VILNIUS UNIVERSITY BUSINESS SCHOOL

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DIGITAL MARKETING PROGRAMME

Student: Umer Farooq Khan

THE FINAL MASTER'S THESIS (PROJECT)

Pokalbių robotų ir dirbtinio intelekto poveikis vartotojų pirkimo sprendimams	*The Impact of Chatbots and Conversational Artificial Intelligence on Consumer Purchasing Decisions*

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Name, surname, academic title, scientific degree of the supervisor

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SUMMARY

VILNIUS UNIVERSITY BUSINESS SCHOOL

DIGITAL MARKETING STUDY PROGRAMME

Umer Farooq Khan

THE IMPACT OF CHATBOTS AND CONVERSATIONAL ARTIFICIAL INTELLIGENCE ON CONSUMER PURCHASING DECISIONS

Supervisor – Lect. Gintarė Gulevičiūtė

Master's thesis was prepared in Vilnius, in 2026

Scope of master's thesis – 62 pages.

Number of tables used in the FMT – 9 pcs.

Number of figures used in the FMT – 1 pcs.

Number of bibliography and references – 149 pcs.

The FMT described in brief: The study was conducted to investigate and compare the impact of chatbots and conversational AI while shopping online on the purchase intentions of the consumers to help the businesses make strategies that would help them to increase their selling's.

Problem, objective, and tasks of the FMT: The lack of distinction in the impact of chatbots and conversational AI on purchase decisions leads to a knowledge gap which businesses struggle to make informed decisions regarding the technology they should adopt. The key objective of this research is to explore and compare the effect of chatbots and conversational AI on consumer purchase behaviors, specifically in context of perceived usefulness (PU), perceived ease of use (PEOU), perceived service quality (PSQ) and satisfaction levels (SAT) in the context of shopping online. The main tasks of paper include to test how consumers respond to interaction with chatbots and conversational AI, to determine the effect of these tools in the purchasing decision and to draw conclusions on how to improve the design of digital assistants to support conversational commerce.

Research methods used in the FMT: The research is conducted using quantitative data collection methods, that require empirical data to be gathered in the form of an online surveys. Differences and relationships among variables are analyzed with the help of statistical tools like t-tests or regression analysis.

Research results obtained in FMT: Conversational AI users reported higher levels of satisfaction and purchase intentions, with substantial differences found between the two groups. The moderation analysis confirmed that Conversational AI strengthens the relationship between PEOU, PSQ, and CPI, making it more effective in driving user engagement and purchasing decisions compared to traditional Chatbots.

Conclusions of the FMT: This study confirms that Conversational AI is a more effective tool in driving engagements and consumer purchase intentions compared to traditional Chatbots. Businesses are encouraged to adopt and further develop conversational AI technologies to stay competitive in the evolving landscape of conversational commerce. This research recommends that those businesses which invest in and optimize Conversational AI will be better positioned to enhance user engagement, satisfaction, and purchasing behavior. By focusing on personalization, service quality, and seamless integration into the customer journey, companies can improve the effectiveness of their digital assistants and gain a competitive edge in the rapidly evolving landscape of conversational commerce.

SANTRAUKA

VILNIAUS UNIVERSITETO VERSLO MOKYKLA

SKAITMENINĖS RINKODAROS STUDIJŲ PROGRAMA

Umer Farooq Khan

Pokalbių robotų ir dirbtinio intelekto poveikis vartotojų pirkimo sprendimams

Darbo vadovė – Lect. Gintarė Gulevičiūtė

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Trumpas darbo apibūdinimas: Tyrimas buvo atliktas siekiant ištirti ir palyginti pokalbių robotų ir dirbtinio intelekto poveikį vartotojų pirkimo ketinimams apsiperkant internetu, siekiant padėti įmonėms kurti strategijas, kurios padėtų joms padidinti pardavimus.

Problema, tikslas ir užduotys: Pokalbių robotų ir pokalbių dirbtinio intelekto poveikio pirkimo sprendimams neatskyrimas lemia žinių spragą, dėl kurios įmonėms sunku priimti pagrįstus sprendimus dėl technologijų, kurias jos turėtų naudoti. Pagrindinis šio tyrimo tikslas – ištirti ir palyginti pokalbių robotų ir pokalbių dirbtinio intelekto poveikį vartotojų pirkimo elgsenai, ypač atsižvelgiant į suvokiamą naudingumą (PU), suvokiamą naudojimo paprastumą (PEOU), suvokiamą paslaugos kokybę (PSQ) ir pasitenkinimo lygį (SAT) apsiperkant internetu. Pagrindiniai straipsnio uždaviniai yra ištirti, kaip vartotojai reaguoja į sąveiką su pokalbių robotais ir pokalbių dirbtiniu intelektu, nustatyti šių įrankių poveikį pirkimo sprendimui ir padaryti išvadas, kaip patobulinti skaitmeninių asistentų dizainą, kad būtų palaikoma pokalbių prekyba.

Darbe naudoti metodai: Tyrimas atliekamas naudojant kiekybinius duomenų rinkimo metodus, kuriems reikalingi empiriniai duomenys internetinių apklausų forma. Kintamųjų skirtumai ir ryšiai analizuojami naudojant statistinius įrankius, tokius kaip t-testai arba regresinė analizė.

Atlikti tyrimai ir gauti rezultatai: Pokalbių dirbtinio intelekto naudotojai nurodė didesnį pasitenkinimo ir pirkimo ketinimų lygį, o tarp šių dviejų grupių nustatyti esminiai skirtumai. Moderavimo analizė patvirtino, kad pokalbių dirbtinis intelektas stiprina ryšį tarp PEOU, PSQ ir CPI, todėl, palyginti su tradiciniais pokalbių robotais, yra veiksmingesnis skatinant naudotojų įsitraukimą ir pirkimo sprendimus.

Pagrindinės išvados: Šis tyrimas patvirtina, kad pokalbių dirbtinis intelektas yra veiksmingesnė priemonė skatinant įsitraukimą ir vartotojų pirkimo ketinimus, palyginti su tradiciniais pokalbių robotais. Įmonės raginamos diegti ir toliau plėtoti pokalbių dirbtinio intelekto technologijas, kad išliktų konkurencingos besikeičiančioje pokalbių prekybos aplinkoje. Šis tyrimas rekomenduoja, kad tos įmonės, kurios investuoja į pokalbių dirbtinį intelektą ir jį optimizuoja, bus geriau pasirengusios didinti vartotojų įsitraukimą, pasitenkinimą ir pirkimo elgseną. Sutelkdamos dėmesį į suasmeninimą, paslaugų kokybę ir sklandų integravimą į kliento kelionę, įmonės gali pagerinti savo skaitmeninių asistentų efektyvumą ir įgyti konkurencinį pranašumą sparčiai besikeičiančioje pokalbių prekybos aplinkoje.

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LIST OF ABBREVIATIONS

AI – artificial intelligence

ELM – Elaboration likelihood module

PSQ –perceived service quality

PU – perceived usefulness

PEOU – Perceived ease of use

PI – purchase intention

SAT – Satisfaction

sRAM – service robot acceptance model

TAM – technology acceptance model

TR – perceived trust

UTAUT – unified theory of acceptance and use of technology

INTRODUCTION

The novelty and relevance of the topic

The digital transformation of retail and service industries has accelerated the adoption of conversational technologies to support consumer engagement and purchasing processes. Among these technologies, chatbots and conversational AI systems have emerged as pivotal tools in e-commerce environments. These systems perform tasks traditionally executed by human agents including answering queries, providing recommendations, and streamlining purchase processes (Chen et al., 2024). The relevance of investigating these technologies in the context of consumer purchase decisions stems from their increasing integration into online shopping ecosystems. E-commerce platforms widely employ AI chatbots to enhance service quality, reduce response times, and increase personalization, thereby directly influencing consumer satisfaction and purchase intent. Understanding how these conversational technologies influence purchase decisions address key gaps in consumer behavior. While traditional studies of e-commerce behavior focused on website design, perceived risk, and human customer service, current research underscores the need to examine how automated conversational systems alter psychological and decision-making processes. This theoretical integration is essential to explain not merely *whether* consumers engage with conversational assistants but *how and why* such engagement alters purchase decisions (Guo & Cai, 2024).

The novelty of this research topic arises from several emerging trends that existing literature has only begun to explore. First, existing research often concentrates on isolated aspects of chatbot performance such as language style effects on brand attitude or continuance intention rather than on a direct causal link to purchase decisions across various consumer segments (Hartford & Stein, 2024). For instance, studies reveal how chatbot language style affects customer brand attitudes and intentions to reuse chatbot services, but they stop short of linking these attributes to *actual* purchase decision outcomes (Liu et al., 2018). Similarly, other research emphasizes specific demographic segments or loyalty outcomes without fully integrating decision-making frameworks relevant to diverse consumer groups.

Second, recent studies highlight persisting gaps in understanding the psychological mechanisms through which chatbots and conversational AI shape consumer responses. Some investigations suggest that consumer trust, perceived interactivity, and personalization significantly shape chatbot effectiveness and outcomes like loyalty and satisfaction. However, the dynamic interplay between these constructs and their consequent impact on purchase choices remains underexplored (Al-Oraini, 2025).

Third, the contextual acceleration of conversational AI uses due to technological advancements and market pressures. Commercial adoption of more sophisticated conversational AI models, including generative AI frameworks that support natural dialogue and personalized recommendations, emphasizes a shift from static interactions to dynamic, context-aware engagement. This shift has implications for consumer cognitive processing, trust development, and decision satisfaction that extend beyond traditional chatbot functionalities (Alotaibi & Hidayat-ur-Rehman, 2025). The emerging landscape demands contemporary research that reflects how advanced conversational AI reshapes purchase decisions in ways that prior models of automated customer service did not fully anticipate (Guo & Cai, 2024).

Finally, although the use of chatbots in e-commerce is well documented, there is limited comprehensive analysis comparing basic rule-based chatbots to more advanced conversational AI systems in terms of their differential effects on consumer purchase behavior. Recent studies largely focus on generic chatbot adoption outcomes or on general satisfaction, without systematically evaluating the distinct impact that varying levels of artificial intelligence sophistication have on consumer decision processes (Al-Oraini, 2025). This comparative gap underscores a pressing need for nuanced inquiry that distinguishes between levels of AI autonomy, natural language processing capabilities and cognitive engagement. Therefore, the current study is unique because the comparative study of chatbots and conversational AI in the context of purchasing decisions has not been well studied in the literature.

Problem of the paper

Although there have been prior studies examining the features and customer satisfaction rates of chatbots and conversational AI individually, the ones that have directly compared their individual influence on consumer buying decisions are few. The lack of distinction in their impact leads to a knowledge gap to which businesses struggle to make informed decisions regarding the technology they should adopt. This study solves this problem by offering empirical data on the effects of each tool on the consumer behavior within a buying situation.

Aim of the paper

The key aim of this paper is to explore and compare the impact of chatbots and conversational artificial intelligence on consumer purchase behaviors, specifically, perceived usefulness, perceived ease of use, perceived service quality and satisfaction in the context of shopping online. Knowing the advantages and disadvantages of both, the businesses could better shape their approach to customer interaction.

Tasks of the paper

1. To distinguish and define chatbots and conversational AI.
2. To examine how consumers respond to contact with chatbots and conversational AI.
3. To determine the test of these tools in affecting the purchasing decision.
4. To determine if there is any significant difference in user experience (UX) between chatbot-aided and conversational AI-aided purchase journeys.
5. Current research and draw conclusions on how to improve the design of digital assistants to support conversational commerce.
6. Give advice to businesses on how to capitalize the capabilities of digital assistant to enhance user interaction and buying intentions.

Structure of the paper

The paper is divided into three sections. Part I presents a theoretical discussion and literature overview of conversational interfaces, including chatbots and conversational AI, discussing major concepts and frameworks i.e. Technology Acceptance Model (TAM), Persuasion Theory, and the Elaboration Likelihood Model (ELM), each of which can shed light on the processes that affect consumer behavior and the decision to buy a product. Moreover, it discusses the impact of chatbots and conversational AI on buying intentions. The second part provides methodology that covers the conceptual model, hypotheses, and the process of data collection including how the survey is designed and the sampling strategy. The third section sets out and analyzes the empirical findings, commenting on their applicability to the hypotheses and drawing conclusions concerning factors affecting customer purchase intentions. The article is completed with the discussion of limitations, implications, and recommendations towards practical applications and further research.

Research methods

The research is conducted using a quantitative research method, which requires empirical data gathered in the form of an online survey. Differences and relationships among variables are analyzed with the help of statistical tools like t-tests or regression analysis. Document and narrative analysis are among the methods of theoretical analysis.

Research limitations

Although this research is a great source of information about the effect chatbots and conversational AI have on the purchasing decisions of users, it has some limitations. First, it is based on self-reported data, which can be affected by biases (socially desirable or recall errors). Second, the simulated environment of interaction scenarios might not reflect the actual dynamics. Also, although common models and variables are included in the study, the results might not be entirely applicable to a broad range of user's demographics or cultural backgrounds. Finally, the fast development of AI technologies can make some findings less relevant in the future.

1. Theoretical aspects of The Impact of Chatbots and Conversational Artificial Intelligence on Consumer Purchasing Decisions

1.1 The growing role of digital technologies in E-commerce

Digital technologies have become an inseparable element of the different industries, in particular, e-commerce. With the growing level of competition among the digital marketplace, companies are using digital technologies to enhance the customer experience, efficiency, and boost profitability (Alotaibi & Hidayat-ur-Rehman, 2025). Ranging from customized suggestions of chatbots, the dynamic price to warehouse robotics, digital technologies are changing the way that e-commerce functions both on the front and the back end (Russell & Norvig, 2021). Within the e-commerce framework, digital technologies are used to process large amounts of information, identify patterns, and make decisions automatically to transform customer experiences and streamline business processes (Nikiforova, 2022). The emergence of big data, cloud computing, and strong algorithms has made the online retail industry more likely to embrace the digital technology (Cukier & Mayer-Schoenberger, 2014). Nowadays, businesses such as Amazon, Alibaba, and Shopify resort to digital tools to handle their inventory, customer service, and much more, which is why they become the cornerstone of the contemporary e-commerce.

Among the most noticeable applications of digital technologies in e-commerce, there is product recommendation that is personalized. The type of customer information analyzed by algorithms includes product recommendations: browsing history, purchase behavior, preferences, and demographics to provide individual customer recommendations (Jannach et al., 2021). This not only boosts the conversion rates but also the customer satisfaction levels. In the case of Amazon, the recommendation engine makes approximately 35% of the sales in the company (McKinsey & Inc., 2020). The digital systems such as collaborative filtering systems and deep learning systems are constantly learning and evolving to make the recommendations more relevant and timelier.

Customer service in e-commerce is being revolutionized by chatbots and virtual assistants that are run by artificial intelligence. These systems are based on natural language processing (NLP) to communicate with customers, respond to queries and help with purchases and deal with complaints in real time (Sharma, 2020). Chatbots providing services 24/7, reduce human workload, and provide instant support, which enhances the shopping process. H&M and Sephora are among brands that have installed chatbots on their websites and use them to offer their customers styling tips and product recommendations, which proves their power in improving customer interaction.

Digital technologies also make it possible to implement the dynamic pricing strategy because e-commerce companies can analyze the market trends, price of competitors, customer demand, and inventory (Chen et al., 2024). This will enable companies to change the prices quickly to maximize the revenue and compete. They can also be applied to demand forecasting, which can be used to manage stocks, prevent overstocking or understocking as well as seasonal demand planning (Li, 2019). Walmart and Amazon are some of the companies that extensively rely on AI to do these as they use predictive analytics to optimize their supply chains.

The visual search technology enables one to find products through images and not text. The image recognition system based on AI processes the uploaded image and reports the results about the similar products based on the catalog (Liu et al., 2018). The technology has been specifically applicable in fashion and home decor where aesthetics is the most important factor. The examples of companies that use visual search to provide the users with a better experience and improve sales are Pinterest and ASOS.

Detection and prevention of fraud in e-commerce is made possible through the use of digital systems. These systems able to identify any suspicious activity in real-time by examining transaction history, geolocation data and user behaviour (Ngai et al., 2011). The machine learning models are trained to detect abnormalities and activate security measures, which minimize risks to the businesses and consumers. PayPal, as one example, applies AI to track millions of transactions and detect potential fraudsters with a high level of precision (Lankton et al., 2015).

The digital tools expand automation to physical features of the e-commerce like inventory and a warehouse. Robots with AI are applied to pick, sort, and pack items in warehouses, whereas predictive analytics is applied to ensure optimal inventory levels (Wamba-Taguimdje et al., 2020).

Amazon has applied AI and robotics in its fulfillment centers to facilitate the operation, shorten the delivery time, and cut down operational expenses.

Digital technologies make the shopping experience more personalized, providing customers with customized suggestions, immediate assistance, and content, which leads to greater customer satisfaction and loyalty. Decision-making is automated with the help of technology and does not require human input, eliminates errors, and accelerates the process (Lee et al., 2023). This results to high savings in the long run. Algorithms gives profound understanding on the customer behavior, market patterns, and performance. The insights can be used to make strategic decisions and assist in the development of successful marketing campaigns. Those who can use digital technologies early have a competitive advantage as they can provide better customer experiences, act more rationally on pricing policies, and react to the market changes faster (Ling et al., 2024).

1.2 Digital interaction tools in e-commerce

Digital interaction tools have spread across the world as a phenomenon that has radically transformed the world of consumer behavior. Since the first discovery of the product, to post purchase follow up consumers are more and more navigating the digital world and this affects them and their perceptions, choices and loyalty. The complex nature of the effects of these tools is the most crucial thing that a business should have to succeed in the modern marketplace (Lim et al., 2022). Digital consumers are mainly dealing with e-commerce websites. Consumer satisfaction, purchase intent, and, finally, loyalty heavily depend on the user experience (UX) of these platforms (Luo et al., 2019). The positive and smooth UX, which implies the presence of an intuitive design, the ability to navigate the site with ease, and quickly loaded sites, influences not only immediate sales but also the development of trust and reliability of customers (Wang et al., 2022). Research has shown that a considerable proportion of customers will give up on making a purchase because of a bad UX, and most of them will be happy to spend more on a better experience.

As Hasan et al. (2024) state, the following are the major aspects of effective e-commerce UX:

- user-friendly Interface: Visual simplicity and clarity are the keys to a convenient user interface.

- Mobile Optimization: Mobile shopping is now the predominant shopping, and responsive design is no longer a choice, but a necessity.
- Personalization: Individualized promotion, recommendations and content related to the interests of users and previous activity has a substantial effect on the satisfaction and solidarity to the brand. Statistics indicate that a considerable proportion of customers would want to deal with brands that provide customized experiences.

The social media has become a juggernaut, significantly affecting the purchase decisions and brand loyalty. Social media such as YouTube, Instagram, Facebook, and Tik Tok also offer interactive, targeted, and data-driven channels through which brands can interact with consumers (Liu & Zheng, 2024). It has been shown in studies that social media has a strong effect on different phases of the customer experience, including brand recognition to the after-sale experience as given below (Alhakimi & Alwadhan, 2021).

Creation of Brand Awareness: social media is essential in creating awareness of products and services to consumers.

Social Proof: The desire of people to copy the behavior of other people, particularly the ones that they trust, is increased on the social media. Favorable review, testimonials, likes, sharing and comments by satisfied customers have a great effect on buying decisions and create brand trust.

Influencer Marketing: Social media influencers through their credibility and reach are important in shaping consumer decisions. Consumers are also consulting influencers more and more to find guidance and recommendations when making a purchase decision (Liu & Zheng, 2024).

User-Generated Content: It is the content exclusively created by consumers (i.e. photos, videos and reviews) and it offers genuine information that can have a great impact on the purchasing decision.

Consumers usually start their search engines to get information regarding products and services. Search engine optimization (SEO) and Search Engine Marketing (SEM) in particular have a significant positive influence on consumer awareness as well as choice of purchases (Ling et al., 2024). Increased presence in search engine results pages (SERPs) will have a direct effect on the purchasing decision by the consumer as the sites ranked on the first page of the search results are the ones that consumers will consider and be willing to visit. Companies which maximize their content based on the relevant keywords and give the consumers the quality information can efficiently lead the consumers through the buying process.

Conversational assistants such as Chatbots allow customers to receive immediate customer service, personalized suggestions, and guidance during the shopping process. The inclusion of AI and machine learning in digital marketing has also helped it to have a stronger influence on consumer behavior (Adam et al., 2021). Such technologies make use of machine learning, natural language processing (NLP) and automation to offer the human-like interactions to the consumer (Aronsson et al., 2021). They are utilized by retailers in diverse situations such as customer service, product recommendations and order tracking to make processes more efficient, user experience better and operational costs lower.

Automated customer support is one of the commonest uses of chatbots in online shopping. The chatbots will be able to answer common questions, refunds, and payment-related issues, and other regular questions without involving a human operator (Gnewuch et al., 2017). They also ensure 24/7 availability and thereby enhances the response time of the agent and eases the burden on the human agents. Følstad and Brandtzæg (2017) claim that customers like the immediacy and convenience of the assistant-based support, especially when the assistants sound competent and more natural to talk to. Nonetheless, there are still restrictions. As an example, chatbots do not always work well in context and emotionally charged scenarios (Chung et al., 2020). It has been found that users are not as angry with bots provided that these agents declare that they are not humans and that they offer human agents the chance to escalate the situation (Luger & Sellen, 2016). Nevertheless, conversational AI in customer service could be an affordable and scalable solution to many e-commerce companies in spite of these challenges.

Personalized product recommendation is another important application of conversational assistants in online shopping where the assistants are used. Conversational agents gather and process all information about customers (browsing history, preferences, and past purchases) to recommend appropriate products. This will improve the shopping experience by decreasing the choice overload and increasing the chances of a purchase (Jain et al., 2018). Indicatively, a conversational assistant on a fashion retailer can propose clothing, depending on the size, the occasion and the color of the user. McLean and Osei-Frimpong (2019) state that this personalization through the use of interactions improves the perceived value and customer satisfaction.

Another area of application of conversational AI that improves the post-purchase experience is real-time order tracking and updates. Customers do not have to physically inquire about the status of their orders, estimated delivery time, and shipping problems because bots will inform them. This is particularly useful whenever there is a high shopping rush or when the logistics is retarded. As evidence provided by Zhu et al. (2020) showed that chatbot order tracing is more effective than order tracking, as it enhances customer retention rate by improving the level of transparency and post-sale anxiety. Besides, chatbots are also capable of managing returns and refunds by guiding the customers on the steps that should be undertaken or even automate the process. This makes the buyer journey less painful and creates higher chances of repeat purchasing (Schuetzler et al., 2020)

Among the major benefits of conversational assistants is their ability to significantly increase efficiency and provide unprecedented accessibility (Balakrishnan & Dwivedi, 2024). Studies have revealed that these tools simplify the customer interactions through automated routine customer inquiries and tasks. The automation will result in reduced response time, faster issues solution, and finally a happier customer. As an example, research indicates that by incorporating the assistant-based solutions into a business, companies are able to achieve tremendous cost reduction up to 30 per cent and also enhance the response rates at the same time.

Conversational assistants provide 24/7 availability, a very important advantage in the globalized and always-on marketplace of the present day. The survey has already discovered that a considerable percentage of customers would like to communicate with chatbots during non-working hours, which explains the necessity of 24/7 availability (Pergantis et al., 2025). This ease of access plays an important role in increasing customer satisfaction because one can have access to assistance at their convenience without wasting time on the human agents.

In addition to efficiency, more intelligent chatbots and conversational AI use machine learning and NLP to provide a more personalized experience, resulting in more customer engagement and loyalty. These AI tools can optimize responses, suggest products, and even promotions to make them individually personalized through customer data analysis, such as previous interaction, purchase history, and Browse behavior analysis (Cheng & Jiang, 2020). Such a high degree of personalization may give the customer a feeling of connection with the brand, and get the customer and the brand to go beyond the generic interactions to more meaningful interactions.

There is also the conversational AI which enables the proactive interaction during the journey of the customer. Since at the stage of awareness, chatbots are able to lead visitors through the pages of the site and suggest product information, to the decision-making stage, where they can give all details and comparisons (Gkinko & Elbanna, 2023). During the conversion stage, chatbots may help with the product setup, payment complications, and checkouts and greatly decrease the lost steps. They will be able to track orders, troubleshoot, and receive feedback, as well as reinforce loyalty and promote repeat business, post-purchase (Gupta et al., 2023).

1.3 Evolution and classification of conversational assistants

The history of chatbot technologies, starting with primitive rule-based applications and leading to advanced conversations AI, has a history of multiple decades, being in tandem with the development of artificial intelligence and natural language processing. The theoretical background of chatbots was developed in the middle of the 20th century. The first and probably the most famous chatbot was named ELIZA that was created by Joseph Weizenbaum in MIT (Weizenbaum, 1966). ELIZA used a pattern-matching algorithm to emulate a Rogerian psychotherapist, the main part of which is to rephrase user input in the form of a question. Though primitive, ELIZA proved that human-computer dialogue was possible and that there existed the so-called Eliza effect which could be described as a human habit of seeing a human-like intelligence in a machine.

After ELIZA, there was PARRY in 1972 designed by Kenneth Colby at Stanford University. PARRY was intended to imitate a paranoid schizophrenic and represented a more sophisticated model of human thought and proved that despite its small functionalities, chatbots were able to provoke emotional reactions in its users (Colby et al., 1971). All these early systems were largely rule-based, which were based on predefined scripts and recognition of keywords to provide a response. Their weakness could be evident when they were faced with complicated or extempore discussions. In the late 20th and early 21st century, the trend was gradual toward more advanced methods of statistical NLP and machine learning. In 1995, with the invention of Markup Language to Conversational Systems (AIML), which was extensively used in ALICE (Artificial Linguistic Internet Computer Entity), more broad knowledge bases and intricate conversational paths were now possible which resulted in responses which are more intelligent (Wallace, 2007). The internet also led to the further development of chatbots, where the applications initially concentrated on simple customer support and information gathering.

The actual paradigm shift was the development of neural networks and deep learning in the 2010s. Conversational assistants were made possible by technologies including transformers and recurrent neural networks, which could now learn based on large volumes of text data, not through predetermined rules, but to produce more contextually relevant and natural responses (Fui-Hoon Nah et al., 2023). The most recent years have seen the introduction of huge language models (LLM) like the GPT series by OpenAI, which have enabled highly subtle, creative, and all-encompassing dialogues and have fundamentally changed the capabilities and uses of modern chatbots (Brown et al., 2020). This historical development highlights an unceasing search towards more natural, intelligent, and useful human-computer interaction. Retailers in the world have made the implementation of chatbots and conversational AI a strategic priority, which has improved their engagement with customers, made their operations more efficient, and boosted their sales. There are well-known companies such as Amazon, Sephora, and H&M that stood out among the digital transformation. Alexa, which is one of the most sophisticated conversational AI systems created by Amazon, can be used in numerous services, and these features are voice-activated shopping, order tracking, and product search (Hoy, 2018). Alexa makes it more convenient since the user can do tasks without using their hands, which creates loyalty due to the easy integration into the Amazon ecosystem.

Sephora, which is a top beauty retailer, has been able to use various chatbot systems. It also has an app and Facebook Messenger, which also supports its Sephora Virtual Artist, enabling people to virtually apply makeup with the help of augmented reality (AR) and get personalized recommendations (Pantano et al., 2017). Such combination of conversational AI and AR not only increases the engagement but also decreases the rates of the product returning, as it helps to make pre-purchase decisions.

Conversational agents are computer applications that attempt to replicate human speech (Ji et al., 2023). Their types are the key to aligning capabilities to those of users as their implementation in various industries spreads, especially online retail and customer service sectors. Chatbots that are based on rules are driven by pre-defined flows and if-then logic, in which the input of the user has to correspond to particular keywords or follow a directed path. Such bots are usually applied to perform simple activities like answering FAQ, or store hours (Shawar & Atwell, 2007). Since they do not understand natural language (NLU), their replies are stiff and they usually miss responding to unforeseen queries (Følstad & Brandtzæg, 2017).

By contrast, AI-based chatbots rely on natural language processing, machine learning (ML) and contextual awareness to process and react to more elaborate and diverse user inputs. These bots are able to learn through previous interactions, personalize and control open-ended conversations (Nicolescu & Tudorache, 2022). An example is the Alexa of Amazon and Google Assistant where AI-based chatbots provide a multi turn conversation and voice recognition. The AI chatbots can be specifically useful in those spheres of activity where flexibility and personalization are needed, including online retail and medical practice.

Hybrid chatbots are the third type that is a combination of rule-based logic and AI. These bots are able to track structured conversations as well as interpret user intent via NLP. Hybrid systems offer a level of reliability as well as flexibility that enables the smooth transition between automated responses and human agents in case of the need to do it (Adamopoulou & Moussiades, 2020). Other categories are voice-based and text-based chatbots and task-based bots as opposed to conversational bots. Task-oriented bots are made to accomplish particular tasks (e.g., booking a ticket), whereas conversational bots are focused on the idea of interacting with users and making them to feel more natural and human-like (Jain et al., 2018).

The changing nature of automated communication triggered the multiplication of comparative studies of the basic, rule-based chatbots and the more advanced conversational AI on user-centric metrics as further explained (Pelau et al., 2024). Conversation quality is the very idea used in this comparative analysis. Although chatbots that operate with rules may be effective, they do not tend to be flexible and emotional as the best interactions. The sentiment and context of conversational AI helps to make conversations more meaningful and useful. Therefore, in the case of companies that need to develop a more user-centered method to interact with people, to increase their loyalty, and manage more sophisticated service requests. A body of evidence indicates that an investment in conversational AI can provide a higher payoff in terms of user satisfaction and overall effectiveness (Sidlauskiene et al., 2023).

Conversational AI is far superior to traditional chatbots as far as personalization is concerned. The systems can analyze user information, trends, and historical dialogs and offer personalized suggestions and experiences using AI (Tripathi et al., 2024). As an example, AI-driven virtual shopping assistants can give recommendations according to preferences, whereas chatbots as an example are generally rule-based and give generic answers.

Rule based chatbots are quick in relation to responsiveness but inflexible in the sense that they tend to fail when the input exceeds the anticipated constraints. They give the predetermined answers irrespective of the context. In contrast, conversational AI reacts to user inputs, tonal and contextual history, to facilitate a natural and more interlude-like dialogue (Letheren et al., 2021). Conversational AI also involves deeper user engagement since these types of systems are designed to simulate a dialogue with a human, develop rapport and have continuity between sessions. Følstad and Brandtzæg (2017) argued that users tend to enjoy and revisit services with emotionally intelligent and responsive and engaging dialogue, which tend to be more in line with the AI-based systems.

Conversational AI is most likely to deal with user preference because it offers a more natural and less frustrating experience. Rule-based chatbots are assistants that rely on predefined scripts and keyword matching and might be seen as fixed and fail to work under the query that lies out of their programmed domain (Kshetri et al., 2023). This may cause frustration of the users and poor experience. On the other hand, conversational AI, which is based on machine learning and natural language processing can comprehend context, handle multifaceted conversations and can learn through previous interactions, providing a more dynamic and personalized user experience, which is usually desirable.

The level of user satisfaction is directly associated with the level of sophistication of the system. Although simple chatbots are capable of effectively performing simple and repetitive jobs, the capability of conversational AI to solve more complex problems without involving a human operator can result in greater levels of satisfaction (Gupta et al., 2023). According to reports published in the industry, the industry has been affected immensely with most businesses recordings accelerated complaint handling and enhanced customer support satisfaction following the adoption of AI-enhanced chat technological solutions. The Customer Effort Score and Customer Satisfaction Score are the key measurement indicators that are typically used to measure this difference, and lower effort and enhanced satisfaction are the attributes of conversational AI done well (George, 2004).

Trust is a less explicit aspect in the debate on the comparison between chatbots and conversational AI. Although the conversational AI is human-like and adaptive, some researchers also suggest that human agents may remain more preferred by users, particularly in the situation when empathy or critical decision-making is needed (Cheng & Jiang, 2020). Reliability of the information submitted is also an important aspect. As an example, a comparative analysis conducted on conversational chatbots and the internet regarding the information search result has revealed that although the internet was initially considered more reliable, this distance decreased as time went on and people communicated with chatbots (Aronsson et al., 2021). It is a critical performance metric, which is more likely to be higher with conversational AI systems because of their dynamical nature of interaction. Conversational AI is a type of chatbot that analyzes user intent, personalizes a conversation, and provides context-related answers using the processing power of machine learning and natural language, unlike scripted chatbots that adhere to predefined rules. Adamopoulou and Moussiades (2020) discovered that AI-driven agents could greatly improve the conversion rates by lowering the amount of friction in the process of making decisions and checkout. On the same note, Huang and Rust (2018) highlight that, as far as emotional intelligence is concerned, AI agents who possess emotional intelligence (e.g. empathy and real time feedback) facilitate more compelling interactions, which make users more apt to make purchases.

The quality of automated service interactions also determines another one of the key indicators of business success. AI-based chatbots that mimic a human-like dialogue improve customer satisfaction and customers trust the system, resulting in a repeat interaction (Grewal et al., 2021). Simple chatbots can be good at answering simple questions, but they do not have the capability to learn or improve with previous interactions, thus limiting their ability to affect customer loyalty after long-term use (Verleye et al., 2014).

Although chatbots and conversational AI are increasingly becoming a part of digital services, these types of artificial intelligence can often cause a lot of frustration among users, adversely affecting their satisfaction with the services and brand perception (Jan et al., 2023). Another major issue is the tendency of conversational agents to misinterpret the intent of users. Such misconceptions are usually the result of Natural Language Processing (NLP) shortcomings that give rise to unrelated answers and dead ends of conversations. It is unproductive and frustrating when a chatbot does not understand the context or details of a request that a user makes.

Research by Chhabra et al. (2025) named poor semantic understanding as one of the main factors that lead to user frustration. This is so widespread that in one study of chatbot failures that generic responses of I don’t understand were identified as causes of failure in 27 per cent. Failure to get it right when interpreting user needs does not just stop the service journey, but also destroys user confidence in the system competence. Many conversational agents also have a poor range, which is equally aggravating to users. Chatbots that are based on rules are especially limited to a set of preset questions and conversation patterns (Balakrishnan & Dwivedi, 2024). Once the query of a user does not fit into this very limited scope, it may get caught in endless loops, posed the same question several times, or receive unproductive deflections. It is a major pain point, as the research has shown that 62 percent of customers will drop a chatbot after only two failed attempts. The common need to have a human handoff, though a feasible solution, highlights the constraints of existing systems and may be a source of tension, in case it is not managed smoothly (Bunea et al., 2024).

The increasing literature indicates that there are serious ethical dilemmas in the paradigm of chatbots and conversational AI, especially in the field of data privacy, manipulation, and consent (Chuah et al., 2021). The capacity of these systems to gather, analyze and take action against large amounts of personal data presents a complicated ethical environment that existing regulatory and design structures are finding hard to negotiate. One of the most significant is data privacy because conversational AI systems can be aware of sensitive user information, including personal identifiers and emotional conditions as well as health-related issues (Ivarsson & Lindwall, 2023). These close, conversational interactions may also prompt users to share more information than they would with other online platforms; these interactions often lack a clear explanation of how their data could be accessed, distributed or stored (Bender et al., 2021). This uncensored and mass-surveillance data collection provokes very serious concerns of surveillance and possible abuse, and thus, to protect users, it would be crucial to apply strong privacy-by-design practices.

1.4 Impact on Consumer Purchasing Decisions

Digital interaction tools have a huge impact on the traditional consumer purchasing decision process, which include need recognition, information search, evaluation of alternatives, purchase decision and post-purchase behavior (Ling et al., 2024). At various touchpoints, chatbots and conversational AI interfere and direct consumers, offer information, and make transactions. Their influence is highly important to businesses that want to maximize their online efforts and establish better relationships with consumers in the modern market (Jonas & Oskar, 2023).

The core aspects of trust and credibility are very critical in the decision of consumers to make purchases and the emergence of conversational AI presents a new approach to these two constructs. Consumers need to trust the conversational assistant and believe that it is credible to depend on the information or advice given by the assistant (Mori et al., 2012). Nevertheless, literature tends to show that the transparency and regular accuracy are the possible methods to build trust in conversational AI (Hussain et al., 2019). Making it clear that the user is dealing with an AI, and not a human being, will help control the expectations and avoid the negative perception of deception. In addition, the credibility of the chatbot is directly proportional to the accuracy and relevance of the information it provides. The higher the rate of providing the conversational assistant with the right information on products, price, and assistance, the higher the trust of the consumer in the brand (Liu et al., 2018). Indicatively, the use of assistants which respond correctly to certain product questions or countercheck order information instill confidence in the assistant features.

The brand reputation which had already been established is also a major factor in promoting the initial trust on its conversational assistants. An assistant that belongs to a trusted brand that is faithful to its products and has earned good customer service is likely to gain the trust of the consumers. On the other hand, a brand that has a history of unsatisfactory customer relationships will have an uphill challenge to win the trust of its AI-driven interactions (Rehman et al., 2019). It has been shown that the reliability of conversational assistant with respect to its application within a company is strongly correlated with its image as a company. The hybrid approach, i.e., chatbots process simple questions and then transition complex or sensitive ones to human operators, is considered an effective approach to establishing trust. This would take advantage of the effectiveness of AI in performing routine jobs and assure the customers that there will be human knowledge and compassion at their disposal (Song & Shin, 2024). The consumers appreciate the ability to be escalated to a human which adds to the perception of the brand as committed to effective solution and therefore the credibility of its AI system.

Conversational AI uses algorithms of machine learning to process extensive data about customers, such as their previous purchases, their browsing history, what they have liked, and even what they say at a specific moment during the conversation (Sutisna & Handra, 2022). This information will help the AI to provide very personalized product suggestions, tailored promotions and content that is relevant and specific to the needs and interests of the individual consumer (Yen & Chiang, 2021). As an illustration, a chatbot may recommend something to add to a newly bought product or inform a client about a sale in the products they have already browsed. Conversational AI can provide real-time, dynamic personalization as opposed to the static methods of personalization (e.g. email marketing). It is also able to change its dialogue and suggestions according to the current conversation and clear up ambiguity, posing follow-up questions, as well as direct the user through the decision-making process more efficiently. This contextual understanding makes the interaction more natural and engaging like an informed sales assistant in a physical place of sale. Research indicates that consumers prefer to buy brands whose experiences are personalized (Alalwan, 2020).

The stage of consumer information search and evaluation of alternatives is greatly influenced by personalization. Conversational assistants can also simplify the process of discovery by actively providing a consumer with the options they would not have learned about otherwise, as part of reducing cognitive load and decision fatigue (Abdul & Soundararajan, 2022). This is the focused strategy that boosts the chances of a purchase as the offerings are matched better with the expressed or implied needs of the consumers. In addition to immediate buying decisions, personalization creates enhanced relationships and loyalty between customers (Alagha & Helbing, 2019). Whenever the consumers are made to feel appreciated and understood they tend to go back to a product. Conversational AI, via its capacity to recall previous encounters and inclinations (memory), serves in this regard by generating a comparable and relative experience with time, solidifying brand loyalty (Rehman et al., 2019).

The strongest advantages of conversational assistants include the fact that it can give immediate answers and assistance, and customers do not have to wait in a queue or the working hours (Baek & Kim, 2023). This instant satisfaction is especially valuable in the process information search and purchase as the consumer usually has urgent questions that may not allow him to carry out a purchase. Studies show that long checkout lines are one of the major reasons it has lost customers, as well as the cart. Assistants handle this situation through provision of real-time access to information and guidance. In contrast to a human customer service team, assistants work 24/7 and cannot be stopped by time zones and holidays (Aslam et al., 2023). This is a key influence to the global consumer and the off-business-hour shoppers. The possibility to immediately answer the question about the product, monitor the status of the order, or solve minor doubts any time eliminates a frequent obstacle on the way to purchase and improves the convenience of the whole shopping process (Blut et al., 2021).

The conversational systems are highly scalable because they can be used to serve a large number of questions concurrently. Promotions, peak times, or sudden rises in customer traffic can be handled by assistants, which handle a higher number of customer interactions without affectively lowering response time and quality (Baek & Kim, 2023). This will make sure that potential customers are attended to within the required time before they make a sale, as they will not be lost to a busy channel. The degree of interest and general satisfaction that results when a consumer interact with a brand will determine consumer loyalty as well as subsequent purchasing behavior to a large extent. Conversational assistants are important in forming these aspects (Passanante et al., 2023).

The current conversational AI is not confined to the Q&A and offers more interactive and engaging experiences. The AI has the capability to maintain a conversation, pose clarifying questions, provide multimedia material, and even project a brand-appropriate personality through its natural language features (Pitts et al., 2024). The information collection process can be made less boring and more pleasant due to this interactivity, turning it into a smooth one. By engaging customers, they will be more inclined to examine the products in detail and have a good attitude towards the brand. Problem resolution is the major objective in customer service interactions. Conversational assistants, working efficiently to address the routine problems, respond to frequent queries, and offer the self-service opportunities, contribute to a significant decrease in customer frustration (Ghorbanzadeh et al., 2025). The more consumers can easily get answers to their questions or solve simple problems without the need to engage a human being, the higher satisfaction they get about the purchasing online. This favorable experience will then be converted to a better attitude towards the brand and they are more likely to be using the brand in future.

Depending on type of conversational assistants, it is possible to have a cohesive brand voice and tone in all interactions, which supports brand identity. Such uniformity helps to create a seamless customer experience, familiarity, and comfort with the digital presence of the brand (Aronsson et al., 2021). Whether the brand establishes a positive and consistent feeling on the consumer through a human agent or a conversational assistant, it enhances satisfaction by boosting emotional attachment. Conversational assistants can be trained to actively seek customer feedback at the conclusion of the session, which gives useful insights into areas of weakness and improvement (Gieselmann & Sassenberg, 2023). Such feedback loop enables companies to optimize their AI models, refine processes, and further improve customer satisfaction which indirectly affects future purchasing decisions (Greilich et al., 2025).

Decision confidence is the feeling of a consumer that he or she makes the right and appropriate purchase. Conversational assistants effectively support this trust with detailed information and instructions at the stages of information search and assessment of alternatives. The consumers attempt to obtain adequate information in order to make a well-founded choice (Gros et al., 2021). These assistants are readily available and having endless information stored, give specifications of products, comparisons, reviews, and responses to specific queries in simple and condensed forms. This available access to all-inclusive information minimizes the uncertainty and ambiguity, resulting in greater confidence in decision-making (Hadfi et al., 2023).

Advanced conversational assistants may be considered a guided selling tool. The assistants can also reduce the number of possible choices and suggest the most appropriate products by posing specific questions to a consumer regarding their needs, preferences, and budget (Han, 2021). This one-on-one service, which resembles an expert salesperson, assists customers in navigating the confusing product lines and make decisions with a higher level of confidence. The assistants are also able to point out the important features, advantages as well as the possible disadvantages and enable the consumer to make a sound judgment. Numerous conversational AI systems are capable of incorporating and displaying the elements of social proof, like customer reviews, ratings, and testimonials, directly in the conversation (Wirtz et al., 2018). With such credible information that is checked by the AI, the consumers can assess the popularity and quality of products as they are viewed by other users, which also increases their trust in their purchasing decision. This is in line with the social proof principle which says that people are shaped by the behavior and thoughts of other individuals.

1.5 Technology Acceptance Model (TAM)

This model as proposed by Davis (1989) is a common model that is used to understand the process of use and acceptance of new technologies by the customers. TAM assumes that the intention to effectively utilize any technology is driven by two underlaying important factors, including perceived usefulness and perceived ease of use which prove to be influential on the actual usage behavior. This model has been extensively used to examine the acceptance of chatbots and conversational AI to users, especially regarding e-commerce and customer services.

Perceived usefulness (PU); the degree to which an individual believes that the usage of a given system will enhance their performance is essential part for the adoption of online shopping. When users feel that the digital agent is useful in executing their tasks like locating information, tracking orders or answering queries, they will tend to interact more with the digital agent. According to Gnewuch et al. (2017), the fact that the users experience positive interactions with the functionality of the digital agent and the efficiency of the tasks the service performs is the key stimulus to the intention to reuse the service. Likewise, the PU is enhanced because users perceive digital agents as useful in cases where they respond with the right and timely responses (Liu & Wei, 2021).

Perceived ease of use is an important concept that determines whether the technology is effortless to use, is also a crucial element in adoption digital assistants (Sarikaya, 2015). Interactive systems with user-friendly interfaces, natural language processing and coherent conversational control are usually regarded as user friendly. As a consequence of frustration, the user might abandon an assistant when they find it difficult to navigate or communicate with a helper (Maduku et al., 2023).

1.6 Theory of Planned Behavior (TPB)

It is among the most well-known theories in explaining and predicting human behavior, especially in the contexts in which the volitional control of the behavior among the individuals differs. This theory was developed by Ajzen (Ajzen, 1991, 2020). TPB assumes that the intention of a customer to participate in a particular behavior is largely influenced by three fundamental construct such as a) the attitude towards the behavior, b) subjective norms, and 3) the perception of behavioral control.

Attitude towards the behavior is the positive or negative judgment of an individual on whether to act or not to act. When it comes to online purchasing, the attitude of the consumer is influenced by the beliefs that he or she has regarding the results of online purchases. The studies have always shown that the intention to purchase online is greatly influenced by a more positive attitude towards online shopping (Sutisna & Handra, 2022). Positive attitude factors usually encompass the perceived convenience, the time-saving advantages, the expansion of the product range, and competitive price (Redda, 2019). On the other hand, other issues like privacy and security, fear of fraud, or the inability to physically examine the products can be considered as causes of negative attitudes. Research shows that consumer attitudes towards online purchasing are directly influenced by consumer beliefs with regards to the trustworthiness of the brand and this translates into purchase behavior (George, 2004).

Subjective norms are the perceived force of social compulsion to do or not to do a given behavior. In online buying, this element presents the perception of consumers about the expectations of significant referent groups in their online shopping, meaning family, friends, colleagues, or even online influencers (Jain et al., 2018; Qi & Kuik, 2022). When one is convinced that other reference groups have accepted or have ventured into online shopping, he or she will develop a stronger intention to shop online (Lee & Ngoc, 2010). The influence of the subjective norms has been enhanced due to the emergence of social media because people are constantly exposed to people and influencers who demonstrate their online purchase, thus impacting the sense of desirable consumer behavior (Jaitly & Gautam, 2021). Although few articles have established a positive impact of subjective norms on an online purchase intention as significant (Tan & Liew, 2020), others have also found unequal levels of impact on subjective norms on the intention to buy based on the cultural background and the target product category (Nguyen et al., 2023; Solomon, 2017).

Perceived behavioral control defined as the belief of an individual about how easy or hard it is to do the behavior (shopping online), which includes a perception of whether an individual has the opportunities and resources to do the behavior or not (Terblanche & Kidd, 2022). With regards to online purchasing, PBC includes internet literacy of the consumer, availability of quality internet service, ownership of the required tools in digital usage, the ease of use of internet platforms, and security of payment (Nainggolan & Sijabat, 2023). The high extent of the perceived control, i.e., a consumer believes that he/she is able and capable of going through the online transactions and dealing with the possible risks, is always associated with a higher intention to online purchase. It has been established that the beliefs concerning self-efficacy in making online purchase have a direct effect on the perceived behavioral control, which ultimately influences the online buying behavior. On the other hand, when they do not feel in control, which may be caused by technology and/or security concerns, online purchasing decisions can be strongly prevented (Hasan et al., 2021).

1.7 Persuasion theory

Another conceptual framework relevant to the study of consumer behavior and its impact on digital technologies is the theory of persuasion, which is becoming more and more popular as the means of explaining the role that chatbots and conversational AI play in consumer behavior. In its most basic form, the persuasion theory studies messages developed and communicated in order to alter beliefs, attitudes, or actions (Perloff, 1993). Conversational agents can be considered as persuasive technologies in the context of e-commerce, which are used to subtly influence users to make a purchase decision by offering personalized communication, interactivity, and appeal to emotions. The theory of persuasion provides a solid perspective on the influence of chatbots and conversational AI on the attitude and choices of the consumer (Kurniawati et al., 2023). With the help of personalization, credibility of the source, and emotional design, these technologies are used as persuasive factors that impact consumers in a variety of cognitive routes.

One of the most outstanding models of persuasion is the Elaboration Likelihood Model (ELM) jointly developed by (Petty & Cacioppo, 2012). ELM proposes two paths to persuasion: central route, where persuasion is based on thoughtful and rational attention to information, and peripheral route, where persuasion is based on such cues as attractiveness, credibility, or emotional appeal (O'Keefe, 2013). Central-route processing may be activated in chatbot communication when the user is interested in comprehensive information about the product or product comparison, but peripheral-route processing may predominate when the chatbot increased the level of engagement through humor, personalization, or anthropomorphism (Bayır & Akel, 2024).

The important concept in persuasion- is the most essential in the success of conversational agents regarding consumer purchasing intention. The users will be more inclined to be affected when they believe that the assistant is trustworthy, knowledgeable, and useful (Lankton et al., 2015). This is in line with the results of the perceived credibility which is an important inducement of purchase intentions in chat mediated interactions. Adaptive information presentation--is an act of persuasion that is based on the relevance theory. When personalized messages are used, it is more engaging, perceived as more valuable and consumes less thought, which increases persuasion by both central and peripheral processes (Araujo, 2018).

1.8 Consumer Decision-Making Models

Consumer decision making is a complicated cognitive activity, which includes a number of stages in sequential manner: information search, alternatives evaluation, purchase decision, and post purchase behavior (Kottler & Keller, 2009). These steps are used to develop the traditional model of decisions, which provide an organized framework of consumer behavior in different situations, such as using digital agents such as chatbots and conversational AI.

The initial step is information search, which entails the collection of information relating to products or services satisfying a need. The process can be facilitated by digital agents in the modern digital age, which allow consumers to find the content they need within a short amount of time (Solomon, 2017). The use of conversational assistants is essential as it gives immediate responses to the inquiries and makes the consumer less strenuous in locating product information (Xu et al., 2022).

Then, there comes the assessment of alternatives that involves the comparison of various products or services by the consumers. This can be determined greatly by the presence of assistant-driven recommendation systems and conversational interfaces. (Pantano & Pizzi, 2020) are of the view that people tend to trust the intelligent agents more because they make suggestions that are personalized, reduce the number of choices based on previous actions and preferences described, leading to better trust and efficiency in making decisions.

The third one is the purchase decision where the consumer chooses an alternative and makes a decision to transact. Responsiveness and human-like interaction of conversational assistants was observed to have a positive impact on consumer confidence and satisfaction at this phase (Malhotra & Ramalingam, 2025). These tools also tend to minimize doubt regarding decisions because the tools are immediate and interactive thus speeding up the process of making purchases.

Lastly, there is the post-purchase behavior of the consumer which entails appraisal of their level of satisfaction, which influences brand loyalty and choices made in the future. Follow-up support or efficient complaints agents introduced by the company to enhance a good post-purchase experience are digital agents. Moreover, conversational AI may receive feedback or can propose attention to other products, which increases customer interaction even after the purchase. The models of consumer decision-making provide an essential perspective that may be used to assess the impact of conversational agents on the purchasing behavior (Massoudi & Zaidan, 2024). With the implementation of chatbot and conversational AI capabilities aligned to every decision phase, companies would be able to impact and assist consumers, which will hopefully increase satisfaction and lead to sales.

Overall, the literature survey highlights the disruptive potential of the conversational agents in influencing consumer buying behavior, especially by utilizing chatbots and conversational AI. Previous literature has indicated that the perceptions of usefulness, ease of use, satisfaction, and trust have been found to play a major role in the purchase intentions of consumers in the digital context. Whereas chatbots offer more structured interaction that follows a set of rules, conversational AI offers a more dynamic and human-like interaction, which may lead to increased user experience and confidence in their choices. The current studies, however, tend to investigate these technologies separately, and there is a gap in the comprehension of their relative impact on consumer behavior. This gap is the reason why the current research will be a direct comparison of the effect of chatbots and conversational AI on the purchase behavior of users, and hence, it will not only add to theoretical knowledge but practical approach to the business trying to optimize customer interactions via conversation-based systems.

2. METHODOLOGY

2.1 Conceptual Framework Model

The present chapter describes the methods about conducting this research based upon all the information provided in literature review. It begins with the description of the purpose of the study and its importance in the advancement of the existing knowledge. The methods used are described in detail and the reasons behind their choice is provided. The conceptual model that supports the research structure is introduced in the chapter as well, and it demonstrates important variables and their interrelationships. Certain hypotheses based on the literature are also addressed and insights about what is expected and how can be made. On the whole, this chapter is a blue print of the study, as it connects theory to practice and presents the research process.

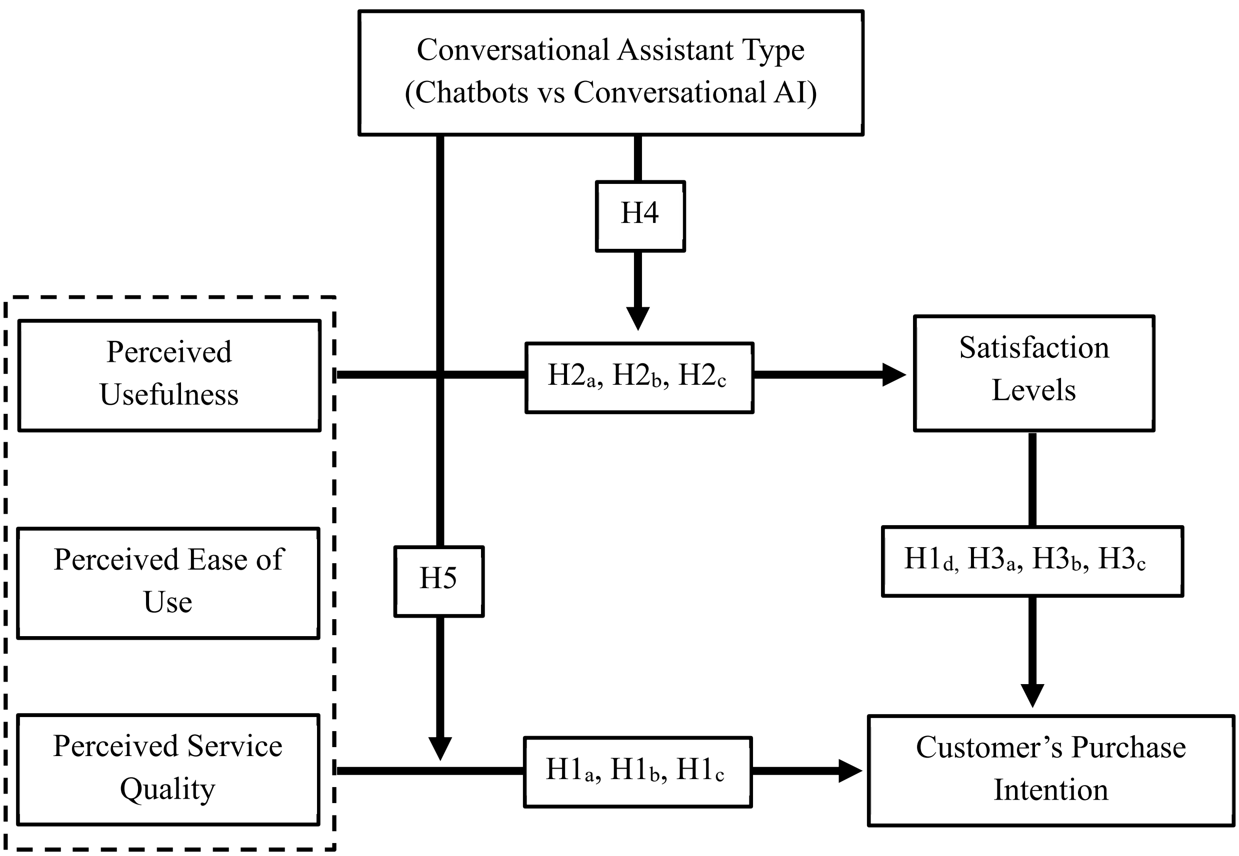

Figure 2.1: Purposed Theoretical Framework

Source: Constructed by author on the basis of (Roy & Naidoo, 2021), (Swain & Singh, 2021), and (Davis, 1989)

The rapid adoption of chatbots and conversational AI in online shopping has changed how consumers engage with the brand. Such smart systems are now being implemented to offer real-time support, respond to questions, and direct customers in their online shopping processes (Adam et al., 2021). Although chatbots and conversational AI serve the same purpose, their design and interaction patterns are different, where chatbots are usually pre-defined script-based but conversational AI exploits the principles of machine learning and natural language processing to replicate more human-like interactions (Grewal et al., 2018). It is vital to comprehend the effect of such technologies on the perceptions and the decision making of consumers in the current competitive market place. This study can offer a lot to businesses who aim to improve customer interactions and generate sales since it explores their influence on perceived usefulness, perceived ease of use, perceived service quality, satisfaction, and purchase intention. This research is likely to enable the marketers and developers to make more efficient AI-based communication tools that resonate with the expectations and behaviors of the consumer.

On the basis of the findings of the literature review and the conceptual framework created for the current study.A number of hypotheses have been developed as a way of empirically investigating the connections between the main constructs, including perceptions of usefulness, perceptions of ease of use, perceptions of service quality, the state of satisfaction levels and intentions to purchase, in the situation of chatbot and conversational AI-initiated interactions. These hypotheses will help explain how the perceptions and experience of the users towards these technologies influence the way they make decision during online shopping. The research will aim to answer the questions by investigating the suggested relationships to determine whether conversational AI provides a more stimulating and persuasive user experience than the traditional chatbots and thus affect the purchasing intentions of the consumers.

2.2 Hypotheses

Direct relations

Perceived usefulness, the belief that a technology enhances the efficiency of task performance, has been repeatedly determined to influence consumer behavioral intentions in technology acceptance research, with recent research showing that the association is present in chatbot and conversational-AI in e-commerce (Davis, 1989; De Cicco et al., 2020). Technology acceptance models (e.g., UTAUT/TAM syntheses) based on meta-analytic evidence have shown that the level of perceived usefulness is among the most consistent and most reliable predictors of behavioral intention in information technologies (Tamilmani et al., 2021). The empirical studies that address conversational agents directly discover that perceived usefulness has a positive effect on user attitudes and satisfaction with chatbots as antecedents of purchase-related outcomes (Schachner et al., 2020). The research on the complementary e-commerce also reveals that the intention to use AI chatbots to shop in online stores is enhanced by perceived usefulness, along with trust and design characteristics (e.g., interactivity, humanness), which, in turn, promotes the intention to purchase in online contexts (Ding & Najaf, 2024). Combined, these results render convergent theoretical and empirical research support to the hypothesis according to which perceived usefulness of chatbots and conversational AI influences purchase intention among the customers when they make online purchases.

The perceived ease of use , a core aspect of Technology Acceptance Module, which represents a measurement of the belief of the user that the use of a system will not involve any effort and will be easy to use (Revels et al., 2010). It is a key aspect that the consumers regard the willingness to interact with and ultimately adopt a chatbot or conversational agent based on the smoothness, the user-friendly experience (Ogutu et al., 2014). By making the AI interface easy to use and understand, the cognitive load is minimized and leads to a more favorable experience of online shopping on the whole (Alalwan, 2020; Beeler et al., 2022). This improved experience, in its turn, is demonstrated to improve the level of satisfaction and interest of the user, which eventually translates to an increased intention to purchase (Nicolescu & Tudorache, 2022). In particular, empirical research has established that ease of use facilitated by AI has a direct and positive effect on the purchase intention, as it makes the process of shopping convenient and efficient. As an illustration, the ease of use enabled by AI has been observed to increase a consumer perception of a sense of control over the shopping process, which enhances the connection between customer perceptions and purchase intent (Pfeuffer et al., 2019). Also, PEOU tends to be involved in the establishment of the primary trust in the chatbot, another important precondition of purchase intention and loyalty (Kelly et al., 2025). Moreover, a high quality of the system with the ease of use as a technical characteristic will guarantee a smooth interaction which will make the user satisfied and leave a favorable impact on the purchase intentions.

Perceived service quality is an important factor in choosing the behavioral intentions of customers in online space, especially when it comes to communicating with chatbots and conversational AI. Excellent service quality, measured in terms of responsiveness, reliability, empathy, and personalization, boosts the degree of customer trust and perceived value, and thus propels customer intention to buy. Empirical studies have also proved that the quality of chatbot service has a direct relationship with consumer satisfaction and purchase intention as it defines their overall experience and perceived utility (Li & Zhang, 2023). On the same note, (Kull et al., 2021) established that dimensions of perceived service quality, e.g., efficiency and assurance, are important in influencing customer attitudes toward AI-based conversational agents in e-commerce. Moreover, the data provided by Mende et al. (2019) showed that customers select chatbots as the ones that can support them in terms of timeliness and accuracy, which enhances their purchase intentions by increasing their engagement and trust. Taken as a whole, this group of studies attests to the fact that the perceived service quality of chatbots and conversational AI has a significant impact on the purchase intention of customers when they go shopping online.

One of the most effective predictors of purchase intention in online shopping situations is customer satisfaction. The expectancy-disconfirmation theory states that when customers have their expectations fulfilled or surpassed in the process of their interaction with an online platform or a conversational agent, they get satisfied, which consequently reinforces their purchase intention. This association has been verified in many studies in an e-commerce setup. As an example, Sari (2023) discovered that customer satisfaction is a significant mediator and predictor of purchase intention in online shopping, meaning that pleasant shopping experiences have a direct positive impact on consumer intentions to purchase. On the same note, a report satisfaction based on the quality of chatbot services shows that it significantly contributes to the engagement and purchase intention of customers (Eren, 2021). In a separate study, the authors proved that the satisfaction of users with AI-powered chatbots is the major antecedent of behavioral intention because satisfied users are likely to build trust and loyalty towards online shopping platforms (Jeon & Kim, 2025). Based on the evidences discussed it is hypothesized that

H1: **For each type of conversational assistant (chatbots vs conversational Ai), Customer's Purchase Intention is directly affected by (a)Perceived Usefulness, (b)Perceived Ease of Use, (c)Perceived service quality and (d)Satisfaction levels while shopping online.**

Perceived usefulness, is always known as one of the leading causes of customer satisfaction when it comes to conversational agents (Jonas & Oskar, 2023). When customers believe that the chatbot is an effective and useful tool that effectively helps them to meet their shopping objectives, they will develop positive opinions and say that they feel more satisfied with it (Goel, 2017; Tandon et al., 2024). This positive direct relationship has been validated by empirical studies that specifically concentrate on the e-commerce environments (Iriani & Andjarwati, 2020). As an example, a study on the use of chatbots on a large e-commerce site revealed that the variables of AI and chatbots, fueled by the characteristics of speed and accuracy of information response, significantly and positively influenced customer satisfaction. In the same vein, a study that used Technology Acceptance Model (TAM) established that perception of usefulness had a strong positive influence on attitude towards chatbots and customer satisfaction (Goli & Singh, 2023).

User perception of ease of use is one of the determinants of user satisfaction with technology-mediated interactions, especially in chatbot and conversational AI contexts. The Technology Acceptance Module opines that the ease of use of a system decreases cognitive effort, improves efficiency and generates positive affective reactions- thus propelling the level of satisfaction. The current empirical studies prove that the simplicity of communication with AI chatbots promotes customer satisfaction in online shopping experiences to a considerable extent (Ciechanowski et al., 2019). On the same note, research showed that perceived ease of use has a positive impact on satisfaction due to the effect it has on perceived usefulness and trust in AI-based shopping interfaces. Additionally, the researchers discovered that ease of use has both a direct and an indirect impact on satisfaction and, as a result, positive behavioral consequences, including repurchase and recommendation intentions (Daniel K et al., 2022). All these results confirm the findings that the perceived ease of use of chatbots and conversational AI is significantly connected to the satisfaction level during the process of online shoppingbbbbbb.

Certain aspects of service quality of conversational assistants are reported as the key determinants of online customer satisfaction. The speed, precision, and timeliness of the assistance offered by an assistant is a decisive condition that contributes to a high level of customer satisfaction (Bansal & Thakur, 2024). The core aspects of service quality including very fast response time, 24/7 access and right information, are valued most by the customers (Bavaresco et al., 2020). The relevance of responses and the ability of the assistant to address problems of clients are the main identifiers of its efficiency (Bhatti & Akram, 2020). Research has demonstrated that the provision of relevant and correct information by a conversational assistant directly leads to customer satisfaction and trust (Xu et al., 2022). Additionally, the two dimensions ability to understand and problem resolution have a considerable and direct influence on the desire of a customer to select a chatbot service instead of a human agent (Shahbandi, 2025). As an example, Personalization, which is attained through recollection of past interactions and making suggestions which are personalized to customers, improves the customer experience. In addition, social-oriented communication style and the use of emotion words, including sorry or thank you, has been determined to increase customer satisfaction through creating warmth perceptions and positively influencing such dimensions as empathy and interactivity (Al-Oraini, 2025; Alagha & Helbing, 2019). Based on the evidences discussed it is hypothesized that

H2: **For each type of conversational assistant (chatbots vs conversational Ai), Satisfaction levels are directly affected by (a)Perceived Usefulness, (b)Perceived Ease of Use and (c)Perceived service quality while shopping online.**

Mediation Analysis

The mediating variable of the relationship between the technology perceptions of consumers, including the perceived usefulness, perceived ease of use, and perceived service quality, and their online shopping purchase intentions could be the satisfaction levels. In the context of the Technology Acceptance Model (TAM) and service quality theory, satisfaction is an effective response, which converts positive cognitive assessments of technology into behavioral responses. This mediating mechanism is always backed up by empirical studies. As an example, Efendioğlu (2024) established that perceived usefulness and ease of use have the same impact on purchase intention via satisfaction in online retail driven by AI, which implies that the perception of ease and utility increases satisfaction, which ultimately leads to purchasing decisions. Equally, as was revealed by Bishowkarma and Pokhrel (2024), perceived service quality mediates its effects on purchase intention via customer satisfaction with chatbot interactions. Moreover, (Lubbe & Ngoma, 2021) presented the evidence that the satisfaction can be considered as a factor that links the perceived technological value to the purchase intention of the consumers through the use of the AI-driven chatbots. Based on the evidences discussed it is hypothesized that

H3: For each type of conversational assistant (chatbots vs conversational Ai), Satisfaction mediates the relationship between Consumer's Purchase Intention and (a)Perceived Usefulness, (b)Perceived Ease of Use and (c)Perceived Service Quality.

Moderation Analysis

Regarding conversational assistants, the perceived usefulness is always determined to be an influential positive predictor of consumer behavioral intention and purchase intention (Nguyen & Malik, 2022; Yu & Chen, 2024). For example, an assistant that will make appropriate fast recommendations and practical solutions is seen to have a high utilitarian value, which enhances the probability of purchase. Intention is also indirectly affected by PEOU that has a positive influence on PU (Ivarsson & Lindwall, 2023). Customer engagement and ultimately, purchase intention are major consequences of Perceived Service Quality (PSQ) of conversational assistants, which can be attributed to such elements as system reliability, response time, and personalization (Conner & Armitage, 1998). The quality of service in an AI-chatbot environment is a stimulus that positively affects the "organism" variables such as trust and interaction of the user, which positively forecasts the purchase intention, the response (Cohen et al., 2023). In particular, the capability of a system to provide quick, precise, and pertinent answers to a natural language increases the perception of the quality of the services provided to the user and directly contributes to their purchase decision (Ciechanowski et al., 2019). The current studies are a good support of the primary implications of PU, PEOU and PSQ on purchase intention. Nevertheless, the particular modulating influence of the difference between a classic Chatbot and a high-tech Conversational AI is one of the areas where the gap in research is identified. The hypothesis will cover the assumption that the more advanced functionality of a genuinely Conversational AI (i.e., superior natural language processing, memory, and more natural communication) would further enhance the favorable impacts of PU, PEOU, and PSQ than a less advanced, rule-based Chatbot.

H4: While purchasing online, conversational assistant (Chatbot vs Conversational AI) moderates the relationship between Satisfaction levels and (a)Perceived Usefulness, (b)Perceived Ease of Use and (c)Perceived Service Quality.

The conversational assistants influence the associations between the perceived usefulness, perceived ease of use, perceived service quality, and customer satisfaction in online shopping. Studies have shown that conversational AI systems are more interactive, understand natural language and personalized, which makes them stronger than conventional chatbots in strengthening these relationships. Luo et al. (2019) discovered that conversational agents powered by AI and large degrees of anthropomorphism and responsiveness could raise the levels of usefulness and satisfaction in the minds of users. Similarly, Gnewuch et al. (2017) also showed that ease of use has the positive impact on satisfaction, which is multiplied by conversational sophistication and adaptive style of communication in AI-based systems. Moreover, the study conducted by Paraskevi et al. (2023) showed that the quality of perceived service has a greater effect on satisfaction when communicating with intelligent AI assistants instead of script-based chatbots, because of the perceived empathy and trust. All these findings would tend to point to the fact that the nature of the conversational assistant is what defines the correlation between the level of satisfaction and the perceived usefulness, ease of use, and quality of the service when shopping online. Based on the evidences discussed it is hypothesized that

H5: While purchasing online, conversational assistant (Chatbot vs Conversational AI) moderates the relationship between Consumer's Purchase Intention and (a)Perceived Usefulness, (b)Perceived Ease of Use and (c)Perceived Service Quality.

Chatbots vs Conversational Ai

Although the comparative analysis was not made with measured mean scores, the literature indicates indirectly that more developed, AI-oriented conversational assistants are positively associated with a higher purchase intention. The key elements of conversational AI, including customization, background knowledge, and active interaction have been described to have a positive impact on the level of satisfaction and trust, in turn, the intention to buy (Lei et al., 2021; Wang et al., 2022). There was a statistically significant difference in mean score between perceived usefulness and ease of use as well as the perceived service quality between the perceived usefulness and ease of use as inferred in the case of the study by response strategy used by the businesses to assist the customers purchasing. Also, the stronger performance expectancy, which is the conviction that the system will facilitate accomplishing the tasks quicker and more efficiently, is a significant addition to the relationship between proactive strategies and purchase intention (Hauser, 2024). The fact that high-level AI can create a more human-like, multi-turn conversation (which is one of the main features of Conversational AI) can be viewed as anthropomorphism (Rabassa et al., 2022). This style of anthropomorphic design has been found to enhance product perceived personalization and the readiness of a consumer to spend more money on the product, therefore, a greater desire to buy it. Hence, it is proposed that the variations in the mean scores of various indicator variables influence the purchase intention.

H6: The mean levels of (a)Perceived Usefulness, (b)Perceived Ease of Use, (c)Perceived Service Quality, (d)Satisfaction levels and (e)Customer's purchase intention between users interacting with Chatbots are statistically different from those interacting with Conversational AI assistants.

2.3 Sample and Data Collection

The study design used was quantitative, cross-sectional, and hypothesis-testing, which is appropriate to investigate the relationship between variables and test theoretical models. The survey-based methodology was selected because it enables the gathering of standardized answers of a significant number of respondents and has been extensively applied in consumer behavior and technology acceptance research (Hair et al., 2019).

The research sample of this study was online consumers who have had previous experience with either chatbots or conversational AI systems when making online purchases or service requests. Since the research was exploratory and comparative, non-probability purposive sampling was used to make sure that only respondents with the relevant experience were involved.

The size of the sample was calculated according to SEM recommendations. Kline (2012) states that a sample size of 200 is regarded as sufficient in SEM, whereas Hair et al. (2019) recommend 10 observations to every estimated parameter. Based on these guidelines, at least 250 responses were aimed at in order to have strong analysis. The sum of received responses was totaled to 393, However, the number of valid responses (380) received were more than the recommended threshold and therefore, sufficient statistical power to test the hypothesis.

These were two versions of the survey question form but the questions and visual materials in both versions were the same. In version A, however, the conversation was with chatbots and in version B, it was with the conversational AI. Both versions contained a video showing a simulation of a conversation with a conversational assistant, presented to the participants prior to the questionnaire. The test made it possible to investigate the effects of the perceived form of the conversational assistant (chatbot vs conversational AI) on responses in terms of the constructs. The data were gathered using a structured questionnaire which was split into seven sections:

- **Essential Demographics (ED),** (e.g., age, gender, education & country etc.)
- **Behavioral Demographics (BD),** (e.g., experience with conversational assistants, frequency of online shopping).
- **Perceived Usefulness (PU)** based on Davis (1989) and subsequent TAM research.
- **Perceived Ease of Use (PEOU)**, which is also a modified version of Davis (1989).
- **Perceived Service Quality (PSQ)**, modified after Roy et al. (2018).
- **Satisfaction Levels (SAT)** based on Oliver (2014) and consumer satisfaction literature.
- **Customer's Purchase Intention (CPI)** based on Dodds et al. (1991) and online shopping research.

The measurement of all constructs in section 3 to 7 was done on a Likert scale that ranged between Strongly Disagree to Strongly Agree. The questionnaire was pre-tested on 30 people to test clarity and reliability (Nainggolan & Sijabat, 2023). Certain changes were done to enhance understanding and wording. In the pilot study, the alpha of all constructs was above 0.70, which validates internal consistency reliability.

2.4 Questionnaire and Measures

This questionnaire was circulated online by the use of Google Forms and distributed both by social media and email invitation to the online consumer communities. Before the participation, the respondents were informed on the informed consent form that the study had the purpose, that participation was entirely voluntary, and confidentiality of their data would be assured.

Data collected in google sheets was transferred to MS excel and coding was done (strongly disagree = 1, disagree = 2, neutral = 3, agree = 4 and strongly agree = 5) for further processing. For statistical analysis SPSS 27.0 and PROCESS macro v5.0 by Andrew F. Hayes were used to analyze the data in preliminary and SEM analyses, respectively. The steps followed were as follows:

I. **Initial Analysis:** Data screening: missing data, outliers, skewness, and kurtosis of normality.

II. **Reliability and Validity:** The internal consistency of the data was measured with the help of Cronbach alpha in SPSS. Confirmatory Factor Analysis and Composite Reliability were used to measure construct validity.

III. **Measurement Model:** CFA was to be used to test the adequacy of the measurement model. CFI, TLI, RMSEA and kh2/df were reported.

IV. **Structural Model:** Structural Equation Modeling is a tool that will allow testing many intricate relationships among latent constructs at the same time. The reason why SEM was deemed suitable is that it takes into account the measurement error as well as the structural relationship, which is better than the traditional regression models (Byrne, 2016).

2.5 Ethical Considerations

In this study, ethical principles have been observed thoroughly. Informed consent was given by the respondents prior to the study and informed them that their replies would be anonymous and confidential. There was no personal identifiable information gathered. Contributors were free to pull out at any point.

3. RESEARCH RESULTS AND ANALYSIS

3.1 Sample structure

The questionnaire was pre-tested on 35 respondents in order to optimize the accuracy and reliability of the constructs of research. This step served to polish the phrasing, to clarify any points of confusion, and to make sure that the questions were well comprehended. The current version of the questionnaire was finally released, and it received 393 responses of which 380 were considered valid. The response was not counted as valid if respondent took less than 2 minutes to complete, responses corresponding to a qualifying question responding with no, with missing values as well as straight-lining behavior. Of valid responses, 187 responses were made to questionnaire A (conversation with chatbots) and 193 to questionnaire B (conversation with conversational AI).

The Table 1 shows a detailed socio-demographic picture of the respondents including the core aspects like age, gender, education, geography, online shopping behavior, and their experience and trust of conversational assistants.

The age of the respondents represents that the majority of the respondents who interacted with conversational technologies are younger. In particular, the Chatbots and the Conversational AI categories were found to have 57.22 and 47.15 percent respectively respondents ranged the ages of 18-30 years. The 31-40 age group followed closely, with 38.50% respondents interacted with Chatbots and 44.56% with Conversational AI. The older age groups (41-50, 51-60, and above 60) had much smaller representation, with 3.74% of Chatbots respondents and 8.29% of Conversational AI respondents aged between 41-50, whereas minimal participation was seen from those aged 51-60 or above.

Gender wise, the data is more skewed towards the male respondents in all categories. To be more precise, 59.36% of the respondents who refer to Chatbots and 62.69% to Conversational AI identified themselves as males, and the same can be said about Aggregate category (61.05). The percentage of female respondents was 40.64 in the Chatbots category, 37.31 in Conversational AI category and 38.95 in the Aggregate category. No participant who had identified themselves with another gender was recorded and there were also no statistics on those who did not want to specify their gender.

Table 1: The socio-demographic and behavioral indicators of the respondents who completed the questionnaire.

Factors	Indicators	Chatbots		Conversational AI		Aggregate	
		N	%age	N	%age	N	%age
Age of respondents	18-30	107	57.22%	91	47.15%	198	52.11%
	31-40	72	38.50%	86	44.56%	158	41.58%
	41-50	7	3.74%	16	8.29%	23	6.05%
	51-60	1	0.53%	0	-	1	0.26%
	Above 60	0	-	0	-	0	-
Gender of respondents	Male	111	59.36%	121	62.69%	232	61.05
	Female	76	40.64%	72	37.31%	148	38.95
	Other	0	-	0	-	0	-
	Prefer not to say	0	-	0	-	0	-
Highest education level of respondents	Less than High School	0	-	0	-	0	-
	High School Diploma or Equivalent	68	36.36%	75	38.86%	143	37.63%
	Associate Degree	0	-	0	-	0	-
	Bachelor's degree	63	33.69%	54	27.98%	117	30.79%
	Master's degree	53	28.34%	63	32.64%	116	30.53%
	Doctoral degree	3	1.60%	1	0.52%	4	1.05%
	Professional Degree	0	-	0	-	0	-
Country of residence of respondents	Austria	4	2.14%	6	3.11%	10	2.63%
	Azerbaijan	3	1.60%	2	1.04%	5	1.32%
	Bangladesh	9	4.81%	6	3.11%	15	3.95%
	Belarus	3	1.60%	2	1.04%	5	1.32%
	China	2	1.07%	3	1.55%	5	1.32%
	Egypt	2	1.07%	3	1.55%	5	1.32%
	Germany	4	2.14%	6	3.11%	10	2.63%
	India	8	4.28%	12	6.22%	20	5.26%
	Italy	3	1.60%	2	1.04%	5	1.32%

	Lithuania	38	20.32%	42	21.76%	80	21.05%
	Morocco	2	1.07%	3	1.55%	5	1.32%
	Netherlands	2	1.07%	3	1.55%	5	1.32%
	Pakistan	93	49.73%	92	47.67%	185	48.68%
	Philippines	2	1.07%	3	1.55%	5	1.32%
	Ukraine	6	3.21%	4	2.07%	10	2.63%
	Uzbekistan	6	3.21%	4	2.07%	10	2.63%
Online shopping frequency	Several times month	39	20.86%	43	22.28%	82	21.58%
	A few times a month	52	27.81%	65	33.68%	117	30.79%
	Once a month	50	26.74%	41	21.24%	91	23.95%
	Less than once a month	39	20.86%	43	22.28%	82	21.58%
Prior experience with conversational assistant	None	8	4.28%	7	3.63%	15	3.95%
	Very little	95	50.80%	27	13.99%	122	32.11%
	Some	48	25.67%	92	47.67%	140	36.84%
	A lot	36	19.25%	67	34.72%	103	27.11%
Trust in conversational assistants	Yes	98	52.41%	175	90.67%	273	71.84%
	No	89	47.59%	18	9.33%	107	28.16%

Source: Compiled based on the self-reported data by respondents

The respondents were relatively varied with regard to educational attainment. The most prevalent level of education in all categories was a High School Diploma or Equivalent with 36.36% in Chatbots, 38.86% in Conversational AI and 37.63% in the Aggregate category. Individuals who had a Bachelor degree included 33.69% in the Chatbots category, 27.98% in the Conversational AI category and 30.79% in the Aggregate category. The percentage of those with a Master degree was also significant, as in the category of Chatbots, 28.34, in Conversational AI, 32.64 and Aggregate, 30.53. Less than 1.6 percent of the respondents had the Doctoral degrees (1.60% in Chatbots, 0.52% in Conversational AI and 1.05 in the Aggregate category).

The international diversity is based on the geographical distribution of respondents. The vast majority of the respondents (49.73% in Chatbots, 47.67% in Conversational AI, 48.68% in the category of Aggregate) were in Pakistan. The second representation was 20.32% in Chatbots, 21.76% in Conversational AI, and 21.05% in the Aggregate group in Lithuania. The other countries that were well represented were India (5.26% of the entire sample), Bangladesh (3.95%), and Austria, Germany, Uzbekistan, Ukraine, and Azerbaijan (1-3% representation respectively). The statistics demonstrate that the representation of the respondents of South Asia and Eastern Europe is high.

The frequency of online shopping among respondents was categorized into four groups. The largest group across all categories reported shopping online a few times a month, representing respondents 27.81% from Chatbots, 33.68% from Conversational AI, and 30.79% in total. A significant portion reported shopped once a month, with 26.74% in Chatbots, 21.24% in Conversational AI, and 23.95% in the Aggregate category. Finally, 20.86% of respondents in Chatbots, 22.28% in Conversational AI, and 21.58% in Aggregate reported shopping less than once a month, indicating a moderate level of engagement with online shopping. Prior experience with conversational assistants varied significantly across respondents. In the Chatbots category, 50.80% of respondents reported very little prior experience, while 25.67% had some experience, and 19.25% had a lot of experience. A smaller percentage, 4.28%, reported no prior experience. In the Conversational AI category, 47.67% of respondents reported some experience, while 34.72% had a lot of experience, and 13.99% had very little experience. While prior experience with conversational assistants varies, trust in these technologies is generally high, particularly in the Conversational AI category. The number of those who had trust in Chatbots was 52.41%, and those who did not trust were 47.59. For Conversational AI, 90.67% of the participants affirmed that they trust conversational assistants with a very small proportion of 9.33% indicating otherwise.

3.2 Variable reliability testing

The research constructs were created after reviewing the available academic sources comprehensively to make them to be in line with the available theoretical frameworks. In an effort to determine how reliable these constructs were, a standard statistical method of internal consistency, Cronbach's Alpha coefficient was determined. All the values were calculated with IBM SPSS v27. Questionnaires A and B were based on the same constructs, but the reliability was assessed on each of them to consider the possible variation of the answers to the questions among the instruments. The results of reliability testing are presented in Table 2.

Table 2: Evaluation of the Reliability of research constructs through the Cronbach's Alpha Coefficient.

Indicator	Value of Cronbach's Alpha	
	Chatbots	**Conversational AI**
Perceived usefulness (PU)	0.877	0.942
Perceived ease of use (PEOU)	0.764	0.926
Perceived service quality (PSQ)	0.765	0.940
Satisfaction levels (SAT)	0.890	0.924
Customer Purchase intention (CPI)	0.907	0.911

Source: estimated based on the self-reported data by respondents

The Cronbach's Alpha values for both Chatbots and Conversational AI indicate strong internal consistency across all measured constructs. For Perceived Usefulness (PU), Chatbots achieved a Cronbach's Alpha value of 0.877, while Conversational AI recorded 0.942, both of which are well above the commonly accepted threshold of 0.70, suggesting high reliability of the constructs.

In terms of Perceived Ease of Use (PEOU), the Cronbach's Alpha values for Chatbots and Conversational AI were 0.764 and 0.926, respectively. These results demonstrate satisfactory internal consistency for both platforms, with Conversational AI showing a slightly higher reliability. Similarly, Perceived Service Quality (PSQ) revealed values of 0.765 for Chatbots and 0.940 for Conversational AI, further indicating that both research instruments exhibit strong consistency.

The same pattern of consistency (higher than the general accepted value) was observed for remaining constructs i.e. Satisfaction Levels (SAT) and Customer Purchase Intention (CPI). For SAT, Chatbots scored 0.890 and Conversational AI scored 0.924, while for CPI, the values were

0.907 for Chatbots and 0.911 for Conversational AI. These high Cronbach's Alpha values across all indicators confirm the reliability and appropriateness of the research instruments for further analysis.

3.3 Statistical analysis of data

This section outlines the complete analysis of the collected data and presents the results used to test the proposed hypotheses. Pearson's correlation coefficient was employed to assess the strength and direction of the linear relationships between continuous variables. The analysis was conducted using IBM SPSS v27, facilitating efficient and accurate computation of statistical relationships. Furthermore, descriptive statistics, including means and standard deviations (SD), were calculated to offer a comprehensive overview of the dataset and assist in the interpretation of the correlation findings.

The correlation analysis was performed to examine the relationships between the constructs in both the Chatbots and Conversational AI groups. The findings reveal strong, positive correlations between all measured constructs in both groups, which suggests that Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Service Quality (PSQ), and Satisfaction (SAT) are all significantly associated with Customer Purchase Intention (CPI). Correlation coefficients, mean and standard deviation for both groups are presented in Table 3.

Same is the case for Conversational AI Group, the consumer purchase intentions are highly correlated with perceived usefulness ($r = 0.820$, $p < 0.01$), perceived ease of use ($r = 0.815$, $p < 0.01$), perceived service quality ($r = 0.747$, $p < 0.01$) and satisfaction levels ($r = 0.832$, $p < 0.01$) indicating that a higher perception of usefulness, ease of use to utilize an assistant, higher quality of service and the level of satisfaction during online shopping respectively leads to greater likelihood of purchasing.

Interestingly, while the strength of the correlations varied slightly between the two groups, the patterns were largely consistent. Both Chatbots and Conversational AI users showed strong relationships between PU, PEOU, PSQ, and SAT with CPI. However, Conversational AI users tended to exhibit slightly stronger correlations overall, especially between PEOU and SAT, and PSQ and CPI. These findings underscore the importance of the key constructs in driving Customer Purchase Intention and suggest that perceived usefulness, ease of use, service quality, and user satisfaction levels play a significant role in influencing consumer purchasing decisions for both Chatbots and Conversational AI assistants.

In Chatbots group, the correlation results demonstrate significant positive relationships between all the constructs. The correlation between Perceived Usefulness (PU) and other constructs was particularly strong. Specifically, PU was strongly correlated with satisfaction levels ($r = 0.745$, $p < 0.01$), as well as consumer purchase intention ($r = 0.802$, $p < 0.01$), highlighting that as users perceive a system as more useful, their satisfaction and intention to purchase also increase. Furthermore, Perceived Ease of Use (PEOU), another key construct, was positively correlated with CPI ($r = 0.706$, $p < 0.01$), showing that users who find the system easier to use are more likely to have higher purchase intentions. The Perceived Service Quality (PSQ) construct was also strongly correlated with consumer purchase intentions ($r = 0.781$, $p < 0.01$), indicating that users who perceive better service quality are more likely to express higher purchase intentions. Finally, Satisfaction (SAT) showed a robust positive correlation with CPI ($r = 0.820$, $p < 0.01$), reinforcing the idea that satisfied users are more likely to intend to make a purchase.

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Table 3: The means, standard deviations and Correlation coefficients of modeled variables

Pairwise Correlations for chatbots group							
	Mean	***SD***	**PU**	**PEOU**	**PSQ**	**SAT**	**CPI**
PU	3.308	0.923	1.000				
PEOU	3.424	0.807	0.789**	1.000			
PSQ	3.516	0.760	0.747**	0.772**	1.000		
SAT	3.345	0.884	0.745**	0.775**	0.821**	1.000	
CPI	3.333	0.997	0.802**	0.706**	0.781**	0.820**	1.000
Pairwise Correlation for chatbots group							
	Mean	***SD***	**PU**	**PEOU**	**PSQ**	**SAT**	**CPI**
PU	3.856	0.940	1.000				
PEOU	4.034	0.872	0.848**	1.000			
PSQ	4.005	0.879	0.839**	0.881**	1.000		
SAT	3.956	0.919	0.839**	0.913**	0.857**	1.000	
CPI	4.014	0.888	0.820**	0.815**	0.747**	0.832**	1.000

Source: estimated based on the self-reported data by respondents

**: Correlation is significant at the 0.01 level (2-tailed).

Results of Hypothesis Testing

To test the H1 hypothesis and to find out the direct relation of perceived usefulness, perceived ease of use, perceived service quality and satisfaction levels on the customer purchase intention, multiple regression was employed using IBM SPSS v27 for both Chatbots and conversational AI groups. The model summary indicates that in chatbot group the independent variables explain 76.5% of the variance for consumer purchase intentions ($R^2 = 0.765$, Adjusted $R^2 = 0.760$), with a standard error of the estimate of 0.48845. The overall regression model was found to be statistically significant ($F(4, 182) = 148.188$, $p < 0.001$), suggesting that the predictors collectively have a significant impact on CPI. The results of multiple regression are given in Table 4.

The unstandardized coefficient for perceived usefulness is 0.444, with a standardized coefficient (Beta) of 0.411. This indicates a significant positive relationship between PU and customer purchase intentions ($t = 6.420$, $p < 0.001$). The unstandardized coefficient for perceived ease of use is -0.106, and the standardized Beta is -0.086. However, the p-value of 0.198 indicates that PEOU does not have a statistically significant effect on consumer purchase intentions for chatbots. The unstandardized coefficient for perceived service quality is 0.263, with a standardized Beta of 0.200. This indicates a significant positive relationship between PSQ and customer purchase intentions for chatbots ($t = 2.852$, $p = 0.005$). Similarly, the unstandardized coefficient for satisfaction levels is 0.467, with a standardized Beta of 0.414, indicating a significant positive relationship with CPI ($t = 6.048$, $p < 0.001$).

For the Conversational AI group, the multiple regression model revealed that the independent variables explain 74.9% of the variance in consumer purchase intentions ($R^2 = 0.749$, Adjusted $R^2 = 0.744$), with a standard error of the estimate of 0.44970. The overall regression model was statistically significant ($F(4, 188) = 140.312$, $p < 0.001$), indicating that the independent variables significantly contribute to the prediction of CPI.

Table 4: Multiple Regression results for predicting Customer Purchase Intention (CPI)

Indicator	**β Coefficients)**		**t- value**	**p-value**
	Unstandardized	**Standardized**		
Chatbot Group				
PU	0.444	0.411	6.420	0.000
PEOU	-0.106	-0.086	-1.291	0.198
PSQ	0.263	0.200	2.852	0.005
SAT	0.467	0.414	6.048	0.000
Model Statistics $R^2 = 0.765$ Adjusted $R^2 = 0.760$ F-statistic = 148.188, p-value = 0.000				
Conversational AI group				
PU	0.388	0.411	5.395	0.000
PEOU	0.212	0.208	2.002	0.047
PSQ	-0.135	-0.134	-1.588	0.114
SAT	0.398	0.092	4.319	0.000
Model Statistics $R^2 = 0.749$ Adjusted $R^2 = 0.744$ F-statistic = 140.312, p-value = 0.000				

Source: estimated based on the self-reported data by respondents

The unstandardized coefficient for perceived usefulness is 0.388, with a standardized Beta of 0.411. This indicates a significant positive effect of PU on CPI ($t = 6.420$, $p < 0.001$). The unstandardized coefficient for perceived ease of use is 0.212, with a standardized Beta of 0.208. This indicates a significant positive relationship between PEOU and CPI ($t = 2.002$, $p = 0.047$). The unstandardized coefficient for perceived service quality is -0.135, with a standardized Beta of -0.134, but the p-value of 0.114 indicates that PSQ does not have a statistically significant effect customers purchase intentions while interacting with conversational AI during shopping online. The unstandardized coefficient for satisfaction levels is 0.398, with a standardized Beta of 0.412, indicating a significant positive relationship with CPI ($t = 4.319$, $p < 0.001$).

These results support the hypothesis that Customer Purchase Intention (CPI) is significantly influenced by Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Service Quality (PSQ), and Satisfaction (SAT), with varying levels of significance across the two groups. In both groups, Satisfaction (SAT) and Perceived Usefulness (PU) emerged as the strongest predictors of CPI.

To test the H2 hypothesis and to find out the direct relation of perceived usefulness, perceived ease of use, perceived service quality on customer satisfaction levels multiple regression was employed using IBM SPSS v 27 for both Chatbots and conversational AI groups. Both models are highly significant, as indicated by the F-statistic and p-value, confirming that the independent variables (PU, PEOU, and PSQ) collectively contribute significantly to explaining Satisfaction in both groups. The results of multiple regression are given in Table 5.

For the Chatbots group, the regression analysis revealed that the independent variables explain 72.5% of the variance in Satisfaction Levels (SAT) ($R^2 = 0.725$, Adjusted $R^2 = 0.720$). The model was highly significant ($F(3, 183) = 160.778$, $p < 0.001$), indicating that PU, PEOU, and PSQ collectively contribute to predicting Satisfaction (SAT).

Table 5: Multiple Regression results for predicting satisfaction levels (SAT)

Indicator	β Coefficients)		t- value	p-value
	Unstandardized	Standardized		
Chatbot Group				
PU	0.200	0.208	3.092	0.002
PEOU	0.206	0.188	2.667	0.008
PSQ	0.606	0.521	7.986	0.000
Model Statistics $R^2 = 0.725$ Adjusted $R^2 = 0.720$ F-statistic = 160.778, p-value = 0.000				
Conversational AI group				
PU	0.174	0.178	3.149	0.002
PEOU	0.654	0.620	9.554	0.000
PSQ	0.168	0.061	2.544	0.012
Model Statistics $R^2 = 0.854$ Adjusted $R^2 = 0.851$ F-statistic = 367.209, p-value = 0.000				

Source: estimated based on the self-reported data by respondents

The unstandardized coefficient for perceived usefulness is 0.200, with a standardized Beta of 0.208 ($p = 0.002$), indicating that PU has a statistically significant positive effect on Satisfaction (SAT) levels. A one-unit increase in PU leads to a 0.200 increase in Satisfaction. The unstandardized coefficient for perceived ease of use is 0.206, with a standardized Beta of 0.188 ($p = 0.008$), showing that PEOU also significantly contributes to Satisfaction (SAT) in the Chatbots group. The unstandardized coefficient for perceived service quality is 0.606, with a standardized Beta of 0.521 ($p < 0.001$), indicating that PSQ is the most significant predictor of Satisfaction (SAT), with a strong positive relationship.

For the Conversational AI group, the regression analysis indicated that the independent variables explain 85.4% of the variance in Satisfaction Levels (SAT) ($R^2 = 0.854$, Adjusted $R^2 = 0.851$). The model was highly significant ($F(3, 189) = 367.209$, $p < 0.001$), suggesting a strong relationship between the predictors (PU, PEOU, and PSQ) and Satisfaction (SAT).

The unstandardized coefficient for perceived usefulness is 0.174, with a standardized Beta of 0.178 ($p = 0.002$), indicating that PU has a statistically significant positive effect on Satisfaction (SAT). The unstandardized coefficient for perceived ease of use is 0.654, with a standardized Beta of 0.620 ($p < 0.001$), showing that PEOU is a strong and significant predictor of Satisfaction (SAT) in the Conversational AI group. The unstandardized coefficient for perceived service quality is 0.168, with a standardized Beta of 0.161 ($p = 0.012$), indicating that PSQ also significantly affects Satisfaction (SAT), but with a smaller effect compared to PEOU and PU.

In order to test the H3, the mediation model was tested to determine if Satisfaction levels (SAT) mediates the relationship between Customer Purchase Intention and Perceived Usefulness, perceived ease of use and perceived service quality. The analysis was performed on IBM SPSS v27 & PROCESS Macro v5.0 by Andrew F. Hayes (Model 4) and the data was split by the groups (Chatbot vs. Conversational AI). The results of mediation analysis are given in Table 6.

The direct effect of Perceived Usefulness (PU) on Customer Purchase Intention (CPI) is significant, $B = 0.462$, $p < 0.001$, indicating a positive relationship between PU and CPI. This suggests that PU directly influences CPI, even when Satisfaction (SAT) is accounted for as a mediator. The indirect effect of PU on CPI through Satisfaction (SAT) was significant, with an indirect effect of 0.404 (Bootstrap CI = [0.259, 0.554], $p < 0.05$). This indicates that Satisfaction

(SAT) significantly mediates the relationship between PU and CPI for the Chatbots group. The confidence interval does not contain zero, confirming the significance of the mediation effect. The total effect of PU on CPI is the sum of the direct effect and the indirect effect through Satisfaction (SAT). Since both the direct and indirect effects are significant, it can be concluded that Satisfaction plays a crucial mediating role in the relationship between PU and CPI.

For conversational AI group the direct effect of PU on Customer Purchase Intention (CPI) was significant ($\beta = 0.391$, $p < 0.01$), with a 95% CI ranging from 0.265 to 0.517. Satisfaction significantly mediated the relationship between PU and CPI, with an indirect effect ($\beta = 0.384$, Boot SE = 0.077) and a 95% bootstrap CI ranging from 0.254 to 0.557. This suggests that Satisfaction plays a pivotal role in mediating the impact of PU on CPI. Higher perceived usefulness of the conversational assistant enhances customer satisfaction, which, in turn, increases customer purchase intentions.

For chatbots the direct effect of Perceived Ease of Use (PEOU) on Customer Purchase Intention (CPI) was significant, B = 0.248, $p = 0.002$, indicating that PEOU positively influences CPI. This suggests that PEOU has a direct effect on CPI for the Chatbots group. The indirect effect of PEOU on CPI through Satisfaction (SAT) was significant, B = 0.623, with a bootstrap confidence interval (CI) = [0.479, 0.761], $p < 0.05$. This indicates that Satisfaction (SAT) significantly mediates the relationship between PEOU and CPI in the Chatbots group. The confidence interval does not contain zero, confirming the mediation effect. The total effect of PEOU on CPI is the combination of both the direct and indirect effects. Since both are significant, it is concluded that Satisfaction (SAT) plays a crucial role in mediating the relationship between PEOU and CPI in the Chatbots group.

The direct effect of Perceived Ease of Use on Customer Purchase Intention (CPI) was significant ($\beta = 0.337$, $p < 0.01$), with a 95% confidence interval (CI) ranging from 0.145 to 0.529, showing that PEOU positively influences CPI in the Conversational AI group. Satisfaction (SAT) acted as a significant mediator between PEOU and CPI, with an indirect effect ($\beta = 0.493$, Boot SE = 0.121) and a 95% bootstrap CI ranging from 0.266 to 0.735. This suggests that in the Conversational AI group, Satisfaction levels act as a key mediator between PEOU and Customer Purchase Intention.

Table 6: Mediation Analysis Results for PU, PEOU, and PSQ with Satisfaction (SAT) as the Mediator variable

Indicator	β Coefficients	t- value	p-value	Bootstrap CI (95%)
Chatbots				
PU → SAT → CPI	0.623		0.01	[0.385, 0.787]
PEOU → SAT → CPI	0.243		0.004	[0.151, 0.313]
PSQ → SAT → CPI	0.223		0.01	[0.104, 0.298]
Conversational AI				
PU → SAT → CPI	0.384		0.01	[0.254, 0.557]
PEOU → SAT → CPI	0.493		0.01	[0.266, 0.735]
PSQ → SAT → CPI	0.624		0.01	[0.428, 0.921]

Source: estimated based on the self-reported data by respondents

The direct effect of Perceived Service Quality (PSQ) on Customer Purchase Intention (CPI) is significant, B = 0.432, $p < 0.001$, indicating that PSQ has a positive impact on CPI. This suggests that PSQ directly influences CPI for the Chatbots group. The indirect effect of PSQ on CPI through Satisfaction (SAT) was significant, B = 0.593, with a bootstrap confidence interval (CI) = [0.385, 0.787], $p < 0.05$. This indicates that Satisfaction (SAT) significantly mediates the relationship between PSQ and CPI in the Chatbots group. The confidence interval does not contain zero, confirming the significance of the mediation effect. The total effect of PSQ on CPI is the sum of the direct and indirect effects. Since both are significant, it can be concluded that Satisfaction (SAT) plays a crucial role in mediating the relationship between PSQ and CPI in the Chatbots group.

For conversational AI group the direct effect of perceived service quality on Customer Purchase Intention (CPI) was positive but not statistically significant ($\beta = 0.130$, $p = 0.098$), with a 95% CI ranging from -0.024 to 0.285. The indirect effect through Satisfaction was significant ($\beta = 0.624$, Boot SE = 0.127), with a 95% bootstrap CI ranging from 0.428 to 0.921. This suggests that Satisfaction plays a significant role in mediating the relationship between PSQ and CPI in the Conversational AI group. Higher Perceived Service Quality enhances customer satisfaction, which, in turn, increases the likelihood of purchase intentions.

In order to test the H4, the moderation analysis was performed to determine if type of conversational assistant a consumer interacted with moderates the relationship between satisfaction levels and Perceived Usefulness, perceived ease of use and perceived service quality. The analysis was performed on IBM SPSS v27 & PROCESS Macro v5.0 by Andrew F. Hayes (Model 1) and the data was split by the groups (Chatbot vs. Conversational AI). The results of moderation analysis are given in Table 7.

The model demonstrated a strong overall fit with an R-squared value of 0.672, indicating that approximately 67.2% of the variance in Satisfaction was explained by the model. The F-statistic for the model was 256.670 ($p < 0.001$), confirming that the relationship between the variables was statistically significant.

For Chatbot group the effect of perceived usefulness on Satisfaction was 0.714 ($SE = 0.043$, $t = 16.431$, $p < 0.001$), indicating a strong, statistically significant positive relationship between PU and Satisfaction when interacting with a Chatbot. For Conversational Ai group the effect of PU on Satisfaction was 0.821 ($SE = 0.042$, $t = 19.535$, $p < 0.001$), showing a stronger positive relationship between PU and Satisfaction when interacting with Conversational AI. These findings suggest that the type of conversational assistant (Chatbot vs. Conversational AI) impacts the strength of the relationship between Perceived Usefulness and Satisfaction, with Conversational AI having a stronger effect.

Table 7: Results of moderation Analysis of conversational assistant type

Indicator	p-value	R^2	β	CI (95%)
PU * Assistant Type → SAT	0.078	0.672	0.107	[-0.012, 0.226]
PEOU * Assistant Type → SAT	0.025	0.739	0.135	[0.017, 0.253]
PSQ * Assistant Type → SAT	0.328	0.736	-0.061	[-0.183, 0.061]
PU * Assistant Type → CPI	0.078	0.696	0.107	[-0.012, 0.226]
PEOU * Assistant Type → CPI	0.025	0.739	0.135	[0.017, 0.253]
PSQ * Assistant Type → CPI	0.001	0.634	-0.270	[-0.403, -0.130]

Source: estimated based on the self-reported data by respondents

The moderation analysis to examine whether the type of Conversational Assistant (Chatbot vs. Conversational AI) moderates the relationship between Perceived Ease of Use (PEOU) and Satisfaction showed a strong model fit ($R^2 = 0.739$, $F (3,376) = 354.478$, $p < 0.001$). Perceived Ease of Use (PEOU) significantly predicted Satisfaction ($b = 0.692$, $SE = 0.098$, $t = 7.100$, $p < 0.001$), while the Conversational Assistant Type (Group) had a marginal effect ($b = -0.437$, $SE = 0.228$, $t = -1.916$, $p = 0.056$). The interaction term (PEOU × Group) was significant ($b = 0.135$, $SE = 0.060$, $t = 2.248$, $p = 0.025$), indicating that the relationship between PEOU and Satisfaction was moderated by the type of assistant. Conditional effects revealed that PEOU had a stronger effect on Satisfaction for Conversational AI ($b = 0.962$, $SE = 0.040$, $t = 23.817$, $p < 0.001$) compared to Chatbots ($b = 0.827$, $SE = 0.044$, $t = 18.640$, $p < 0.001$). Bootstrap results confirmed the robustness of the findings, with the interaction term showing a significant bootstrapped confidence interval of [0.016, 0.254]. These results suggest that Conversational AI significantly enhances the relationship between PEOU and Satisfaction, while Chatbots show a weaker effect.

The results of moderation analysis of the type of Conversational Assistant (Chatbot vs. Conversational AI) to test the relationship between Perceived Service Quality (PSQ) and Satisfaction (SAT) demonstrated a strong overall model fit ($R^2 = 0.736$, $F (3,376) = 350.077$, $p < 0.001$). Perceived Service Quality (PSQ) significantly predicted Satisfaction ($b = 1.017$, $SE =$

0.103, t = 9.887, $p < 0.001$), whereas the main effect of Conversational Assistant Type (Group) was marginally significant (b = 0.387, SE = 0.237, t = 1.633, p = 0.103). The interaction term (PSQ × Group) was not significant (b = -0.061, SE = 0.062, t = -0.980, p = 0.328), suggesting that the type of assistant does not significantly moderate the relationship between PSQ and Satisfaction. The bootstrap results for the regression coefficients were robust, with the interaction term having a bootstrapped confidence interval of [-0.221, 0.080], indicating that the moderation effect was not supported by the data. These findings suggest that while PSQ has a strong effect on Satisfaction, the type of Conversational Assistant does not significantly influence this relationship.

In order to test the H5, the moderation analysis was performed to determine if type of conversational assistant a consumer interacted with moderates the relationship between customer purchase intentions and Perceived Usefulness, perceived ease of use and perceived service quality. The analysis was performed on IBM SPSS v27 & PROCESS Macro v5.0 by Andrew F. Hayes (Model 1) and the data was split by the groups (Chatbot vs. Conversational AI). The results of moderation analysis are given in Table 7.

The moderative analysis of the effect of Conversational Assistant Type on the relationship between Perceived Usefulness (PU) and Consumer's Purchase Intention (CPI) revealed a strong model fit ($R^2 = 0.696$, $F(3,376) = 287.202$, $p < 0.001$), indicating that PU and Conversational Assistant Type explained 69.6% of the variance in CPI. Perceived Usefulness (PU) had a significant positive effect on CPI (b = 0.955, SE = 0.098, $p < 0.001$), while Conversational Assistant Type also significantly influenced CPI (b = 0.553, SE = 0.227, p = 0.015), with Conversational AI showing a higher CPI compared to Chatbots. However, the interaction term (PU × Group) was not significant (b = -0.090, SE = 0.061, p = 0.143), suggesting that Conversational Assistant Type does not moderate the relationship between PU and CPI. Bootstrap results confirmed these findings, with the interaction term showing a confidence interval that included zero, further supporting the conclusion that Assistant Type does not significantly moderate the relationship between PU and CPI.

The moderation analysis was conducted to examine whether Conversational Assistant Type moderates the relationship between Perceived Ease of Use (PEOU) and Consumer's Purchase

Intention (CPI) revealed a strong overall model fit ($R^2 = 0.622$, $F (3, 376) = 206.221$, $p < 0.001$), indicating that PEOU and Conversational Assistant Type explained 62.2% of the variance in CPI. PEOU had a significant positive effect on CPI ($b = 0.914$, $SE = 0.123$, $t = 7.400$, $p < 0.001$), suggesting that increased PEOU leads to a higher CPI. However, the main effect of Conversational Assistant Type was not significant ($b = 0.320$, $SE = 0.289$, $t = 1.107$, $p = 0.269$), and the interaction term (PEOU × Group) was also not significant ($b = -0.042$, $SE = 0.076$, $t = -0.556$, $p = 0.579$), indicating that Conversational Assistant Type does not moderate the relationship between PEOU and CPI. These findings were further supported by bootstrapping results, which showed a confidence interval for the interaction term that included zero (Boot LLCI = -0.198, Boot ULCI = 0.120).

The result of moderation analysis of type of Conversational Assistant between Perceived Service Quality (PSQ) and Consumer's Purchase Intention (CPI) indicated a strong overall model fit ($R^2 = 0.634$, $F (3, 376) = 217.534$, $p < 0.001$), with PSQ and Conversational Assistant Type explaining 63.4% of the variance in CPI. PSQ had a significant positive effect on CPI ($b = 1.295$, $SE = 0.128$, $t = 10.153$, $p < 0.001$), and the Conversational Assistant Type also significantly influenced CPI ($b = 1.263$, $SE = 0.294$, $t = 4.295$, $p < 0.001$), with Conversational AI showing a higher CPI compared to Chatbots. The interaction term (PSQ × Group) was significant ($b = -0.270$, $SE = 0.077$, $t = -3.509$, $p = 0.001$), indicating that Conversational Assistant Type moderates the relationship between PSQ and CPI. The bootstrapping results, with 5000 samples, confirmed the significance of the moderation effect (Boot LLCI = -0.403, Boot ULCI = -0.130). These findings suggest that Conversational Assistant Type significantly strengthens the effect of PSQ on CPI, particularly for Conversational AI, thus supporting the hypothesis that Assistant Type moderates this relationship.

To test H6, the mean levels of Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Service Quality (PSQ), Satisfaction (SAT), and Consumer's Purchase Intention (CPI) were compared between users interacting with Chatbots and those interacting with Conversational AI using independent sample t-test. The key objective is to determine if there are statistically significant differences between these two groups on the mentioned variables**.** The results of independent sample t-test are given in Table 8.

Table 8: Comparison of Mean Levels Between Chatbot and Conversational AI Users

Indicator	Mean value		t-statistics	df	p-value (2-tailed)	Cohen's d
	Chatbot	Conversational Ai				
PU	3.3075	3.8562	-5.740	378	0.000	0.93172
PEOU	3.4238	4.0337	-7.069	378	0.000	0.84085
PSQ	3.5160	4.0052	-5.795	378	0.000	0.82266
SAT	3.3449	3.9560	-6.600	378	0.000	0.90231
CPI	3.3329	4.0142	-7.039	378	0.000	0.94332

Source: estimated based on the self-reported data by respondents

The results of the independent samples t-test for Perceived Usefulness (PU) between users interacting with Chatbots and Conversational AI revealed a statistically significant difference ($p < 0.001$). Users interacting with Conversational AI (M = 3.8562, SD = 0.93978) reported higher levels of Perceived Usefulness compared to those interacting with Chatbots (M = 3.3075, SD = 0.92332). The mean difference between the groups was -0.54873, with a 95% confidence interval ranging from -0.73671 to -0.36075, indicating that the true difference in PU is likely to fall within this range. The effect size (Cohen's d = 0.93) suggests a large effect, highlighting the substantial difference in Perceived Usefulness between the two assistant types. These findings indicate that Conversational AI provides significantly higher Perceived Usefulness compared to Chatbots.

The results of the independent samples t-test for Perceived Ease of Use (PEOU) between users interacting with Chatbots and Conversational AI revealed a statistically significant difference ($p < 0.001$). Users interacting with Conversational AI (M = 4.0337, SD = 0.87248) reported significantly higher levels of PEOU compared to those interacting with Chatbots (M = 3.4238, SD = 0.80690). The mean difference between the two groups was -0.60988, with a 95% confidence interval ranging from -0.77953 to -0.44023, indicating that the true difference in PEOU lies within this range. The effect size (Cohen's d = 0.84) suggests a large effect, highlighting the substantial difference in Perceived Ease of Use between the two assistant types. These findings suggest that Conversational AI is perceived as significantly easier to use than Chatbots.

The results of the independent samples t-test for Perceived Service Quality (PSQ) between users interacting with Chatbots and Conversational AI revealed a statistically significant difference ($p < 0.001$), with Conversational AI users reporting significantly higher levels of PSQ ($M = 4.0052$, $SD = 0.87944$) compared to Chatbot users ($M = 3.5160$, $SD = 0.75962$). The mean difference between the groups was -0.48914, with a 95% confidence interval ranging from -0.65512 to -0.32316, indicating that the true difference in PSQ lies within this range. The effect size (Cohen's $d = 0.82$) suggests a large effect, highlighting a substantial difference in Perceived Service Quality between the two assistant types. These findings suggest that Conversational AI is perceived as providing significantly higher service quality than Chatbots.

The results of the independent samples t-test for Satisfaction (SAT) between users interacting with Chatbots and Conversational AI revealed a statistically significant difference ($p < 0.001$), with Conversational AI users reporting significantly higher levels of Satisfaction ($M = 3.9560$, $SD = 0.91927$) compared to Chatbot users ($M = 3.3449$, $SD = 0.88446$). The mean difference between the two groups was -0.61104, with a 95% confidence interval ranging from -0.79309 to -0.42899, indicating that the true difference in Satisfaction lies within this range. The effect size (Cohen’s $d = 0.90$) suggests a large effect, highlighting a substantial difference in Satisfaction between the two assistant types. These findings suggest that Conversational AI is perceived as providing significantly higher Satisfaction compared to Chatbots.

The results of the independent samples t-test for Consumer’s Purchase Intention (CPI) between users interacting with Chatbots and Conversational AI revealed a statistically significant difference ($p < 0.001$), with Conversational AI users reporting significantly higher levels of CPI ($M = 4.0142$, $SD = 0.88836$) compared to Chatbot users ($M = 3.3329$, $SD = 0.99688$). The mean difference between the groups was -0.68136, with a 95% confidence interval ranging from -0.87168 to -0.49104, indicating a significant difference in CPI between the two groups. The effect size (Cohen’s $d = 0.94$) suggests a large effect, highlighting a substantial difference in Consumer’s Purchase Intention between the two assistant types. These findings suggest that Conversational AI has a significantly higher CPI compared to Chatbots.

Table 9: Summary of hypotheses and their testing results

No.		Hypotheses	Findings
H1	a	For chatbots Customer's Purchase Intention is directly affected by PU	Accepted
		For conversational Ai Customer's Purchase Intention is directly affected by PU	Accepted
	b	For chatbots Customer's Purchase Intention is directly affected by PEOU	Rejected
		For conversational Ai Customer's Purchase Intention is directly affected by PEOU	Accepted
	c	For chatbots Customer's Purchase Intention is directly affected by PSQ	Accepted
		For conversational Ai Customer's Purchase Intention is directly affected by PSQ	Rejected
	d	For chatbots Customer's Purchase Intention is directly affected by SAT	Accepted
		For conversational Ai Customer's Purchase Intention is directly affected by SAT	Accepted
H2	a	For chatbots Satisfaction levels are directly affected by PU	Accepted
		For conversational Ai Satisfaction levels are directly affected by PU	Accepted
	b	For chatbots Satisfaction levels are directly affected by PEOU	Accepted
		For conversational Ai Satisfaction levels are directly affected by PEOU	Accepted
	c	For chatbots Satisfaction levels are directly affected by PSQ	Accepted
		For conversational Ai Satisfaction levels are directly affected by PSQ	Accepted
H3	a	For chatbots Satisfaction levels mediate b/w CPI and PU	Accepted
		For conversational Ai Satisfaction levels mediate b/w CPI and PU	Accepted
	b	For chatbots Satisfaction levels mediate b/w CPI and PEOU	Accepted
		For conversational Ai Satisfaction levels mediate b/w CPI and PEOU	Accepted
	c	For chatbots Satisfaction levels mediate b/w CPI and PSQ	Accepted
		For conversational Ai Satisfaction levels mediate b/w CPI and PSQ	Accepted
H4	a	Type of conversational assistant moderates b/w SAT and PU	Rejected
	b	Type of conversational assistant moderates b/w SAT and PEOU	Accepted
	c	Type of conversational assistant moderates b/w SAT and PSQ	Rejected
H5	a	Type of conversational assistant moderate's b/w CPI and PU	Rejected
	b	Type of conversational assistant moderates b/w CPI and PEOU	Accepted
	c	Type of conversational assistant moderates b/w CPI and PSQ	Accepted
H6	a	Mean levels of PU are statiscally different for chatbots and Conversational Ai	Accepted
	b	Mean levels of PEOU are statiscally different for chatbots and Conversational Ai	Accepted
	c	Mean levels of PSQ are statiscally different for chatbots and Conversational Ai	Accepted
	d	Mean levels of SAT are statiscally different for chatbots and Conversational Ai	Accepted
	e	Mean levels of CPI are statiscally different for chatbots and Conversational Ai	Accepted

Source: estimated based on the statistical results of self-reported data by respondents

CONCLUSIONS

The aim of this research was to investigate the differences in user experience and purchasing intentions between chatbots and conversational AI systems while shopping online. Based on the research results and hypotheses testing, the findings offer the following valuable insights into the influence these digital assistants have on consumer behavior.

1. The analysis revealed that Conversational AI outperforms Chatbots across all key variables examined: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Service Quality (PSQ), Satisfaction (SAT), and Consumer's Purchase Intention (CPI). The significant differences between the two groups, as evidenced by the independent samples t-tests, suggest that Conversational AI provides a superior user experience, driving higher satisfaction and purchase intentions. The effect sizes for all variables were large, indicating that the differences are substantial and practically significant.
2. The research also highlighted the important role of Satisfaction (SAT) in mediating the relationship between Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Perceived Service Quality (PSQ), and Consumer's Purchase Intention (CPI). The mediation analysis confirmed that satisfaction significantly influences consumer purchase decisions, emphasizing its importance in designing effective digital assistants. Furthermore, the moderation analysis revealed that while Conversational AI strengthened the relationship between PEOU and Satisfaction, Chatbots showed weaker effects, underlining the greater potential of Conversational AI to enhance user experience and purchase intentions.
3. The findings suggest that businesses seeking to optimize their digital assistant technologies should prioritize the use of Conversational AI over traditional chatbots. By doing so, they can enhance user interactions, improve satisfaction, and ultimately drive higher sales. Additionally, the research provides actionable insights into how businesses can leverage AI-powered systems to create more personalized, efficient, and satisfying online shopping experiences. Businesses are encouraged to adopt and further develop conversational AI technologies to stay competitive in the evolving landscape of conversational commerce.

RECOMMENDATIONS

Based on the findings of this research, the following recommendations can be made for businesses aiming to enhance customer engagement, satisfaction, and purchase intentions through digital assistants.

1. The results of this study clearly demonstrate that Conversational AI outperforms traditional Chatbots in terms of user experience and influencing consumer behavior. Therefore, businesses can benefit from focusing on the following strategies to improve their use of digital assistants.
2. Given that Conversational AI significantly improves Perceived Usefulness, Perceived Ease of Use and Satisfaction levels (translated into more purchases), businesses should prioritize the implementation of AI-driven assistants for consumer interactions. Unlike chatbots, which rely on scripted responses, conversational AI systems leverage machine learning algorithms and natural language processing to engage users in more meaningful and personalized conversations. This capability makes them far more adaptable to customer needs, leading to a better overall user experience.
3. One of the key drivers of satisfaction and purchase intention is the ability of the assistant to understand and meet the specific needs of the user. Businesses should invest in AI technologies that allow for personalized interactions based on user data and behavior. This could include customizing product recommendations, providing tailored customer support, and remembering user preferences. Personalization enhances the perceived usefulness of the assistant and builds stronger customer loyalty, leading to increased sales and repeat business.
4. Perceived Service Quality (PSQ) was found to be a significant factor in Consumer's Purchase Intention (CPI). Companies should leverage Conversational AI to provide quick, efficient, and accurate customer service. AI-powered assistants can handle a large volume of inquiries simultaneously, resolve customer issues in real-time, and provide 24/7 support. This improves the overall quality of service and customer satisfaction, making it more likely that customers will complete their purchases.
5. The findings suggest that Conversational AI significantly impacts the consumer purchase decision process. Businesses should integrate conversational AI seamlessly into the

purchase journey—from discovery to post-purchase. For instance, AI can assist in navigating product catalogs, providing real-time answers to product queries, offering personalized discounts, and even guiding users through checkout. A seamless experience improves both satisfaction and conversion rates, as it reduces friction during the buying process.

6. Businesses should implement robust analytics to monitor the performance of their digital assistants in terms of key performance indicators such as customer engagement rates, satisfaction levels and conversion rates to evaluate the effectiveness of their AI-driven interactions. Regular performance analysis will allow businesses to fine-tune their conversational assistants and maximize their impact on user experience and purchasing behavior.

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ANNEXES

Annex a:

Questionnaire

Participation in this study survey is **entirely voluntary.** All the responses will remain **anonymous** and will be used solely for academic and research purposes.

Consent:

I do hereby give my consent to voluntarily participate in the research study.

☐ Agree

1. Have you watched the video?

- Yes (goes automatically to Section 1)
- No (goes automatically to question 2)

2. Thank you for your honesty. This questionnaire can only be filled after watching the video. Please return and watch the video to complete this survey.

Would you like to go to video section again?

- Yes (goes automatically to video section and then Question 01)
- No (goes automatically to thank you page and close the response)

Section 1: Essential Demographics

Ed1. What is your age?

☐ 18-30
☐ 31-40
☐ 41-50
☐ 51-60
☐ Above 60

Ed2. What is your gender?

☐ Male
☐ Female
☐ Other
☐ Prefer not to say

Ed3. What is the highest level of education you have completed?

☐ Less than High School
☐ High School Diploma or Equivalent
☐ Associate Degree
☐ Bachelor's degree
☐ Master's degree
☐ Doctoral degree
☐ Professional Degree

Ed4. Which country do you belong to?

A complete list of all countries was provided as dropdown menu.

Section 2: Behavioral Demographics

Bd1. How often do you typically shop for products online?

☐ Several times month
☐ A few times a month
☐ Once a month
☐ Less than once a month

Bd2. Before this interaction, how much experience did you have with using conversational assistant for customer service or shopping?

☐ None
☐ Very little
☐ Some
☐ A lot

Bd3. In general, I trust the information provided by conversational assistants while shopping online.

☐ Yes

☐ No

SECTION 3: Perceived Usefulness (On Likert Scale from 1-5)

Pu1. Based on the video, the Conversational assistant enabled customer to find the product more quickly.

Pu2. The Conversational assistant provided valuable information (e.g., product comparisons, stock availability, shipping details) that helped finalizing purchase decision.

Pu3. Based on the video, the conversational assistant helped customer make a more informed purchase decision.

Pu4. Overall, the assistant improved the effectiveness of the shopping experience.

SECTION 4: Perceived Ease of Use (On Likert Scale from 1-5)

Peou1. The customer's interaction with the conversational assistant was clear and understandable.

Peou2. Using the conversational assistant did not require the customer a lot of mental effort.

Peou3. The conversational assistant 's conversational style was user friendly and pleasant.

Peou4. It seemed easy to get the conversational assistant to do what customer wanted it to do.

SECTION 5: Perceived Service Quality (On Likert Scale from 1-5)

Psq1. The assistant provided quick and timely responses.

Psq2. The assistant's replies were accurate and relevant to the customer's questions.

Psq3. The assistant handled the conversation professionally and politely.

Psq4. Overall, the quality of service provided by the assistant was high.

SECTION 5: Satisfaction (On Likert Scale from 1-5)

Sat1. The customer could rely on the conversational assistant's responses.

Sat2. The overall experience shown in the video was pleasant and satisfactory.

Sat3. The customer trusted the recommendations provided by the conversational assistant.

Sat4. The customer in the video seemed satisfied with the assistant's help.

SECTION 6: Customer's Purchase Intention (On Likert Scale from 1-5)

Cpi1. The arguments conversational assistant made for purchasing the product were convincing.

Cpi2. The assistant encouraged me to consider buying the featured product.

Cpi3. I would be willing to use such an assistant in my own online shopping.

Cpi4: I would recommend this shopping assistant to my friends or family.