.396	0
C2	3.316	0.882	-0.013	-0.334	0
C3	3.489	0.814	0.762	-0.543	0
C4	3.519	0.817	0.42	-0.36	0
PEU1	3.607	0.759	1.399	-0.84	0
PEU2	3.524	0.795	1.325	-0.807	0
PEU3	3.324	0.819	0.546	-0.539	0
CCC1	3.511	0.913	0.671	-0.781	0
CCC2	3.461	0.911	0.259	-0.578	0
CCC3	3.727	0.85	0.897	-0.683	0
CCS1	3.436	0.853	0.515	-0.578	0
CCS2	3.418	0.91	0.299	-0.547	0
CCS3	3.274	0.89	0.392	-0.436	0
CCA1	3.057	0.915	-0.061	-0.297	0
CCA2	3.233	0.858	0.385	-0.506	0
CCA3	3.46	0.871	0.641	-0.709	0
CCM1	3.324	0.928	0.018	-0.364	0
CCM2	2.997	1.007	-0.33	-0.321	0
CCM3	2.983	0.975	-0.221	-0.165	0

CE1	3.578	0.906	0.571	-0.535	0
CE2	3.464	1.026	-0.091	-0.528	0
CE3	3.555	0.912	0.577	-0.544	0

4.3.1.2 Assessment of Construct Validity and Reliability:

To construct a model consisting of both general and higher order constructs as from the below figure:4.7, the study has assessed the constructed model with outer loadings, composite reliability (CR), average variance extracted (AVE) and discriminant validity based on (Hair et al., 2017). Construct validity and reliability are essential for research using Structural equation modelling with SmartPLS (Sepasgozar et al., 2019). Construct validity refers to the degree to accurately measure the instruments (items) used for the theoretical construct it is intended to analyse. At the same time, reliability deals with consistency and stability of measurement over time to produce consistent results. Construct validity refers to the degree to which a measurement instrument accurately measures the theoretical construct, and construct validity refers to ensuring that the instrument measures what it claims to measure. All the outer loadings of the first-order reflective construct are above the minimum threshold value as shown in table no: 4.3, Composite reliability > 0.7 and Cronbach > 0.7. suggest the data has a high degree of internal consistency, and the convergent validity was shown by AVE 0.5 (Hair et al., 2017).

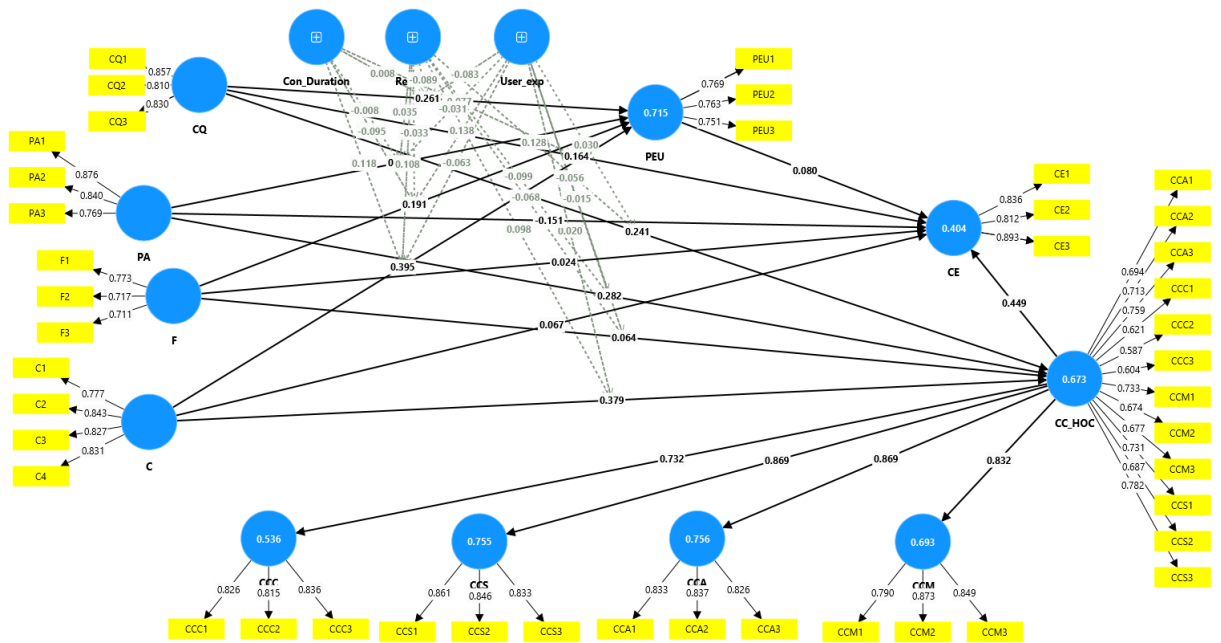


Figure 4.7: Path Analysis Model

To assess the higher-order construct (reflective-reflective) construct. We have assessed the higher-order construct using the PLS algorithm and bootstrapping technique. The VIF and the significance of the indicator and weights were used to determine the reflective-reflective assessment. The VIF values are below the threshold limit of 3.3, suggesting no collinearity issue through bootstrapping. We have assessed the significance of the weights, and the results suggest that all the weights of the indicators are significant at $p < 0.001$ level, demonstrating the relative contribution of constructing a reflective-reflective constructs.

Table 4.3: Construct Validity and reliability

Construct	Item	VIF	T-value	P-value	Outer loading	AVE	CR	Cronbach's alpha	rho_A
Controllability	C1	1.584	39.489	0	0.777	0.672	0.891	0.837	0.84
	C2	1.992	50.262	0	0.827				
	C3	2.175	54.067	0	0.843				
	C4	1.853	62.536	0	0.831				
Customer engagement	CE1	2.023	49.807	0	0.836	0.702	0.904	0.859	0.864
	CE2	2.072	41.321	0	0.811				
	CE3	2.794	89.714	0	0.892				
Conversation Quality	CQ1	1.905	43.934	0	0.792	0.675	0.912	0.879	0.88
	CQ2	2.469	65.437	0	0.857				
	CQ3	1.924	48.183	0	0.81				
Flexibility	F1	1.235	28.023	0	0.773	0.539	0.778	0.731	0.742
	F2	1.199	22.628	0	0.717				
	F3	1.122	24.022	0	0.711				
Perceived anthropomorphism	PA1	1.748	98.055	0	0.876	0.688	0.868	0.773	0.793
	PA2	1.732	51.947	0	0.84				
	PA3	1.425	28.914	0	0.769				
Ease of use	PEU1	1.692	32.106	0	0.769	0.622	0.868	0.796	0.803

Customer Characteristics	PEU2	2.16	64.32	2	0	0.866					
	PEU3	1.45	35.17	3	9	0	0.764				
	CCA 1	1.66	52.58	6	5	0	0.832	0.69	0.87	0.777	0.778
	CCA 2	1.66	38.64	3	2	0	0.837				
	CCA 3	2.14	51.68	1	2	0	0.826				
	CCC1	1.79	51.31	8	8	0	0.826	0.68	0.86	0.766	0.767
	CCC2	1.53	42.82	5	5	0	0.815				
	CCC3	1.61	50.39	8	2	0	0.836				
	CCM 1	1.37	44.96	5	8	0	0.79	0.70	0.87	0.787	0.786
	CCM 2	2.34	77.9	7	7	0	0.873				
	CCM 3	2.02	57.41	1	2	0	0.849				
	CCS1	2.22	58.88	4	4	0	0.861	0.71	0.88	0.803	0.804
	CCS2	1.85	50.89	1	9	0	0.846				
	CCS3	2.20	58.48	7	6	0	0.833				

4.3.1.3 Discriminant Validity

Discriminant validity is a crucial concept in Quantitative methodology, especially when assessing the validity of a measurement. Discriminant validity refers to the extent to which a construct is distinct and does not overlap with other constructs (O’leary-Kelly & Vokurka, 1998). Researchers can employ various methods to assess discriminant validity, such as the Fornell-Larcker criterion and HTMT (Heterotrait-Monotrait ratio). The most commonly used method is the Fornell-Larcker criterion to assess discriminant

validity while comparing the square root of average variance extracted for each construct; if the square root of AVE is greater than the correlation between the construct, then the discriminant validity is established. The HTMT has been proposed as a superior alternative to the FLC technique. The entire HTMT ratio values are far below the conservative threshold value of 0.85 (Henseler et al., 2015; Kline, 2015) except for a few which are showing above the threshold limit as per the study of Franke & Sarstedt (2019) the HTMT limit has been considered up to 0.9 to establish the discriminant validity. The table below indicates that the study has established convergent and discriminant validity.

Table 4.4: Results of Hetrotrait-Monotrait Ratio. Discriminant Validity

HTMT (Hetrotrait-Monotrait Ratio)										
	C	CCA	CCC	CCM	CCS	CE	CQ	F	PA	PEU
C										
CCA	0.750									
CCC	0.740	0.602								
CCM	0.588	0.9	0.567							
CCS	0.835	0.849	0.711	0.747						
CE	0.559	0.568	0.704	0.543	0.563					
CQ	0.677	0.621	0.673	0.507	0.839	0.564				
F	0.878	0.684	0.827	0.607	0.896	0.618	0.838			
PA	0.672	0.786	0.521	0.679	0.755	0.440	0.720	0.787		
PEU	0.819	0.756	0.773	0.619	0.917	0.605	0.827	0.892	0.760	

Table 4.5: The findings of the Fornel and Larcker criterion; Discriminant Validity

FLC										
	C	CCA	CCC	CCM	CCS	CE	CQ	F	PA	PEU
C	0.82									
CCA	0.612	0.832								
CCC	0.597	0.468	0.826							
CCM	0.484	0.709	0.444	0.838						
CCS	0.69	0.678	0.561	0.601	0.847					
CE	0.486	0.474	0.57	0.45	0.475	0.838				
CQ	0.584	0.517	0.553	0.426	0.705	0.494	0.822			
F	0.678	0.464	0.545	0.418	0.609	0.439	0.596	0.734		
PA	0.55	0.611	0.407	0.532	0.607	0.36	0.606	0.531	0.829	
PEU	0.754	0.601	0.607	0.495	0.734	0.507	0.694	0.672	0.607	0.789

4.4 Assessment of the Hypothesis:

Once the reliability and validity of the measurement model are established, To assess the hypothesis, the study has ensured there are no multi-collinearity issues; through the PLS algorithm, the study has examined the collinearity, and the obtained results suggest that the tolerance level of the predictor construct is far below the critical level of VIF 5. Further, to assess the structural model, we evaluated the significance of the path coefficient, the R-square, and the predictive relevance Q-square. Using Stone-Geisser Q2 (Geisser, 1947; Stone, 1974), predictive relevance was evaluated, where the value is greater than 0 for all the attributes, which shows the model predictiveness. Further, the study also checked the goodness of fit (GOF) index through SRMR (standardized root mean square residuals), which opted from the study of Hu & Bentler (1999) to approximate fit to test the structural model. The estimated value of the SRMR should be less than 0.08. The threshold value is less than the estimated value (SRMR = 0.072), which means the model can be considered a good fit.

Table 4.6: Model Fitness

Endogenous latent constructs	R-Square	R-Square Adjusted	Q ² _predict	RMSE	MAE
CCA	0.756	0.756	0.463	0.736	0.57
CCC	0.536	0.535	0.391	0.784	0.598
CCM	0.693	0.692	0.304	0.838	0.639
CCS	0.755	0.755	0.613	0.625	0.45
CE	0.381	0.376	0.296	0.842	0.63
PEU	0.69	0.688	0.683	0.565	0.406

Value effect size. 0.02 = Small; 0.15 = Medium; 0.35 = Large

4.4.1 Hypothesis Assessment

The researchers have utilized bootstrapping from the constructed model to assess the hypothesis with 5000 sub-samples. The results obtained were significant, as per the expectations of the researcher. To validate the hypothesis as per the study of Hair et al. (2017), the P-value > 0.05 and T-value of more than 1.96 of the constructs are used, as shown in Table no: 4.7 below.

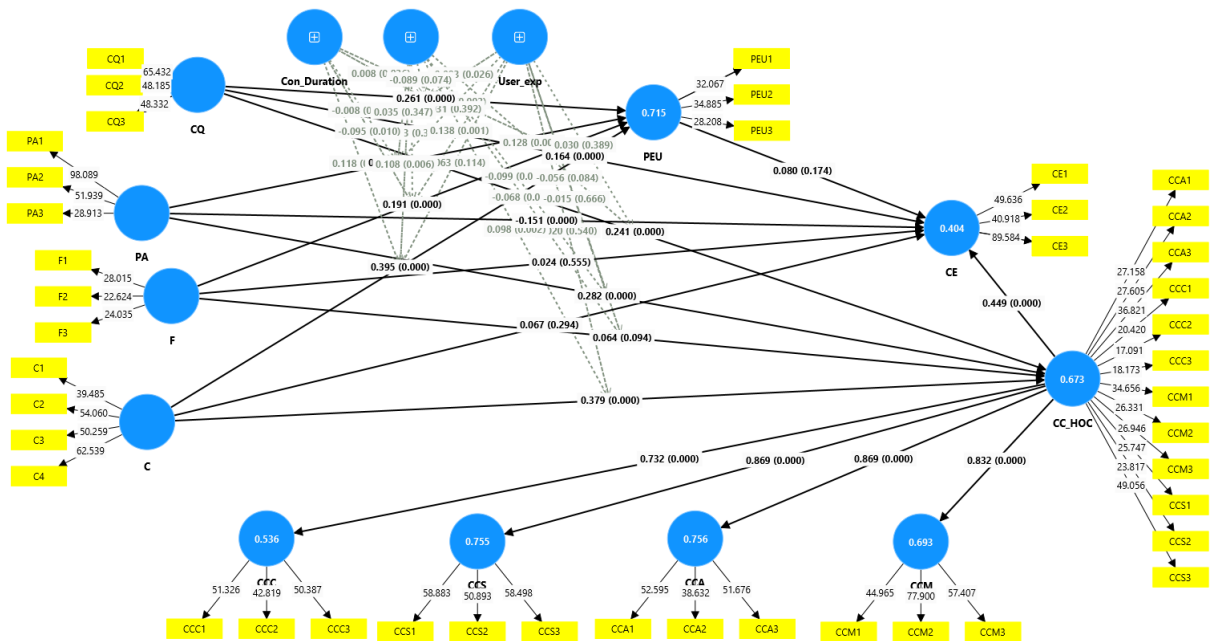


Figure 4.8: Analysis Model; Hypothesis Assessment model

Table 4.7: Path Coefficient of Research Hypothesis; Direct effect of customer executive

Hypothesis	Path	Path Coefficient	SE	t-statistics	p-values	Decision
Direct Effect						
H.1a.1	C -> CE	0.313	0.037	8.556	0	Supported
H.1a.2	CQ -> CE	0.198	0.035	5.587	0	Supported
H.1a.3	F -> CE	0.174	0.037	4.673	0	Supported
H.1a.4	PA -> CE	0.088	0.035	2.532	0.012	Supported
H.1a.5	C -> PEU	0.255	0.052	4.904	0	Supported
H.1a.6	CQ -> PEU	0.292	0.052	5.621	0	Supported
H.1a.7	F -> PEU	0.099	0.05	1.98	0.048	Supported
H.1a.8	PA -> PEU	-0.01	0.046	0.225	0.822	Not Supported
H.1a.9	C -> CC-HOC	0.393	0.028	14.048	0	Supported
H.1a.10	CQ -> CC-HOC	0.245	0.039	6.363	0	Supported
H.1a.11	F -> CC-HOC	0.069	0.035	1.959	0.051	Not Supported
H.1a.12	PA -> CC-HOC	0.256	0.029	8.816	0	Supported
H.1a.13	CC-HOC -> CE	0.189	0.04	4.746	0	Supported
H.1a.14	PEU -> CE	0.053	0.031	1.732	0.084	Not Supported
H.1a.15	CC-HOC -> CCA	0.869	0.012	75.229	0	Supported
H.1a.16	CC-HOC -> CCC	0.731	0.026	28.511	0	Supported
H.1a.17	CC-HOC -> CCM	0.83	0.015	57.025	0	Supported
H.1a.18	CC-HOC -> CCS	0.872	0.012	73.478	0	Supported

The variables labels are given below which are utilized for the construction of the model which can be observed in the table below Table no: 4.8, to provide a better understanding of the conceptual model it can be observed below.

Table 4.8: Variables Heads Labels; Short Heading of Customer executive Data set

Variables Heads Labels	
C	Controllability
CQ	Conversation Quality
F	Flexibility
PA	Perceived Anthropomorphism
PEU	Ease of Use
CC-HOC	Customer Characteristics Higher Order Construct
CCA	Attitude
CCC	Customer Inertia
CCM	Motivation
CCS	Satisfaction
CE	Customer Engagement

From the above table, it can be observed that all the direct assessments support the hypothesis except for a few, like H.1a.8 (PA -> PEU), H.1a.11 (F -> CC-HOC), and H.1a.14 (PEU -> CE) are the only few hypotheses do not show the significant results to support the hypothesis. At the individual level, the hypothesis assessment is mentioned below.

The results indicate a direct relationship between Controllability and customer engagement ($t = 8.556$, $P = 0.00$), which supports hypothesis H.1a.1: There is a significant relationship between Controllability and customer engagement.

The results of conversation quality to customer engagement ($t = 5.587$, $p = 0.00$) support hypothesis H.1a.2: There is a significant relationship between Conversation Quality and customer engagement.

The results of Flexibility to customer engagement ($t = 4.673$; $p = 0.00$) show significant results supporting the hypothesis. H.1a.3: There is a significant relationship between Flexibility and customer engagement.

The results of Perceived anthropomorphism to customer engagement ($t = 2.532$; $P = 0.00$) show significant results supporting the hypothesis. H.1a.4: There is a significant relationship between Perceived anthropomorphism and customer engagement.

The results of Controllability to Ease of Use ($t = 4.904$; $P = 0.00$) show significant results supporting the hypothesis. H.1a.5: There is a significant relationship between Controllability and Ease of Use.

The results of Conversation Quality to Ease of Use ($t = 5.621$; $P = 0.00$) show significant results supporting the hypothesis. H.1a.6: There is a significant relationship between Conversation Quality and Ease of Use.

The results of Flexibility to Ease of Use ($t = 1.98$; $P = 0.048$) show significant results supporting the hypothesis. H.1a.7: There is a significant relationship between Flexibility and Ease of Use.

The results of Perceived Anthropomorphism to Ease of Use ($t = 0.225$; $P = 0.822$) did not show significant results or support the hypothesis. H.1a.8: There is a significant relationship between Perceived anthropomorphism and Ease of Use.

The results of Controllability to Customer Characteristics ($t = 14.048$; $P = 0.00$) show significant results supporting the hypothesis H.1a.9: There is a significant relationship between Controllability to Customer Characteristics. The results of Conversation Quality to Customer Characteristics ($t = 6.363$; $P = 0.00$) show significant results supporting the hypothesis H.1a.10: There is a significant relationship between Conversation Quality and Customer Characteristics.

The results of Flexibility to Customer Characteristics ($t = 1.959$; $P = 0.051$) did not show significant results and did not support the hypothesis H.1a.11: There is a significant relationship between Flexibility to Customer Characteristics. The results of Perceived Anthropomorphism to Customer Characteristics ($t = 8.816$; $P = 0.0$) support

hypothesis H.1a.12: There is a significant relationship between Perceived Anthropomorphism to Customer Characteristics. The results indicate a direct relationship between Customer characteristics and customer engagement ($t = 4.746$, $P = 0.00$), which supports hypothesis H.1a.13: There is a significant relationship between Customer characteristics and Customer engagement.

The results indicate no direct relationship between Ease of Use and customer engagement ($t = 1.732$, $P = 0.084$). They did not show significant results and did support hypothesis H.1a.14: There is a difference between Ease of Use and customer engagement. The Customer Characteristics to Attitude ($t = 75.229$; $p = 0.00$) indicate a significant result supporting hypothesis H.1a.15: Customer Characteristics and Attitude is a significant relationship.

The results of Customer Characteristics to Customer inertia ($t = 28.511$; $p = 0.00$) indicate a significant result supporting hypothesis H.1a.16: There is a significant relationship between Customer characteristics and Customer inertia. The results of Customer Characteristics to motivation ($t = 57.025$; $p = 0.00$) indicate a significant result supporting hypothesis H.1a.17: There is a significant relationship between Customer characteristics and motivation.

The results of Customer Characteristics to Satisfaction ($t = 73.478$; $p = 0.00$) indicate a significant result supporting hypothesis H.1a.18: There is a significant relationship between Customer Characteristics and Satisfaction.

This concludes the assessment of the direct hypothesis from H.1a.1 to H.1a.18, except for a few of the direct constructs supporting the hypothesis.

4.4.1.1 Assessment of Mediation Effect:

The mediation effect is generally explained as when a latent construct variable acts as a mediator between two other related constructs. More precisely, a change in the exogenous causes a change in the mediator variable, which will influence the relation of the endogenous constructs in the PLS path model. Furthermore, recent studies indicated that mediator variable relationships with other constructs generally rely upon the cause-effect relationship between all the exogenous constructs. There is no fixed

rule that only one variable acts as a mediating variable, and the path model can simultaneously include many mediators. Hair et al. (2017), Nitzl et al. (2016) and Cepeda et al. (2017) proposed multiple models and assessment techniques for the mediation effect. The current study has adopted Zhao et al. (2010) and Rungtusanatham et al. (2014). The transmittal method primarily focuses on developing the hypothesis that M as a mediator between X and Y to know either X has an indirect effect on Y through M, to release the articulate process of path X to M and M to Y. through the Bootstrapping technique with 5000 subsamples used to estimate 95% of the bias-corrected confidence interval of indirect effect. The researcher used the path model to construct a mediation path to assess the mediation effect, as seen in Table 4.8.

Table 4.9: Assessment of Mediation

Hypothesis	Path	Path Coefficient	SE	t-statistics	P-values	Decision
Indirect Effect						
H.2a.1	CQ -> PEU -> CE	0.016	0.01	1.489	0.137	Not Supported
H.2a.2	F -> PEU -> CE	0.005	0.004	1.195	0.233	Not Supported
H.2a.3	PA -> PEU -> CE	-0.001	0.003	0.193	0.847	Not Supported
H.2a.4	C -> PEU -> CE	0.014	0.008	1.765	0.078	Not Supported
H.2a.5	CQ -> CC-HOC -> CE	0.046	0.012	3.768	0	Supported
H.2a.6	F -> CC-HOC -> CE	0.013	0.007	1.762	0.079	Not Supported
H.2a.7	PA -> CC-HOC -> CE	0.048	0.012	4.145	0	Supported
H.2a.8	C -> CC-HOC -> CE	0.074	0.016	4.545	0	Supported

Through Bootstrapping->specific indirect effect, the researcher evaluated the mediation effect, and the results indicate that only a few constructs support the proposed hypothesis from the model. Furthermore, the path that supports the hypothesis supports partial mediation, as the direct assessment supports the hypothesis.

The results indicate that Ease of Use does not mediate between conversation quality and customer engagement ($t = 1.489$; $p = 0.137$). Results are insignificant, suggesting

it does not support hypothesis H.2a.1: There is a significant mediation relationship between Ease of Use in Conversation quality and customer engagement.

The results indicate that Ease of Use does not mediate between Flexibility and customer engagement ($t = 1.195$; $p = 0.233$). Results are insignificant, suggesting it does not support hypothesis H.2a.2: There is a significant mediation relationship between Ease of Use in Flexibility and customer engagement.

The results indicate that Ease of Use has no role in the mediation effect between Perceived Anthropomorphism and customer engagement ($t = 0.193$; $p = 0.847$). Results are insignificant, suggesting it does not support hypothesis H.2a.3: A significant mediation relationship exists between Ease of Use in Perceived Anthropomorphism and customer engagement.

The results indicate that Ease of Use does not mediate Controllability and customer engagement ($t = 1.765$; $p = 0.078$). Results are insignificant, suggesting it does not support hypothesis H.2a.4: There is a significant mediation relationship between Ease of Use in Controllability and customer engagement.

The results indicate that customer characteristics play a role in the mediation effect between conversation quality and customer engagement ($t = 3.768$; $p = 0.00$). Results show significance, suggesting it supports hypothesis H.2a.5: There is a significant mediation relationship between Customer characteristics in Conversation quality and customer engagement. The results indicate that Customer Characteristics does not mediate between Flexibility and customer engagement ($t = 1.762$; $p = 0.079$). Results are insignificant, suggesting it does not support hypothesis H.2a.6: There is a significant mediation relationship between Customer characteristics in Flexibility and customer engagement.

The results indicate that Customer Characteristics have a role in the mediation effect between Perceived Anthropomorphism and customer engagement ($t = 4.145$; $p = 0.00$). Results show significance, suggesting it supports hypothesis H.2a.7: There is a significant mediation relationship between Customer characteristics and Perceived Anthropomorphism to customer engagement.

The results indicate that Customer Characteristics have a role in the mediation effect between Controllability and customer engagement ($t = 4.545$; $p = 0.00$). Results show significance, suggesting it supports hypothesis H.2a.8: There is a significant mediation relationship between Customer characteristics in Controllability and customer engagement.

4.4.1.2 Assessment of Moderation Effect:

To assess the construct moderation effect in the proposed model the researcher has taken conversation duration, User Expertise, and Reason as a moderator to see its impact on the construct model. The Smart-PLS Bootstrapping study has obtained results which indicate only a few constructs support the hypothesis. As the study is related to the service industry, the results are justifiable.

Moderation with respect to Ease of Use and Customer Characteristics:

The following hypotheses are framed to analyses the first objective Moderating factors impact on the Ease of Use and Customer Characteristics

Table 4.10: Customer executive data Moderation with respect to Ease of Use and Customer Characteristics

Hypothesis	Path	Path Coefficient	SE	t-statistics	p-values	Decision
H.3a.1	Reason x PA -> PEU	0.035	0.037	0.94	0.347	Not Supported
H.3a.2	Reason x CQ -> PEU	-0.089	0.05	1.787	0.074	Not Supported
H.3a.3	Reason x F -> PEU	-0.033	0.036	0.901	0.368	Supported
H.3a.4	Reason x C -> PEU	0.108	0.039	2.771	0.006	Supported
H.3a.5	Con_Duration x PA -> PEU	-0.008	0.036	0.215	0.83	Not Supported
H.3a.6	Con_Duration x CQ -> PEU	0.008	0.038	0.207	0.836	Not Supported
H.3a.7	Con_Duration x F -> PEU	-0.095	0.037	2.576	0.01	Supported
H.3a.8	Con_Duration x C -> PEU	0.118	0.03	3.881	0	Supported
H.3a.9	User Expertise x CQ -> PEU	-0.083	0.037	2.23	0.026	Supported
H.3a.10	User Expertise x PA -> PEU	-0.031	0.036	0.856	0.392	Not Supported
H.3a.11	User Expertise x F -> PEU	0.138	0.041	3.377	0.001	Supported
H.3a.12	User Expertise x C -> PEU	-0.063	0.04	1.583	0.114	Not Supported
H.3a.13	Reason x PA -> CC_HOC	-0.099	0.034	2.964	0.003	Supported
H.3a.14	Reason x CQ -> CC_HOC	0.122	0.048	2.544	0.011	Supported
H.3a.15	Reason x F -> CC_HOC	-0.062	0.04	1.572	0.116	Not Supported
H.3a.16	Reason x C -> CC_HOC	0.097	0.033	2.964	0.003	Supported
H.3a.17	Con_Duration x PA -> CC_HOC	-0.025	0.034	0.716	0.474	Not Supported
H.3a.18	Con_Duration x CQ -> CC_HOC	0.06	0.041	1.445	0.149	Not Supported
H.3a.19	Con_Duration x F -> CC_HOC	-0.046	0.037	1.243	0.214	Supported
H.3a.20	Con_Duration x C -> CC_HOC	0.008	0.028	0.276	0.783	Not Supported
H.3a.21	User Expertise x PA -> CC_HOC	-0.052	0.038	1.384	0.167	Supported
H.3a.22	User Expertise x CQ -> CC_HOC	0.01	0.039	0.253	0.8	Not Supported
H.3a.23	User Expertise x F -> CC_HOC	0.006	0.039	0.153	0.879	Not Supported
H.3a.24	User Expertise x C -> CC_HOC	0.012	0.034	0.356	0.722	Supported

The reason as a moderator in between Perceived anthropomorphism to Ease of Use does not support the hypothesis which can be observed from the above table. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the reason as a moderator in between conversation quality to Ease of Use does not support the hypothesis. Again, reason as a moderator in between flexibility to Ease of Use does not support the hypothesis. The reason as a moderator is between controllability to Ease of Use supports the hypothesis as it is above the threshold of acceptance.

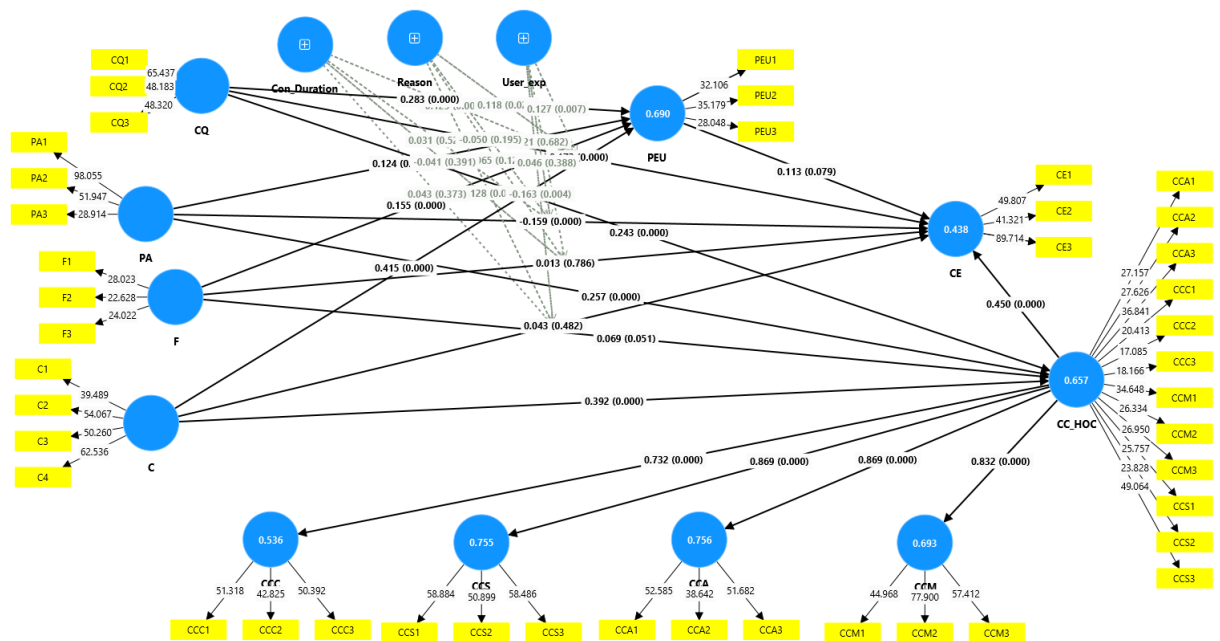


Figure 4.9: Assessment of moderation analysis with respect to Customer executives

The conversation duration as a moderator between Perceived anthropomorphism to Ease of Use does not support the hypothesis which can be observed from the above table. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the conversation duration as a moderator in between conversation quality to Ease of Use does not support the hypothesis. Again, conversation duration as a moderator in between flexibility to Ease of Use supports the hypothesis. The conversation duration as a moderator is between controllability to Ease of Use supports the hypothesis as it is above the threshold of acceptance.

The User Expertise as a moderator between Perceived anthropomorphism to Ease of Use supports the hypothesis which can be observed from the above table. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the User Expertise as a moderator in between conversation quality to Ease of Use does not support the hypothesis. Again, User Expertise as a moderator between flexibility to Ease of Use supports the hypothesis. The conversation duration as a moderator between controllability to Ease of Use does not support the hypothesis as it is above the threshold of acceptance.

The reason as a moderator in between Perceived anthropomorphism to Customer Characteristics supports the hypothesis which can be observed from the above table no. 4.10. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the reason as a moderator in between conversation quality to Customer Characteristics supports the hypothesis. Again, reason as a moderator in between flexibility to Customer characteristics does not support the hypothesis. The reason as a moderator is between controllability to Customer characteristics supports the hypothesis as it is above the threshold of acceptance.

The conversation duration as a moderator between Perceived anthropomorphism to Customer characteristics does not support the hypothesis which can be observed from the above table. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the conversation duration as a moderator in between conversation quality to Customer characteristics does not support the hypothesis. Again, conversation duration as a moderator in between flexibility to Customer characteristics does not support the hypothesis. The conversation duration as a moderator between controllability to Customer characteristics does not support the hypothesis as it is above the threshold of acceptance.

The User Expertise as a moderator between Perceived anthropomorphism to Customer characteristics does not support the hypothesis which can be observed from the above table. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the User Expertise as a moderator in between conversation quality to Customer characteristics does not support the hypothesis. Again, User Expertise as a moderator between flexibility to Customer characteristics does not support the hypothesis. The User Expertise as a moderator between controllability to Customer characteristics does not support the hypothesis as it is above the threshold of acceptance.

Additional Hypothesis for Assessment of moderation on customer engagement with respect to customer executives:

To assess the construct moderation effect in the proposed model, the researcher has used conversation duration, User Expertise, and reason as moderators to see their impact on the constructed model. The SmartPLS Bootstrapping study obtained results that indicated that only a few constructs supported the hypothesis. The results are justifiable because the study is related to the service industry. The results are given below in Table no: 4.11. Through the proposed model, we have constructed additional 12 hypotheses.

Table 4.11: Customer executive (Moderation Table)

Hypothesis	Path	Path Coefficient	SE	t-statistics	p-values	Decision
H.3a.1.1	Reason x PA -> CE	0.06	0.036	1.644	0.101	Not Supported
H.3a.1.2	Reason x CQ -> CE	-0.121	0.047	2.578	0.01	Supported
H.3a.1.3	Reason x F -> CE	-0.023	0.032	0.722	0.471	Not Supported
H.3a.1.4	Reason x C -> CE	0.092	0.038	2.414	0.016	Supported
H.3a.1.5	Con_Duration x PA -> CE	-0.005	0.035	0.145	0.885	Not Supported
H.3a.1.6	Con_Duration x CQ -> CE	0.005	0.036	0.14	0.889	Not Supported
H.3a.1.7	Con_Duration x F -> CE	-0.081	0.034	2.373	0.018	Supported
H.3a.1.8	Con_Duration x C -> CE	0.11	0.029	3.799	0	Supported
H.3a.1.9	User Expertise x PA -> CE	-0.022	0.033	0.677	0.499	Not Supported
H.3a.1.10	User Expertise x CQ -> CE	-0.092	0.033	2.783	0.006	Supported
H.3a.1.11	User Expertise x F -> CE	0.135	0.04	3.351	0.001	Supported
H.3a.1.12	User Expertise x C -> CE	-0.056	0.04	1.411	0.159	Not Supported

The results of Reason*perceived anthropomorphism to customer engagement (t = 1.644; p = 0.101) did not show significant results, suggesting it did not support the hypothesis H.3a.1.1 There is a significant moderating role of Reason in between the Perceived Anthropomorphism to customer engagement.

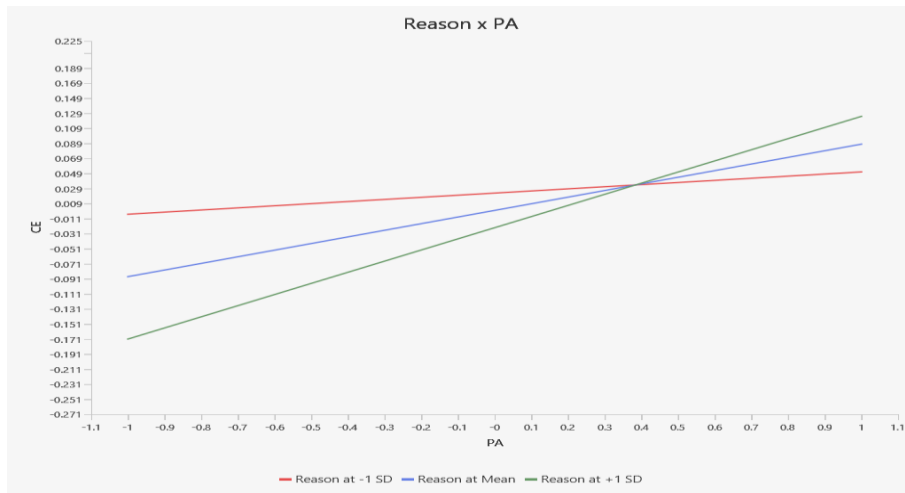


Figure 4.10: Reason*Perceived Anthropomorphism

Though the hypothesis was not supported, Through the slope analysis it can be observed that reason has a moderating role in perceived Anthropomorphism and customer engagement. The reason is that a potential moderator with a precise scale and customer feedback played a huge role in the perceived Anthropomorphism of customer engagement. The results of Reason*Conversation Quality to customer engagement ($t = 2.578$; $p = 0.01$) showed significant results, suggesting it supports the hypothesis H.3a.1.2 There is a significant moderating role of reason iReasoneen the Conversation Quality to customer engagement.

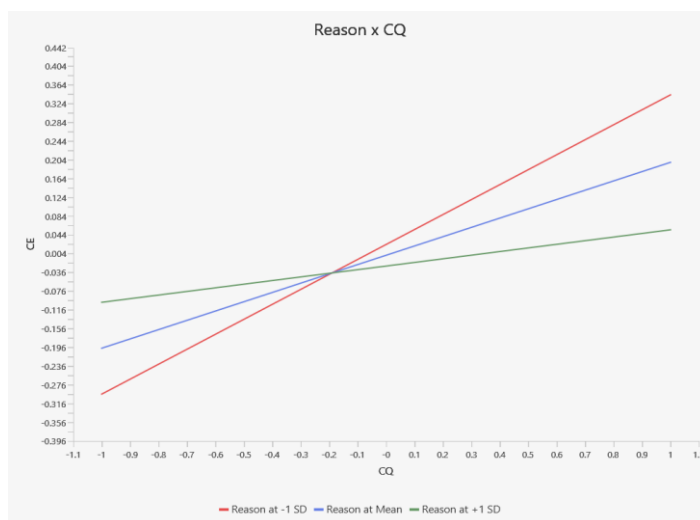


Figure 4.11: Reason*Conversation Quality

The hypothesis supported the above moderating effect; Even in the slope analysis it shows a significant moderating role; on an information basis, customers try to moderate conversation quality to customer engagement.

The results of Reason*Flexibility to customer engagement ($t = 0.722$; $p = 0.47$) did not show significant results, suggesting it did not support the hypothesis H.3a.1.3 There is a significant moderating role of Reason between the Flexibility to customer engagement.

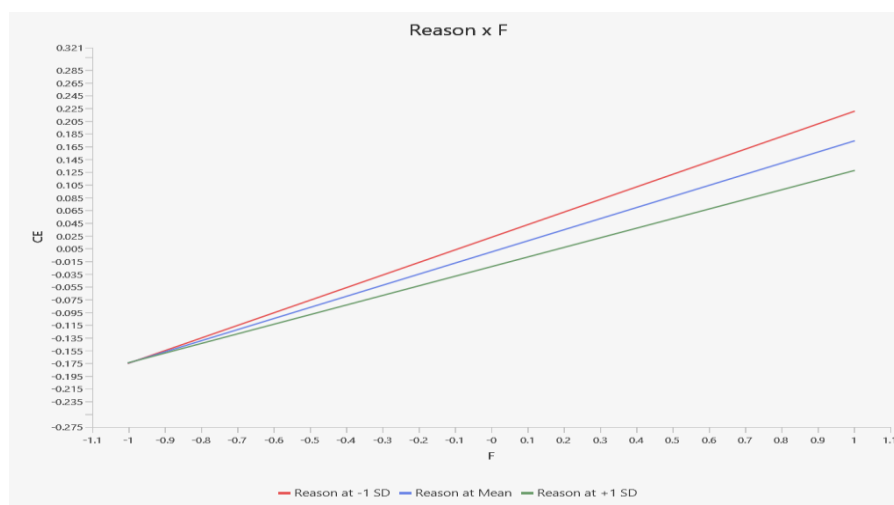


Figure 4.12: Reason*Flexibility

Though the hypothesis was not supported, Through the slope analysis it can be observed that there is a moderating role of reason between flexibility and customer engagement. The reason might act as a potential moderator with a precise scale, and based on information, the customers played a huge moderating role in the flexibility of customer engagement.

The results of Reason*controllability to customer engagement ($t = 2.414$; $p = 0.016$) showed significant results, suggesting it supports the hypothesis H.3a.1.4 There is a significant moderating role of reason between Controllability and customer engagement.

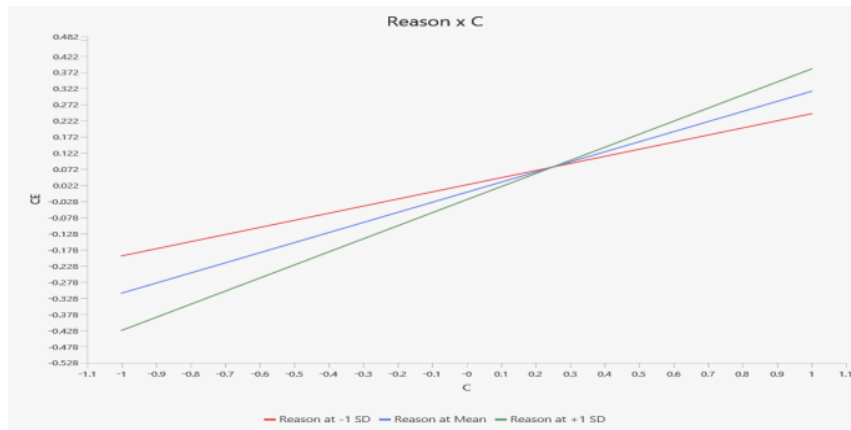


Figure 4.13: Reason*Controllability

The hypothesis supported the above moderating effect; Even in the slope analysis it shows a significant moderating role on feedback, as customers try to moderate conversation quality to customer engagement.

The results of Conversation duration*perceived anthropomorphism to customer engagement ($t = 0.145$; $p = 0.885$) did not show significant results, suggesting it did not support the hypothesis H.3a.1.5 There is a significant moderating role of Conversation Duration in between the Perceived Anthropomorphism to customer engagement.

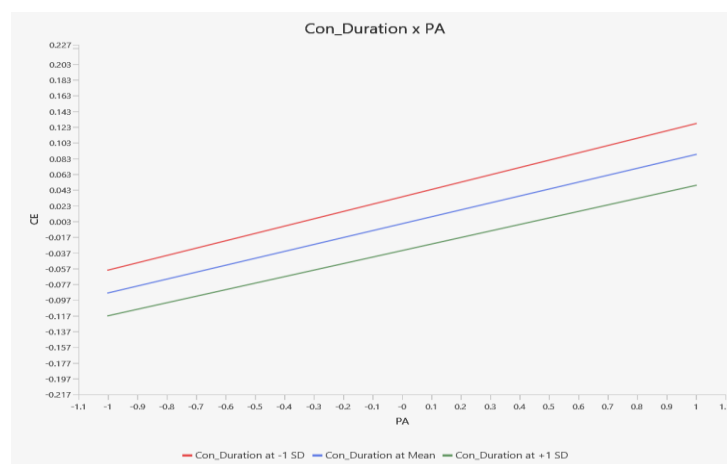


Figure 4.14: Conversation Duration*Perceived Anthropomorphism

The slope analysis also justifies that there is no moderating role of conversation duration between perceived anthropomorphism and customer engagement.

The results of Conversation duration*Conversation Quality to customer engagement ($t = 0.14$; $p = 0.889$) did not show significant results, suggesting it did not support the hypothesis H.3a.1.6 There is a significant moderating role of Conversation Duration in between the Conversation Quality to customer engagement.

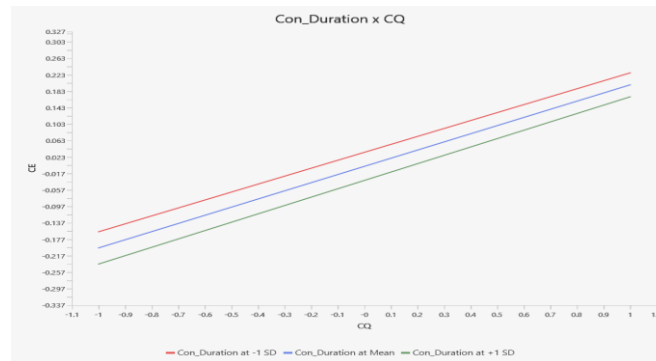


Figure 4.15: Conversation Duration*Conversation Quality

The slope analysis also justifies that there is no moderating role of conversation duration between Conversation Quality and customer engagement.

The results of Conversation duration*Flexibility to customer engagement ($t = 2.373$; $p = 0.018$) showed significant results, suggesting it supports the hypothesis H.3a.1.7 There is a significant moderating role of Conversation Duration between the Flexibility to customer engagement.

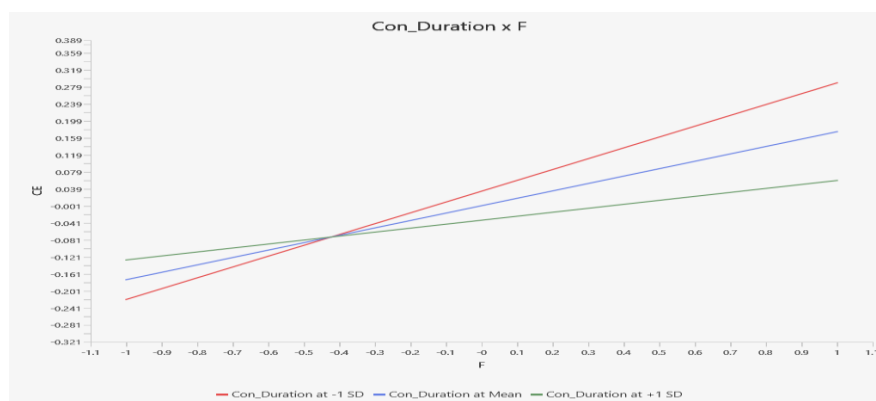


Figure 4.16: Conversation Duration*Flexibility

The hypothesis supported the above moderating effect; Even in the slope analysis it shows a significant moderating role; customers with short conversation duration try to moderate with Flexibility to customer engagement.

The results of Conversation duration*Controllability to customer engagement ($t = 3.799$; $p = 0.00$) showed significant results, suggesting it supports the hypothesis H.3a.1.8 There is a significant moderating role of Conversation Duration in between the Controllability to customer engagement.

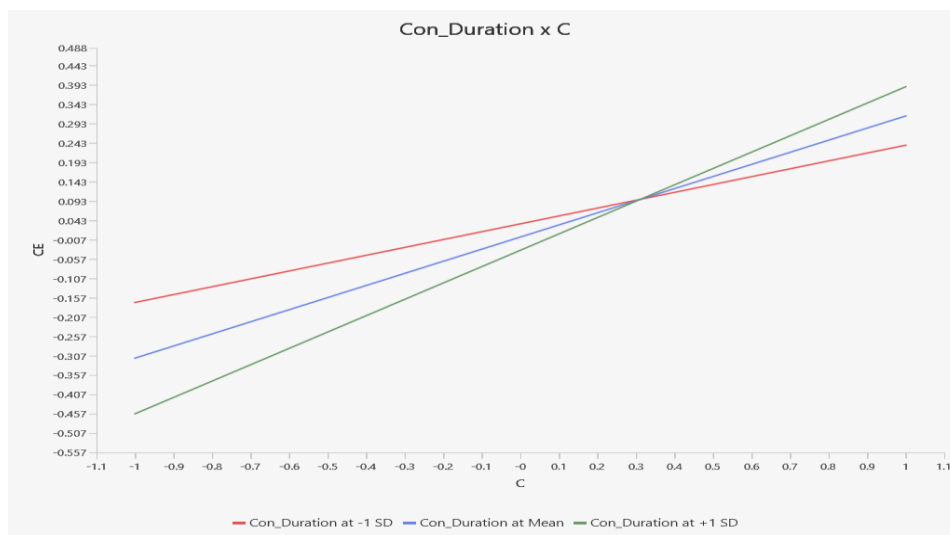


Figure 4.17: Conversation Duration*Controllability

The hypothesis supported the above moderating effect; Even in the slope analysis, it shows a significant moderating role; customers with long conversation duration try to moderate with Controllability to customer engagement.

The results of User Expertise*perceived anthropomorphism to customer engagement ($t = 0.677$; $p = 0.499$) did not show significant results, suggesting it did not support the hypothesis H.3a.1.9 There is a significant moderating role of User Expertise in between the Perceived Anthropomorphism to customer engagement.

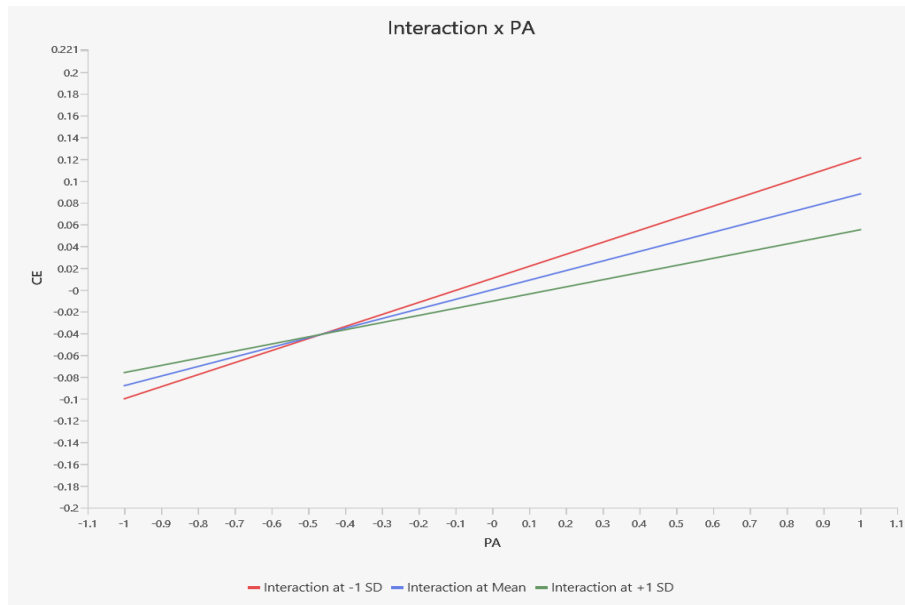


Figure 4.18: User Expertise*Perceived Anthropomorphism

Though the hypothesis did not support, Through the slope analysis there is a moderating role of User Expertise between perceived anthropomorphism and customer engagement. Suggesting the reason might act as a potential moderator with a precise scale, and the customers' prepurchase/information search phase played a huge moderating role in perceived anthropomorphism and customer engagement.

The results of User Expertise*conversation Quality to customer engagement ($t = 2.78$; $p = 0.006$) showed significant results, suggesting it supports the hypothesis H.3a.1.10 There is a significant moderating role of User Expertise between the Conversation Quality and customer engagement.

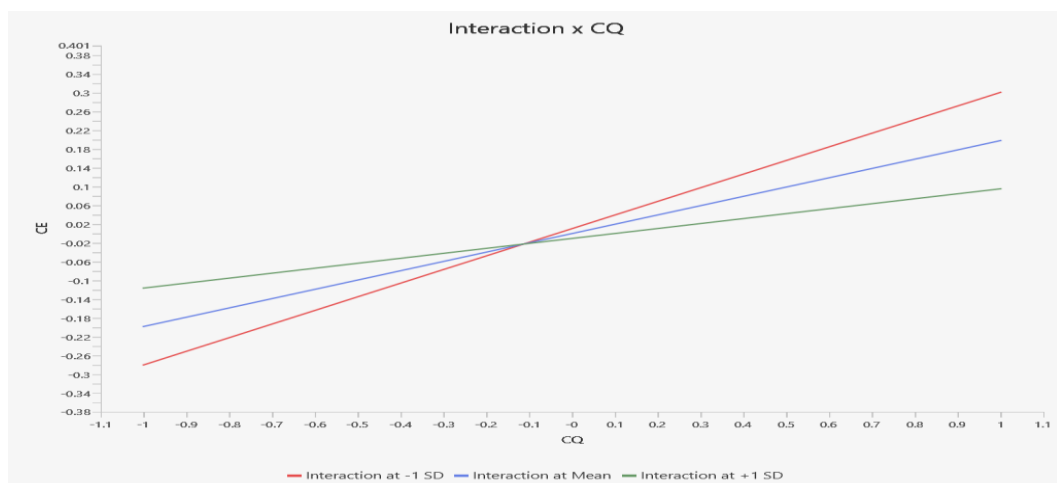


Figure 4.19: User Expertise*Conversation Quality

The hypothesis supported the above moderating effect; it shows a significant moderating role even in the slope analysis. In the prepurchase/information search phase, customers try to moderate conversation quality to customer engagement.

The results of User Expertise*Flexibility to customer engagement ($t = 3.351$; $p = 0.001$) showed significant results, suggesting it supports the hypothesis H.3a.1.11 There is a significant moderating role of User Expertise in between the Flexibility to customer engagement.

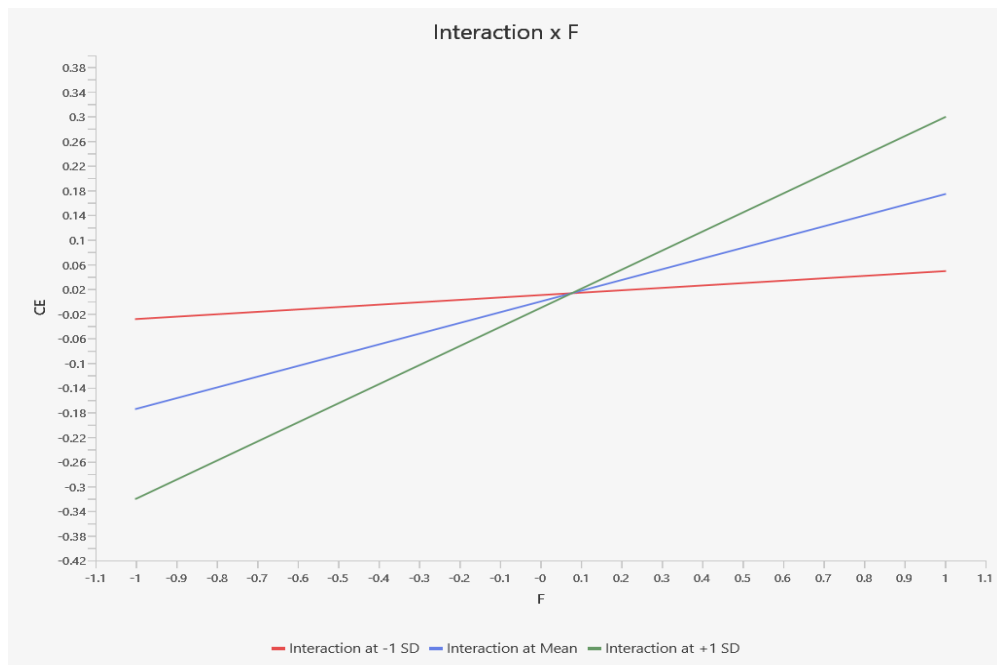


Figure 4.20: User Expertise*Flexibility

The hypothesis supported the above moderating effect, and even in the slope analysis, it shows a significant moderating role; in the post-purchase phase, customers are trying to moderate flexibility to customer engagement.

The results of User Expertise*Controllability to customer engagement ($t = 1.411$; $p = 0.159$) did not show significant results, suggesting it did not support the hypothesis H.3a.1.12 There is a significant moderating role of User Expertise in between the Controllability to customer engagement.

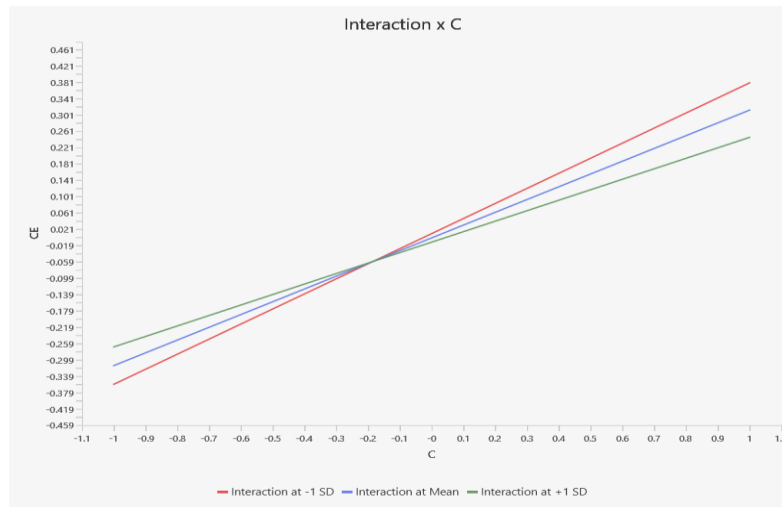


Figure 4.21: User Expertise*Controllability

Though the hypothesis did not support, Through slope analysis the User Expertise between Controllability and customer engagement has a moderating role. The reason might act as a potential moderator with a precise scale and that the customers' prepurchase/information search phase significantly moderated the perceived anthropomorphism and customer engagement.

4.3.2 Chatbots

4.3.2.1 Data Validation:

We are utilizing the SmartPLS to test the normality of the data to understand and construct a model to predict accurately. Most of the values of Kurtosis and Skewness lie in between the range of -1 to +1. However, some parts of the data exhibit abnormal behaviour as kurtosis is on the positive side; meanwhile, all the Cramér-von Mises p-values have also shown significance, which does not suggest that the data is normal or non-normal. The study has utilised a web-based calculator (Zhang & Yuan, 2018) to test the Multivariate normality by using Mardia's (1970) test, which shows the data has outcome Mardia's Skewness (Beta = 10.56, $p < 0.05$) and Kurtosis (beta = 98.27, $P < 0.05$) suggest that data as non-normality. To predict the constructed model more accurately, a study has adopted SmartPLS, which handles non-normal data very well, Hair et al., (2019).

Table 4.12: Chatbot Data structure and Distribution

Name	Mean	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
User Expertise	1.842	0.534	0.143	-0.124	0
Con_Duration	1.555	0.547	-1.003	0.262	0
Reason	1.54	0.559	-0.864	0.39	0
UCT	2.042	0.924	-1.829	-0.083	0
CQ1	3.211	0.879	0.475	-0.693	0
CQ2	3.463	0.861	0.621	-0.718	0
CQ3	3.165	0.91	-0.068	-0.375	0
PA1	2.675	1.032	-0.834	-0.053	0
PA2	3.065	1.014	-0.497	-0.259	0
PA3	2.855	1.056	-0.675	-0.046	0
F1	3.154	0.96	-0.354	-0.34	0
F2	3.262	1.042	-0.355	-0.502	0
F3	3.665	0.936	0.902	-0.87	0
C1	3.226	0.925	-0.033	-0.462	0
C2	3.108	0.922	-0.193	-0.365	0
C3	3.191	0.856	0.234	-0.443	0
CE1	3.542	0.828	1.484	-0.924	0
CE2	3.506	0.851	1.328	-0.985	0
CE3	3.328	0.894	-0.07	-0.472	0
CCC1	3.339	0.863	0.441	-0.831	0
CCC2	2.856	1.035	-0.718	-0.22	0
CCC3	3.148	0.974	-0.024	-0.453	0
CCS1	3.24	0.937	0.235	-0.646	0
CCS2	3.309	0.904	0.114	-0.558	0
CCS3	3.006	0.93	-0.113	-0.395	0
CCA1	3.216	0.974	-0.055	-0.543	0
CCA2	3.109	0.945	-0.095	-0.328	0
CCA3	3.388	0.827	0.613	-0.693	0
CCM1	3.17	0.924	-0.133	-0.439	0
CCM2	2.802	1.022	-0.589	-0.18	0
CCM3	3.111	0.968	-0.217	-0.452	0
PEU1	3.064	0.971	-0.267	-0.31	0

PEU2	2.921	0.955	-0.299	-0.081	0
PEU3	3.141	0.893	0.159	-0.374	0

4.3.2.2 Assessment of Construct Validity and Reliability:

To construct a model consisting of both general and higher order constructs as from the below figure: 4.22, the study has assessed the constructed model with outer loadings, composite reliability (CR), average variance extracted (AVE) and discriminant validity based on (Hair et al., 2017). Construct validity and reliability are essential for research using Structural equation modelling with SmartPLS (Sepasgozar et al., 2019). Construct validity refers to the degree to accurately measure the instruments (items) used for the theoretical construct it is intended to analyse. At the same time, reliability deals with consistency and stability of measurement over time to produce consistent results. Construct validity refers to the degree to which a measurement instrument accurately measures the theoretical construct, and construct validity refers to ensuring that the instrument measures what it claims to measure. All the outer loadings of the first-order reflective construct are above the minimum threshold value as shown in table no: 4.13, Composite reliability > 0.7 and Cronbach > 0.7 suggest the data has a high degree of internal consistency, and the convergent validity was shown by AVE 0.5 (Hair et al., 2017).

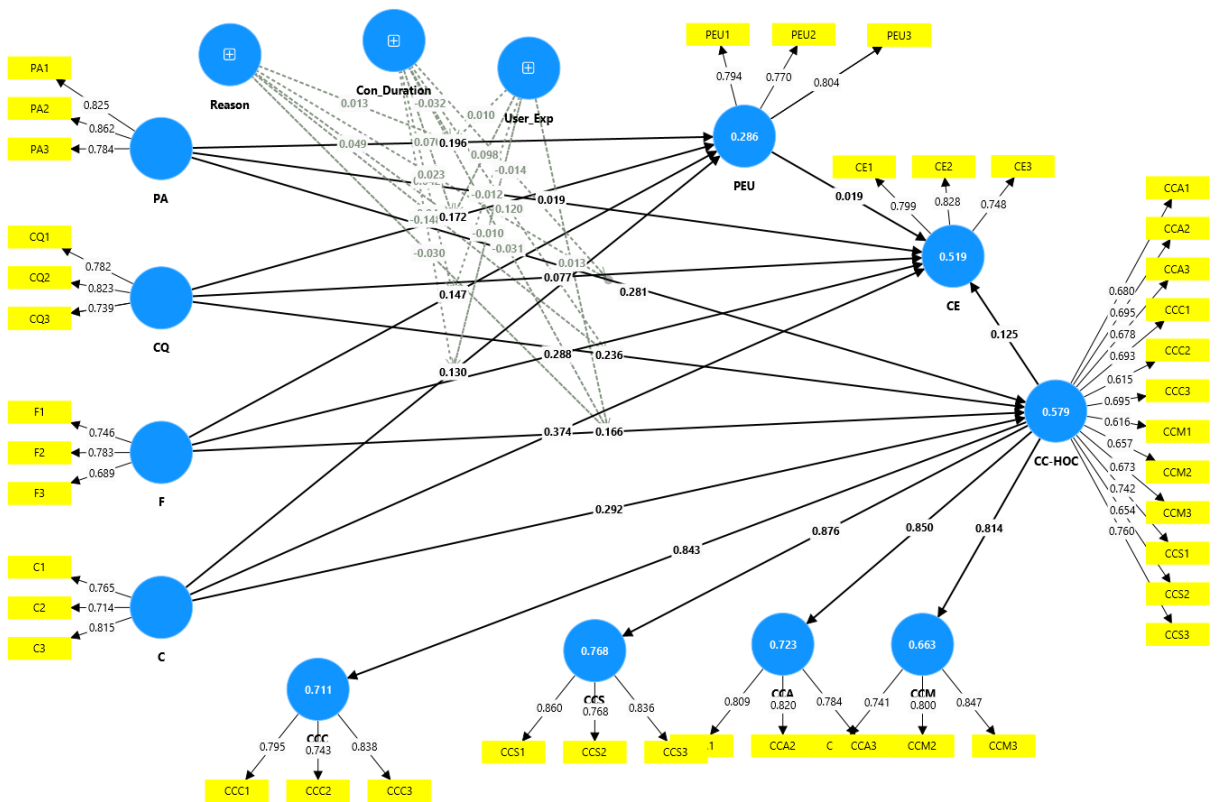


Figure 4.22: Analysis model PLS-Model

To assess the higher-order construct (reflective-reflective) construct. We have assessed the higher-order construct using the PLS algorithm and bootstrapping technique. The VIF and the significance of the indicator and weights were used to determine the reflective-reflective assessment. The VIF values are below the threshold limit of 3.3, suggesting no collinearity issue through bootstrapping. We have assessed the significance of the weights, and the results suggest that all the weights of the indicators are significant at $p < 0.001$ levels, demonstrating the relative contribution of constructing a reflective-reflective construct.

Table 4.13: Path Coefficient of Research Hypothesis Construct Validity and Reliability

Construct	Item	VIF	Outer loading	AVE	CR	Cronbach's alpha	rho_A
Controllability	C1	1.304	0.771	0.595	0.815	0.742	0.743
	C2	1.369	0.74				
	C3	1.248	0.802				
Customer engagement	CE1	1.402	0.802	0.628	0.835	0.704	0.709
	CE2	1.448	0.825				
	CE3	1.303	0.749				
Conversation Quality	CQ1	1.652	0.8	0.624	0.869	0.799	0.802
	CQ2	1.825	0.824				
	CQ3	1.607	0.78				
Flexibility	F1	1.278	0.755	0.568	0.797	0.751	0.752
	F2	1.361	0.808				
	F3	1.147	0.694				
Perceived Anthropomorphism	PA1	1.602	0.829	0.686	0.868	0.771	0.773
	PA2	1.69	0.852				
	PA3	1.491	0.804				
Ease of Use	PEU1	1.651	0.79	0.639	0.898	0.86	0.871
	PEU2	1.864	0.768				
	PEU3	1.945	0.798				
Customer Characteristics	CCA1	2.147	0.834	0.669	0.858	0.752	0.752
	CCA2	1.586	0.833				
	CCA3	1.422	0.8				
	CCC1	1.951	0.819	0.644	0.844	0.722	0.728
	CCC2	1.318	0.749				
	CCC3	1.563	0.837				
	CCM1	1.321	0.751	0.649	0.847	0.728	0.732
	CCM2	1.504	0.804				
	CCM3	1.706	0.859				
	CCS1	2.329	0.868	0.687	0.868	0.772	0.777
	CCS2	1.462	0.781				
	CCS3	2.145	0.835				

4.3.2.3 Discriminant Validity

Discriminant validity is a crucial concept in Quantitative methodology, especially when assessing the validity of a measurement. Discriminant validity refers to the extent to which a construct is distinct and does not overlap with other constructs (O’leary-Kelly

& Vokurka, 1998). Researchers can employ various methods to assess discriminant validity, such as the Fornell-Larcker criterion and HTMT (Heterotrait-Monotrait ratio). The most commonly used method is the Fornell-Larcker criterion to assess discriminant validity while comparing the square root of average variance extracted for each construct; if the square root of AVE is greater than the correlation between the construct, then the discriminant validity is established. The HTMT has been proposed as a superior alternative to the FLC technique. The entire HTMT ratio values are far below the conservative threshold value of 0.85 (Henseler et al., 2015; Kline, 2015) except for a few which are showing above the threshold limit as per the study of Franke & Sarstedt (2019) the HTMT limit has been considered up to 0.9 to establish the discriminant validity. The table below indicates that the study has established convergent and discriminant validity.

Table 4.14: HTMT (Hetrotrait-Monotrait Ratio)

HTMT (Hetrotrait-Monotrait Ratio)										
	C	CCA	CCC	CCM	CCS	CE	CQ	F	PA	PEU
C										
CCA	0.680									
CCC	0.642	0.83								
CCM	0.592	0.876	0.799							
CCS	0.734	0.871	0.892	0.8						
CE	0.874	0.705	0.664	0.59	0.664					
CQ	0.556	0.59	0.685	0.528	0.744	0.608				
F	0.715	0.722	0.662	0.618	0.744	0.9	0.71			
PA	0.476	0.738	0.62	0.665	0.63	0.526	0.643	0.625		
PEU	0.434	0.609	0.677	0.732	0.72	0.469	0.429	0.505	0.477	

Table 4.15: Discriminant Validity

FLC										
	C	CCA	CCC	CCM	CCS	CE	CQ	F	PA	PEU
C	0.766									
CCA	0.480	0.805								
CCC	0.458	0.595	0.793							
CCM	0.416	0.631	0.567	0.797						
CCS	0.533	0.649	0.700	0.589	0.822					
CE	0.621	0.502	0.476	0.410	0.484	0.793				
CQ	0.413	0.445	0.508	0.391	0.571	0.458	0.781			
F	0.459	0.471	0.429	0.398	0.493	0.579	0.482	0.740		
PA	0.352	0.553	0.458	0.492	0.482	0.389	0.496	0.415	0.824	
PEU	0.356	0.484	0.525	0.574	0.582	0.373	0.360	0.364	0.390	0.799

4.3.2.4 Assessment of the Hypothesis:

Once the reliability and validity of the measurement model. To assess the hypothesis, the study has ensured there are no multi-collinearity issues; through the PLS algorithm, the study has examined the collinearity, and the obtained results suggest that the tolerance level of the predictor construct is far below the critical level of VIF 5. Further, to assess the structural model, we evaluated the significance of the path coefficient, the R-square, and the predictive relevance Q-square. Using Stone-Geisser Q² (Geisser, 1947; Stone, 1974), predictive relevance was evaluated, where the value is greater than 0 for all the attributes, which shows the model predictiveness. Further, the study also checked the goodness of fit (GOF) index through SRMR (standardized root mean square residuals) and opted from the study of Hu & Bentler (1999) to approximate fit to test the structural model. The estimated value of the SRMR should be less than 0.08. The threshold value is less than the estimated value (SRMR = 0.072), which means the model can be considered a good fit.

Table 4.16: Model Fitness

Endogenous constructs	latent	R-Square	R-Square Adjusted	Q ² _predict	RMSE	MAE
CCA		0.723	0.723	0.415	0.768	0.578
CCC		0.712	0.711	0.366	0.799	0.61
CCM		0.663	0.662	0.315	0.83	0.654
CCS		0.768	0.768	0.459	0.739	0.534
CE		0.559	0.546	0.512	0.702	0.524
PEU		0.237	0.233	0.225	0.883	0.667

Value effect size. 0.02 = Small; 0.15 = Medium; 0.35 = Large

4.3.2.5 Hypothesis Assessment

The researchers have utilized bootstrapping from the constructed model to assess the hypothesis with 5000 sub-samples. The results obtained were significant, as per the expectations of the researcher. To validate the hypothesis as per the study of Hair et al. (2017), the P-value > 0.05 and T-value of more than 1.96 of the constructs are used, as shown in table 4.17 below.

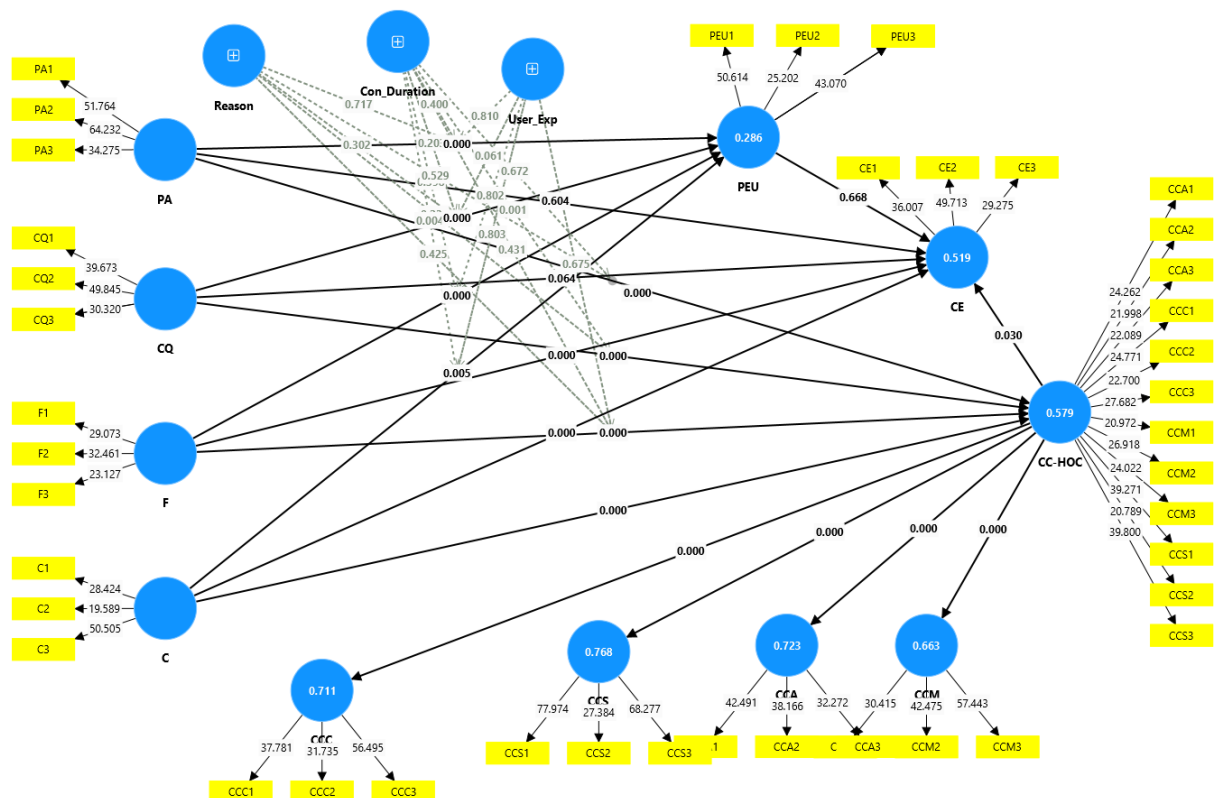


Figure 4.23: Hypothesis Assessment Model

Table 4.17: Direct effect

Hypothesis	Path	Path Coefficient	SE	t-statistics	p-values	Decision
Direct Effect						
H.1.b.1	C -> CE	0.32	0.039	8.111	0	Supported
H.1.b.2	CQ -> CE	0.099	0.038	2.576	0.01	Supported
H.1.b.3	F -> CE	0.294	0.035	8.446	0	Supported
H.1.b.4	PA -> CE	0.048	0.034	1.436	0.151	Not Supported
H.1.b.5	C -> PEU	0.167	0.042	3.939	0	Supported
H.1.b.6	CQ -> PEU	0.116	0.048	2.429	0.015	Supported
H.1.b.7	F -> PEU	0.143	0.042	3.439	0.001	Supported
H.1.b.8	PA -> PEU	0.214	0.036	5.886	0	Supported
H.1.b.9	C -> CC-HOC	0.286	0.034	8.424	0	Supported
H.1.b.10	CQ -> CC-HOC	0.219	0.038	5.795	0	Supported
H.1.b.11	F -> CC-HOC	0.168	0.037	4.545	0	Supported
H.1.b.12	PA -> CC-HOC	0.306	0.034	9.123	0	Supported
H.1.b.13	CC-HOC -> CE	0.145	0.054	2.702	0.007	Supported
H.1.b.14	PEU -> CE	-0.007	0.042	0.159	0.874	Not Supported
H.1.b.15	CC-HOC -> CCA	0.85	0.013	64.179	0	Supported
H.1.b.16	CC-HOC -> CCC	0.844	0.014	59.061	0	Supported
H.1.b.17	CC-HOC -> CCM	0.814	0.016	49.38	0	Supported
H.1.b.18	CC-HOC -> CCS	0.876	0.01	84.613	0	Supported

The variable labels are given below, which are utilized for constructing the model. They can be observed in Table 4.18 below to provide a better understanding of the conceptual model.

Table 4.18: Chatbot Data Variable Heads

Variables Heads Labels	
C	Controllability
CQ	Conversation Quality
F	Flexibility
PA	Perceived Anthropomorphism
PEU	Ease of Use
CC-HOC	Customer Characteristics Higher Order Construct
CCA	Attitude
CCC	Customer Inertia
CCM	Motivation
CCS	Satisfaction
CE	Customer Engagement

From the above table, it can be observed that all the direct assessments support the hypothesis except for a few like H.1.b.4 (PA → CE) and H.1.b.14 (PEU → CE) are the only two hypothesis that do not show significant results to support the hypothesis. At the individual level, the hypothesis assessment is mentioned below.

The results indicate a direct relationship between Controllability and customer engagement ($t = 8.11$, $P = 0.00$), which supports hypothesis H.1.b.1: There is a significant relationship between Controllability and customer engagement.

The results of conversation quality to customer engagement ($t = 2.576$, $p = 0.01$) support hypothesis H.1.b.2: There is a significant relationship between Conversation Quality and customer engagement.

The results of Flexibility to customer engagement ($t = 8.446$; $p = 0.00$) show significant results supporting the hypothesis. H.1.b.3: There is a significant relationship between Flexibility and customer engagement.

The results of Perceived anthropomorphism to customer engagement ($t = 1.436$; $P = 0.151$) show insignificant results, indicating that they do not support the hypothesis.

H.1.b.4: There is a significant relationship between Perceived anthropomorphism and customer engagement.

The results of Controllability to Ease of Use ($t = 3.939$; $P = 0.00$) show significant results supporting the hypothesis. H.1.b.5: There is a significant relationship between Controllability and Ease of Use.

The results of Conversation Quality to Ease of Use ($t = 2.429$; $P = 0.015$) show significant results supporting the hypothesis. H.1.b.6: There is a significant relationship between Conversation Quality and Ease of Use.

The results of Flexibility to Ease of Use ($t = 3.439$; $P = 0.001$) show significant results supporting the hypothesis. H.1.b.7: There is a significant relationship between Flexibility and Ease of Use.

The results of Perceived Anthropomorphism to Ease of Use ($t = 5.886$; $P = 0.00$) show significant results that support the hypothesis. H.1.b.8: There is a significant relationship between Perceived anthropomorphism and Ease of Use.

The results of Controllability to Customer Characteristics ($t = 8.424$; $P = 0.00$) show significant results supporting the hypothesis H.1.b.9: There is a significant relationship between Controllability to Customer Characteristics.

The results of Conversation Quality to Customer Characteristics ($t = 5.795$; $P = 0.00$) show significant results supporting the hypothesis H.1.b.10: There is a significant relationship between Conversation Quality and Customer Characteristics.

The results of Flexibility to Customer Characteristics ($t = 4.545$; $P = 0.00$) show significant results that support hypothesis H.1.b.11: There is a significant relationship between Flexibility and Customer Characteristics.

The results of Perceived Anthropomorphism to Customer Characteristics ($t = 9.123$; $P = 0.00$) support hypothesis H.1.b.12: There is a significant relationship between Perceived Anthropomorphism to Customer Characteristics.

The results indicate a direct relationship between Customer characteristics and customer engagement ($t = 2.702$, $P = 0.007$), showing significance supporting hypothesis H.1.b.13, which is a significant relationship between Customer characteristics and Customer engagement.

The results indicate no direct relationship between Ease of Use and customer engagement ($t = 0.159$, $P = 0.874$) did not show significant results and support hypothesis H.1.b.14: A significant relationship exists between Ease of Use and customer engagement.

The Customer Characteristics to Attitude ($t = 64.179$; $p = 0.00$) indicate a significant result supporting hypothesis H.1.b.15: Customer Characteristics and Attitude is a significant relationship.

The results of Customer Characteristics to Customer inertia ($t = 59.061$; $p = 0.00$) indicate a significant result supporting hypothesis H.1.b.16: There is a significant relationship between Customer characteristics and Customer inertia.

The results of Customer Characteristics to motivation ($t = 49.38$; $p = 0.00$) indicate a significant result supporting hypothesis H.1.b.17: There is a significant relationship between Customer characteristics and motivation.

The Customer Characteristics to Satisfaction ($t = 84.613$; $p = 0.00$) indicate a significant result supporting hypothesis H.1.b.18: Customer Characteristics and Satisfaction is a significant relationship.

This concludes the assessment of the direct hypothesis from H.1.b.1 to H.1.b.18, except for a few of the direct constructs supporting the hypothesis.

4.3.2.6 Assessment of Mediation Effect:

The mediation effect is generally explained as when a latent construct variable acts as a mediator between two other related constructs. More precisely, a change in the exogenous causes a change in the mediator variable, which will influence the relation of the endogenous constructs in the PLS path model. Furthermore, recent studies indicated that mediator variable relationships with other constructs generally rely upon

the cause-effect relationship between all the exogenous constructs. There is no fixed rule that only one variable acts as a mediating variable, and the path model can simultaneously include many mediators. Hair et al. (2017), Nitzl et al. (2016) and Cepeda et al. (2017) proposed multiple models and assessment techniques for the mediation effect. The current study has adopted Zhao et al. (2010) and Rungtusanatham et al. (2014). The transmittal method primarily focuses on developing the hypothesis that M as a mediator between X and Y to know either X has an indirect effect on Y through M, to release the articulate process of path X to M and M to Y. through the Bootstrapping technique with 5000 subsamples used to estimate 95% of the bias-corrected confidence interval of indirect effect. The researcher used the path model to construct a mediation path to assess the mediation effect, as seen in Table 4.19.

Table 4.19: Assessment of Mediation

Hypothesis	Path	Path Coefficient	SE	t-statistics	p-values	Decision
Indirect Effect						
H.2b.1	CQ -> PEU -> CE	-0.001	0.005	0.143	0.886	Not Supported
H.2b.2	F -> PEU -> CE	-0.001	0.006	0.151	0.88	Not Supported
H.2b.3	PA -> PEU -> CE	-0.001	0.009	0.156	0.876	Not Supported
H.2b.4	C -> PEU -> CE	-0.001	0.007	0.154	0.877	Not Supported
H.2b.5	CQ -> CC-HOC -> CE	0.032	0.013	2.44	0.015	Supported
H.2b.6	F -> CC-HOC -> CE	0.024	0.01	2.401	0.016	Supported
H.2b.7	PA -> CC-HOC -> CE	0.044	0.017	2.556	0.011	Supported
H.2b.8	C -> CC-HOC -> CE	0.042	0.017	2.461	0.014	Supported

Through Bootstrapping->specific indirect effect, the researcher evaluated the mediation effect, and the results indicate that only a few constructs support the proposed hypothesis from the model. Furthermore, the path that supports the hypothesis supports partial mediation, as the direct assessment supports the hypothesis.

The results indicate that Ease of Use does not mediate between conversation quality and customer engagement ($t = 0.143$; $p = 0.886$). Results are insignificant, suggesting it does not support hypothesis H.2b.1: There is a significant mediation relationship between Ease of Use in Conversation quality and customer engagement.

The results indicate that Ease of Use has no role in the mediation effect between Flexibility and customer engagement ($t = 0.151$; $p = 0.88$). Results are insignificant, suggesting it does not support hypothesis H.2b.2: There is a significant mediation relationship between Ease of Use in Flexibility and customer engagement.

The results indicate that Ease of Use has no role in the mediation effect between Perceived Anthropomorphism and customer engagement ($t = 0.156$; $p = 0.876$). Results are insignificant, suggesting it does not support hypothesis H.2b.3: There is a significant mediation relationship between Ease of Use in Perceived Anthropomorphism and customer engagement.

The results indicate that Ease of Use does not mediate Controllability and customer engagement ($t = 0.154$; $p = 0.877$). Results are insignificant, suggesting it does not support hypothesis H.2b.4: There is a significant mediation relationship between Ease of Use in Controllability and customer engagement.

The results indicate that Customer Characteristics have a role in the mediation effect between Conversation quality and customer engagement ($t = 2.44$; $p = 0.015$). Results show significance, suggesting it supports hypothesis H.2b.5: There is a significant mediation relationship between Customer characteristics in Conversation quality and customer engagement.

The results indicate that Customer characteristics have a role in the mediation between Flexibility and customer engagement ($t = 2.401$; $p = 0.016$). Results show significance, suggesting it supports hypothesis H.2b.6: There is a significant mediation relationship between Customer characteristics in Flexibility and customer engagement.

The results indicate that Customer Characteristics have a role in the mediation effect between Perceived Anthropomorphism and customer engagement ($t = 2.556$; $p = 0.011$). Results show significance, suggesting it supports hypothesis H.2b.7: Customer

characteristics in Perceived Anthropomorphism and customer engagement have a significant mediation relationship.

The results indicate that Customer Characteristics have a role in the mediation effect between Controllability and customer engagement ($t = 2.461$; $p = 0.014$). Results show significance, suggesting it supports hypothesis H.2b.8: There is a significant mediation relationship between Customer characteristics in Controllability and customer engagement.

4.3.2.7 Assessment of Moderation Effect:

The following hypotheses are framed to analyse the first objective Moderating factors impact on the Ease of Use and Customer Characteristics from the Chatbot data set.

Table 4.20: Chatbot Moderation concerning Ease of Use and Customer Characteristics

Hypothesis	Path	Path Coefficient	SE	t-statistics	p-values	Decision
H.3b.1	Reason x PA -> PEU	0.02	0.037	0.533	0.594	Not Supported
H.3b.2	Reason x CQ -> PEU	0.065	0.054	1.201	0.23	Not Supported
H.3b.3	Reason x F -> PEU	-0.028	0.044	0.635	0.525	Not Supported
H.3b.4	Reason x C -> PEU	-0.011	0.04	0.274	0.784	Not Supported
H.3b.5	Con_Duration x PA -> PEU	-0.026	0.038	0.683	0.494	Not Supported
H.3b.6	Con_Duration x CQ -> PEU	0.072	0.055	1.301	0.193	Not Supported
H.3b.7	Con_Duration x F -> PEU	0.038	0.05	0.756	0.45	Not Supported
H.3b.8	Con_Duration x C -> PEU	-0.154	0.051	3.017	0.003	Supported
H.3b.9	User Expertise x PA -> PEU	0.005	0.042	0.125	0.901	Not Supported
H.3b.10	User Expertise x CQ -> PEU	0.094	0.053	1.772	0.077	Not Supported
H.3b.11	User Expertise x F -> PEU	-0.008	0.05	0.154	0.877	Not Supported
H.3b.12	User Expertise x C -> PEU	-0.004	0.042	0.107	0.915	Not Supported
H.3b.13	Reason x PA -> CC-HOC	0.038	0.037	1.011	0.312	Not Supported
H.3b.14	Reason x CQ -> CC-HOC	0.058	0.042	1.379	0.168	Not Supported
H.3b.15	Reason x F -> CC-HOC	-0.03	0.04	0.761	0.446	Not Supported
H.3b.16	Reason x C -> CC-HOC	-0.049	0.037	1.317	0.188	Not Supported
H.3b.17	Con_Duration x PA -> CC-HOC	0.001	0.034	0.022	0.983	Not Supported
H.3b.18	Con_Duration x CQ -> CC-HOC	0.158	0.043	3.683	0	Supported
H.3b.19	Con_Duration x F -> CC-HOC	-0.024	0.046	0.517	0.605	Not Supported
H.3b.20	Con_Duration x C -> CC-HOC	-0.08	0.044	1.805	0.071	Not Supported
H.3b.21	User Expertise x PA -> CC-HOC	-0.016	0.032	0.505	0.614	Not Supported
H.3b.22	User Expertise x CQ -> CC-HOC	-0.052	0.041	1.278	0.201	Not Supported
H.3b.23	User Expertise x F -> CC-HOC	0.015	0.048	0.312	0.755	Not Supported
H.3b.24	User Expertise x C -> CC-HOC	0.079	0.039	2.027	0.043	Supported

The reason as a moderator in between Perceived anthropomorphism to Ease of Use does not support the hypothesis which can be observed from the above table. Based on the T-statistics and Significance level study evaluates the hypothesis.

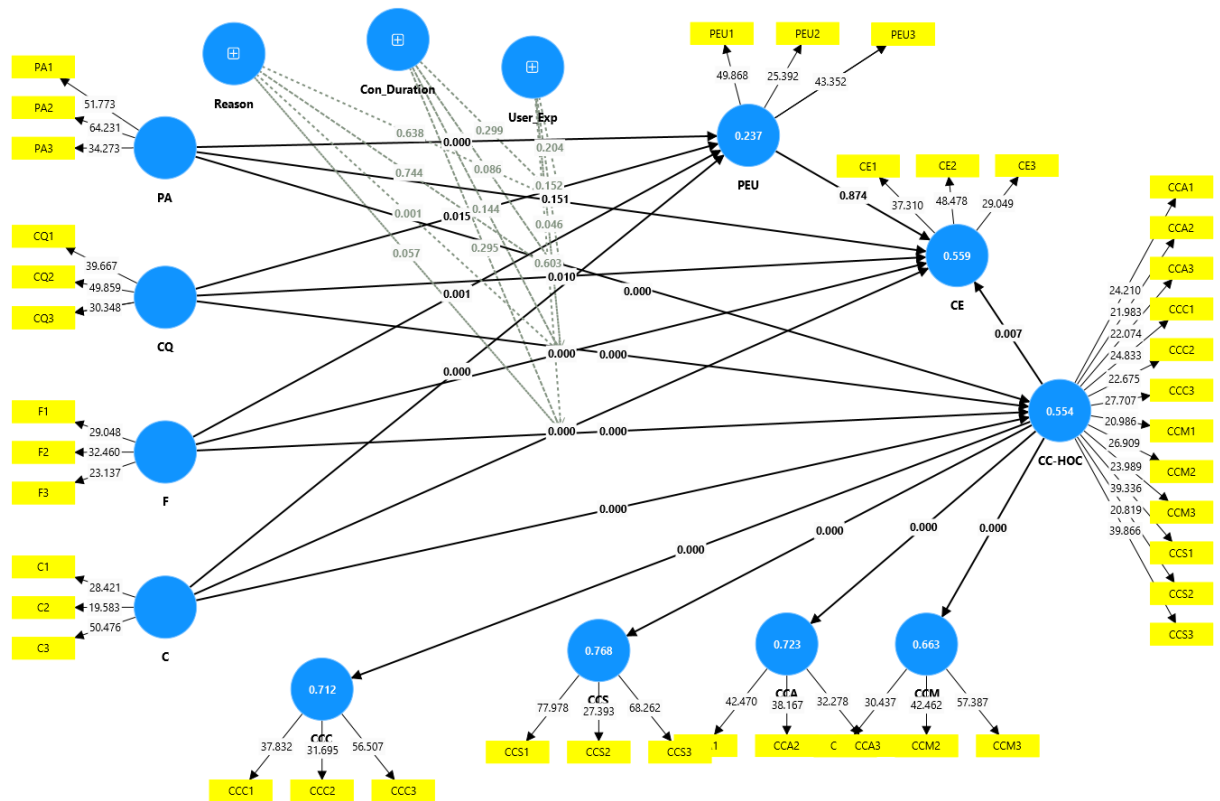


Figure 4.24 : Assessment of moderation with respect to Chatbots

Similarly, the reason as a moderator in between conversation quality to Ease of Use does not support the hypothesis. Again, reason as a moderator in between flexibility to Ease of Use does not support the hypothesis. Reason as a moderator between controllability to Ease of Use does not support the hypothesis as it is above the threshold of acceptance.

The conversation duration as a moderator between Perceived anthropomorphism to Ease of Use does not support the hypothesis which can be observed from the above table. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the conversation duration as a moderator in between conversation quality to Ease of Use does not support the hypothesis. Again, conversation duration as a moderator in between flexibility to Ease of Use does not support the hypothesis. The

conversation duration as a moderator is between controllability to Ease of Use supports the hypothesis as it is above the threshold of acceptance.

The User Expertise as a moderator between Perceived anthropomorphism to Ease of Use does not support the hypothesis which can be observed from the above table. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the User Expertise as a moderator in between conversation quality to Ease of Use does not support the hypothesis. Again, User Expertise as a moderator between flexibility to Ease of Use does not support the hypothesis. The User Expertise as a moderator between controllability to Ease of Use does not support the hypothesis as it is above the threshold of acceptance.

The reason as a moderator in between Perceived anthropomorphism to Customer Characteristics does not support the hypothesis which can be observed from the above table. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the reason as a moderator in between conversation quality to Customer Characteristics does not support the hypothesis. Again, reason as a moderator in between flexibility to Customer characteristics does not support the hypothesis. The reason as a moderator between controllability to Customer characteristics does not support the hypothesis as it is above the threshold of acceptance.

The conversation duration as a moderator between Perceived anthropomorphism to Customer characteristics does not support the hypothesis which can be observed from the above table. Based on the T-statistics and Significance level study evaluates the hypothesis.

The conversation duration as a moderator in between conversation quality to Customer characteristics supports the hypothesis. Again, conversation duration as a moderator in between flexibility to Customer characteristics does not support the hypothesis. The conversation duration as a moderator between controllability to Customer characteristics does not support the hypothesis as it is above the threshold of acceptance.

The User Expertise as a moderator between Perceived anthropomorphism to Customer characteristics does not support the hypothesis which can be observed from the above table. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the User Expertise as a moderator in between conversation quality to Customer characteristics does not support the hypothesis. Again, User Expertise as a moderator between flexibility to Customer characteristics does not support the hypothesis. The User Expertise as a moderator between controllability to Customer characteristics supports the hypothesis as it is above the threshold of acceptance.

Additional Hypothesis for Assessment of moderation on customer engagement with respect to Chatbots:

The obtained results are given below in **Table No. 4.21**, through the proposed model we have constructed a total of 12 hypotheses.

Table 4.21: Moderation Table

Hypothesis	Path	Path Coefficient	SE	t-statistics	p-values	Decision
H.3b.1.1	Reason x PA -> CE	0.016	0.034	0.47	0.638	Not Supported
H.3b.1.2	Reason x CQ -> CE	0.09	0.047	1.905	0.057	Not Supported
H.3b.1.3	Reason x F -> CE	0.014	0.043	0.327	0.744	Supported
H.3b.1.4	Reason x C -> CE	-0.128	0.038	3.407	0.001	Supported
H.3b.1.5	Con_Duration x PA -> CE	-0.035	0.034	1.04	0.299	Not Supported
H.3b.1.6	Con_Duration x CQ -> CE	-0.041	0.039	1.048	0.295	Not Supported
H.3b.1.7	Con_Duration x F -> CE	0.073	0.043	1.718	0.086	Supported
H.3b.1.8	Con_Duration x C -> CE	-0.054	0.037	1.46	0.144	Not Supported
H.3b.1.9	User Expertise x PA -> CE	-0.022	0.042	0.52	0.603	Supported
H.3b.1.10	User Expertise x CQ -> CE	0.088	0.044	1.993	0.046	Not Supported
H.3b.1.11	User Expertise x F -> CE	-0.049	0.039	1.269	0.204	Supported
H.3b.1.12	User Expertise x C -> CE	0.061	0.042	1.431	0.152	Not Supported

The results of Reason*perceived anthropomorphism to customer engagement ($t = 0.47$; $p = 0.638$) did not show significant results, suggesting it didn't support the hypothesis H.3b.1.1 There is a significant moderating role of Reason in between the Perceived Anthropomorphism to customer engagement.

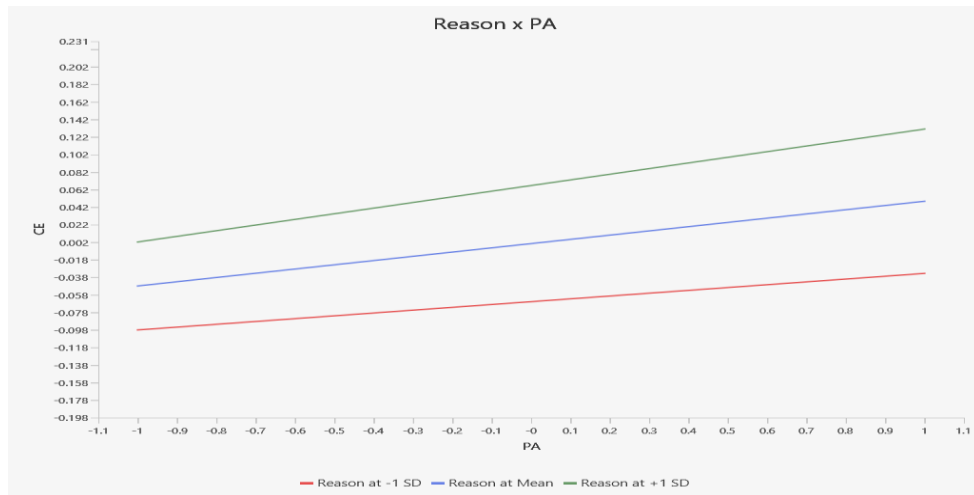


Figure 4.25: Reason*Perceived Anthropomorphism

The slope analysis also justifies that there is no moderating role of conversation duration in between perceived anthropomorphism to customer engagement.

The results of Reason*conversation Quality to customer engagement ($t = 1.905$; $p = 0.057$) results show insignificant results, suggesting it doesn't support the hypothesis H.3b.1.2 There is a significant moderating role of Reason in between the Conversation Quality to customer engagement.

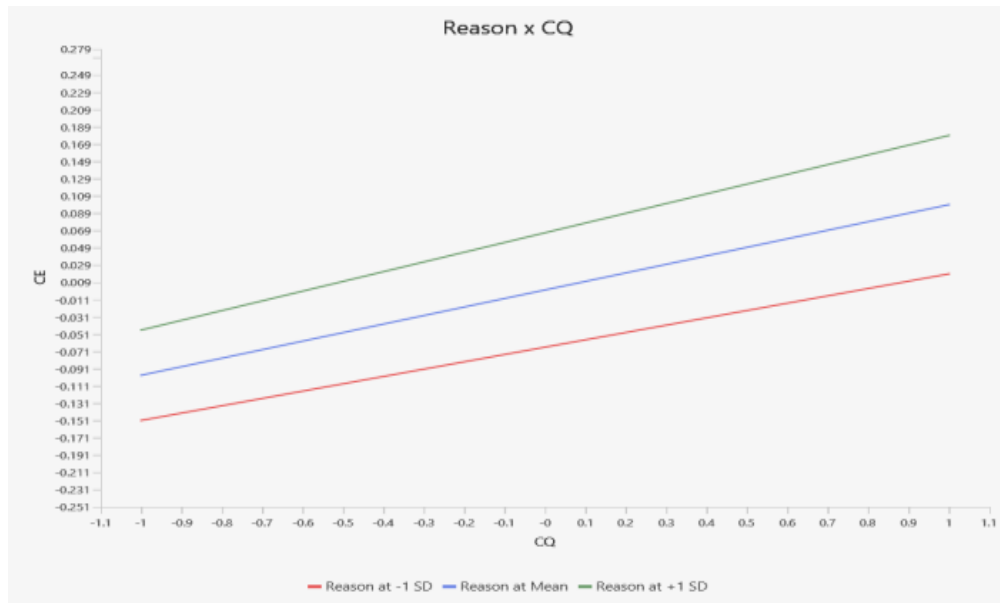


Figure 4.26: Reason*Conversation Quality

Hypothesis didn't support the above moderating effect, Even in the slope analysis it didn't show any significant moderating role, on a feedback basis customers are trying to moderate with conversation quality to customer engagement.

The results of Reason*Flexibility to customer engagement ($t = 0.327$; $p = 0.744$) did not show significant results, suggesting it didn't support the hypothesis H.3b.1.3 There is a significant moderating role of Reason in between the Flexibility to customer engagement.

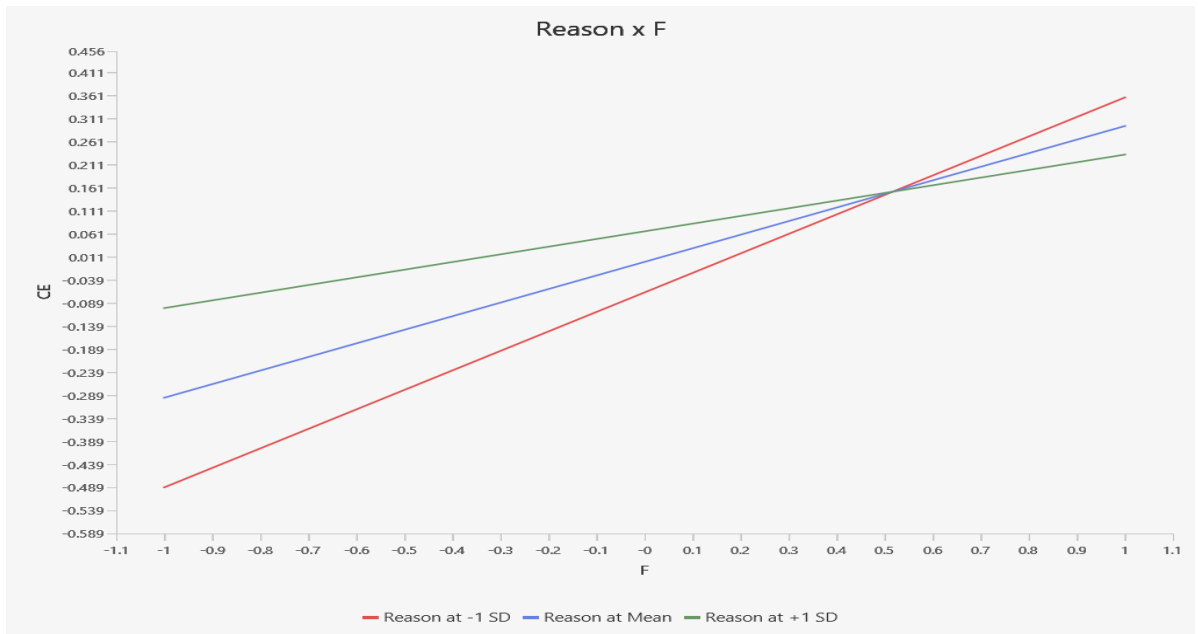


Figure 4.27: Reason*Flexibility

Though the hypothesis didn't support, Through the slope analysis it can be observed that there is a moderating role of Reason in between the Flexibility to customer engagement. Suggesting the reason might act as a potential moderator with a precise scale and on the basis of Information the customers played a huge moderating role in between the Flexibility to customer engagement.

The higher the reasons of the customer, the higher the impact of flexibility to customer engagement.

The results of Reason*controllability to customer engagement ($t = 3.407$; $p = 0.001$) showed significant results, suggesting it supports the hypothesis H.3b.1.4 There is a significant moderating role of Reason in between the Controllability to customer engagement.

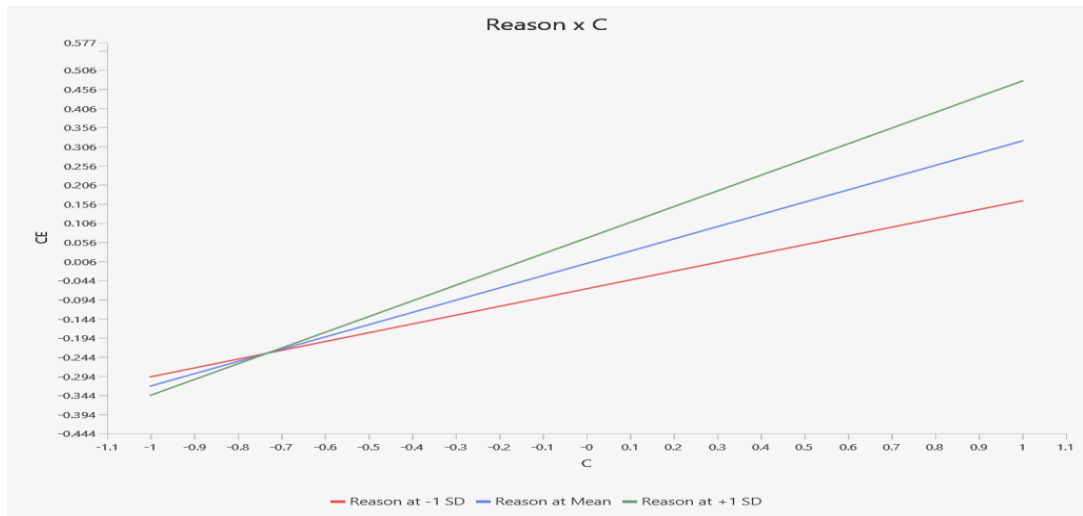


Figure 4.28: Reason*Controllability

Hypothesis supported the above moderating effect, Even in the slope analysis it shows a significant moderating role, on a Feedback basis customers are trying to moderate with controllability to customer engagement. The Feedback customers are more likely to moderate in between controllability to customer engagement. The lower the reasons of customer the higher the impact of controllability to customer engagement.

The results of Conversation duration*perceived anthropomorphism to customer engagement ($t = 1.04$; $p = 0.299$) did not show significant results, suggesting it didn't support the hypothesis H.3b.1.5 There is a significant moderating role of Conversation Duration in between the Perceived Anthropomorphism to customer engagement.

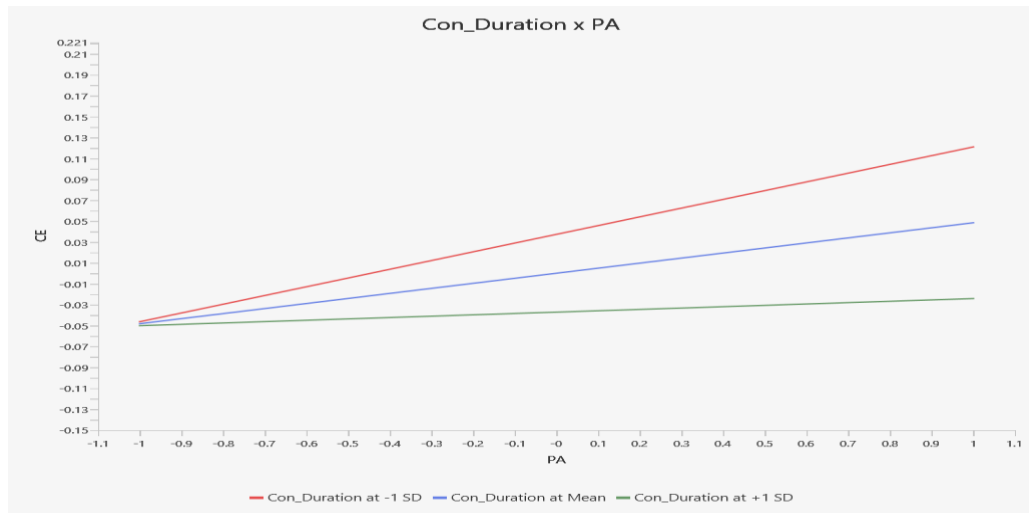


Figure 4.29: Conversation Duration*Perceived Anthropomorphism

The slope analysis indicates that there is a moderating role of conversation duration in between perceived anthropomorphism to customer engagement. The shorter conversation duration has a significant moderating role in between perceived anthropomorphism to customer engagement. The lower the Conversation duration, the higher the impact of conversation quality on customer engagement.

The results of Conversation_duration*Conversation Quality to customer engagement ($t = 1.048$; $p = 0.295$) did not show significant results, suggesting it didn't support the hypothesis H.3b.1.6 There is a significant moderating role of Conversation Duration in between the Conversation Quality to customer engagement.

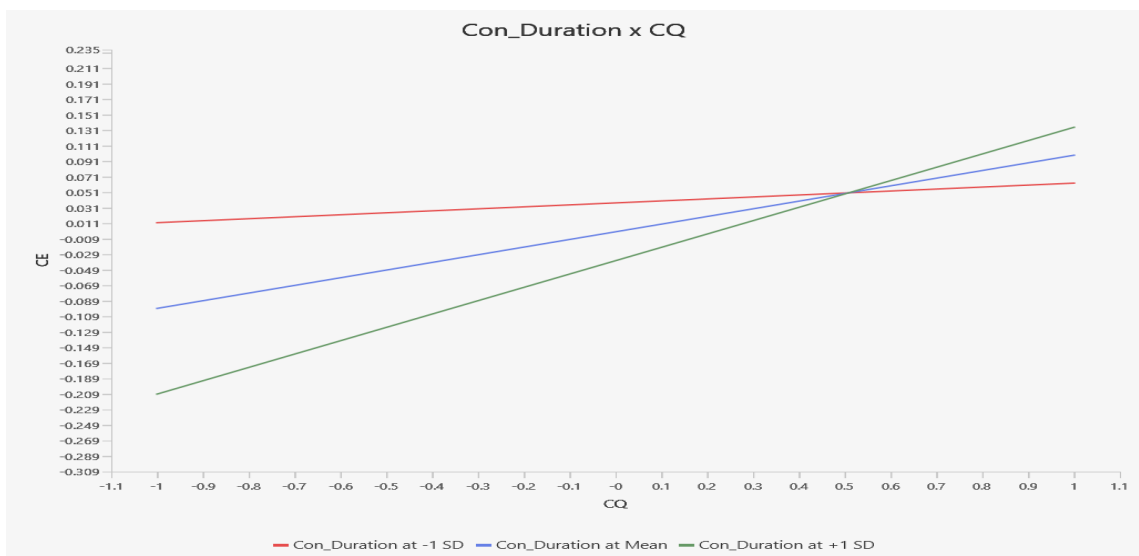


Figure 4.30: Conversation Duration*Conversation Quality

The slope analysis indicates that there is a moderating role of conversation duration in between Conversation Quality to customer engagement. The higher the conversation duration, higher the impact of conversation quality on customer engagement.

The results of Conversation_duration*Flexibility to customer engagement ($t = 1.718$; $p = 0.08$) show insignificant results, suggesting it doesn't support the hypothesis H.3b.1.7 There is a significant moderating role of Conversation Duration in between the Flexibility to customer engagement.

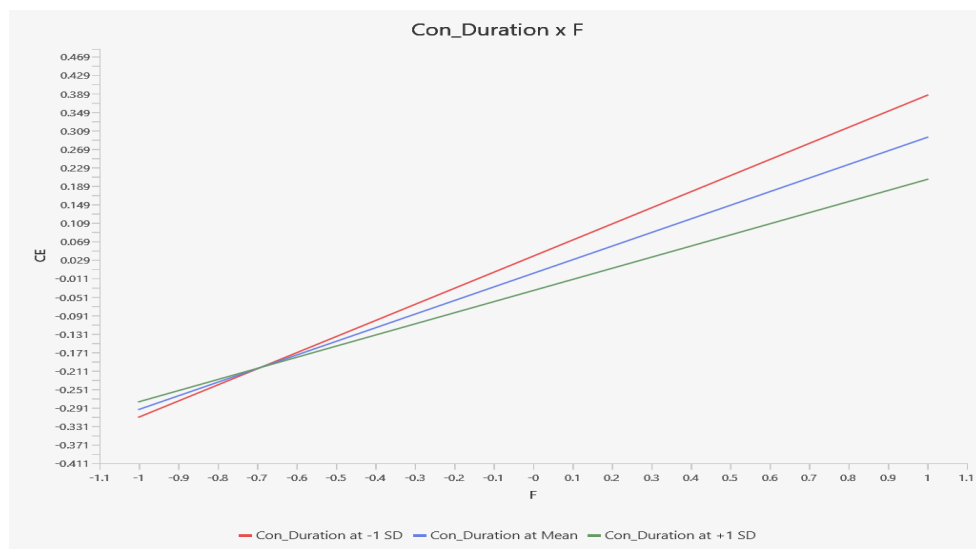


Figure 4.31: Conversation Duration*Flexibility

Hypothesis didn't support the above moderating effect, the slope analysis shows a significant moderating role, and Customers who have short conversation duration are trying to moderate with Flexibility to customer engagement. The lower the conversation duration higher the impact of flexibility on customer engagement

The results of Conversation_duration*Controllability to customer engagement ($t = 1.46$; $p = 0.144$) show insignificant results, suggesting it doesn't support the hypothesis H.3b.1.8 There is a significant moderating role of Conversation Duration in between the Controllability to customer engagement.

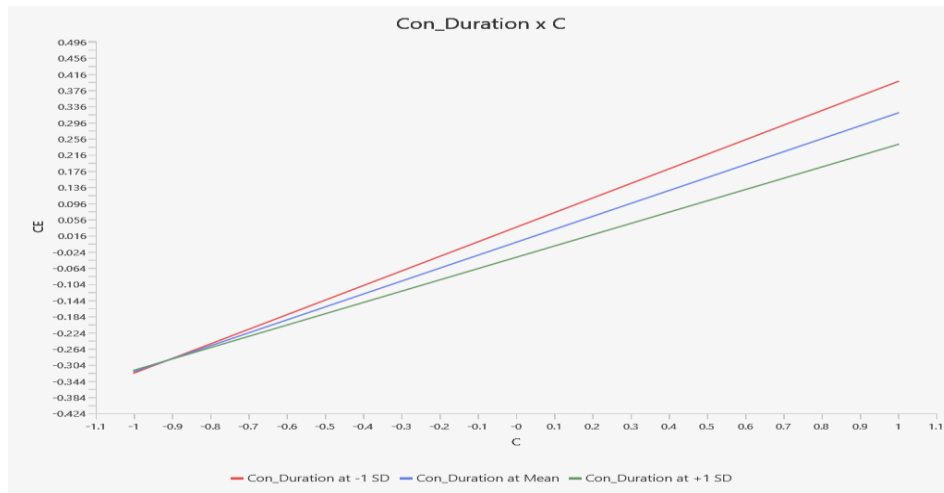


Figure 4.32: Conversation Duration*Controllability

Hypothesis didn't support the above moderating effect, The slope analysis shows a significant moderating role, customers who have short conversation duration are trying to moderate with Controllability to customer engagement. The lower the conversation duration the higher the impact of controllability on customer engagement.

The results of User Expertise*perceived anthropomorphism to customer engagement ($t = 0.52$; $p = 0.603$) did not show significant results, suggesting it didn't support the hypothesis H.3b.1.9 There is a significant moderating role of User Expertise in between the Perceived Anthropomorphism to customer engagement.

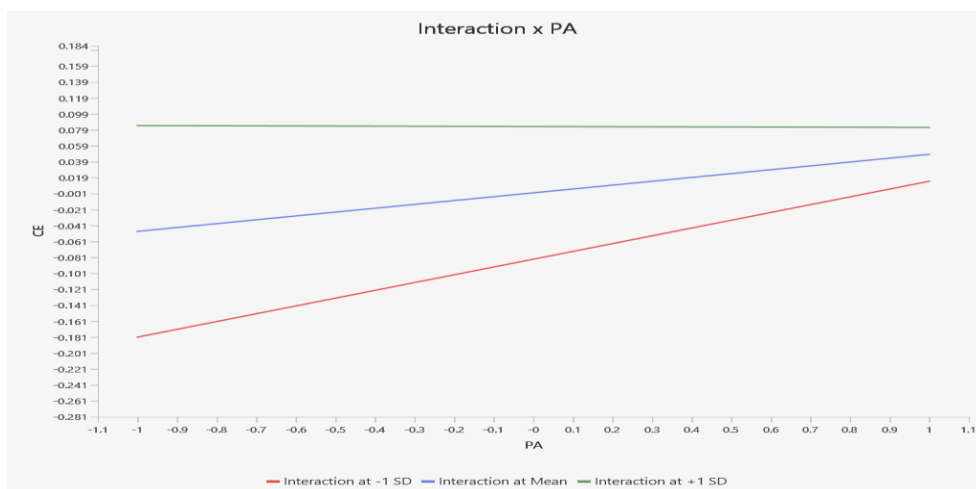


Figure 4.33: User Expertise*Perceived Anthropomorphism

Though the hypothesis didn't support slope analysis it can be observed that there is a moderating role of User Expertise between the perceived Anthropomorphism to customer engagement. Suggesting the reason might act as a potential moderator with a precise scale and the Prepurchase/Information search phase of the customers played a huge moderating role in between the perceived Anthropomorphism to customer engagement. The more the User Expertise the higher the impact of perceived anthropomorphism on customer engagement.

The results of User Expertise*conversation Quality to customer engagement ($t = 1.993$; $p = 0.046$) showed significant results, suggesting it supports the hypothesis H.3b.1.10 There is a significant moderating role of User Expertise in between the Conversation Quality to customer engagement.

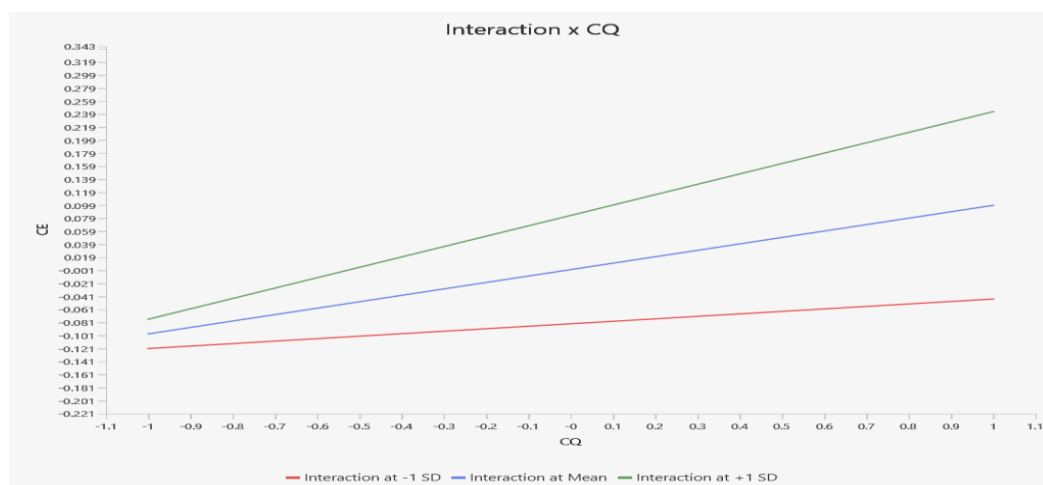


Figure 4.34: User Expertise*Conversation Quality

Hypothesis supported the above moderating effect, even in the slope analysis it shows a significant moderating role, on the prepurchase/Information search phase customers are trying to moderate conversation quality to customer engagement. Furthermore, it suggests that lower the User Expertise the more the moderation of the chatbot users

The results of User Expertise*Flexibility to customer engagement ($t = 1.269$; $p = 0.204$) show insignificant results, suggesting it doesn't support hypothesis H.3b.1.11 There is a significant moderating role of User Expertise in between the Flexibility to customer engagement.

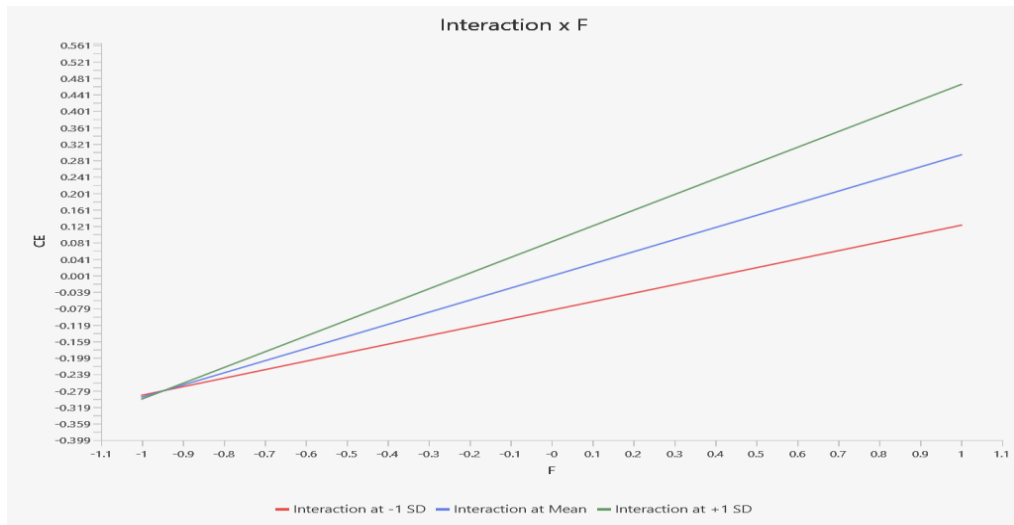


Figure 4.35: User Expertise*Flexibility

The hypothesis didn't support the above moderating effect, however in the slope analysis it shows a significant moderating role, In the post-purchase phase customers are trying to moderate flexibility to customer engagement.

The results of User Expertise*Controllability to customer engagement ($t = 1.431$; $p = 0.152$) did not show significant results, suggesting it didn't support the hypothesis H.3b.1.12 There is a significant moderating role of User Expertise in between the Controllability to customer engagement.

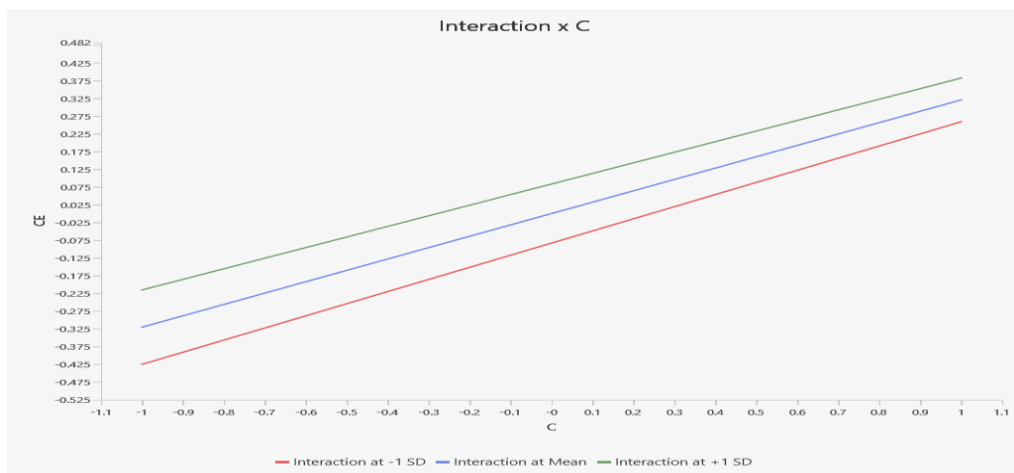


Figure 4.36: User Expertise*Controllability

The slope analysis also justifies that there is no moderating role of conversation duration in between perceived anthropomorphism to customer engagement.

In conclusion, the data analysis chapter offers valuable insights into the comparison between chatbots and customer executives in customer engagement. By carefully examining the data, we've identified important trends and connections, which provide meaningful implications for businesses and customer service strategies. Our findings not only confirm our initial ideas but also reveal new discoveries, showing how complex the User Expertise's between chatbots and human agents can be.

Overall, this data analysis chapter adds to our understanding of customer engagement and provides a foundation for further study in the comparison between chatbots and human executives. By using these insights, businesses can make better decisions about how to leverage technology and human resources effectively.

CHAPTER - 5

**FINDINGS, CONCLUSION, STUDY
IMPLICATIONS, LIMITATIONS AND
RECOMMENDATIONS**

Chapter - 5

FINDINGS, CONCLUSION, STUDY IMPLICATIONS, LIMITATIONS AND RECOMMENDATIONS

5.1 Findings

The study aims to examine the role of Chatbots and customer executives in the service industry. Furthermore, to explore the customer engagement concerning these services opted by the customers. Based on the previous studies the current study has identified a research gap that both chatbot and customer executives haven't been considered for the study. To evaluate the impact of chatbots and customer executives on customer engagement, the study has considered Ease of Use and customer characteristics as a mediator to observe their role. There, appropriate tools like SmartPLS have been utilised to test the hypothesized model to obtain a better understanding of the model, as the study has relied on SEM (structural equation Modeling) and the data structure is non-normal. The study has utilised SmartPLS services to test the hypothesis.

The study has tried to explore the following objectives to validate the study:

1. To examine the role of Ease of Use & Customer characteristics between service attributes and customer engagement.
2. To study the effect of 'Reason of Interaction', 'user expertise' and 'Conversation Duration' between service attributes and Ease of Use & Customer characteristics.
3. To compare the effectiveness of chatbots and customer executives for customer engagement.

Based on these following objectives and conceptual model the study has formulated the following hypothesis:

Furthermore, they have been categorized as per the Chatbot and customer executive for better understanding.

The descriptive model has been evaluated through SmartPLS to obtain a better understanding of the role of both chatbots and customer executives.

The findings have been presented objective wise to provide a better understanding of the current study.

Objective 1: To examine the role of Ease of Use & Customer characteristics between service attributes and customer engagement.

a. Assessing the mediating role of Ease of use and customer characteristics concerning customer executives.

The results indicate that Ease of Use has no role in the mediation effect between conversation quality to customer engagement.

The results indicate that Ease of Use has no role in the mediation effect between Flexibility to customer engagement.

The results indicate that Ease of Use has no role in the mediation effect between Perceived Anthropomorphism to customer engagement.

The results indicate that Ease of Use has no role in the mediation effect between Controllability to customer engagement.

The results indicate that Customer Characteristics have a role in the mediation effect between Conversation quality and customer engagement.

The results indicate that Customer Characteristics has no role in the mediation effect between Flexibility to customer engagement.

The results indicate that Customer Characteristics have a role in the mediation effect between Perceived Anthropomorphism and customer engagement.

The results indicate that Customer Characteristics have a role in the mediation effect between Controllability and customer engagement.

From the previous chapter 4 , Table 4.9, the study concludes that Ease of Use does not have any significant moderating role in between service attributes to Customer engagement. The study concluded that Customers try to engage with these customer executives in case of severity as that is the only reason to engage with customer executives. The role of customer characteristics has a significant moderating role in

between service attributes to customer engagement, In the study customer executives were evaluated based on customer satisfaction, customer motivation, customer attitude, and customer inertia. The study has constructed a higher model to make it a part of mediation analysis and to reduce the load on the conceptual model.

Customer characteristics have played a significant mediating role in between the service attributes the conversation quality, perceived anthropomorphism, and controllability to Customer engagement, meanwhile concerning flexibility the customer executive doesn't have a mediating role in Customer engagement.

The path perceived anthropomorphism and controllability have a significant and more strong mediating role out of all the constructs.

b. Assessing the mediating role of Ease of use and customer characteristics concerning chatbots.

The results indicate that Ease of Use has no role in the mediation effect between conversation quality and customer engagement.

The results indicate that Ease of Use has no role in the mediation effect between Flexibility to customer engagement.

The results indicate that Ease of Use has no role in the mediation effect between Perceived Anthropomorphism to customer engagement.

The results indicate that Ease of Use has no role in the mediation effect between Controllability to customer engagement.

The results indicate that Customer Characteristics have a role in the mediation effect between Conversation quality and customer engagement.

The results indicate that Customer Characteristics have a role in the mediation effect between Flexibility to customer engagement.

The results indicate that Customer Characteristics have a role in the mediation effect between Perceived Anthropomorphism and customer engagement.

The results indicate that Customer Characteristics have a role in the mediation effect between Controllability and customer engagement.

From the previous chapter 4 (Table 4.19), the study concludes that Ease of Use does not have any significant moderating role in between service attributes to Customer

engagement. The study concludes that Customers try to engage with these customer executives in case of severity as that is the major or key reason to engage with customer executives. The role of customer characteristics has a significant moderating role in between service attributes to chatbots, in the study customer executives were evaluated based on customer satisfaction, customer motivation, customer attitude, and customer interest. The study has constructed a higher model to make it a part of mediation analysis and to reduce the load on the conceptual model.

Customer characteristics have played a significant mediating role in between the service attributes the conversation quality, flexibility, perceived anthropomorphism, and controllability to Customer engagement.

Objective 2: To study the effect of ‘Reason of Interaction’, ‘user expertise’ and ‘Conversation Duration’ between service attributes and Ease of Use & Customer characteristics.

a. Moderation in between Service attributes to ease of use and customer characteristics concerning customer executive has given below.

The reason as a moderator in between Perceived anthropomorphism to Ease of Use does not support the hypothesis which can be observed from the table no. 4.10. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the reason as a moderator in between conversation quality to Ease of Use does not support the hypothesis. Again, reason as a moderator in between flexibility to Ease of Use does not support the hypothesis. The reason as a moderator is between controllability to Ease of Use supports the hypothesis as it is above the threshold of acceptance.

The conversation duration as a moderator between Perceived anthropomorphism to Ease of Use does not support the hypothesis which can be observed from the table no. 4.10. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the conversation duration as a moderator in between conversation quality to Ease of Use does not support the hypothesis. Again, conversation duration as a moderator in between flexibility to Ease of Use supports the hypothesis. The conversation duration as a moderator is between controllability to Ease of Use supports the hypothesis as it is above the threshold of acceptance.

The User Expertise as a moderator between Perceived anthropomorphism to Ease of Use supports the hypothesis which can be observed from the table no. 4.10. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the User Expertise as a moderator in between conversation quality to Ease of Use does not support the hypothesis. Again, User Expertise as a moderator between flexibility to Ease of Use supports the hypothesis. The conversation duration as a moderator between controllability to Ease of Use does not support the hypothesis as it is above the threshold of acceptance.

The reason as a moderator in between Perceived anthropomorphism to Customer Characteristics supports the hypothesis which can be observed from the table no. 4.10. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the reason as a moderator in between conversation quality to Customer Characteristics supports the hypothesis. Again, reason as a moderator in between flexibility to Customer characteristics does not support the hypothesis. The reason as a moderator is between controllability to Customer characteristics supports the hypothesis as it is above the threshold of acceptance.

The conversation duration as a moderator between Perceived anthropomorphism to Customer characteristics does not support the hypothesis which can be observed from the table no. 4.10. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the conversation duration as a moderator in between conversation quality to Customer characteristics does not support the hypothesis. Again, conversation duration as a moderator in between flexibility to Customer characteristics does not support the hypothesis. The conversation duration as a moderator between controllability to Customer characteristics does not support the hypothesis as it is above the threshold of acceptance.

The User Expertise as a moderator between Perceived anthropomorphism to Customer characteristics does not support the hypothesis which can be observed from the table no. 4.10. Based on the T-statistics and Significance level study evaluates the hypothesis.

- From the above observations, the study defines that reason, conversation duration and User Expertise have a partial moderation effect on Ease of Use and customer characteristics. At an individual level, the study has observed that reason plays a significant role as a moderator between service attributes to customer characteristics and vice-versa in the case of Ease of Use where only controllability acts as a moderator remaining doesn't act as a moderator.
- Similarly, conversation duration has also a weak moderating role in between service attributes to Ease of Use and customer characteristics. In the case of Ease of Use,

both flexibility and controllability conversation duration have a significant moderating role meanwhile perceived anthropomorphism and conversation quality don't have any. With customer characteristics, all the relations do not have any moderation role similar to the case of User Expertise also none of the relations do not have a moderation role. In the case of Ease of Use conversation quality and flexibility have a moderating effect and remaining do not have any moderating effect.

b. Moderation in between Service attributes to ease of use and customer characteristics concerning Chatbot is given below.

The reason as a moderator in between Perceived anthropomorphism to Ease of Use does not support the hypothesis which can be observed from the table no. 4.20. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the reason as a moderator in between conversation quality to Ease of Use does not support the hypothesis. Again, reason as a moderator in between flexibility to Ease of Use does not support the hypothesis. The reason as a moderator between controllability to Ease of Use does not support the hypothesis as it is above the threshold of acceptance.

The conversation duration as a moderator between Perceived anthropomorphism to Ease of Use does not support the hypothesis which can be observed from the table no. 4.20. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the conversation duration as a moderator in between conversation quality to Ease of Use does not support the hypothesis. Again, conversation duration as a moderator in between flexibility to Ease of Use does not support the hypothesis. The conversation duration as a moderator is between controllability to Ease of Use supports the hypothesis as it is above the threshold of acceptance.

The User Expertise as a moderator between Perceived anthropomorphism to Ease of Use does not support the hypothesis which can be observed from the table no. 4.20. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the User Expertise as a moderator in between conversation quality to Ease of Use does not support the hypothesis. Again, User Expertise as a moderator between flexibility to Ease of Use does not support the hypothesis. The User Expertise as a moderator between controllability to Ease of Use does not support the hypothesis as it is above the threshold of acceptance.

The reason as a moderator in between Perceived anthropomorphism to Customer Characteristics does not support the hypothesis which can be observed from the table no. 4.20. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the reason as a moderator in between conversation quality to Customer Characteristics does not support the hypothesis. Again, reason as a moderator in between flexibility to Customer characteristics does not support the hypothesis. The reason as a moderator between controllability to Customer characteristics does not support the hypothesis as it is above the threshold of acceptance.

The conversation duration as a moderator between Perceived anthropomorphism to Customer characteristics does not support the hypothesis which can be observed from the table no. 4.20. Based on the T-statistics and Significance level study evaluates the hypothesis.

The conversation duration as a moderator in between conversation quality to Customer characteristics supports the hypothesis. Again, conversation duration as a moderator in between flexibility to Customer characteristics does not support the hypothesis. The conversation duration as a moderator between controllability to Customer characteristics does not support the hypothesis as it is above the threshold of acceptance.

The User Expertise as a moderator between Perceived anthropomorphism to Customer characteristics does not support the hypothesis which can be observed from the above table. Based on the T-statistics and Significance level study evaluates the hypothesis.

Similarly, the User Expertise as a moderator in between conversation quality to Customer characteristics does not support the hypothesis. Again, User Expertise as a moderator between flexibility to Customer characteristics does not support the

hypothesis. The User Expertise as a moderator between controllability to Customer characteristics supports the hypothesis as it is above the threshold of acceptance.

The results of the study indicate that reason, conversation duration and User Expertise don't play any role as a moderator in between service attributes to customer characteristics and Ease of Use. As conversation duration as a moderator in between controllability to Ease of Use has a significant moderating role and in the case of customer characteristics concerning to conversation quality and controllability have significant moderating while remaining factors don't have any moderating role.

At a combined level the study perspective is that reason, conversation duration and User Expertise as a moderator can be viewed from the customer executive side only as the chatbot results do not show any significance so the study states that customers are more likely to engage with customer executives than compared to chatbots.

Objective 3: To compare the effectiveness of chatbots and customer executives for customer engagement.

Through the entire results of the study, we have evaluated the following objective to determine which customer service is preferred by the customers most of the time and we tried to correlate both customer executive and chatbot services by writing a detailed conclusion to give a brief explanation.

1. Direct assessment results and findings of the study are given below,

Table 5.1: Comparison table (Direct Assessment)

S.NO	Construct	(1a)	(1b)	Findings
		Customer executive	Chatbot	
1	Controllability to Customer engagement	Supported	Supported	By analyzing the data collected through the interactions with AI chatbots, it is possible to support the hypothesis that customer executive controllability directly impacts Customer engagement (Hu et al., 2009). The ability to control the conversation and provide relevant and timely support through AI chatbots has shown to have a positive effect on customer satisfaction and overall engagement levels. This supports the idea that giving customers

				<p>more control over their interactions with brands can lead to increased engagement and ultimately, stronger customer relationships. Customer executives play a crucial role in building and maintaining customer engagement. The trustworthiness and reliability of customer executives can significantly impact the overall customer experience. When customers feel that they can rely on the support and guidance provided by customer executives, it enhances their engagement with the brand (Chuah et al., 2020) . This trust can lead to long-term relationships and loyalty, as customers are more likely to continue engaging with a brand that consistently delivers reliable and trustworthy customer support (Cambra-Fierro et al., 2014). Therefore, prioritizing the training and development of customer executives to ensure they embody these qualities is essential for fostering meaningful customer engagement. In conclusion, the findings of this study support the hypothesis that controllability, specifically through AI chatbots, positively impacts Customer engagement (Yun & Park, 2022).</p>
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2	Conversation Quality to Customer engagement	Supported	Supported	<p>After analyzing the data and conducting in-depth reviews, it is clear that there is a strong correlation between conversation quality and customer engagement (Yun & Park, 2022). The findings indicate that when conversations are personalized, proactive, and responsive, it leads to higher levels of customer satisfaction and retention (Al-Safar et al., n.d). Additionally, the use of positive language, active listening, and empathy significantly impact the overall quality of interactions and customer perception (Wang et al., 2020).</p> <p>In conclusion, it is imperative for businesses to prioritize conversation quality as a key driver of customer engagement. By implementing strategies to improve the quality of conversations, such as training employees in active listening and empathy, utilizing personalized communication, and being proactive in addressing customer needs, businesses can enhance customer engagement, loyalty, and ultimately, drive business growth.</p>
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3	Flexibility to Customer engagement	Supported	Supported	<p>The ability to adapt to varying Customer preferences and behaviors is crucial for companies in today's dynamic market. By leveraging flexible strategies, businesses can better cater to the diverse needs of their customer base and ultimately drive greater satisfaction and loyalty (Zhang et al., 2018). Moving forward, it is imperative for organizations to prioritize and integrate flexibility into their Customer engagement approaches to stay competitive and effectively meet evolving Customer demands (Jin & Oriaku, 2013). This is a satisfactory completion of the sentence. In conclusion, the research findings indicate that flexibility in Customer engagement has a positive impact on employee engagement (Anderson & Kelliher, 2009). In conclusion, the research findings demonstrate that flexibility in Customer engagement is crucial for businesses to enhance customer experience and drive customer engagement (Wiktor, 2021). By offering Customers a degree of choice in when, where, and how they engage with a brand, companies can create a more personalized and tailored experience. This leads to increased customer satisfaction, loyalty, and overall engagement (Roy et al., 2018).</p>
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4	Perceived anthropomorphism to Customer engagement	Supported	Not Supported	<p>The study found that age group (8-25) years [Gen Z], had a higher perception of warmth and competence in chatbots compared to age group above 45 years [Gen X]. This perception led to modifications in Customer attitudes and enhanced Customer engagement (Hildebrand & Bergner, 2019). Additionally, the study found that personalizing chatbots to basic Customer characteristics increased trust perception and improved the perception of intimacy between the customer, the chatbot, and ultimately the brand (Adam et al., 2020). The use of chatbots in customer service interactions was found to have high acceptance in society and added value by reducing potential customer embarrassment compared to service employees. In conclusion, the findings of the study clearly demonstrate the significant impact of perceived anthropomorphism, specifically in the form of chatbots, on Customer engagement (Han, 2021). Furthermore, personalizing chatbots to basic Customer characteristics was found to increase trust perception and enhance the perception of intimacy between the customer, the chatbot, and the brand (Klein & Martinez, 2022). The high acceptance of chatbots in customer service interactions and their ability to reduce potential customer embarrassment</p>
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				<p>compared to service employees further adds value to their use. This study highlights the importance of leveraging perceived anthropomorphism in chatbots to enhance Customer engagement and improve brand-Customer relationships. The study found that perceived anthropomorphism, specifically in the form of chatbots, has a significant impact on Customer engagement (Yun & Park, 2022).</p>
5	<p>Controllability to Ease of Use</p>	Supported	Supported	<p>The impact of controllability on users' perception of ease of use has been a subject of interest in various fields (Gefen & Straub, 2008), including user experience design and human-computer interaction. This relationship not only sheds light on the importance of controllability but also provides actionable insights for creating user-friendly products and systems (Keil et al., 1995). In this light, further exploration of the interplay between controllability and</p>

				<p>Ease of Use can offer valuable guidance for enhancing user experiences and driving innovation in product development. Given the findings from the selected sources (Venkatesh, 2000), it can be concluded that there is a significant relationship between controllability and Ease of Use. This relationship suggests that when users feel a sense of control over a system or product, they are more likely to perceive it as easy to use. The analysis of the data indicated that a higher sense of controllability leads to an increased perception of ease of use among users. This finding suggests that enhancing the controllability of a system or product can positively influence the user's perception of its ease of use. Furthermore, the study highlights the importance of considering controllability as a key factor in the design and development of user-friendly products and systems. Overall, the findings support the idea that controllability plays a crucial role in shaping the Ease of Use, and this insight can be valuable for various fields such as user experience design, human-computer interaction, and product development.</p>
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6	Conversation quality to Ease of Use	Supported	Supported	<p>The study conducted by (Xu et al., 2022) aimed to investigate the moderating role of chatbots and customer executives on customer experience and engagement (Nguyễn et al., 2020). The study found that customers are more satisfied with chatbots compared to customer executives in terms of Ease of Use (Yun & Park, 2022). Specifically, the study found that chatbots are 40% more engaging than traditional customer executives and provide faster and more efficient customer service. Another study focused on the interactivity dimension of chatbot service quality and its impact on customer satisfaction (Adam et al., 2020). This study found that interactivity, which includes prompt reactions and problem-solving, can lead to high customer satisfaction and sustain close relationships between customers and the brand. The findings from these studies suggest that conversation quality, particularly in the context of chatbots, has a significant impact on Ease of Use. Furthermore, the study found that the interactivity dimension of chatbot service quality plays a vital role in enhancing customer satisfaction (Yun & Park, 2022). The impact of conversation quality on Ease of Use, particularly in the context of chatbots, has been clearly established by the findings</p>
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				<p>of the studies mentioned. It is evident that chatbots are not only perceived as easier to use compared to traditional customer executives, but they also contribute significantly to customer satisfaction and engagement. The prompt reactions and problem-solving abilities of chatbots play a crucial role in enhancing the interactivity dimension of chatbot service quality, thereby sustaining close relationships between customers and the brand. These findings underscore the importance of prioritizing conversation quality in the design and implementation of user interfaces to ensure a positive user experience. In conclusion, the impact of conversation quality on Ease of Use, particularly in the context of chatbots, is significant. It suggests that designing chatbots with prompt reactions and effective problem-solving abilities can greatly enhance customer satisfaction, foster closer relationships between customers and brands, and ultimately improve overall user experience and engagement.</p>
7	Flexibility to Ease of Use	Supported	Supported	<p>The study(Kaur, 2020)(Çalışır & Çalışır, 2004) explores the relationship between flexibility and Ease of Use and examines the potential implications of these findings. This suggests that the</p>

			<p>flexibility offered by chatbots, in terms of their availability, responsiveness, and ability to provide personalized assistance, contributes to a higher perception of ease of use and satisfaction among users. The findings from this study shed light on the significant impact of flexibility on the Ease of Use in the context of customer interactions (Çalışır & Çalışır, 2004). The implications of these findings are far-reaching, particularly for organizations seeking to enhance their customer service experiences. Firstly, the study(Yun & Park, 2022) underscores the importance of providing users with flexible options when interacting with customer service systems . Offering choices between automated chatbots and human customer representatives can lead to improved user satisfaction and Ease of Use. Moreover, the ability for users to seamlessly transition between chatbots and human agents when encountering complex issues highlights the value of flexibility in customer service.</p> <p>The findings of this study provide compelling evidence of the positive impact of flexibility on the Ease of Use in customer service interactions. From the adoption of chatbots to the ability to seamlessly escalate to human agents, the flexibility offered to users</p>
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				<p>significantly contributes to their satisfaction and overall perception of ease of use. These insights hold valuable implications for organizations aiming to enhance their customer service experiences. By prioritizing flexible options for users, investing in adaptable technological solutions, and integrating user feedback into system design, organizations can create user-friendly and efficient customer service interactions. Moving forward, it is crucial for organizations to consider the role of flexibility in shaping user experiences and perceptions of ease of use, as it can be a key differentiator in the competitive landscape of customer service offerings. As technology continues to evolve, the need for flexibility in customer interactions will remain paramount in delivering optimal user experiences and satisfaction.</p>
8	perceived anthropomorphism to Ease of Use	Not Supported	Supported	<p>Research studies on the impact of perceived anthropomorphism to Ease of Use have provided valuable insights into the relationship between human-like qualities in products and systems and their ease of use (Blut et al., 2021) (Abdi et al., 2022)(Li & Sung, 2021)(Adam et al., 2020). The findings from these studies have</p>

			<p>indicated the following:</p> <ol style="list-style-type: none"> 1. Positive Influence on Customer Intentions: The research confirms that perceived anthropomorphism plays a positive role in shaping Customers' intentions to purchase through chatbot commerce. This suggests that the perceived human-like qualities in chatbots contribute to favorable attitudes and purchase intentions among users. 2. Significant Relationship with Customer Engagement: The results indicate a significant relationship between perceived anthropomorphism and customer engagement. This implies that the extent to which a product or system is perceived to possess human-like qualities directly impacts the level of engagement from users. 3. Moderating Role of User Expertise: The studies reveal that the moderating role of User Expertise between perceived anthropomorphism and customer engagement varies based on specific factors. For example, the level of User Expertise with a chatbot influences the impact of perceived anthropomorphism on
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			<p>customer engagement. Additionally, the findings support the hypothesis of a significant moderating role of User Expertise between conversation quality and customer engagement, while no significant moderating role is found for flexibility and customer engagement.</p> <p>These research studies underscore the significance of perceived anthropomorphism in the design and development of user-friendly technologies. They highlight the impact of human-like qualities in products and systems on Customer behavior and user experiences, providing valuable insights for technology developers and human-computer User Expertise researchers.</p> <p>In my research, we delve deeper into the relationship between perceived anthropomorphism and Ease of Use, building upon existing research and incorporating new analysis to contribute to the ongoing dialogue in this field. By examining the influence of perceived anthropomorphism on customer engagement and intentions to purchase, we hope to provide valuable insights for the design and development of user-friendly technologies.</p>
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				<p>My exploration of the moderating role of User Expertise between perceived anthropomorphism and customer engagement will shed light on how the level of User Expertise with anthropomorphized systems impacts user behavior. By investigating the varying influences of conversation quality, flexibility, and other specific factors, we aim to offer a comprehensive understanding of the nuanced dynamics at play in this context.</p>
9	Controllability to customer characteristics	Supported	Supported	<p>The impact of 'controllability' on 'customer characteristics' has been examined through various studies and research (Liu et al., 2021)(Lassar, 1998)(Joshi & Randall, 2001)(Zhao, 2022). These findings suggest that controllability plays a significant role in influencing customer characteristics and behaviors. Specifically, the research has shown that when customers perceive a higher level of controllability in their interactions with businesses or service providers, they tend to be more engaged and satisfied with the service. Additionally, controllability has been found to have a moderating effect on customer engagement. Specifically, the moderating effect of controllability has been observed in relation to</p>

				<p>various customer characteristics such as reason, conversation duration, flexibility, and User Expertise. The results indicate that controllability moderates the relationship between these customer characteristics and customer engagement. This means that the level of perceived controllability can either enhance or constrain the impact of these customer characteristics on customer engagement. Furthermore, the research findings highlight the importance of creating an attractive social commerce environment to increase customers' purchase intentions (Liu et al., 2021). In this context, technical environmental characteristics such as interactivity, stickiness, personalization, and sociability have been found to increase customers' purchase intentions by enhancing customer-to-customer interaction and perceived value. Overall, the impact of controllability on customer characteristics and behaviors is significant and should be considered by businesses in order to improve customer engagement and satisfaction. The empirical findings indicate that controllability plays a significant role in shaping customer engagement and behaviors.</p>
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10	Conversation quality to customer characteristics	Supported	Supported	<p>According to (Zhao et al., 2019)(Ashfaq et al., 2020), interactivity in conversations, which includes prompt reactions and problem-solving, can lead to high customer satisfaction and stronger relationships between customers and the brand. Additionally, the study found that chatbots, which are increasingly being used as customer service representatives, can be 40% more engaging than traditional customer executives and can provide faster and more efficient service.</p> <p>My research underscores the significance of interactivity in conversations, emphasizing the importance of prompt reactions and effective problem-solving in driving customer satisfaction and fostering stronger relationships between customers and the brand. These insights highlight the critical role of conversation quality in enhancing customer satisfaction, loyalty, and overall business performance.</p>
11	Flexibility to customer characteristics	Not Supported	Supported	<p>The impact of flexibility on customer characteristics has been found to be significant. Organizations that prioritize flexibility are better equipped to align with the diverse needs and preferences of</p>

			<p>their customers. It has been observed that considering customer characteristics in designing flexible strategies and approaches is crucial for effective customer engagement and satisfaction. Based on the findings from multiple studies (Tang et al., 2022)(Liu et al., 2021)(Jin & Oriaku, 2013)(Roy et al., 2018), it can be concluded that there is a significant relationship between flexibility and customer characteristics. Flexibility plays a vital role in shaping customer characteristics and behaviors (Liu et al., 2021). Organizations that prioritize flexibility are more likely to meet the varied needs and preferences of their customers. This ultimately leads to increased customer engagement, satisfaction, and loyalty. The impact of flexibility on customer characteristics has been found to be significant.</p> <p>The findings of this research underscore the critical importance of flexibility in aligning with diverse customer characteristics. Organizations need to prioritize flexibility in order to better cater to the evolving needs and preferences of their customers.</p>
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12	Perceived Anthropomorphism to customer characteristics	Supported	Supported	<p>Studies from various international sources (Golossenko et al., 2020)(Agrawal et al., 2020)(Blut et al., 2021)(Fan et al., 2016) have consistently demonstrated the significant impact of perceived anthropomorphism on customer characteristics. Through in-depth analyses, it has been established that when customers perceive a human-like quality in products or services, their emotional connection and loyalty to the brand tend to increase. This phenomenon has been observed across a wide range of industries and Customer demographics, highlighting the universal nature of this effect. Furthermore, studies have shown that businesses can strategically leverage perceived anthropomorphism (Jin & Qian, 2021)to enhance customer satisfaction, trust, and overall engagement with their offerings. These findings emphasize the importance of understanding and incorporating perceived anthropomorphism into marketing and customer experience strategies for businesses seeking to strengthen their relationships with their customer base.</p>
13	Customer characteristics to	Supported	Supported	<p>Research studies (Jansom et al., 2022)(Huang et al., 2019)(Aggarwal et al., 2023)(Nichifor et al., 2021) on customer</p>

	Customer engagement		<p>engagement have shown that customer characteristics play a significant role in shaping Customer engagement. Factors such as cultural background, socioeconomic status, and demographic profiles can impact how customers interact with AI chatbots and other customer service technologies. Understanding these diverse customer characteristics is crucial for businesses to effectively tailor their strategies and AI chatbot interactions to meet the specific needs and preferences of their customer base. Moreover, studies have highlighted the importance of considering global diversity in customer engagement initiatives, as cultural nuances and communication styles can vary widely across different regions and markets.</p> <p>The research highlights the significant impact of customer characteristics on Customer engagement, particularly in the context of AI chatbot interactions and customer service technologies. It is evident from the findings that factors such as cultural background, socioeconomic status, and demographic profiles play a crucial role in shaping how customers interact with AI chatbots. This understanding underscores the importance for businesses to tailor</p>
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				their strategies and AI chatbot interactions to accommodate the diverse needs and preferences of their customer base.
14	Ease of Use to Customer engagement	Not Supported	Not Supported	The impact of Ease of Use on Customer engagement has been studied in various contexts. Several studies have found a significant relationship between Ease of Use and Customer engagement. For instance, a study conducted by (Gu et al., 2015) found that Ease of Use positively influences Customer engagement, as Customers are more likely to engage with products or services that they find easy to use. In addition, another study mentioned that Ease of Use indirectly affects Customer engagement through its impact on attitude towards use. This suggests that when Customers perceive a product or service as easy to use, they are more likely to engage with it and have a positive attitude towards its usage. Furthermore, the study also explored the moderating role of chatbots and customer executives in enhancing customer experience and subsequently impacting Customer engagement.

15	Customer characteristics to Customer attitude	Supported	Supported	<p>Research studies from across the globe have shed light on the significant impact of customer characteristics on Customer attitude. For instance, a study conducted in Europe (Hayes et al., 2023)(Zhang & Li, 2012)(Fitzgerald & Arnott, n.d)found that demographic factors, such as age and income, have a strong influence on Customer attitudes towards different products and services. Similarly, research in the United States (Kwak et al., 2009) has highlighted the role of attitudes and behaviors in shaping Customer attitudes. These findings emphasize the importance of considering customer characteristics when designing marketing strategies to effectively target specific Customer segments. Understanding the unique needs and behaviors of different customer groups enables companies to tailor their marketing efforts and connect with their target audience in a more meaningful way. Therefore, it can be concluded that customer characteristics have a significant impact on Customer attitude. The results of various studies indicate that there is a significant relationship between customer characteristics and Customer attitude. This relationship suggests that customer characteristics, such as demographics,</p>
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				attitudes, and behaviors, play a critical role in shaping Customer attitudes towards products and services.
16	Customer characteristics to customer inertia	Supported	Supported	<p>Research studies (Liu et al., 2021)(Roy et al., 2020)(Han et al., 2011)(Shaffiullah & Rao, 2018) conducted internationally have yielded significant findings on the impact of 'Customer Characteristics' on 'Customer Inertia'. These studies have shown that certain customer characteristics, such as brand loyalty, perceived switching costs, and satisfaction levels, play a crucial role in affecting Customer inertia. Additionally, research has found that demographic factors, including age, income level, and cultural background, can also have a significant impact on Customer inertia. Understanding these findings can provide valuable insights for businesses in developing effective strategies to address Customer inertia and ultimately improve customer retention and satisfaction. The results of various studies support the hypothesis that there is a significant relationship between customer characteristics and Customer inertia. Furthermore, the research findings also suggest that there is a significant relationship between customer</p>

				characteristics and customer engagement, attitude, motivation, and satisfaction.
17	Customer characteristics to Customer motivation	Supported	Supported	Based on international research studies (Liu et al., 2021)(Lian & Lin, 2008)(Dölarslan, 2014)(Mittal & Kamakura, 2001), customer characteristics have been found to significantly impact Customer motivation. These characteristics include demographics such as age, gender, income level, and education level, as well as psychographics such as personality traits, values, and lifestyle choices. Research has shown that understanding these customer characteristics is crucial for businesses to effectively motivate Customers to make purchasing decisions. By tailoring marketing strategies and product offerings to align with the preferences and needs of different customer segments, companies can enhance Customer motivation and drive sales. Additionally, the study also found that customer characteristics play a moderating role in the relationship between customer satisfaction and loyalty. Specifically, variables such as variety-seeking behavior, age, and income influence the strength of the satisfaction-loyalty relationship. Moreover, research has indicated that customer

				characteristics also impact other important Customer outcomes such as customer engagement, attitude, inertia, and satisfaction.
18	Customer characteristics to Customer satisfaction	Supported	Supported	Research studies (Lim et al., 2020)(Fornell et al., 1996)(Froehle & Masterson, n.d)(Otaibi & Yasmeen, 2014) from various countries have consistently shown that customer characteristics have a significant impact on Customer satisfaction. Factors such as age, gender, income level, education, and cultural background have been found to influence the satisfaction levels of Customers across different industries. Understanding these customer characteristics can help businesses tailor their products and services to better meet the needs and expectations of their target audience. Additionally, these findings emphasize the importance of conducting market research and segmentation to effectively cater to diverse customer groups and enhance overall Customer satisfaction. Based on the sources provided, it can be concluded that there is a significant relationship between customer characteristics and Customer satisfaction.

2. Through mediation analysis the study tried to evaluate the 3rd objective, to compare chatbots and customer executives for customer engagement.

Table 5.2: Comparison table (Through mediation analysis)

S.NO	Construct	(2a)	(2b)	Findings
		Customer executive	Chatbot	
1	Conversation quality to Ease of Use to Customer engagement	Not Supported	Not Supported	Research studies (Yun & Park, 2022)(Rheu et al., 2020)(McLean & Osei-Frimpong, 2017)(See et al., 2019)(Klein et al., 2020)from various countries have consistently shown a strong correlation between conversation quality, Ease of Use, and Customer engagement. High conversation quality, characterized by clear and relevant communication, has been found to positively influence Ease of Use. When Customers find a product or service easy to use, they are more likely to engage with it. This connection between conversation quality and Ease of Use directly impacts Customer engagement, as satisfied and engaged Customers are more inclined to interact with the brand, make repeat purchases, and recommend the product or service to others. These findings emphasize the importance of focusing on conversation quality and Ease of Use

				to foster Customer engagement in international markets. Based on the sources mentioned above, it can be concluded that there is a direct relationship between conversation quality and Ease of Use, which in turn impacts
2	Flexibility to Ease of Use to Customer engagement	Not Supported	Not Supported	<p>Research studies (Yun & Park, 2022)(Rheu et al., 2020)(McLean & Osei-Frimpong, 2017)(See et al., 2019)(Klein et al., 2020)from various countries have consistently shown a strong correlation between conversation quality, Ease of Use, and Customer engagement. High conversation quality, characterized by clear and relevant communication, has been found to positively influence Ease of Use. When Customers find a product or service easy to use, they are more likely to engage with it. This connection between conversation quality and Ease of Use directly impacts Customer engagement, as satisfied and engaged Customers are more inclined to interact with the brand, make repeat purchases, and recommend the product or service to others. These findings emphasize the importance of focusing on conversation quality and Ease of Use to foster Customer engagement in international markets.</p> <p>Some studies (Gao & Bai, 2014)(Xu et al., 2017)(Dart et al., 2020)have suggested that there are other factors, such as product quality, brand loyalty, and marketing strategies, that also play a significant role in driving Customer engagement . It's possible that while conversation quality and Ease of Use are important, they may not be the sole</p>

				determinants of Customer engagement. Additionally, in certain markets or demographic segments, Customers might prioritize different factors over conversation quality and Ease of Use when making purchasing decisions. Therefore, it's essential to consider a broader range of variables and perspectives when assessing the drivers of Customer engagement.
3	Perceived Anthropomorphism to Ease of Use to Customer engagement	Not Supported	Not Supported	<p>Numerous international research studies (Esfahani et al., 2020)(Venkatesh, 2000)(Abdi et al., 2022)(Reavey et al., 2018)(Blut et al., 2021)have shown a strong connection between perceived anthropomorphism and Ease of Use in Customer engagement. The findings suggest that when Customers perceive a product or system as more human-like, they are more likely to find it easy to use, which in turn leads to higher levels of Customer engagement. This relationship has been consistently observed across various cultures and Customer demographics, indicating its universal significance in Customer behavior. These findings have significant implications for businesses looking to enhance Customer engagement and user experience through anthropomorphic design elements.</p> <p>On the other hand, some researchers argue that perceived anthropomorphism may not always lead to higher Ease of Use and Customer engagement(Jin & Qian, 2021)(Araujo, 2018)(Yang et al., 2019)(Hadi, 2019)(Han, 2021). They posit that while Customers may find anthropomorphic design elements endearing, they may also view them as more</p>

				<p>complex or difficult to use. Additionally, there are concerns about the potential for perceived anthropomorphism to lead to unrealistic expectations from the product or system, which could result in disappointment and disengagement when the product does not meet those expectations.</p>
4	<p>Controllability to Ease of Use to Customer engagement</p>	<p>Not Supported</p>	<p>Not Supported</p>	<p>Research studies (Lim & Weissmann, 2021)(Dwivedi et al., 2020)(Venkatesh, 2000)from around the world have extensively investigated the relationship between controllability, Ease of Use, and Customer engagement. These studies have consistently found that when Customers perceive a high level of controllability and ease of use in a product or service, their engagement increases. This has significant implications for businesses and marketers, as it highlights the importance of designing products and services that empower Customers and make their interactions more seamless. As such, understanding and leveraging these factors can lead to enhanced Customer engagement and ultimately drive business success. Additionally, these findings suggest that Ease of Use acts as a mediator between controllability and Customer engagement.</p> <p>On the other hand, there are researchers who argue that controllability and Ease of Use do not always lead to increased Customer engagement (Henderson & Divett, 2003)(Venkatesh, 2000)(Collier & Sherrell, 2009). They point out that in certain cases, too much control given to Customers can overwhelm them and lead to decision fatigue,</p>

				resulting in disengagement. Additionally, products that are perceived as extremely easy to use may not always be seen as valuable or sophisticated, which can affect Customer engagement negatively. These studies suggest that Customer engagement is influenced by various other factors such as brand loyalty, marketing strategies, and social influence, and that controllability and Ease of Use may have a less direct impact than previously thought
5	Conversation quality to Customer characteristics to Customer engagement	Supported	Supported	Several international research studies (Li et al., 2023)(Vinerean et al., 2014)(Merdiaty & Aldrin, 2022)(Santini et al., 2020)have provided valuable insights into the relationship between conversation quality, customer characteristics, and Customer engagement. These studies have indicated that high-quality conversations between customers and service providers lead to increased Customer engagement and satisfaction. Furthermore, the studies have emphasized the influence of customer characteristics, such as demographics and purchasing behaviors, on the quality of interactions and subsequent levels of Customer engagement. Understanding these findings can help businesses tailor their customer service strategies to better meet the needs and preferences of their diverse customer base. In conclusion, the research findings highlight the significant impact of conversation quality on Customer engagement and satisfaction. Moreover, the influence of customer characteristics on the

				quality of interactions emphasizes the need for businesses to adapt their customer service strategies to effectively engage with their diverse customer base.
6	Flexibility to Customer characteristics to Customer engagement	Not Supported	Supported	<p>Based on international research studies (Ziemba et al., 2020)(Roy et al., 2018)(Tang & Tseng, 2015)(Jussani et al., 2018), flexibility to customer characteristics has been found to have a substantial impact on Customer engagement. Studies have consistently shown that companies that tailor their products, services, and communication to the specific characteristics and preferences of their customers experience higher levels of Customer engagement. This flexibility allows companies to better meet the needs of their customers, resulting in increased satisfaction, loyalty, and advocacy. Additionally, the research indicates that personalized experiences created through flexibility to customer characteristics can lead to a stronger emotional connection between the customer and the brand, further enhancing Customer engagement. Furthermore, the adoption of AI chatbots as a tool for enhancing customer service and experience has also been found to positively impact Customer engagement. Research suggests that customers are more satisfied with chatbots compared to customer executives, indicating that incorporating AI chatbots can enhance the customer experience and ultimately lead to higher levels of Customer engagement (Hildebrand & Bergner, 2019).</p> <p>However, it's important to consider that not all customers may appreciate the same level</p>

				<p>of flexibility when it comes to tailoring products and services(Ashfaq et al., 2020)(Liu et al., 2021)(Hadi, 2019)(André et al., 2017). Some Customers may feel overwhelmed by too many choices and customization options, leading to decision fatigue and a decrease in satisfaction. Moreover, there is a risk of alienating certain customer segments if the focus on flexibility results in a lack of consistency in the brand experience.</p> <p>Additionally, the adoption of AI chatbots may not be universally welcomed by all customers. While some may find them efficient and helpful, others may prefer human interaction and perceive chatbots as impersonal and lacking the ability to fully understand their unique issues and concerns.</p> <p>Therefore, while flexibility to customer characteristics may indeed have some positive impacts on Customer engagement, it is essential for companies to consider the potential drawbacks and varying preferences of their customer base before implementing such strategies.</p>
7	Perceived Anthropomorphism to Customer	Supported	Supported	Based on international research studies (Jin & Qian, 2021)(Agrawal et al., 2020)(Yang et al., 2019)(Hart et al., 2013)(Blut et al., 2021), perceived anthropomorphism in marketing has been found to significantly impact Customer engagement. Customer

	characteristics to Customer engagement			<p>characteristics, such as age, gender, and cultural background, also play a crucial role in shaping the level of perceived anthropomorphism that Customers perceive in products and services. Understanding these factors can help businesses tailor their marketing strategies to enhance Customer engagement and build stronger brand relationships. For example, Wang Chun's research suggests that the type of product affects the relationship between brand personification and Customers' attitude towards the brand (Jin & Qian, 2021). Furthermore, Customers' cognitive level moderates this relationship, indicating that individual differences in cognitive processing can influence the perception of Perceived Anthropomorphism. Additionally, factors such as Customer perceived freedom, Customer synesthesia, and prosocial environment have been identified as mediating variables in the study of Perceived Anthropomorphism in marketing. Overall, the research highlights the importance of considering Customer characteristics and their perception of Perceived Anthropomorphism in marketing strategies. The results of the study support the hypothesis that there is a significant relationship between perceived anthropomorphism and customer characteristics.</p>
8	Controllability to Customer characteristics to	Supported	Supported	<p>Based on international research studies (Liu et al., 2021)(Roy et al., 2018)(Santini et al., 2020)(Bowden, 2009), controllability from customer characteristics to Customer engagement has been the subject of extensive investigation. Studies have demonstrated that certain customer characteristics, such as demographics, psychographics, and</p>

	Customer engagement			<p>sociographics, can significantly impact Customer engagement with a product or service. These findings have provided valuable insights for businesses and marketers in understanding how to effectively tailor their products and marketing strategies to different customer segments, ultimately leading to enhanced Customer engagement and satisfaction. Furthermore, the research suggests that customer controllability is particularly influential in the service industry. Therefore, it is important for service firms to consider customer characteristics when designing and delivering their services in order to enhance Customer engagement. The findings from various studies suggest that customer characteristics, including demographic, psychographic, and store format choice, play a significant role in influencing Customer engagement. Additionally, the findings suggest that there is a lack of research specifically focused on customer characteristics and their impact on Customer engagement in the retail sector. The studies suggest that demographic and psychographic characteristics of customers are important factors in determining their engagement with a product or service.</p>
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5.2 CONCLUSION

The current study conclusion would also be a part of this innovation. The study tried to understand the service attributes' impact on Customer engagement while taking Ease of Use and customer characteristics (motivation, customer inertia, satisfaction, and attitude) as mediators. Later, the study tried to take Customer daily usage stats as a moderator like conversation duration, User Expertise and reason as a moderator between the service attributes to all three factors Ease of Use, customer characteristics, and Customer engagement to check whether these moderators strengthen the relationship or weakens the relationship. As per objectives, the study has provided a conclusion.

Objective: 1

Conclusion based on objective 1:

- The study concludes that customer characteristics have a significant mediation role in between service attributes to Customer engagement concerning customer executives.
- The study concludes that customer characteristics have a significant mediation role in between conversation quality to Customer engagement concerning customer executives.
- The study concludes that customer characteristics have a significant mediation role in between Perceived Anthropomorphism to Customer engagement concerning customer executives.
- The study concludes that customer characteristics have a significant mediation role in between controllability to Customer engagement concerning customer executives.
- The study concludes that customer characteristics have a significant mediation role in between service attributes to Customer engagement concerning Chatbot.
- The study concludes that customer characteristics have a significant mediation role in between conversation quality to Customer engagement concerning chatbots.

- The study concludes that customer characteristics have a significant mediation role in between flexibility to Customer engagement concerning chatbots.
- The study concludes that customer characteristics have a significant mediation role between Ease of Use to Customer engagement concerning chatbots.
- The study concludes that customer characteristics have a significant mediation role in between controllability to Customer engagement concerning chatbots.

Objective: 2

Conclusion based on Objective: 2.

- The study concludes that conversation duration with customer executives has a significant moderating role. The more the conversation with customer executives from the Customer side the stronger the relationship. Conversation duration has a strong relationship with flexibility and controllability to Ease of Use.
- The study concludes that the reason of interaction with customer executives to Ease of use has a weak moderating role concerning service attributes. It has been observed that with controllability only a strong relationship has been observed.
- The study concludes that User Expertise with customer executives to perceive ease of use as a moderator has a moderating role concerning service attributes. It has been observed that the higher the User Expertise the stronger the relationship. The results study concludes that conversation quality and flexibility to Ease of Use in between User Expertise's have a strong moderating role.
- The study concludes that reason has a significant moderating role in between service attributes (Conversation quality, flexibility, controllability, and perceived anthropomorphism) to customer characteristics, the higher the reason the stronger the moderating role. Concerning perceived anthropomorphism, conversation quality, and controllability to customer characteristics in between reasons of Customers have a strong moderating role.

- The study concludes that only a few construct paths exhibit moderating effects with conversation duration as a moderator controllability to Ease of Use and conversation quality to customer characteristics having a medium moderating effect. User Expertise as a moderator concerning controllability to customer characteristics has a medium moderating effect. There is a moderating effect that partially affects the above construct paths concerning the chatbots.

Objective: 3

Conclusion based on objective: 3.

- The study concludes that Customers are likely to use both services as all the direct assessments and indirect assessments provides largely similar results.
- The conclusion based on the results is that Customers engage with both customer executives and chatbots.
- The study concludes that based on the customer requirement the engagement will differ. In case of urgency, the customer finds it difficult to follow the entire procedure.
- The study concludes that in the case of general queries, Customers are more likely to engage with chatbots as they provide more useful information and are more likely to engage with these platforms.
- The study concludes that customer characters play a unique role in customer engagement. As each customer is unique and with a unique preference their preference will also differ according to their necessities and requirements. Through the results, the study concludes that Customer attitude, motivation, satisfaction, and customer inertia have a high internal consistency.

Through overall analysis, the study concludes that Customers will engage with both customer executives and chatbots. Based on the results, scholar and academic observations the study concludes this conclusion.

5.3 Discussions:

The rapid humanization of chatbots with the help of Artificial intelligence has paved the path to engaging with Customers in less time, which has redefined the way of engagement with Customers via brand. While many brands are now using chatbots to

engage and interact with Customers, there is still a need to understand the impact of these chatbots compared to traditional customer executive services on Customer engagement (Chung et al., 2020). As per the study results, there are differences in attitudes towards chatbot utilization across different age groups and educational backgrounds, suggesting that Customer preferences may vary as per age and interaction rate (Li et al., 2020). This implies that companies should consider offering Customers a choice between chatbots and human agents to cater to their individual preferences and improve overall service quality. The study results suggest that Customers are likely to engage with both customer executives and chatbots.

The service attributes of both customer executives and chatbots have shown a positive relationship towards Customer engagement which provides the validity of the study. The current model has proposed a robust framework of Customer engagement model with respect to service attributes, to understand the growing interest in chatbot engagement in digital platforms. The results respond to De Keyser et al., (2019) empirical findings on Customer behaviour in the context of VAs, the current study has filled the gap in the literature on Customer engagement with respect to chatbots and Customer acceptance of these platforms. The study results also suggest that Ease of Use does not have any mediating role though customers perceive using chatbots but not engaging via Ease of Use. With chatbots, no mediation role has been observed which could provide literature to the current research going to happen.

5.4 Study Implications:

In the current study, customers engage with both customer executives and chatbots, however the construct of perceived anthropomorphism has a stronger impact on customer engagement for executives compared to chatbots. This emphasizes the need to improve the anthropomorphic characteristics of chatbots in order to enhance their effectiveness and increase user adoption. By making chatbots appear more human-like, businesses can foster deeper customer engagement and interaction. These results underscore the importance of advancing chatbot design to align more closely with human attributes, ultimately driving higher utilization and satisfaction in customer service interactions.

The study's findings suggest that perceived anthropomorphism enhances ease of use for chatbots more effectively than for customer executives. This underscores the need for companies to invest in upskilling their customer service executives, ensuring they continuously refine their verbal communication and engagement skills to keep pace with evolving customer expectations. As customer demands grow more sophisticated, service representatives must adapt by improving their ability to interact meaningfully with customers in real time.

Simultaneously, companies must focus on optimizing the design of chatbots by embedding AI technology into user interfaces. This allows chatbots to self-learn, adapt, and iteratively improve their verbal behaviour and customer engagement capabilities. However, a key challenge lies in maintaining a balance between technological sophistication and ease of use. Businesses must ensure that chatbots remain user-friendly and accessible, avoiding overly complex systems that could deter users. In conclusion, while chatbots benefit from perceived anthropomorphism in ease of use, continuous training for human executives is crucial, and chatbot design must prioritize both innovation and simplicity to meet customer expectations effectively.

For the construct of flexibility to customer characteristics, chatbots are supported over customer executives, indicating that customers highly appreciate the adaptability chatbots provide. By leveraging this flexibility, businesses can address customer inquiries more quickly and efficiently, offering faster and more responsive service. The ability of chatbots to adjust in real time to varying customer needs not only improves the speed of interactions but also enhances overall customer engagement. This flexibility allows for more personalized experiences, enabling businesses to create tailored interactions that drive customer satisfaction. Utilizing chatbots' adaptability in business operations can ultimately foster stronger relationships with customers and improve service outcomes.

5.5 Limitations:

The study has successfully conveyed findings and Implications to be made, but this doesn't mean that the study is free of limitations. Through a series of discussions, a study has identified the following limitations.

1. Data has been collected from Indian Customers only, wherein the majority of the participants are educated. Very few participants have participated in below-the-threshold education.
2. Time constraints, the data collection has been carried out under time restrictions.
3. Lack (limited) of literature on chatbots and customer executives has been a limitation of the study.
4. The selection of sampling techniques is quite challenging due to limited time and data collection from both ends to identify the participants who have interacted with both services is quite challenging.

5.6 Recommendations for Future Studies:

Through the findings of the study, here are some suggestions for future reference, chatbot services have and will revolutionize the service demography which has a lot of scope in future. Moreover, India's Current internet consumption and average time spent on multiple activities have led to the following suggestions.

1. The studies should focus on collecting qualitative data to obtain a better understanding of Customer perception.
2. A mix of stratified random sampling and purposive sampling techniques needs to be applied to collect data from a larger geography.
3. A Cross-section study can also be applied to understand the perception among various generations.
4. The use of ANN to predict the future perception of the Customers can be implemented.
5. Respondents from two different nationalities can be utilised to understand the differences among the different nationalities and their perceptions.

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APPENDICIES

7. Appendices - Survey Questionnaire used for Data Collection

1. Customer Engagement through- Customer Executives

Part (1): Please select your answer for the following questions:

1. What is your gender?

Male () Female ()

2. What is your Age?

18 - 25() 26 – 35 () 36 - 45 above 45 ()

3. What is your current level of education?

High school or below () Intermediate () Bachelor's () Master's and above ()

Part (2): Please select your answer for the following questions:

4. Have you ever interacted with customer executives on e-commerce sites ? ()

a. Yes b. No

5. Have you ever interacted with Chatbots on e-commerce sites? ()

a. Yes b. No

Part (3): Please select your answer for the following questions:

6. Please specify your expertise in interacting with customer executives on e-commerce sites. ()

a. Low b. Medium c. High

7. Please specify your conversation duration with customer executives on e-commerce sites. ()

a. Long b. Average c. Short

8. What is your average conversation duration (in Mins) with customer executives on e-commerce sites? ()

9. Please select the most frequent reason for interaction with customer executives on e-commerce sites. ()

- a. Information b. Complaint c. Feedback

10. Where have you interacted with the customer executives the most _____?

- a. Pre-purchase/Information search stage b. Purchase stage c. Post-purchase stage

Part (4): This section is concerned with asking questions about the research variables.

Instructions:

- 1) Please consider your interaction with Customer executives from e-commerce sites. Then, give your answers.
 2) Please circle the number indicating your agreement or disagreement with the following statements.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

1. Conversation quality

Items Description	SD	D	N	A	SA
The customer executive provided good-quality information.	1	2	3	4	5
The information provided by the customer executive was helpful regarding my questions/problems	1	2	3	4	5
The Customer executive provided responses to queries as I asked.	1	2	3	4	5

2. Perceived Anthropomorphism

Items Description	SD	D	N	A	SA
I experienced a feeling of warmth with customer executives.	1	2	3	4	5
I experienced friendliness with customer executives.	1	2	3	4	5
Interaction with customer executives gave me a feeling of personal communication.	1	2	3	4	5

3. Flexibility

Items Description	SD	D	N	A	SA
I feel that customer executive was adaptable to the situation.	1	2	3	4	5
It was easy to explain the customer executives what I wanted.	1	2	3	4	5
I found it easy to start a conversation with the customer executives.	1	2	3	4	5

4. Controllability

Items Description	SD	D	N	A	SA
I felt secured while communication with Customer executive.	1	2	3	4	5
The Customer executive was dependable.	1	2	3	4	5
The Customer executive was trustworthy.	1	2	3	4	5
The customer executive was honest.	1	2	3	4	5

5. Ease of Use

Items Description	SD	D	N	A	SA
My interaction with customer executive was understandable.	1	2	3	4	5
I find interacting with customer executives was user-friendly.	1	2	3	4	5
It was easy to gain expertise in interacting with customer executives.	1	2	3	4	5

6. Customer Characteristics-Customer inertia

Items Description	SD	D	N	A	SA
I intend to use customer executive services the next time for my queries.	1	2	3	4	5
I consider customer executive to be a single point of contact for my queries.	1	2	3	4	5
Customer executives are important to me for my queries.	1	2	3	4	5

7. Customer Characteristics-Satisfaction

Items Description	SD	D	N	A	SA
I am satisfied with customer executives' services.	1	2	3	4	5
The customer executive performed as expected.	1	2	3	4	5
The customer executive made me happy when I interacted with them.	1	2	3	4	5

8. Customer Characteristics-Attitude

Items Description	SD	D	N	A	SA
It was fun to interact with customer executive	1	2	3	4	5
The customer executive gave me an impression of friendliness.	1	2	3	4	5
The experience of interacting with the customer executive was positive.	1	2	3	4	5

9. Customer Characteristics-Motivation

Items Description	SD	D	N	A	SA
I can enrich my knowledge through customer executives.	1	2	3	4	5
Interacting with customer executives gave me pleasure.	1	2	3	4	5
Interacting with customer executives was exciting.	1	2	3	4	5

10. Customer Engagement

Items Description	SD	D	N	A	SA
I encourage friends and relatives to buy from an e-commerce site that employs a customer executive.	1	2	3	4	5
An e-commerce sites that employs customer executives is my first choice when buying.	1	2	3	4	5
I am likely to revisit the e-commerce sites that have customer executives.	1	2	3	4	5

2. Customer Engagement through-Chabot's

Part (1): Please select your answer for the following questions:

1. What is your gender?

Male () Female ()

2. What is your Age?

18 - 25() 26 – 35 () 36 - 45 () 46 - 49 () Above 50 ()

3. What is your current level of education?

High school or below () Intermediate () Bachelor's () Master's and above ()

Part (2): Please select your answer for the following questions:

4. Have you ever interacted with customer executives on e-commerce sites ?

a. Yes b. No

5. Have you ever interacted with Chatbots on e-commerce sites?

a. Yes b. No

Part (3): Please select your answer for the following questions:

6. Please specify your expertise in interacting with Chatbot on e-commerce sites.

a. High b. Medium c. Low

7. Please specify your conversation duration with Chatbot on e-commerce sites.

a. Long b. Average c. Short

8. What is your average conversation duration (in Mins) with Chatbots on e-commerce sites? ()

9. Please select the most frequent reason for interaction with Chatbots on e-commerce sites. ()

a. Information b. Complaint c. Feedback

10. Where have you used the Chabot the most _____?

a. Pre-purchase/Information search stage b. Purchase stage c. Post-purchase stage

Instructions:

1) Please consider your interaction with Chatbots on e-commerce sites. Then, give Your answers.

2) Please select the option indicating your agreement or disagreement with the following statements.

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5

1. Conversation quality

Items Description	SD	D	N	A	SA
The Chabot provided good-quality information.	1	2	3	4	5
The information provided by the Chabot was helpful regarding my questions/problems.	1	2	3	4	5
The Chatbot provided responses to queries as I expected.	1	2	3	4	5

2. Perceived Anthropomorphism

Items Description	SD	D	N	A	SA
I experienced a feeling of warmth with Chabot.	1	2	3	4	5
I experienced friendliness with Chatbot.	1	2	3	4	5
Interaction with Chatbot gave me a feeling of personal communication.	1	2	3	4	5

3. Flexibility

Items Description	SD	D	N	A	SA
I feel that Chatbot was adaptable to the situation.	1	2	3	4	5
It was easy to explain the Chatbot what I wanted.	1	2	3	4	5
I found it easy to start a conversation with the Chatbot.	1	2	3	4	5

4. Controllability

Items Description	SD	D	N	A	SA
I felt secured while communication with Chatbot.	1	2	3	4	5
The Chatbot was dependable.	1	2	3	4	5
The Chatbot was trustworthy.	1	2	3	4	5
The Chatbot was honest.	1	2	3	4	5

5. Ease of Use

Items Description	SD	D	N	A	SA
My interaction with Chatbot was understandable.	1	2	3	4	5
I find interacting with Chatbot was user-friendly.	1	2	3	4	5
It was easy to gain expertise in interacting with Chatbot.	1	2	3	4	5

6. Customer Characteristics-Customer inertia

Items Description	SD	D	N	A	SA
I intend to use Chatbot services the next time for my queries.	1	2	3	4	5
I consider Chatbot to be a single point of contact for my queries.	1	2	3	4	5
Chatbots are important to me for my queries.	1	2	3	4	5

7. Customer Characteristics-Satisfaction

Items Description	SD	D	N	A	SA
I am satisfied with the Chatbot services.	1	2	3	4	5
This Chatbot performed as expected.	1	2	3	4	5
This Chatbot made me happy when I interacted with them.	1	2	3	4	5

8. Customer Characteristics-Attitude

Items Description	SD	D	N	A	SA
It was fun to interact with the Chatbot.	1	2	3	4	5
The Chatbot gave me an impression of friendliness.	1	2	3	4	5
The experience of interacting with the Chabot was positive.	1	2	3	4	5

9. Customer Characteristics-Motivation

Items Description	SD	D	N	A	SA
I can enrich my knowledge through Chatbot.	1	2	3	4	5
Interacting with Chatbot gave me pleasure.	1	2	3	4	5
Interacting with Chatbot was exciting.	1	2	3	4	5

10. Customer Engagement

Items Description	SD	D	N	A	SA
I encourage friends and relatives to buy from an e-commerce site that provides a Chatbot.	1	2	3	4	5
An e-commerce sites that provides Chatbot is my first choice when buying.	1	2	3	4	5
I am likely to revisit the e-commerce sites that provides a Chatbot.	1	2	3	4	5