TÜRKİYE CUMHURİYETİ

ADANA ALPARSLAN TÜRKEŞ SCIENCE AND TECHNOLOGY UNIVERSITY

GRADUATE SCHOOL

BUSINESS ADMINISTRATION DEPARTMENT

CHATBOTS AND CHATBOTS IN THE METAVERSE USAGE DIFFERENCE AMONG GENERATIONS (X, Y, Z)

MOHAMMAD ABOUSH

M. A.

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ÖZET

KUŞAKLARIN (X, Y, Z) CHATBOT VE METAVERSDE CHATBOT KULLANIM FARKLILIKLARI

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Bu çalışma, farklı kuşakların temsilcisi olan tüketicilerin Chatbot kullanımının ve metaverse'de Chatbot kullanımının ile ilgili tutumlarının, tüketici davranışları ile olan ilişkisini ortaya koymak amacıyla yapılmıştır. Chatbotlar, kullanıcılarla sohbet eden ve bilgi ve destek sağlama, rezervasyonları onaylama ve temel müşteri sorularını yanıtlama gibi belirli işlevleri yerine getiren yapay zeka destekli programlardır. Örneklem büyüklüğü X, Y ve Z kuşaklarından 600 katılımcıdan oluşmuştur. Çalışmada yeni teknolojilerin gelişimi, yanı sıra kuşaklar arasında kullanım farklılıkları araştırılmış ve kuşaklar arasında farklılık olduğu belirlenmiştir.

Chatbot kullanımını etkileyen faktörleri belirlemek için açıklayıcı faktör analizi yapılmış ve varyansın %56,4'ünü açıklayan 4 faktör elde edilmiştir (teknoloji meraklısı ve yenilikçi, heyecanla karar verici- müşteri odaklı, şüpheci kullanıcı, açık fikirli olanlar).

Sonuçlar, chatbot kullanımının ve metaverse'de chatbot kullanımının orta düzeyde olduğunu gösterirken, bazı mal ve hizmetlerin satın alımında (ev aletleri, aksesuarlar, mobilya, dekorasyon, online alışveriş, telekomünikasyon, turizm, eğitim ve sağlıkta) kullanımın düşük düzeyde olduğu belirlenmiştir. Kuşaklar arasında metaverse'de chatbot kullanımı ve chatbot kullanım farklılığı Z kuşağında istatistiksel olarak anlamlı farklılık göstermiştir. Ayrıca chatbot ve metaverse kullanımında, 4 faktör ile satin alma davranışları arasında ilişkide sadece açık fikirlilik alt boyutu ile online alışverişe yönelik tüketici davranışı arasında istatistiksel olarak anlamlılık belirlenmiştir.

Bulgular, chatbot teknolojisinin tüketici davranışındaki rolünün yüksek olmadığını göstermekte, tüketicilerin çevrimiçi alışveriş sitelerinde zihinsel kontrolün olması, içgörü ve kullanım deneyimi yaşatmasının chatbot kullanımını teşvik ettiğini ortaya koymaktadır. Bu deneyimlerin yaygınlaşması, kullanım kolaylıklarının sağlanması ve sürekli iyileştirilmenin yapılması cahatbot kullanımını sınırlı alanlardan çıkaracaktır. Ayrıca kuşaklar arasında kullanım farklılıklarının dikkate alınarak özel etkileşim stilleri ve içeriğe sahip sohbet robotları oluşturmak faydalı olacaktır.

Anahtar Kelimeler: Chatbotlar, Metaverse, Yapay Zeka, Tüketici Davranışı, Nesiller.

ABSTRACT

CHATBOTS AND CHATBOTS IN THE METAVERSE USAGE DIFFERENCE AMONG GENERATIONS (X, Y, Z)

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This study was conducted to reveal the relationship between the use of chatbots by consumers from different generations and their attitudes towards the use of chatbots in the metaverse and their consumer behavior. Chatbots are AI-powered programs that chat with users and perform specific functions such as providing information and support, confirming reservations, and answering basic customer queries. The sample size consisted of 600 participants from Generations X, Y and Z. In the study, the development of new technologies, as well as usage differences between generations were investigated and it was determined that there were differences between generations.

Exploratory factor analysis was conducted to determine the factors affecting chatbot usage and 4 factors were obtained (Tech-savvy, innovative and efficient; Excited decision-maker, Tech-skeptical, and worry from chatbot; Open-minded and tech-adaptable) explaining 56.4% of the variance.

The results show that the use of chatbots and the use of chatbots in the metaverse is at a moderate level, while the use of chatbots for the purchase of some goods and services (household appliances, accessories, furniture, decoration, online shopping, telecommunications, tourism, education and health) is at a low level. The difference in chatbot use and chatbot usage in the metaverse between generations showed a statistically significant difference in Generation Z. In addition, in the use of chatbot and metaverse, statistical significance was determined only between the open-mindedness sub-dimension and consumer behavior towards online shopping in the relationship between 4 factors and purchasing behavior.

The findings show that the role of chatbot technology in consumer behavior is not high, and that consumers' mental control, insight and usage experience on online shopping sites encourage the use of chatbots. Expanding these experiences, providing ease of use and continuous improvement will take the use of chatbots out of limited areas. In addition, it would be useful to create chatbots with special interaction styles and content, considering the differences in usage between generations.

Keywords: Chatbots, Metaverse, Artificial Intelligence, Consumer Behavior, Generations.

Dedication

With heartfelt gratitude, I dedicate my thesis to my wife and children, whose unwavering support is my constant strength, and to my great parents, whose sacrifices and guidance have shaped my life.

Your collective love and encouragement are my greatest blessings and the driving force behind every achievement.

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I want to express my sincere gratitude to my thesis advisor, Prof. Dr. Celile ÖZÇIÇEK DÖLEKOĞLU. Her unwavering support and insightful guidance have been the cornerstone of my journey through my master's degree. Her encouragement was particularly crucial during the challenging phases of research and writing. In addition to my advisor, my sincere thanks go to Assoc. Prof. Dr. Selim GÜNDÜZ. His valuable contributions have enriched my academic experience and added depth to my research.

I am also immensely grateful to my friends. Their support and encouragement have strengthened and motivated me throughout my MBA work.

Finally, my utmost appreciation extends to my parents, my wife, and my children, especially my daughter Taj. Their endless love and support have been my anchor and inspiration; I am eternally thankful for this.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AI	: Artificial intelligence
3D	: 3 Dimensions
ATM	: Automated Teller Machine
ROI	: Return on Investment
USA	: United states of America
SEM	: Structural Equation Modeling
MIT	: Massachusetts Institute of Technology
TAM	: Technology Acceptance Model

1. INTRODUCTION

In recent years, the world has witnessed unimaginable changes in every aspect. The technological progress made in hundred years has been experienced in the Millenium and continues to advance with a power that pushes the limits of human imagination. Since its existence, mankind has been to adapt, develop and improve the conditions in which it exists. This effort has gradually shortened the life of innovations, and with the developments that emerge day by day and the dynamics in the demands and needs of consumers, technology has started to be used and demanded in all areas of life. With the so-called "industry 4.0", the fourth industrial revolution, different applications have become widespread in the deep world of informatics; internet of things, cloud technologies, artificial intelligence, unmanned vehicles, big data analytics, machine learning, etc. With Industry 4.0, there are modern and efficient developments in the production of goods and services. With the increased use of new technologies, data collection, processing and classification have become easier. Nowadays, the increasing use of artificial intelligence in marketing and customer service has caused companies to reconsider the way they interact with their customers (Paliwal, Bharti and Mishra, 2020). Many companies are investing in AI-powered chatbots to adopt innovative ways of interacting and communicating with customers, as data shows that customers have already developed to preferences for interacting with chatbots for better and quick service than human agents (Kushwaha and Kar, 2021). It has been a major factor for continuous development and digital transformations by supporting the improvement of quality and costs, especially in service businesses (Akbaba and Gündoğdu, 2021). The increased use of technology among consumers, their expectation of constant service, and businesses' quick adoption of new technologies have made it possible to communicate with customers using artificial intelligence (Chatbot) as a substitute.

In the past, consumers could only interact directly with service employees for customer service. While visiting stores for shopping and communicating directly with service employees, the first steps of chatbot use were taken with the introduction of Eliza in 1966 (Paliwal et al. 2020). The first steps of chatbot use were taken. However, its use did not gain popularity until Facebook placed the chatbot in the messenger in 2016. Nowadays, Chatbot has gained real popularity among businesses and consumers, and this growing interest and awareness can be attributed to advances in machine learning, artificial intelligence, and messaging app technology (Friend, 2018).

Chatbots, in essence, are AI-powered programs that chat with the users and perform certain functions like providing information and support, confirming bookings, and answering basic customer queries (Paliwal et al. 2020). Chatbots are conversational agents that accept text/voice commands from users and are being actively used to perform different operations like- entertaining customers, personal consultancy, ordering services, handling customer relations, and offering customer services (Ojapuska, 2018). Many instant messaging apps are using chatbots to interact with customers, and their massive success and larger user base than social networks are compelling business enterprises to invest in chatbots and launch their messaging apps to expand access to potential customers. As chatbots interact with customers in a more engaging and natural way than traditional media, investment in chatbots has become critical to offer a more trusted and enjoyable user experience (Hildebrand, and Bergner, 2019). Chatbots are instantly available 24/7, which not only benefits customers but also relieves the stress of employees. Chatbots are also being actively used to make payments, make bookings, order, and handle basic customer complaints, and in the future, the role of chatbots is expected to gain even more importance in different e-service areas (Friend, 2018).

The review of the literature has identified various gaps that need to be filled to gain a better understanding of how chatbot technology is influencing consumer behavior in different usage situations. For instance, the existing literature offers different findings about how chatbot technology influences the consumer behavior, as some studies (Aarthi, Keerthana, Pavithra, and Pavithra, 2020) consider chatbots to be more effective conversational agents than live human agents, while some studies (Wirtz, Paul, Kunz, Gruber, Nhat Lu, Paluch, and Martins, 2018; Song, Xing, Duan, Cohen, and Mou, 2022) discuss how chatbot's limited capabilities decrease their effectiveness compared to human agents. Literature also offers divergent findings about how older and younger generations are responding to chatbot technology (Rodríguez, Werth, Schönborn, and Breitner, 2019; Santosa, Taufik, Prabowo, and Rahmawati, 2021).

Moreover, limited number of studies are conducted in the Turkish context. Bacaksız and Pınar (2020) discussed the case studies on this chatbot in Türkiye during the Covid-19 pandemic crisis period, he found that Chatbots provide businesses with a competitive edge in marketing by offering efficient, consistent communication. In another study conducted with online shoppers aged 15 and over to reveal the factors affecting users' attitudes and intentions towards chatbots, it was found that artificial intelligence tools were used at a low level (Kamran, 2021). In recent years, research has been conducted with the use of chatbots in banking (Sevda et. al., 2022; Denetçli et. al., 2022; Eren and Arzu, 2021a; Eren, 2021b). So, responding to these literature gaps, the current study conducts an empirical investigation on Turkish consumers to assess their perceptions towards using chatbot technology, and its influence on their behavior towards the brand. Although existing literature suggests that the chatbot effectiveness varies depending on the usage area, there aren't enough studies available to compare the chatbot effectiveness across different usage areas. The current study has potential responds to this literature gap by comparing whether different age groups consumers' perceptions towards chatbot vary when they use chatbot for- 1) doing online shopping, 2) online banking, and 3) general customer service.

Even though chatbots are becoming more and more common in our lives, little is known about how users feel about using them, where they are most prevalent, and what influences their use. The purpose of this study is to determine whether Generations X, Y and Z, who have different perspectives and interests in technology, use chatbots differently from each other. Also, to provide insight into chatbot usage is another aim.

The thesis is organized in five chapters. The first chapter, 'Introduction', provides an overview of why it is theoretically and practically important to assess the impact of chatbot use on online customers' purchase behavior. The second chapter reviews the practical use and developments of chatbots and artificial intelligence, and literature review', evaluates related concepts and theories and presents previous studies on the effectiveness of chatbot use from a consumer behavior perspective. In the third chapter, "Research Methodology", details the materials and methods used in the research and explains how the data was analyzed to achieve the proposed research objectives. The 4th chapter, 'Findings', presents and interprets the survey data and then analyzes these results. The final section, 'Conclusion, Limitations and Recommendations', summarizes the main findings of the research and discusses practical implications.

2. THEORETICAL FOUNDATIONS AND LITERATURE REVİEW

2.1. Artificial Intelligent and Chatbots

The chatbot could be defined as an artificially intelligent, social, and proactive conversational agent simulating human-like conversations with the users (Srivastava, Kalra, and Prabhakar, 2020). The term chatbot is a combination of the words "chat" and "robot" (Zumstein, and Hundertmark, 2017). The chatbot technology functions by analyzing the typed content and link to the databases having possible answers to the asked queries (Borsci, Malizia, Schmettow, Der Velde, Tariverdiyeva, Balaji, and Chamberlain, 2022).

Marketers around the world use platforms like Facebook, Instagram, and WhatsApp to use chatbots for interacting with existing and potential customers, delivering content, and advertising/promote their products. Use of machine learning in technologically advanced chatbots allows the technology to adapt response according to new information (Balasudarsun, Sathish, and Gowtham, 2018).

Chatbot is an umbrella term that covers related concepts like conversational agents, virtual agents and chatter bots. The software responds to the queries with textual or auditory inputs. Mostly, chatbots with textual inputs are used to engage and interact with the customers (Hussain, Sianaki, and Ababneh, 2019). A more recent chatbot definition suggests that the chatbot automatically responds to the inputted information in human like manner and executes specific commands where instant response by the chatbot consists of a call-to-action buttons, links, images and structured messages. The exchange of information in various media types creates a dialogue. The dialogue could be initiated by the company or customers, involving the exchange of real time information to the users' individual questions (Zarouali, den Broeck, Walrave, and Poels, 2018).

There are various types of chatbots, ranging from voice bots, hybrid bots, menu based chatbots, social messaging chatbots, keyword based chatbots, rule based chatbots and AI powered contextual chatbots (Kandpal, Jasnani, Raut, and Bhorge, 2020). Among these, the AI powered contextual chatbots are the most advanced and can give more contextually appropriate responses to the customers' queries (Bharti, Bajaj, Batra, Lalit, Lalit, and Angwani, 2020).

Among conversational chatbots, rule based and AI powered chatbots are commonly used. Rule-based chatbots cannot smoothly switch between different conversations, but AI-powered chatbots can create a link between different questions and can connect users to the live agents when needed. Due to their use in wide business areas, chatbots are becoming an almost necessary tool in the services industry (McTear, 2020).

Looking over chatbot history, AI, or Artificial Intelligence, represents a broad branch of computer science dedicated to building smart machines capable of performing tasks that typically require human intelligence. chatbots powered by AI can learn from interactions to improve their understanding and responses over time, providing more relevant and personalized experiences for users. This connection transforms simple automated responders into dynamic tools for customer service, personal assistance, and a wide range of interactive applications.

The world's first chatbot, named Eliza, was introduced by an MIT professor in 1966. The chatbot mimicked human conversations. After almost four decades, a second and more advanced chatbot was introduced by WeChat in 2009, which made online interactions with customers much easier (Paliwal et al. 2020). During 1966 and 2009, various initiatives were taken. For instance, in the following decades after 1966, Parry and Jabberwocky chatbots were introduced in 1972 and 1988, respectively. These chatbots performed better by using the AI technique of matching contextual patterns. In 1995, ALICE introduced simulated chatting with real people on the internet (Hard, 2016). In 2001, Smarter-Child was introduced, which carried fun conversations with users along with providing quick data access. In 2009, WeChat's chatbot brought a major revolution in the chatbot market. In 2010, Siri was another famous chatbot that acted as an intelligent personal assistant and learning navigator with deeper integration of image, video, and audio files. Siri offers a more interactive experience to customers in different public spheres (Adamopoulou and Moussiades, 2020).

In 2012, Google launched 'Google Now,' which offered contextually relevant information based on day, time and location. Compared to previous chatbot versions, it was more complicated and performed various actions, responded to requests and queries, and made recommendations (Wei, Yu, and Fong, 2018). Another major development occurred in 2016 when Facebook allowed developers to develop chatbots for customers to manage their routine activities (Friend, 2018). In 2017, Google replaced 'Google Now' with 'Google Assistant, which provides information in an easily readable format before users even ask for it. Some other latest chatbot examples are Cortana and Alexa. Cortana is integrated into Windows 10 PC and phone devices and uses algorithms to respond to the users' voice commands. While Alexa is Amazon's personal assistant that assists users in online shopping, gives the latest news, sets alarms, and responds to voice messages during web searching (Kepuska, and Bohouta, 2018).

2.2. Chatbots in Metaverse

Metaverse is a complex 3D environment in which users interact with others, three dimensional digital objects and virtual avatars. The three-dimensional version of chatbots responds and reacts in the virtual world. The trend of recruiting virtual avatars to help customers in online shopping is likely to grow in the future (Kovacova, Horak, and Higgin, 2022).

To provide customer support, and assist in online processes, the virtual avatars are equipped with AI powered conversational capabilities. Such AI powered chatbots understand users' intent, and carry the conversations by providing advice, and even giving emotional responses like human agents (Joy, Zhu, Peña, and Brouard, 2022). An effective use of this technology can open endless ways for brands to acquire, engage and support customers. The combination of artificial intelligence and augmented/virtual reality technologies is re-defining how brands interact with the customers (Hopkins, 2022).

The use of virtual assistants and AI powered chatbots has started gaining momentum since 2017. Companies are investing in sophisticated chatbot technologies to provide information and perform different tasks (Bhat, AlQahtani, and Nekovee, 2022). As shown in Figure 2.1, the use of chatbots as a communication tool increased from 13 percent to 25 percent from 2019 to 2020 (Moran, 2022). However, the virtual avatars or digital humans are a step ahead, as they have a personality and a face, which makes engagement more meaningful and realistic, as these digital avatars tend to show the emotions through facial expressions and overall body language. In the future, voice technology will gain more importance than text based chatbot interactions in different areas, like sales, marketing and customer support (Joy et al. 2022).

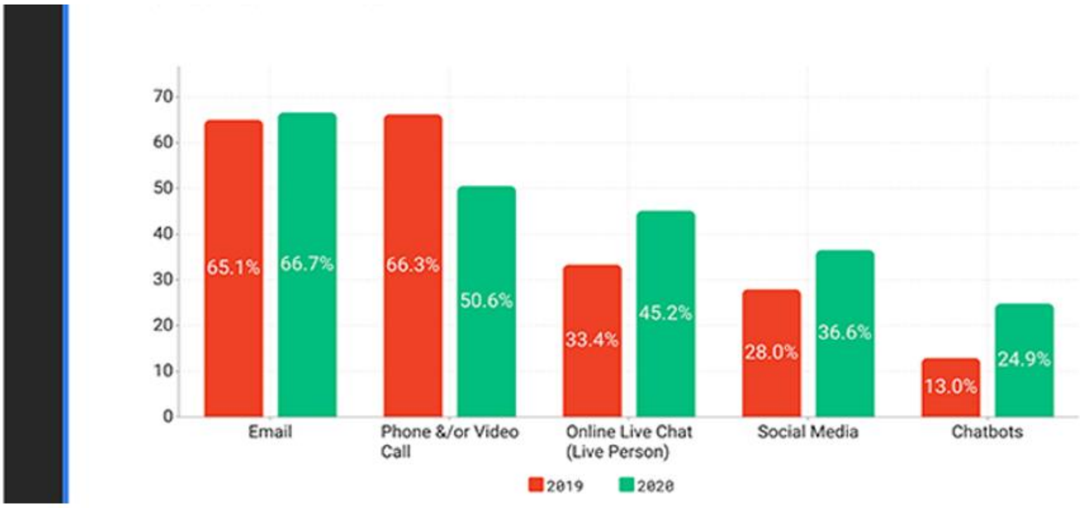

Figure 2. 1: Chatbots- a fastest growing communication tool (Moran, 2022)

Note: The above figure was produced by Moran in 2022 to show the use of chatbot as a brand communication tool between 2019 and 2020

In future, customers would prefer talking to the brands rather than communicating through texts, and use of AI powered chatbots in the Metaverse would bring the best customer experience, because such sophisticated and advanced chatbots can make online interactions smoother and more natural (Kovacova et al. 2022). By translating the language within seconds, the AI powered chatbots will be able to interact with customers around the globe, and virtual avatars will be able to interact with customers in their local language, which will strengthen the customers' bond with the organization (Hopkins, 2022). The reports suggest that the brands would start populating the metaverse with digital avatars that would be more refined communication skills, will be able to offer more seamless experience to the users (Nica, Poliak, Popescu and Pârvu, 2022).

During the pandemic, the chatbot market flourished significantly, and to manage the huge volume of user requests, chatbots became must-have equipment for many companies (Amer, Hazem, Farouk, Louca, Mohamed, and Ashraf, 2021). Analysts suggest that the use of chatbots is growing tremendously in various business fields, and the trend of using a chatbot for online customer service is here to stay. The chatbot market size was \$2.6 billion in 2019 and is expected to grow to \$9.4 billion by 2024 (Nguyen, Chiu, and Le, 2020). According to Fortune Business Insights Report the chatbot market may have \$1,953 million worth by 2027 (Fortune Business Insights, 2021).

Although chatbot usage will vary for performing different tasks, the highest growth is expected to be in retailing and online customer service segment (Nguyen, 2020). The following graph shows that the use of chatbots in retailing industry is the highest compared to other major industries. The Figure 2.2 was produced by (Jassova, 2021); based on survey findings, Jassova explained the share of consumers who have used chatbots to engage with companies, also, he mentioned that the future of customer service is expected to depend on AI-powered chatbots that will play an important role in developing personalized customer relationships.

The Figure 2.2 is produced based on a survey conducted in 2019, and data was collected from different industries within the USA. So, retailers have the highest share of consumers that use chatbots, followed by healthcare and utilities.

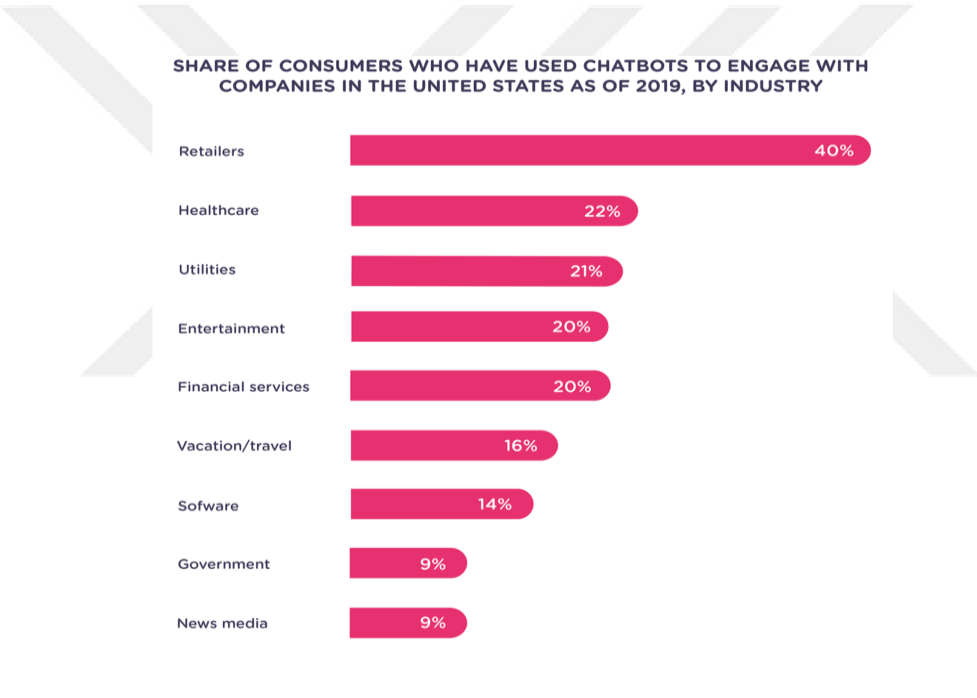

Figure 2. 2: Chatbot use growth in different industries (Jassova, 2021)

According to the MMR research which is a global consumer market research agency in 2022 that is explain the use of chatbots by the application from 2020 to 2027. Important forecasts are made to show how different chatbot applications will gain popularity during the next few years across the globe (Figure 2.3). While payment and order processing bots were in close development in 2020, it is predicted that the growth rate of social media bots will be higher.

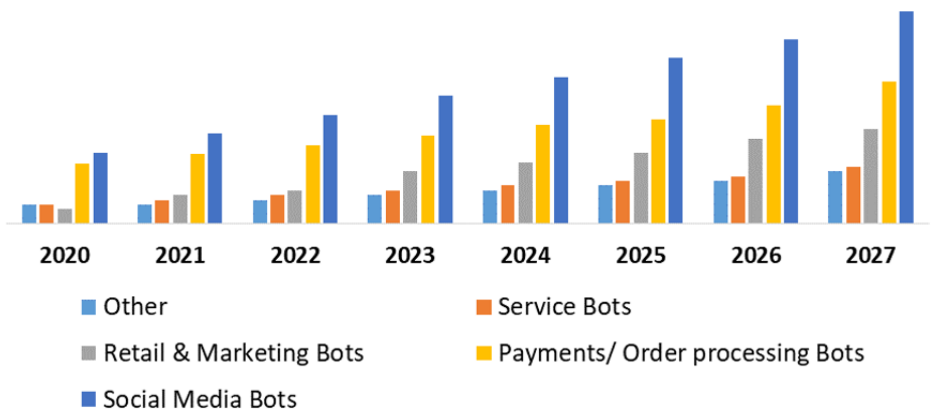

Figure 2. 3: Growth of the global chatbot market by the application from 2020 to 2027 (USD Billion, MMR research, 2022)

Chatbots enable companies to offer hyper-personalized customer service, enable real-time communication and assist in sales transactions (Leszkiewicz, Hormann, and Krafft, 2022). In the e-service field, chatbots provide engaging, interactive, convenient and personalized customer service interactions (Aarthi et al., 2020). AI-powered chatbots benefit businesses in various ways, like- making conversations easier, providing instant responses to customers' queries with humor, compassion and depth, and handling conversations in a polite manner without getting exhausted. Particularly in call centers, investment in chatbot technology has made scaling up to a large volume possible without facing staff shortage issues (Xueming, Tong, Fang, and Qu 2019). Business Insider's survey, as cited by Beaver (2017), revealed that 48 percent of customers prefer interacting with a chatbot with an interesting and entertaining personality. It shows companies can encourage chatbot usage by customers by improving the chatbot features that make up the overall chatbot personality. A survey by Inc., as cited by Roesler (2017), however, found that around 23 percent of customers still have preferences for face-to-face interactions over chatbot, particularly when issues are complex, like resolving complaints/disputes. Patel (2022) also determined why and for what reasons customers use chatbots (Figure 2.4). He shows that the top three reasons why customers prefer using chatbots include- when they are in an emergency, when they seek quickly resolve a complaint, and when they need detailed answers/explanations.

Figure 2. 4: Predicted use cases of chatbots (Patel, 2022).

According to a 2020 Statista report, Türkiye had the highest adoption rate of chatbots in Europe, with 44% of participants using chatbots in the previous month. The most common uses in Türkiye were for customer service (54%), entertainment (38%), and education (27%). Young people aged 18-34 were the most likely demographic to use automated chat programs.

A study published in Hürriyet Daily News in 2020 reported the growing popularity of chatbots in Turkish universities, with some developing their own chatbots to provide information and support to students. A 2021 report by the Turkish Ministry of Education outlined plans to integrate chatbots into the education system for personalized learning experiences. While there's no specific data on chatbot use among Turkish students in 2020, general trends indicate increasing popularity among students for purposes like academic support, mental health, and career guidance.

2.3. Chatbots and Services Industry

The importance of delivering excellent customer service has risen more than ever before, business enterprises must respond quickly, precisely, and more effectively, leaving customers fully satisfied (Okuda and Shoda, 2018). Up till now, customer services have been delivered by human agents who are well trained to handle their job with accuracy, speed, and empathy. However, humans have limits, and they can deliver customer services within their physical and psychological constraints (Ukpabi, Aslam, and Karjaluoto, 2019). People under pressure may get exhausted, unable to stay focused and may also experience mood fluctuations. On the other side, customers expect excellent service quality disregarding the amount of pressure on customer services' agents (Li, Emokpae, and Yang, 2021). These customers' expectations increase the need to invest in chatbot technology in the services industry. The purpose behind using the chatbot is not only to save the costs, reduce the burden and enhance productivity, but chatbots are also being deployed to enhance the quality of customer service quality, and improve their overall experience (Ukpabi et al. 2019).

Today, the services of tourism, hospitality, retail, banking, and financial organizations are adopting chatbots to gain their desired objectives. The use of chatbots has reduced customer service costs, increased cross selling activity, and provided a more secured user experience in the banking industry (Ukpabi et al. 2019; Li et al. 2021). Chatbots are facilitating customers in their online purchase journey by making the search easier for them. It is also benefiting companies by improving their return on investment, and reducing operating costs (Desai and Ganatra, 2022). All the benefits have raised chatbot services.

Some common uses of chatbots in the services industry include- using chatbots to make payments, handle customer complaints, and respond to their queries. This widespread use increases the possibility of using chatbots in different service scenarios (Dihingia, Ahmed, Borah, Gupta, Phukan, and Muchahari,2021). Chatbots are also driving the customer engagement in the entertainment and retail space and are being used to predict the customers' behavior in the hospitality industry (Sung, Bae, Han, and Kwon, 2021). During a pandemic, the service enterprises realized how the use of chatbots helped them in handling customer queries even with limited staff without getting exhausted. The chatbots have provided 24/7 services to customers in various service sectors, including the hospitality and banking industry (Alotaibi, Khan, 2022; Mulyono and Sfenrianto, 2022). American Eagle, Outfitters, Domino's Pizza, Amazon, eBay, Facebook, and WeChat are some examples of highly renowned companies that heavily invested in chatbot technology to handle customer conversations.

Recent studies like (Chen and Jiang, 2021; Quintino, 2019) suggest business organizations take a broader view of how they can create value for their customers and even other stakeholders. By re-imagining how they can interact and engage with the customers, service enterprises can enrich the overall customer experience, and chatbots here can play an important role. However, the literature also informs that inability to make effective use of chatbot technology without understanding the consumers' preferences and interests can instead destroy the value (Melián-González, Gutiérrez-Taño, and Bulchand-Gidumal, 2021).

2.3.1. Online shopping/e-commerce

In the online shopping context, the AI powered chatbots assist customers by providing necessary suggestions and product information. While it tries to offer a physical store experience by providing guidance, being able to do this in many languages can also provide convenience to consumers (Satu, Akhund, and Yousuf, 2017). Different chatbot features enhance the online shopping experience of customers, and by picking the nuances from the databases, chatbots offer personalized and customized suggestions, The in-depth understanding of customers' preferences makes interactions more meaningful for customers (Ruan and Mezei, 2022). A combination of human agents and chatbots further enhances the experience when the problem at hand is too complex for chatbot to handle alone. While chatbots alone can be more effective in providing detailed, up to date product information when customers do not have any complex queries (Wien and Peluso, 2021).

A study by (Illescas-Manzano, 2021) was to evaluate the effectiveness of a chatbot deployed via Facebook Messenger using the ManyChat platform in increasing lead generation, compared to the company's previous methods of collecting contact information. The research demonstrates that implementing a chatbot on the ManyChat platform positively impacts lead capture for online marketing companies. The findings suggest that using a chatbot as a tool for lead generation is both efficient and effective.

2.3.2. Online banking

Online banking is another area in which chatbots are being commonly used. The banking industry is becoming more self-service oriented, as customers are becoming digital savvy. The use of chatbots is not only reducing the work burden, but also reducing the waiting time for customers as they do not have to stand in long queues (Alt, Vizeli, and Săplăcan, 2021). Customers' preferences for chatbot banking are growing slowly due to instant feedback without requiring waiting (Wiliam, Sasmoko, and Prabowo, 2019). As per Juniper Research (2017), around 90 percent of the banking interactions are automated through AI powered chatbots. The role of chatbot in the financing industry grew during the pandemic, and in coming years, AI chatbots are likely to play an even bigger role in the banking sector (Mulyono and Sfenrianto, 2022; Wiliam et al. 2019).

Today, chatbots are being used to handle routine banking tasks like fund transfers, and with technological development, chatbots are likely to handle more complex tasks and customers' interactions (Nguyen et al. 2021). Staff shortages, cost reduction motives, growing demand for banking services and increasingly demanding customers are some common factors that are driving banking organizations to invest on chatbots (Alt et al. 2021; Nguyen et al. 2021). The use of chatbots not only reduces the customer service costs, enhances productivity, reduces workload, and improves customer satisfaction due to quick and more accurate customer service, but at the broader level, it can also assist in developing the country and region (Bruhn and Love, 2014).

As per Mogaji, Soetan, and Kieu (2020), emerging digital technologies are presenting opportunities to fill the gap between banks and financially excluded customers. Other than the developed world, the use of such technologies is also gaining popularity among financial institutions from the developing world. Investment in these technologies is accelerating institutional, technological, and social innovation. Considering the advantages of chatbots and other emerging digital technologies for the financial industry, the potential of chatbots and chatbot marketing in the banking sector is largely underexplored, both in developed and developing world (David-West, Iheanachor, and Umukoro, 2019) Investment in digitalization can spur social and economic growth and can accelerate the progress of the financial services industry.

Chatbots by Accenture (2022) revealed that around 57 percent of the banks that implemented Chatbots expect to get direct ROI without exerting significant efforts. Interestingly, chatbot use has also made service delivery more personalized. In the future, chatbots are going to play an even wider role in the banking industry. Eren (2021) expects chatbots to be more humanlike and able to show empathy while interacting with customers. Voice bots may also gain more popularity in the future, and customers' preferences to use a chatbot for performing various banking operations may also grow with time. So, it is important to understand the chatbot use implications in the banking industry.

2.3.3. Chatbot used for customer services.

In the tourism industry, companies are using chatbots as tour guides. An example of such usage is the chatbot named CLARA, which was developed to act as a local tour guide to help first time visitors (D'Haro, Kim, Yeo, Jiang, Niculescu, Banchs, and Li, 2015). Tourism, hospitality, and many other service organizations are paying more emphasis towards online service delivery. Hospitality organizations are particularly using chatbots as marketing tools, like to increase the sales. So, mostly hospitality chatbots have only information about the tourist and hotel topics and respond to only related queries (Lasek and Jessa, 2013).

2.3.4. Chatbot features and usage.

The literature review highlights some chatbot features that positively influence consumer behavior. For instance, as mentioned by (Köhler, Rohm, Ruyter, and Wetzels, 2011), firms can positively influence the consumers' behavior by making chatbots more friendly and giving them interesting personalities in a way that users consider conversational chatbots as their peers rather than mere agents. Chen et al. (2020) also found that a personality driven chatbot can drive the co-design activities and make interactions with customers more fun and meaningful. Köhler et al. (2011) and Chen et al. (2020), Galitsky (2021) also stressed the importance of giving chatbots friendly personality, and adding further, Galitsky (2021) further said that it is also important to modify the Chatbot's personality according to the personality of the user. A recent study by Zarouali et al. (2018) evaluated chatbot effectiveness, and findings showed that the cognitive and affective determinants of Facebook messenger chatbot exert a direct positive impact on customers' brand attitude, and an indirect influence on the customers' intentions to recommend chatbots to others. Research by Araujo (2018) found that when chatbots have human-like cues, they are more likely to influence the customers' perceptions, and therefore, it is important to make interactions between chatbots and users more realistic to build relationships and develop emotional connections between the company and users. When chatbots have attractive personalities and depict human cues, it arises positive and pleasurable emotions. As per **(**Chatterjee, Goyal, Prakash, and Sharma, 2021), arousal of positive emotions because of favorable marketing stimuli enhances customer satisfaction and appraisal of the brand. Although, studies like (Jiménez-Barreto, Rubio, and Molinillo, 2021) contend that the AI powered chatbots tend to exhibit the human cues, Lechner and Paul (2019) mentioned that although, AI powered chatbots are technologically sophisticated, and extensive chatbot training enables them to mimic human's emotions, people still prefer interacting with the human agents, as they consider chatbots to be incapable of effectively responding to the human emotions.

This argument was refuted by Jiménez-Barreto et al. (2021), who contended that customers' interaction with chatbots could trigger emotional and experiential responses and agreeing with Jiménez-Barreto et al. (2021), Trivedi (2019) contended that chatbots could be used as a tool to strengthen the customers' emotional connection with the brand. By surveying 258 bank customers, Trivedi (2019) found that when used effectively, AI powered chatbots provide not only basic information, but also evoke positive emotions, which increase the customers' love for the brand. However, Lechner and Paul (2019) contended that to strengthen the brand-customer relationship through chatbot, it is important for chatbots to show authentic emotions, and inauthentic positive emotions cannot build a strong connection with the brand. For a chatbot, the display of such authentic emotions is more difficult than for human agents, but as per Schill and Godefroit (2022), customers' positive emotions are also influenced by the high-quality service, and for chatbots, delivering high quality service by offering more accurate, high-quality information instantly is easier than human agents. These reasons suggest that the degree to which chatbot use induces positive feelings determines the beneficial impact on consumer behavior.

Other than having an attractive chatbot personality, depicting human like cues, and evoking positive emotions, it is important to ensure that the chatbots provide high quality information to users.

Recent research by (Chung, Joung, and Kim 2020) found that the luxury fashion retailers are able to use the chatbots to enhance communication quality, and provide convenience to their customers, which ultimately enhances the effectiveness of their marketing efforts, also, he found that to achieve the desired objectives, it is important to ensure that the chatbots provide high quality information and give instant response to the customers, as many users prefer chatbots due to their convenient and instant messaging features.

As per (Zhang, Sun, Qin, and Wang, 2021), conveying high quality information is critical for satisfying and building a relationship with customers. Perceived information quality during online shopping shows the users' object-based beliefs. The importance of providing high quality information is emphasized in traditional as well as the new context of AI powered chatbot customer service.

Another important feature of the chatbot is its ability to provide instant feedback. Waiting time is an important factor that shapes the customer experience, both- in online and offline contexts (Djelassi, Diallo, and Zielke, 2018). The waiting time denotes the customers' perceptions of the amount of time they spend before their request is responded to; the customers' perceived waiting time is not only defined by the objective time, but also derives influence from the customers' waiting tolerance. AI-powered chatbots are more advantageous as they can respond to customers' requests faster than human agents. As customers usually have a high desire to save time, and conveniently access information, chatbots here enhance their online shopping experience by fulfilling these expectations. However, Li et al. (2020) suggested that while making hedonic purchases, customers have a high tolerance of waiting, and in such cases, the effectiveness of using chatbots decreases compared to human agents.

2.4. Social Exchange Theory Explaining the Influence of Chatbots on Consumer Behavior

Social exchange theory will help us explain and understand how the effective use of chatbot technology can influence consumer behavior. Social exchange theory assumes that the major driver in the interpersonal relationship is the mutual satisfaction of both parties. The influence of chatbot features on the online purchase decision is analyzed in light of exchange theory, which suggests by increasing benefits and decreasing costs of availing chatbot services (which can be done by enhancing the chatbot features and reducing the risks of using a chatbot), customers are likely to respond by showing favorable behavior (assessed by considering their online purchase decision) towards the company (Skjuve, Følstad, Fostervold, and Brandtzaeg, 2021).

The costs could be reduced by reducing the risks (like privacy and security related), and increasing the benefits (like making interactions with technology more user friendly, more entertaining, and informative etc.) (Jiang et al. 2022). When this is done, the theory guides that a mutually beneficial exchange relationship, in which users having positive chatbot use experience tends to reciprocate by showing a favorable attitude towards the brand (Lv, Huang, and Long, 2022). The current study employs social exchange theory because the study is also interested in evaluating how companies' services can encourage chatbot usage to positively influence consumer behavior. Social exchange theory here guides how companies can use chatbot usage as a tool to achieve desired consumer behavior objectives (Kim and Wirtz, 2022).

The literature highlights some studies that employed the social exchange theory to understand the influence of chatbot on consumer behavior. For instance, Jiang et al. (2022) employed social exchange theory to evaluate the influence of chatbot conversations on consumers' behavior. By surveying 965 respondents, he found that the responsiveness and conversational tone directly influenced user satisfaction and increased consumers' purchase intentions. On a similar note, another study by (Luo, Tong, Fang, and Qu, 2019) noted that when chatbot does not meet the consumers' conversational expectations, it negatively influences their purchase behavior. It particularly happens when customers expect a highly personalized interaction, while the chatbot gives a standardized response. Here, the negative exchange relation develops, and customers tend to respond to unmet expectations by showing a negative attitude towards the brand. The current study also evaluates whether the use of different chatbot features exerts any influence on the consumers' online purchase behavior.

2.5. Research Problem and Aim

Although various studies (Rajnerowicz, 2022; Sweezey, 2019) have confirmed that customers' preferences to interact with chatbots are increasing, Nechifor (2021) reported that in some cases, ineffective use of chatbot technology could rather destroy business value. he reported that around 40 percent of the consumers in the USA still prefer getting approached by a real person rather than a chatbot, while findings of a global survey by Rese, Ganster and Baier (2020) (as cited by Nechifor, 2021) reported that 34 percent of the respondents feel comfortable while interacting with a chatbot to get personalized recommendations at pre-purchase phase. Another survey by Smutny and Schreiberova (2020) reported around 52 percent of users are dissatisfied with the immature technology and impersonal approach of chatbots lacking the human touch. Differences in findings of these surveys suggest that the consumers' behavior towards using chatbots may vary depending on various factors, like- chatbot characteristics, usage area, underlying situation, consumers' personal preferences, and purpose/nature of the interaction (Følstad, Nordheim, and Bjørkl,2018; Sanny, Susastra, Roberts, and Yusramdaleni, 2020).

To understand how chatbots may influence consumer behavior, it is important to evaluate the role of chatbots in consumers' journeys. In the marketing funnel, the customer journey has four main stages- awareness, consideration, purchase intentions and satisfaction. AI-powered chatbots play their role at the consideration stage. At this point, chatbots (when effectively used) can increase the purchase desire (Meyer, 2019). Here, a reference to the technology acceptance model (TAM) could be made. The TAM model emphasizes the perceived usage ease and perceived utility to enhance the user experience with the technology (Nichifor, Trifan, and Nechifor, 2021).

In the current context, the chatbot use experience could be enhanced if users find the chatbot to be highly informative, easy to use and able to give reliable and high-quality information instantly. When chatbots fulfill these customers' expectations, companies can expect positive behavioral responses in return. On the contrary, when chatbots do not fulfill these expectations, it creates dissatisfaction and negatively influences the customers' behavior toward the brand (Jiang, Cheng, Yang, and Gao, 2022). To complete the customer journey process and keep customers moving through all funnel stages, it is important to enhance their interaction with the brand by enhancing the chatbot experience (Nechifor, 2021). So, it is important for companies to carefully invest in chatbot technology by considering the customers' preferences and possible implications on consumer behavior.

Some studies like a survey conducted by Simplr (2022) have noted stark generational differences in consumers' perceptions towards the use of chatbot technology, according to a survey with 1000 global customers, the findings revealed that Boomers, Millennials, Generation X and Generation Z differently perceive chatbot technology. Survey further found that 20 percent of generation Z customers have preferences for chatbots compared to only 4 percent of baby boomers, and meanwhile, 71 percent of the baby boomers have preferences to interact with the live agents, while only 41 percent of generation Z customers prefer talking to a live agent. Another interesting survey finding was that around 53 percent of baby boomers mentioned that uninitiated chatbot conversations annoyed them, while only 28 percent of the Millennials and 24 percent of generation Z customers got annoyed by uninitiated chatbot conversations.

As people today are spending more time online, it provides another reason for businesses to adapt and prioritize being online to increase the opportunities of interacting with existing/potential customers. Online communication plays an important role in shaping the overall online customer experience. Companies can use online communication as a tool to optimize the customers' experience (Siswi and Wahyono, 2020), provided online communication fulfills the customers' expectations. The intensifying competition in today's business world, along with the increasingly demanding nature of customers, is making it difficult for businesses to satisfy and retain customers (Brandtzaeg and Følstad, 2017). Companies today are fighting for individual customers fiercely and do not want to miss any chance to optimize their online experience. Due to growing competition, customers do not need to search a lot to get the products they desire (Maroengsit, Piyakulpinyo, Phonyiam, Pongnumkul, Chaovalit, and Theeramunkong, 2019). Therefore, companies need to explore how they can satisfy and retain customers.

However, as per (Wirtz, Patterson, Kunz, Gruber, Lu, Paluch, Martins, 2018), although chatbots have become smarter than ever before, there is still a long way ahead to attain the human level of interaction through deep acting and out-of-the-box thinking. Therefore, the use of chatbots is still limited to offering basic or additional customer services, and in many cases, chatbots exist along with human agents, and debate about whether chatbots will be able to replace humans is still ongoing (Song et al. 2022). The current study extends this debate by evaluating whether customers prefer only interacting with chatbots, human agents or both. Existing literature suggests a combination of both- in which the chatbot handles basic queries and forwards technical matters to the human agent (Wilson and Daugherty, 2018). The literature review further suggests that most of the previous studies focused on the technical side of chatbot usage, but evaluating the value of chatbots from consumers' perspective, particularly in, Europe, requires further empirical investigation (Syarova, 2022). It is important to consider these differences as these differences influence customers' willingness to accept the technology and determine its impact on online purchase behavior (Solis-Quispe, Quico-Cauti, and Ugarte, 2021).

This study focuses on evaluating the impact of chatbots on consumer behavior in different services, such as tourism, health, education, technology, and banking. It aims to understand how chatbot usage affects customer perceptions of service quality.

In the context of Türkiye, there is a need to evaluate how customers perceive chatbot usage and do they appreciate the instant service provided by chatbots or prefer interacting with human agents. The key theme of current research is to evaluate the influence of chatbot usage on the behavior of Turkish customers belonging to generations X, Y and Z. The rationale for conducting an inter-generational comparison is that compared to older people, Millennials and Generation Z show a higher interest in using chatbots (Nechifor, 2021), but not enough empirical literature is available to confirm how generational difference may play a role in determining perceptions towards chatbot use.

Also, the current literature offers different results on whether the use of chatbots brings any significant changes in consumer behavior, whether positive or negative. This knowledge gap weakens the generalizability of the findings, and there are few studies that take intergenerational differences into account. However, chatbot usage varies depending on the generation of users and the underlying social context (Ameen, Hosany, & Tarhini, 2021).

This research study has high significance as it focuses on Turkish consumer behavior and conducts inter-generational comparisons (X, Y and Z). Although findings of some previous surveys (like Leah, 2021) proved that young users are more likely to prefer interacting with chatbots than older users, empirical evidence is limited in the context of Turkish consumers. So, this study contributes to the literature by comparing which generation shows more interest and derives stronger behavioral influence from chatbot usage. By knowing which generation has high or low chatbot preferences, companies can re-direct the customers according to their generation to personal agents (if needed) rather than compelling them to complete the whole conversation with a chatbot.

Another key reason for doing this research study in Türkiye is that the Turkish market has a large capacity, and there is a high percentage of social media users that visit online websites to do online shopping (Figure 2.5).

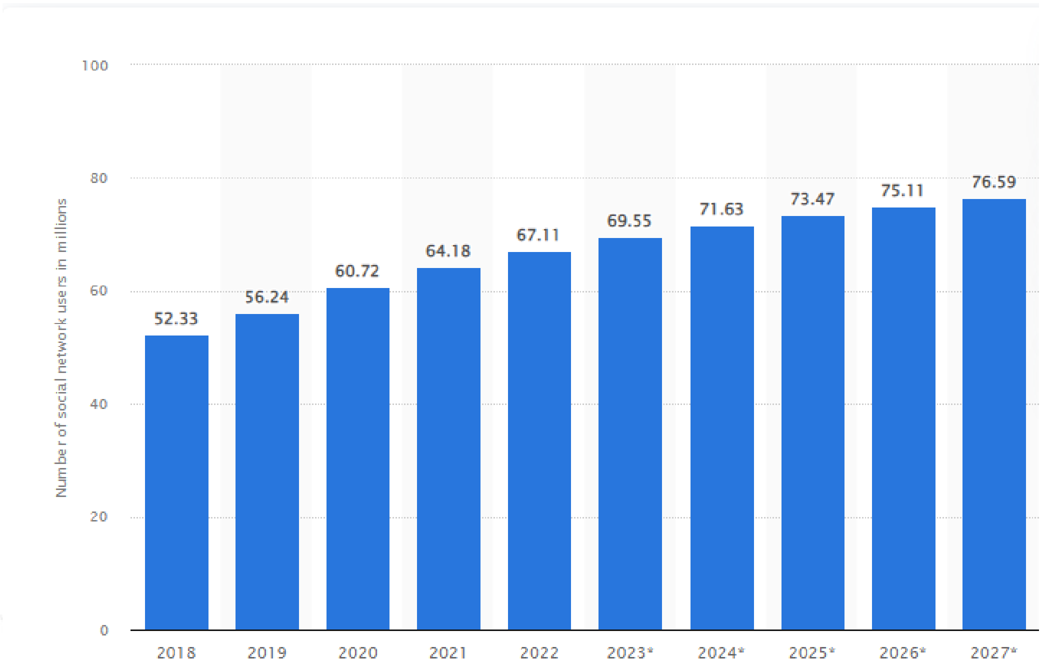

Figure 2. 5: Growing number of social network users in Türkiye from 2018 to 2027 (Statista, 2023)

So, conducting this research adds value to the service companies in the Turkish market, who can use the results to improve their chatbot marketing efforts (Dierks, 2022). Other than possible positive implications related to consumer behavior, chatbots are also expected to bring promising economic advantages to companies by cutting business costs. The possible cost reduction further increases the need to invest in chatbots to avail economic and marketing advantages and provides a reason for doing this research (Markoski, Simić, Premčevski, Petrović, and Stanisavljev, 2018).

The above point gains validation from the following graph (figure 2.6), which shows that chatbots can give significant cost savings to businesses.

Figure 2. 6: Potential savings from chatbot usage (Avinash, 2022)

Following points sum up the theoretical rationale for doing this research:

- Not enough empirical evidence is available in the Turkish context.
- The analysts predict (like Business Insider as cited by Cheng and Jiang, 2021) the chatbot market will experience tremendous growth from 2019 to 2026, with 31.6 percent growth in customer service engagement.
- During the pandemic, customers and companies' reliance on chatbots increased significantly, and this chatbot usage is unlikely to decline in the post-pandemic era. It has brought some permanent changes in customers' preferences to interact with companies in the online world (Tunç, 2021).
- Only limited literature is available to evaluate the influence of chatbots on online consumer behavior, and there is only limited information about their interests and preferences while using chatbots. Literature is also limited to understanding how customers from different generations may perceive chatbot usage and how such differences may influence the relationship between chatbot usage and online consumer behavior (Leah, 2021; Nechifor, 2021).

Considering the above reasons, the research focused on two objectives.

1. Chatbot Usage Across Generations and in the Metaverse: The study focuses on understanding the usage patterns of chatbot usage and in the metaverse among different generations of Turkish customers, specifically Generation X, Y, and Z.
2. Differences in Consumer Behavior by Generation: The study aims to uncover potential consumer behavior differences among these generations X, Y, and Z.

The research scope is narrowed down by focusing on only Turkish customers, and chatbot effectiveness is evaluated only from customers' perspectives. Online data collection, focus on customers' perspective, geographic restriction (Türkiye), and sole reliance on the quantitative methodology collectively formulate the context and scope of research.

2.6. Literature Review

The study by (Nyagadza Muposhi, Mazuruse, Makoni, Chuchu, Maziriri, and Chare, 2022) aimed to investigate the reasons why customers might be willing to use chatbots in Zimbabwe as a gateway for customer service in electronic banking. The study employed a descriptive methodology and involved a sample of 430 individuals from five commercial banks in Harare, the capital of Zimbabwe. The results showed that the use of chatbots has an impact on banking services. These chatbots, as a trending technology, were well-received by the participants of the study. Additionally, the study highlighted the reasons behind the customers' desire to use chatbots in these five commercial banks. This study was considered pioneering in enhancing customer service through recommended electronic methods.

Zogaj, Mähner, Yang, and Tscheulin (2023) conducted a study to understand how the interaction between consumer characteristics and chatbot features influences consumer behavior. This study particularly focused on how visual signals of chatbots, such as embodiment and gender, affect consumer behavior while also considering the consumers' self-concept. The results revealed that there are differences in how chatbots are used and their impact on consumer behavior based on gender. This highlights the importance of considering demographic factors in the design and deployment of chatbots, especially in areas like marketing and customer service, where understanding and influencing consumer behavior is crucial.

In the study by (Omarov, Tursynbayev, Zhakypbekova, and Beissenova, 2022), a comprehensive overview of artificial intelligence strategies employed in the marketing services sector was provided, with a specific focus on the use of chatbots in digital marketing communications. This study investigated the effectiveness of chatbots in influencing consumer purchase intentions. The findings demonstrated that the implementation of chatbots in marketing communications significantly impacts consumer buying behavior, highlighting the growing importance and effectiveness of AI tools in the marketing and consumer engagement landscape.

A study by (Kamran, et al. 2021) focuses on understanding the role and characteristics of artificial intelligence (AI) tools in marketing. Specifically, it explores how user attitudes and intentions towards shopping chatbots are shaped, using the technology acceptance model as a framework. The research targets individuals in Türkiye aged 15 and above who make online purchases using smart devices. The findings indicate that AI tools are currently underutilized in Türkiye shopping sector. The results reveal that perceived enjoyment and intelligence of AI tools positively influence user attitudes towards them. Furthermore, a positive correlation was found between these attitudes and the intention to use AI tools.

A study by (Deneçli, Yıldız and Deneçli, 2022) explores the development of AI-based chatbots and their integration into the rapidly digitalizing banking sector. It evaluates the responses of innovative consumers to bank chatbot applications. Conducted with 407 participants selected through convenience sampling, the study ultimately analyzed responses from 394 individuals who use the Internet or mobile banking. The research included a correlation analysis to examine the relationship between consumer innovativeness and their trust in chatbot applications. Results indicated no significant link between consumer innovativeness and the competence or benevolence dimensions of trust towards chatbots. However, a significant relationship was found between consumer innovativeness and the integrity dimension of trust in these applications.

The study of (Eren, 2021) aimed to verify customer satisfaction with the use of banking chatbots and the impact of perceived trust in these chatbots and the banks' reputation on customer satisfaction. A survey in Türkiye involved 240 customers who had experienced banking transactions using chatbots. Results showed that customer expectations positively influence perceived performance. Customer expectations indirectly affect customer satisfaction through perceived performance. Perceived performance has a positive impact on the confirmation of customer expectations, but customer expectations do not significantly impact the confirmation of their expectations. This highlights the complex dynamics between customer expectations, the perceived performance of chatbots, and overall satisfaction in the banking sector.

The literature review suggests that the consumers' demographic characteristics play an important role in determining perceptions towards chatbot technology. For instance, Soni and Tyagi (2012) surveyed 170 millennials (generation Y) from India and found that generation Y customers are increasingly interested towards using chatbots, but they also have privacy and security concerns. They suggested future researchers examine the chatbot acceptance by baby boomers. In response, a study by (Rodríguez Cardona, Werth, Schönborn, and Breitner, 2019) compared the generational difference in chatbot acceptance in German insurance sector and found that the generation Y and generation Z were more willing to use chatbots and held positive perceptions towards chatbots compared to generation X, while baby boomers held the negative perceptions and were least willing to accept and use the chatbot technology.

Another research by Santosa et al. (2021) employed a unified theory of acceptance technology model, and by surveying 320 bank customers, the study found that both- generation X and baby boomers hold positive perceptions towards chatbot technology, and recommended marketers to stretch focus from millennials and generation Z and focus on older generations as well while using a chatbot as a marketing tool to influence consumer behavior. Santosa et al. (2021) refutes the findings of Rodríguez Cardona et al. (2019) by finding older generations to be more welcoming of chatbot technology. A possible reason for this inconsistency could be that Rodríguez Cardona et al. (2019) conducted research on the insurance sector, while Santosa et al. (2021) focused on banking customers. It suggests the chatbot usage and its influence on consumer behavior could differ depending on the usage situation.

Other than generational differences, the literature suggests that the users' gender and education level also play an important role in determining the perceptions towards the usefulness of chatbot technology. For instance, Kasilingam (2020) explored the understanding, attitude and intentions towards using smartphone chatbots for online shopping. The study employed a technology acceptance model and surveyed 350 respondents who were asked to share their responses after using the Facebook eCommerce chatbot. The findings confirmed significant differences in gender, age and previous experience with using mobile shopping applications. In terms of gender, men exhibited a more positive attitude towards using the chatbot technology than women and considered it considerably less risky than women. In terms of age, the findings suggested that younger respondents consider chatbot technology to be more useful than older customers. On the same note (Schmidlen, Schwartz, DiLoreto, Kirchner, and Sturm, 2019) found that college educated (and higher) users were more likely to accept and positively view the chatbot technology than comparatively less educated users. Agreeing to Schmidlen et al. (2019), (Van Deursen, Van Dijk, and Peter 2015) also found that the users' education level plays an important role in determining their perceptions towards using new technologies. Van Deursen et al. (2015) surveyed 1418 respondents in 2010; 1114 respondents in 2011; 1224 respondents in 2012, and 1125 respondents in 2013. The survey was conducted with Dutch population, and findings confirmed a significant association between users' education level and their acceptance of internet technologies.

The study by Gkinko and Elbanna (2022) focused on understanding the emotional experiences of individuals using AI-supported chatbots, a specific type of AI system that exhibits a social presence for users. The study adopted an interpretative case study methodology and inductive analysis, gathering data through interviews, document review, and observation of usage. Findings indicated that employees' assessments of chatbots were influenced by the design and functional form of the AI-supported chatbots, as well as their organizational and social context, leading to a broader range of evaluations and multiple emotions. In addition to positive and negative emotions, users felt feelings of connection. The results suggest that experiencing multiple emotions can encourage continued use of AI-supported chatbots.

In a study conducted by (Winkler and Söllner, 2018) researchers, it was found that chatbots have become increasingly popular in various fields such as medicine, product and service industries, and education. Chatbots are computer programs designed for voice or text conversations and are recognized for their potential to change the way students learn and seek information. The findings indicate that chatbots are in the early stages of entering the education sector. Few studies suggest the capability of chatbots to improve learning processes and outcomes. Research reveals that the effectiveness of chatbots in education is complex and depends on a variety of factors.

Research by (Belen, Nurse, and Hodges ,2021) examined the concerns of users regarding the handling of sensitive data by chatbot providers, surveying 491 British citizens. The study revealed that users are primarily worried about the deletion of personal information and potential misuse of their data. The research found that user concerns varied with age, with those over 45 expressing more worries than younger users, but saw no significant differences based on gender or education. The study also explored factors that build trust in chatbots, identifying technical aspects like response quality as key. While gender and education level again showed no impact, younger users (under 45) placed more importance on social factors like avatars or perceived 'friendliness'.

The study of Xie, Zhang, Zhu, and Wang, 2023 showed that the use of a metaverse in the university platform creates an immersive and interactive virtual environment, making education more engaging and accessible. In this paper, they highlighted the representative applications for chatbot integration for metaverse on a university platform. To achieve this, they propose a three-tier metaverse architecture that includes a chatbot platform, a university platform and a metaverse platform from a macro perspective. They argued that the integration of chatbots into a university platform prototype for a metaverse is a promising way to enhance user experience and facilitate education in the digital age.

Lo Presti, Maggiore, and Marino (2021) conducted two experiments to see how consumers' interactions with chatbots on official websites influenced their value perceptions of product and brand and found that the chatbots contribute to the brand awareness, and suggested retailers to include chatbots as online assistants to stimulate the consumers' online shopping intentions.

Another study by Khoa (2021) analyzed the influence of chatbots on online purchase behavior. By surveying 886 online consumers in Vietnam, Khoa (2021) found that the chatbot interactions positively influence the online purchase behavior, provided the chatbots are easy to use, and offer instant, high-quality information that meets the consumers' needs. It also increased impulse buying and increased their re-purchase intentions. Both these studies found a significant positive influence of chatbot use on consumer behavior. However, findings of these studies were not supported by another research conducted by Luo et al. (2019), who conducted an experiment on 6200 online customers, and found that when chatbots interacted with the customers, such interactions negatively influenced the consumers' behavior, and decreased their purchase intentions, as customers considered chatbots to be less empathetic and less knowledgeable. It is an important finding, which indicates the need to firstly understand the consumers' perceptions towards chatbot technology before making the investment decision.

A similar study by (Mozafari, Weiger, and Hammerschmidt, 2020) explored the desirable and undesirable influence of chatbots on consumer behavior. By conducting two scenario based experimental studies, he found that chatbots can exert positive as well as a negative influence on the consumer behavior, and this influence depends on the extent to which chatbot features match the customers' desires and expectations. These experimental studies were conducted by firstly collecting data from the European online panel provider, and secondly, by collecting data from a European university. The first study recruited 252 respondents, while the second study recruited 270 respondents. On the same line, Kasilingam (2020) found that the chatbot's positive influence on online shopping behavior depends on how much customers think about chatbot technology to be useful, enjoyable, risk free and easy to use. It also depends on the consumers' personal innovation and an overall attitude towards chatbot technology.

Nguyen et al. (2021) explored factors that determine continuous intention towards banks' chatbot services in Vietnam. Survey with 359 Vietnamese bank customers revealed that the perceived information quality, overall service quality and perceived trust on chatbot technology are some strong drivers of chatbot usage. (De Cicco, Iacobucci, Aquino, Romana Alparone, and Palumbo ,2021) adopted technology acceptance model and conducted an online survey with 208 retail customers to evaluate the factors that determine the users' chatbot use. The survey findings suggested that perceived trust, enjoyment, and compatibility influenced the attitude and intentions to use chatbot technology while doing online shopping.

Research further suggests that customers prefer interacting with chatbots to handle minor issues or when they seek quick service (Meyer-Waarden, Pavone, Poocharoentou, Prayatsup, Ratinaud, Tison, and Torné, 2020). Looking over some recent statistics, a survey by Rajnerowicz (2022) confirmed that around 62 percent of customers like to interact with chatbots instead of human agents when they are short of time. Survey by Sweezey (2019) also revealed that around 69 percent of customers prefer using chatbots as they respond quickly. Another survey by PSFK (AI-powered, predictive trends analysis with supporting data and tools), as cited by Zabój (2022), suggested around 74 percent of customers prefer chatbots when seeking answers to basic queries. Findings of a survey by Ad-Week, as reported by Bazilian as cited by Zabój (2022), also confirmed that around 65 percent of customers feel comfortable interacting with chatbots for simple issues. A survey by The Chatbot (2022) showed around 64 percent of customers prefer chatbot as it is available 24/7, while another survey by HubSpot (2022) confirmed that around 40 percent remain indifferent whether a chatbot or a human agent serves them provided the service quality offered by both remains same.

3. MATERIAL AND METHODS

This chapter covers the methodological and philosophical aspects of the study as well as the organized methods for gathering and analyzing data in order to meet the study's goals.

3.1. Theoretical Aspects of The Research Methodology

3.1.1. Research philosophy

Research philosophy represents a set of assumptions and beliefs about how research could be conducted. On the philosophical continuum, positivism and interpretivism lie at two opposite ends. Positivism philosophy advocates the use of statistical methods and techniques to answer research questions, while interpretivists tend to adopt qualitative methods to investigate the problem at hand (Alharahsheh and Pius, 2020). Choice of an appropriate philosophy depends on the purpose that research needs to fulfil and nature of research objectives. Positivists tend to evaluate research problems on logical grounds and collect objective facts to answer the research question. Whereas interpretivists tend to explore the problem by exercising subjective evaluation (Pather and Remenyi, 2005).

In the current case, the positivist philosophy was adopted to reveal the relationship between chatbot use and consumer behavior, i.e., rather than conducting in-depth research through subjective evaluation, the relationship between chatbot use and consumer behavior was measured, and statistical evidence was collected to measure the strength of the relationship between both variables from an objective and logical perspective (Antwi and Hamza, 2015).
Under the positivism philosophy, the study inherits the assumption that reality is independent and detached, and hence to understand it, the researcher should hold an independent stance. This assumption is applied by keeping detached from the data collection and analysis process to avoid reflecting personal opinions and judgments while analyzing and reporting the data (Mkansi and Acheampong, 2012). As positivism philosophy advocates the use of quantitative methods, it enhances the results' reliability, and enables the researcher to get a broader understanding by adding multiple variables into the framework. The improved reliability also enhances the practical applicability of results, which are backed with statistical evidence (Alharahsheh and Pius, 2020). However, there are some limitations of positivism philosophy as well. Like, positivists tend to adopt rigid methods with restrictive interpretation.

In this context, in relation to the aims of the research; first objective involves the evaluation of Turkish customers' perceptions and preferences of chatbot features and their overall satisfaction with chatbot usage, which could be assessed through quantitative survey, as it enables researcher to evaluate perceptions across multiple dimensions. Second and third objectives are quantitative in nature, as they need statistical testing to confirm the relationship between chatbot usage, socio-demographic characteristics, and consumer behavior. Fourth objective is also quantitative as it required researcher to run the mediation test to confirm whether usage area mediated the relationship between chatbot use and consumer behavior. Overall, the accomplishment of these objectives required researchers to collect objective data that could be used to test the relationship between identified variables. So here, positivism suits more due to its support for quantitative methods, objectivity and relationship testing than interpretivism.

Overall, the positivism philosophy's inclination towards the quantitative side, suitability for the proposed research objectives, and advocacy to propose the results that are backed with reliable statistical evidence, makes it more suitable for current research than interpretivist philosophy.

3.1.2. Research approach

The study has used the descriptive correlational approach to suit the purpose of the study related to "Chatbots and Chatbots in the Metaverse Usage Difference Among Generations (X, Y, Z)".

The research approach here denotes a step wise procedure that is followed to generate the desired knowledge. In academic research, the studies can employ either inductive or deductive research approaches, depending on what they want to achieve through investigation (Antwi and Hamza, 2015). If the research purpose is to propose a new theory at the end of the research because the chosen problem is new to literature, and very limited prior knowledge is available, then the inductive approach is applied through which researcher applies divergent thinking to unveil new patterns and insights, and then uses the new knowledge to develop new theory (Frisendal, 2012). Generally, inductive studies are followed by later deductive studies, which test the proposed theories in a real-world context. Now, connected to this, if the purpose of the research is to test an already existing theory, then the deductive approach is applied (Gregory and Muntermann, 2011).

In the current case, the research purpose is to test the existing knowledge to evaluate the extent to which chatbot usage influences consumer behavior. The chosen problem is not entirely new or unexplored, but needs further testing to understand the application, use and influence of chatbot on consumer behavior in different contexts. In this study, the deductive approach is preferred as it aims to propose practically applicable results (Antwi and Hamza, 2015). Based on existing theories and knowledge, hypotheses were designed that were tested through empirical research. The deductive approach was found to be appropriate for this research, which includes multiple variables and aims to provide a broader understanding of the problem that can help marketers promote the use of chatbots by understanding consumers' preferences and perceptions—even though it discourages different thinking due to its strong support for logic and objectivity (Al-Ababneh, 2020).

3.1.3. Research strategy.

The research strategy sets an overall direction for the research and includes the processes through which the empirical investigation is conducted. Researchers choose from different research strategies that better fulfil the research purpose. Survey and case studies are among the commonly employed research strategies. There are other research strategies as well, like grounded theory, ethnography, and action research, but these strategies are not relevant to current research (Saunders, Lewis, and Thornhill, 2009). In comparison, case study and survey strategies are more relevant, among which the survey strategy suits this research more than the case study research.

Typically, academic researchers choose the case study strategy when the researcher is interested in conducting empirical research in a single organization or setting. The survey strategy is chosen when the researcher wants to propose results that can be generalized to a larger population (Jones, Baxter, and Khanduja, 2013). The survey strategy is particularly useful when the aim is to understand the problem based on perceptions and opinions. It also facilitates data collection on different variables and dimensions in a time and cost-effective manner (Fowler, 2013).

The survey strategy also has some limitations. For example, the statistical methods used are based on technical and structural assumptions and the quality of the data is highly dependent on how the survey is administered. The accuracy of the findings assumes that all respondents fill in the questionnaire carefully and share their honest opinions (Groves, Fowler, Couper, Lepkowski, Singer, and Tourangeau, 2011). This limitation was overcome by excluding the questionnaires with incorrect answers from the analysis.

In this study applies a cross-sectional time horizon, which means the survey is conducted at a single time to capture the snapshot of reality (Yee and Niemeier, 1996). The cross sectional is applied for this study because of time and financial constraint. Furthermore, because of how people currently view and feel about using chatbots, they were also interested, which strengthened the case for using a cross-sectional timeframe rather than a longitudinal one (Saunders et al. 2009).

3.2. Theoretical Framework

The research design provides an overall roadmap that a study follows to achieve its research objectives. It is a framework of research techniques and methods that are chosen by researchers to conduct the research. By choosing the appropriate design, researchers tend to employ the methods that are appropriate for the underlying research problem (Akhtar, 2016).

Based on the overall literature insights, the study develops the following theoretical framework, which is tested by collecting empirical data. The framework provides the basis for the testable hypotheses:

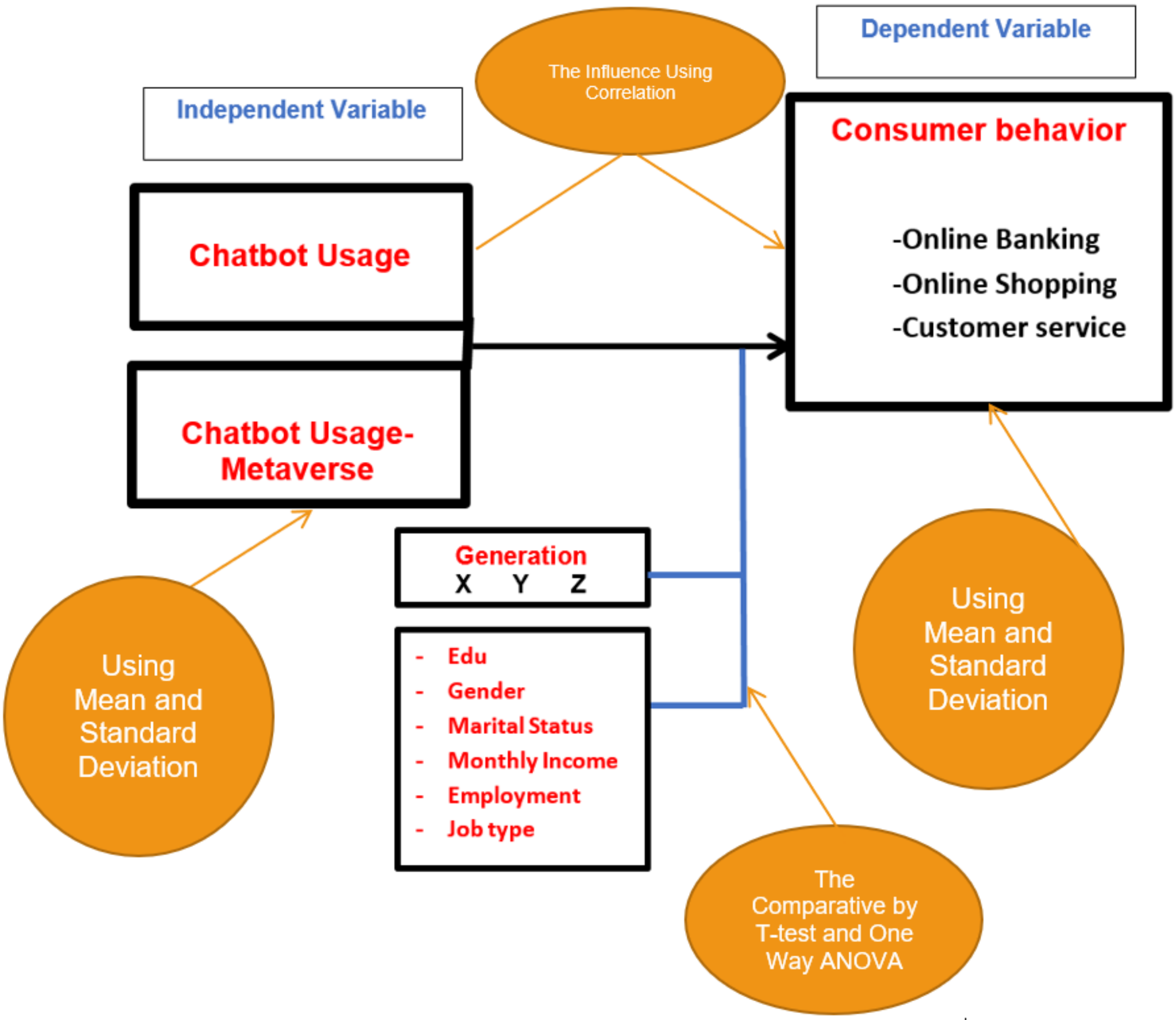

Figure 3. 1: Theoretical framework

The framework has two independent variables: chatbot usage and chatbot usage in the metaverse world. Consumer behavior is the dependent variable, which is operationalized by evaluating consumers' behavior towards purchase intentions. The study has evaluated the influence of chatbot use on usage area and compares whether the influence of chatbot use varies when consumers use a chatbot for online shopping, online banking, and customer service. And the study concentrated about some of socio-demographical data to show how the behavior deference in using Chatbot and Chatbot metaverse, beside the consumer behavior related to the sub-demographical data for the participants from the Chatbot users in Turkish community.

So, what is consumer behavior, it can be defined as the acts of consumers who are directly involved in acquiring, utilising, and discarding economic goods and services. Based on the cognitive model of psychology, which forms the foundation of consumer behaviour, it integrates components from sociology, economics, and psychology that affect consumer decision-making Altinigne, (2024).

The above framework is empirically tested by collecting data from Turkish consumers. Based on the above framework, the study hypotheses were as following:

H1- There are no statistically significant differences in the level of Chatbot usage according to the Generation (X, Y, and Z).

H2- There are no statistically significant differences in the level of Chatbot usage and Chatbot usage in the metaverse world according to sociodemographic factors (educational, Gender, Marital status, Monthly Income, Employment, and Job type).

H3- There are no statistically significant differences in the type of consumer behavior according to sociodemographic factors (educational level, Gender, Marital status, Monthly Income, Employment, and Job type).

3.3. Population and Sampling Design

The study's sample consists of Turkish men and women who utilize chatbots and make various online service purchases from various businesses. The simple random selection approach is used to choose a sample frame from generation X, Y, and Z for the cross-sectional survey research. Initially, the all relevant information were provided to participants and approval received. The ethical approval for this work was obtained from the Scientific Research and Publication Ethics Board of Adana Alparslan Türkeş Science and Technology University (Date: 30.0l.2024, Decree No: 06).

Determining the sample size correctly is important in marketing research. Malhotra, Nunan, and Birks, (2020) gives the optimum sample sizes used in different marketing researches. This study is a problem definition research and the minimum sample size is recommended as 500 and the ideal range as 1,000 to 2,500. In this study, 600 surveys were conducted considering time and financial constraints. To make the data collection process more convenient, time-efficient and cost-effective, and easy to administer, online data collection methods were selected. The research methodology literature recommends preferring online over offline surveys when minimal to no fieldwork is needed (Granello and Wheaton, 2004).

The study has used a 5-point Likert scale to measure response and define and operationalize variables, and defined variables. The study's scales are described in Table 3.1. In order to forward the goals of the research, some of the statements were changed and used. The 5-point Likert agreement scale was used, which included five options, in which 1 represented strong disagreement, 2 showed disagreement, 3 showed neutral, 4 showed agreements, and 5 showed strong agreement. The Likert scale is extensively used when the research studies intended to measure the respondents' perceptions and opinions towards a particular research problem (Nemoto and Beglar, 2014). A key reason for choosing the survey as the study instrument was that the close-ended questions made it possible for the researcher to generate a large amount of data by asking multiple questions (Fowler, 2013).

Table 3.1. Scales items used in the questionnaire form.

Scales	**Number of Items**	**Referances**
Tech-savvy	11	Følstad, A., and Brandtzaeg, P.B. 2020 Pompe, B. L. 2023
Excited decision-maker	8	Brandtzaeg, P.B., and Følstad, A. 2017 Li et al. 2020 Ruan and Mezei, 2022
Tech-skeptical	7	Jiang et al. 2022
Open-minded and tech-adaptable	2	Illescas-Manzano, 2021
Chatbots acceptance in Metaverse	10	Xie et al., 2023 Kovacova et al. 2022

The questionnaire form (Appendix A) prepared in accordance with the research objectives is given in the appendix.

As respondents only had to click the most appropriate response option, they were able to respond to multiple questions in a limited time. The collected data was in a form on which different statistical tests could be applied to test the relationship between chosen variables (Fowler, 2013). The research methodology literature also suggests that the use of a quantitative questionnaire is a more cost-effective option, and when an anonymous questionnaire is used, it enhances the accuracy of results, as respondents freely share their opinions without any fear of judgement (Jones et al. 2013). Moreover, as data is collected from a large sample size, it also enhances the generalizability of findings. Here in the current case, to improve the findings' validity, the study identified the variables and their descriptions from previous studies (like Khoa, 2021; Luo et al. 2019; Mozafari et al. 2020; Cheng and Jiang, 2021; Nguyen et al. 2021) while developing the questionnaire.

In academic studies, it is important for researchers to take care of reliability and validity aspects when reporting practically applicable findings. The findings with weak reliability and validity tend to have weak practical applicability as well. So, as in the current case, the purpose is to propose findings that could be used in the real world to understand consumer behavior, so it is important to ensure the reported results are reliable and valid (Taherdoost, 2016). Reliability shows how consistently the method measures something. To ensure high validity of the reported results before publishing the survey, a pre-test was conducted on the study and questions were simplified and refined based on pre-test feedback, ensuring clarity for your respondents. The following steps were then followed. First, simple and easy-to-understand language was used to develop the questionnaire. Secondly, variables and their definitions were identified from the literature and thirdly, data were collected from large samples to increase external validity. Thus, valid and reliable results were obtained (Saunders et al. 2009).

3.4. Data analysis methods

In this research, SPSS software was utilized, a sophisticated tool for statistical analysis, to meticulously analyze our data. This software enabled us to conduct advanced statistical tests and procedures, ensuring a robust examination of our dataset.

Explanatory factor analysis was done to employ the scales as a new variable. The foundation of factor analysis is the idea that, when many variables are assessed, some of them can measure distinct aspects of the same phenomena. In the analysis, the varimax rotation and principal components approach were applied. Also, the has evaluated the direct impact of Chatbots on consumer behavior using Pearson Correlation Test. Additionally, Independent Samples T-test and One Way-ANOVA tests were employed to highlight statistical differences in Chatbot usage and consumer behavior based on the demographic data of the respondents.

4. RESULTS AND DISCUSSIONS

Generation X, born between the early 1960s and early 1980s, is known for their adaptability, transitioning from analog to digital, and valuing independence, pragmatism, and work-life balance. Millennials (Y Generation), born roughly between the early 1980s and mid-1990s, grew up immersed in technology and diversity, prioritizing experiences over possessions, and seeking purposeful work. They are tech-savvy and value their freedom, often excelling in using technology as a central aspect of their lives. Generation Z, born between the mid-1990s and early 2010s, are true digital natives. They are highly adept at multitasking, value authenticity and global connectivity, and have grown up with instantaneous access to information, facilitating easy communication and transportation through technological advancements. Each generation shows a progressive enhancement in technological engagement and a shift in social values and lifestyle priorities (Çelik and Gürcüoğlu, 2016). According to 2020 data, there are 22.603.338 million Generation X, 25.416.508 million Generation Y, and 5.623.319 million Generation Z in Türkiye (Ersoz and Demir,2020). It constitutes approximately 2/3 of the population.

4.1. Socio-Demographics Characteristics

The percentage distribution of different generations' socio-demographic profile in Table (4.1) showed that most participants were from the Male category with a percentage of (56.7%) where the females were (43.3%) from the distribution, and this indicates that there was a homogeny between a sample of the study. The participants were married (37.2%), and the single participants (62.8%). The occupation had the lowest distribution with (5.2%), and then the Operator (6.2%), while the White Color and students were very close with (43.7% and 39.5%) respectively, from the general distribution. There seemed to be a disproportionately higher number of respondents in their 25s and 40s from the Y Generation; those less than 24 years of Z Generation came in second, while the respondents from the X generation were third. Almost half of the participants held a bachelor’s degree, which is likely because of the target in which the survey was carried out. More than half (53,8%) of participants work full-time. 39.5 percent of our participants are students, which is normal because 37.8 percent are from Z Gen, while white-collar owners represent 43.6 percent of the respondents. The monthly household income of approximately 48.2% of participants is less than 15.000 Turkish Liras and 11.2 times more than 45.001 TL. It makes sense that there would be a clustering at the low-income level given the age distribution and occupations of the participants.

Table 4.1. Descriptive Statistics

Variable	Freq.	%	Variable	Freq.	%
Gender			**Marital Status**		
Female	260	43.3	**Married**	223	37.2
Male	340	56.7	**Single**	377	62.8
Occupation			**Educational level**		
Blue Color	31	5.2	**Primary School**	8	1.3
Operator	38	6.3	**Middle School**	11	1.8
White Color	262	43.7	**High School**	245	40.8
student	237	39.5	**Bachelor's degree**	289	48.2
other	32	5.3	**Inception**	47	7.8
Employment Status			**Generation**		
Full time	323	53.8	**Less than 24 years (Z Gen)**	227	37.8
Part-time	30	5.0	**25 – 40 years (Y Gen)**	256	42.7
Retried	8	1.3	**41-56 years (X Gen)**	109	18.2
Unemployed	239	39.8	**(57-66 years (Baby boomers)**	8	1.3
Total	600	100.0			
Monthly Income					
less than 15.000 TL	289	48.2			
15.001 – 30.000 TL	125	20.8			
30.001- 45.000 TL	119	19.8			
more than 45.001 TL	67	11.2			

4.2. Factor Analysis

On the other hand factor analysis was used to show the statement relation with its dimension in section three of the questionnaire and a names was assigned for each factor, the study has conducted some of the tests to show the data suit for sample as (Kaiser-Meyer-Olkin) KMO which value was of (0.932) indicating an excellent level of sampling adequacy and with significant level less than (0.01) and if a "KMO value above 0.9 is considered excellent," (Noor Ul Hadi, 2016). Although the reliability values of the scale using the Cronbach Alpha test were acceptable for this study, the reliability values ranged between 0.775 and 0.922 with total value = (0.939) and these values higher than (0.70) and these values were between (Good and Excellent evaluation) which these values were acceptable as (Hair, Black, Babin, Anderson, and Tatham, 2010), as shown in table (4.2).

Table 4.2. KMO and Bartlett's Test to show the sampling adequacy

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.932
Bartlett's Test of Sphericity	Approx. Chi-Square	8394.997
	df	378
	Sig.	.000

As a rule of thumb, Tabachnick and Fidell, (2013) stated that the interpretation of factors with loadings of 0.32 and higher would reduce the overlapping variance. In this study, factor loadings of 0.30 and above were interpreted. In the exploratory factor analysis, factor loadings of 6 items weights were found to be low and overlapping. The difference between the maximum loading value of one item in the factors and the next highest loading value must be at least 0.10. In the initial analysis, since the difference(s) between the factor loading values in six items was less than 10%, they were considered overlapping and were removed from the study (Tabachnick and Fidell, 2013). For this reason, the statements numbered (1,7, 8, 10, 16, and 17) as per the questionnaire below in the Appendix were removed from the analysis. An exploratory factor analysis was conducted again with the remaining items.

As a result of the analysis, four factors were obtained, and these factors explain 56.4% of the variance. indicates that more than half of the total variability in our dataset is captured by these factors, reflecting their collective significance in representing the underlying structure of the sample data. The first factor is named "Tech- savvy" which this group of the statements Interacted with chatbots highlights their adeptness with technology and their creative mindset, that was explained 35.275% of the variance, second factor is " Excited decision-maker and this group of statements refer to leveraging chatbot technology to enhance decision-making and customer experiences. customer-centric influencer (9.971%) from the variance. The 6.252% from the variance came from Tech-skeptical, and worry from chatbot, and the statements collection means apprehensive about chatbots, cautious about their growing role and impact in daily life, finally the Open minded consisted of two statements which measured the level of adaptable, embracing new technologies and innovations with flexibility and enthusiasm, and the tech adaptable explained (4.898%) from the variance, as shown in table (4.3).

Table 4.3. Factor Analysis Results

Statement	Component			
	F1	F2	F3	F4
Factor 1 Tech-savvy, innovative and efficient				
Using chatbots is satisfying	.803			
Chatbots can handle my returns and exchanges without any problems	.761			
Having a conversation with chatbots is enjoyable	.760			
Chatbots can offer me products and services I need help finding from another brand	.746			
Chatbots are like a fun game in the free time	.739			
Chatbots give me new information	.733			
E-Shopping is faster using chatbots	.664			
Chatbots make it easier for me to review products	.638			
I can talk to chatbots easily because I know they are not human.	.617			
Chatbots are skilled at finding innovative solutions to problems	.598			
Chatbot is more empathetic than customer representative	.552			
Factor 2 Excited decision-maker, customer-centric influencer				
Chatbots can easily recognize our picture		.697		
Chatbots can easily recognize our voice		.683		
Chatbots can easily recognize us based on our sentences or the way we write.		.643		
Chatbots are a fascinating technology		.619		
Chatbots help us choose our needs rationally		.604		
Chatbots have changed online shopping habits and online service style		.594		
Chatbots like Microsoft chatbot can always support you to solve your laptop problem		.585		
Chatbots have a huge impact on our personal and family lives		.547		
Factor 3 Tech-skeptical, and worry from chatbot				
The lifeless interlocutor annoys me			.776	
I can't explain my problem to chatbots			.689	
Chatbot creates anxiety in finding the correct goods and services			.681	
Chatbots etc. Technologies increase my privacy concerns			.676	
I'm worried from using chatbots			.635	
I worry that our lives will increasingly be ruled by chatbots			.502	
Chatbots must be able to react emotionally			.495	
Factor 4 Open-minded and tech-adaptable				
I am open to innovations				.857
I am successful and willing to use technology				.843
Cronbach's Alpha	0.922	0.872	0.775	0.808
Eigenvalues	9.877	2.792	1.751	1.371
Variance %	35.275	9.971	6.252	4.898

4.3. Construct Validity

The rule of construct validity refers to the principle that a test or measurement tool must accurately and reliably measure the theoretical construct it is intended to assess. This principle is foundational in research and testing across various fields like psychology, education, and social sciences. And the current study needs to use this type of the validity measurement to discriminant and Convergent Validity: Part of establishing construct validity involves showing that the test does not measure unrelated constructs (discriminant validity) and correlates well with other tests supposed to measure the same construct (convergent validity).

The study has used the Pearson Correlation test to show the statistically significant relationship between the statements and their dimensions that assure the discriminant of the statements and who many extents related with its dimensions as shown in table (4.4) below. And it's noted from table 4.4 that the correlation coefficient values between scale statements and their dimensions related to it were higher than the value of 0.30 and it's the minimum value for acceptance to discriminate the statements (Pallant, 2005), and its measure the same idea, which confirms the construction validity, and the scale was contained from (28) statements.

Table 4.4. Construct Validity Scale of Chatbots

Tech-savvy, innovative and efficient		Excited decision-maker, customer-centric influencer		Tech-skeptical, and worry from chatbot		Open-minded and tech-adaptable	
#	**R**	**#**	**R**	**#**	**R**	**#**	**R**
A30	.847**	A3	.660**	A18	.733**	A33	.914**
A29	.782**	A2	.696**	A25	.672**	A34	.918**
A26	.797**	A14	.721**	A15	.684**		
A28	.774**	A5	.735**	A24	.688**		
A31	.761**	A13	.798**	A4	.628**		
A27	.772**	A6	.706**	A35	.585**		
A22	.755**	A11	.741**	A20	.588**		
A23	.727**	A12	.751**				
A36	.652**						
A21	.705**						

**: significant at level of 0.01

Also, for Chatbots in the metaverse, the correlation coefficient values between scale statements and their dimensions related to it were higher than the value of 0.30 and it's the minimum value for acceptance to discriminate the statements (Pallant, 2005), and its measure the same idea, which confirms the construction validity, and the scale was contained from (10) statements (table 4.5).

Table 4.5. Construct Validity Scale of Chatbots acceptance in Metaverse world

Chatbots acceptance in Metaverse world	
1	.819**
2	.829**
3	.835**
4	.816**
5	.798**
6	.831**
7	.428**
8	.797**
9	.867**
10	.801**

****: significant at level of 0.01**

Five Likert scale was used (strongly disagree:1, disagree:2, neutral/undecided:3, agree: 4, strongly agree:5).

Relative importance, assigned due to:

$$\text{Class Interval} = \frac{\text{Maximum Class} - \text{Minimum Class}}{\text{Number of Level}}$$

$$\text{Class Interval} = \frac{5 - 1}{3} = \frac{4}{3} = 1.00$$

- The Low degree from 1.00- less than 2.33.
- The Medium degree from 2.34 – less than 3.67.
- The High degree from 3.68 – 5.00.

4.4. The Results of Factor Analysis as an Independent Variable

The arithmetic Mean, standard deviation, item importance, and importance level were calculated to show the level of innovative technology, usage, and technology concerns of the chatbot.

4.4.1. Tech-savvy, innovative and efficient

Based on the data presented in the following table (4.6), the mean values of the dimension ranged between 3.48 and 2.83, where the whole dimension earned a total mean of 3.18, which is a medium level. The "Chatbots make it easier for me to review products" item was ranked first a mean of (3.48), a standard deviation of (1.02), which is of a medium level. While the statement "Chatbots are like a fun game in the free time" ranked last with mean of (2.83), and a Standard Deviation of (1.21), which is of a medium. Participants rated chatbots as moderately effective, with overall mean scores between 2.83 and 3.48. According to Wald, Heijselaar, and Bosse (2020) gamification and personalization to increase user engagement can lead to chatbots being perceived as fun.

Table 4.6. Descriptive Statistics of Tech-savvy

Statements	Mean	S.D.	Rank	Level
Chatbots make it easier for me to review products	3.48	1.02	1	Medium
E-Shopping is faster using chatbots	3.42	1.08	2	Medium
Chatbots give me new information	3.34	1.09	3	Medium
Chatbots can offer me products and services I need help finding from another brand	3.30	1.12	4	Medium
Chatbots are skilled at finding innovative solutions to problems	3.23	1.09	5	Medium
I can talk to chatbots easily because I know they are not human.	3.22	1.25	6	Medium
Chatbots can handle my returns and exchanges without any problems	3.15	1.10	7	Medium
Using chatbots is satisfying	3.06	1.14	8	Medium
Having a conversation with chatbots is enjoyable	2.99	1.18	9	Medium
Chatbot is more empathetic than customer representative	2.94	1.21	10	Medium
Chatbots are like a fun game in the free time	2.83	1.21	11	Medium
Total	3.18	0.85		Medium

4.4.2. Excited decision-maker, customer-centric influencer

The mean values of the "enthusiastic decision maker, customer-oriented influencer" dimension vary between 3.45 and 2.88; the total average of the entire dimension (3.28) can be interpreted as moderate. When evaluated according to Mean (3.45) and Standard Deviation (1.00), the statement "Chatbots can easily recognize our picture" is above the general average and ranks first. "Chatbots have a great impact on our personal and family lives" is ranked last. The data shows that respondents perceived chatbots to be moderately effective at facilitating enthusiastic decision-making and being customer-centric, with mean scores ranging from 2.88 to 3.45, with the overall mean for the dimension being 3.28. These results also suggest that respondents are aware of the success of new technologies in predicting consumer behavior.

Table 4.7. Descriptive Statistics of Excited decision-maker

Statements	Mean	SD	Rank	Level
Chatbots can easily recognize our picture	3.45	1.00	1	Medium
Chatbots can easily recognize our voice	3.36	1.04	2	Medium
Chatbots are a fascinating technology	3.35	1.08	3	Medium
Chatbots have changed online shopping habits and online service style	3.35	1.08	3	Medium
Chatbots like Microsoft chatbot can always support you to solve your laptop problem	3.32	1.06	5	Medium
Chatbots can easily recognize us based on our sentences or the way we write.	3.29	1.07	6	Medium
Chatbots help us choose our needs rationally	3.23	1.10	7	Medium
Chatbots have a huge impact on our personal and family lives	2.88	1.21	8	Medium
Total	3.28	0.78		Medium

4.4.3. Tech-skeptical and worry from chatbots

The results in table 4.8 show that the participants mean values of this dimension (Tech-skeptical and worry from chatbot) ranged between 3.44 and 2.99, where the whole dimension earned a total mean of 3.17, which is a medium level. The statement is "I worry that our lives will increasingly be ruled by chatbots" ranked first with mean of (3.44), with standard deviation of (1.23), which is of a medium level. The statement of 20, which stipulated (Chatbots must be able to react emotionally) ranked last with a mean of (2.99), and a standard deviation of (1.23), which is of a medium level. The data indicates that participants perceive chatbots as moderately tech-skeptical and concerned, with mean scores ranging from 2.99 to 3.44 and an overall mean of 3.17 for the dimension. Devi and Chanda (2022) found in their research that customers are still skeptical about shopping online through these digital assistants. The existence of security risks such as hacking, misuse of personal information, unauthorized access was listed as reasons for skepticism. In the other study about health, it was determined that participants distrust chatbots in understanding their worries and concerns and are skeptical about giving detailed answers and empathy (Tsai, Lun, Carcioppolo, and Chuan, 2021). However, based on risk-benefit analysis, Kim, Ryoo, Lee, and Lee (2023) imparted that people who typically have doubts about how chatbots will utilize their personal data can really benefit from saving time and money, improving themselves, and enjoying chatbot ads.

Table 4.8. Descriptive Statistics of Tech-skeptical

Statements	Mean	SD.	Rank	Level
I worry that our lives will increasingly be ruled by chatbots	3.44	1.23	1	Medium
I can't explain my problem to chatbots	3.42	1.15	2	Medium
Chatbots etc. Technologies increase my privacy concerns	3.23	1.14	3	Medium
I'm worried from using chatbots	3.07	1.13	4	Medium
The lifeless interlocutor annoys me	3.04	1.24	5	Medium
Chatbot creates anxiety in finding the correct goods and services	3.02	1.07	6	Medium
Chatbots must be able to react emotionally	2.99	1.23	7	Medium
Total	3.17	0.77		Medium

4.4.4. Open-minded and tech adaptable.

The participants mean values of dimension Open-minded and tech-adaptable dimension ranged between 4.16 and 4.03, where the whole dimension earned a total mean of 4.10, which is a high level. Statement stipulated (I am open to innovations) ranked first with mean of 4.16, with Standard Deviation of 0.95, which is of a high level, and statement "I am successful and willing to use technology" ranked second with mean of 4.03, and standard deviation of 0.97, which is of a high level also. The data indicates that participants perceive themselves as open-minded and tech-adaptable, with mean scores ranging from 4.03 to 4.16 and an overall mean of 4.10 for the dimension, while according to Gümüs and Çubukçu (2011) open innovation awareness in top Turkish companies is still very low.

Table 4.9. Descriptive Statistics of Open-minded

Statements	Mean	SD	Rank	Level
I am open to innovations	4.16	0.95	1	High
I am successful and willing to use technology	4.03	0.97	2	High
Total	4.10	0.88		High

The mean values of dimension "Chatbots acceptance in Metaverse world", ranged between 3.68 and 2.99, where the whole dimension earned a total mean of 3.46, which is a medium level. The statement "Chatbots in the Metaverse can guide and help us" ranked first with a Mean of 3.68, with a Standard Deviation of 0.93, which is of a high level. Participants' view of the acceptance of chatbots in the Metaverse environment as moderate. The responses reveal that consumers are wary of new technologies and are consistent with the tech-skeptical attitude factor. Mittal and Garg (2024) determined that 28.5 percent of consumers were cautious about artificial intelligence chatbots in terms of interest level, effectiveness, and fluency.

Table 4.10. Descriptive Statistics of Chatbots acceptance in Metaverse world

Statements	Mean	SD	Rank	Level
Chatbots in the Metaverse can guide and help us	3.68	0.93	1	High
Chatbots can offer a different experience in the Metaverse world	3.65	0.96	2	Medium
Businesses should develop their online shopping stores in the Metaverse environment	3.62	1.02	3	Medium
Chatbots on Metaverse are helpful and add value to your e-shopping experience	3.56	0.91	4	Medium
Chatbots in the Metaverse provide visual and Meaningful recommendations and prevent children from purchasing inappropriate products	3.49	1.01	5	Medium
Metaverse will be very useful as they can advise us on online stores	3.48	1.01	6	Medium
I believe it will provide a safer e-shopping opportunity	3.45	1.04	7	Medium
I'm excited to try Chatbots for e-shopping in the Metaverse	3.37	1.03	8	Medium
I think it is more satisfying than classic e-shopping	3.33	1.07	9	Medium
It seems scary for me to go through this experience	2.99	1.13	10	Medium
Total	3.46	0.79		Medium

4.5. The results of Consumer Behavior (Online Banking, Online Shopping, Customer Services)

The study has used frequency and percentages to show the Online Banking Usage of the participants. In Table 4.11, it shows that 94% of participants use online banking, primarily for routine transactions like bill payments 72.2%. However, more complex activities like stock and coin trading 17,0 % see significantly lower usage. These figures suggest that while digital banking is widely accepted for basic financial management, there is a notable reluctance or lack of need to engage in more sophisticated banking tasks online. This disparity highlights potential areas for banks to enhance service offerings, increase user trust and simplicity. It has been stated that personalization and ease of use in chatbots will especially affect the perceived intention to use in the banking sector (Alt et.al, 2021).

Table 4.11. Frequency and Percentages of Online Banking Usage

	Answers	Freq.	%
Using online banking in the current year	No	564	6.0
	Yes	36	94.0
Money Transfer	No	85	14.2
	Yes	515	85.8
Paying bills	No	167	27.8
	Yes	433	72.2
Foreign exchange buying / selling	No	430	71.7
	Yes	170	28.3
Stok, Coin buying selling	No	498	83.0
	Yes	102	17.0
Loan request	No	480	80.0
	Yes	120	20.0
Other	No	526	87.7
	Yes	74	12.3

It has been determined that consumer behavior in online banking varies significantly, with average scores varying between 0.86 and 0.17. Money transfers and bill payments are the most common activities, with averages of 0.86 and 0.72 respectively, and both are categorized at high levels (Table 4.12). Other activities such as foreign exchange, loan requests, and stock or coin trading are rated at low levels.

Table 4.12. Online banking

Statements (Online Banking)	Mean	Std. Deviation	Rank	Level
Money Transfer	0.86	0.35	1	High
Paying bills	0.72	0.45	2	High
Foreign exchange buying/selling	0.28	0.45	3	Low
Loan request	0.20	0.40	4	Low
Stok, Coin buying, selling	0.17	0.38	5	Low

It would not be unrealistic to say that today's people are rapidly adopting the increasing use of technology in every field. Especially the integration of smart systems, the ease of receiving services digitally, the increase in social communities and communication digitally increase the use of the internet day by day. According to 2021 data, there are 5.4 billion internet users in the world. Although Asian countries with high population take the first place in terms of the number of users, the countries with the highest usage rate according to population are North America (93.4%), Europe (89.2%) and Latin America/Car (80.5%) (https://www.internetworldstats.com/stats.htm). It is estimated that the number of people using the Internet will increase by 47 per cent to 7.9 billion in 2029. The Global Web Index states that people use the internet for an average of 6.5 hours a day, although the time spent online varies across age groups. However, compared to 55–64-year-olds, 16–24-year-olds spend 2.5 hours more time online (https://www.forbes.com/home-improvement/internet/internet-statistics). Internet usage is increasing rapidly in Turkey. According to TÜİK (2023) data, the rate of individuals using the Internet was 87.1%. According to the We are social 2023 report, an average of 7 hours and 24 minutes a day is spent on the internet in Turkey and 39.2 % of this time is spent on social media (https://datareportal.com/reports/digital-2023-turkey). Table 4.13 shows the daily internet usage rates of the participants. Accordingly, it was found that 64.8% of the participants were online between 1-5 hours and 12.8% were online for more than 9 hours.

Table 4.13. Online hours per day

Per day hours	Freq.	%
1-3 hours	200	33.3
4-5 hours	189	31.5
6-8 hours	134	22.3
more than 9 hours	77	12.8
Total	600	100.0

In addition to the potential benefits of increased exposure to, acceptance of, and readiness to try new technologies, businesses are finding it easier to reach customers with new technologies and expose them to stimuli. Finding out how different generations use the internet is crucial for AI applications where personalization is involved. The result showed that most of the participants using the internet were from the Z generation, compared with Y and X generations for the three categories 4 to 5 hrs., 6 to 8 hrs. and more than 9 hrs. except the range between 1 and 3 hrs. the variants were in favor of Y generation (Table 4.14).

Table 4.14. Generations daily internet use

		Age			Total
		Z	Y	X	
1-3 hours	Count	44	90	59	193
	% within Q11Code	22.8	46.6	30.6	100.0
4-5 hours	Count	79	76	33	188
	% within Q11Code	42.0	40.4	17.6	100.0
6-8 hours	Count	67	55	12	134
	% within Q11Code	50.0%	41.0%	9.0%	100.0
more than 9 hours	Count	37	35	5	77
	% within Q11Code	48.1	45.5	6.5	100.0
Total	Count	227	256	109	592
	% within Q11Code	38.3	43.2	18.4	100.0

0 – 0.33 Low, 0.34 – 0.67 Medium, 0.68 – 1.00 High

The findings showed a difference between consumer behavior regarding Online Shopping and Customer service, with consumer behavior regarding technology purchasing 1% versus furniture and decoration 4%. Additionally, there were differences in the level of customer service in tourism services 8.8%, healthcare services 94.5% and educational services 92.5% (Table 4.15).

Table 4.15. Frequency and percentages for the consumer behavior

	Using	Freq.	%
Ready to Wear	Yes	31	5.2
	No	569	94.8
Technology	Yes	66	11.0
	No	534	89.0
Household appliances	Yes	31	5.2
	No	569	94.8
Accessories	Yes	32	5.3
	No	568	94.7
Furniture Decoration	Yes	24	4.0
	No	576	96.0
Tourism Services	Yes	53	8.8
	No	547	91.2
Health Services	Yes	33	94.5
	No	567	5.5
Education Services	Yes	45	92.5
	No	555	7.5
Telecommunication	Yes	64	10.7
	No	536	89.3
Banking Finance	Yes	71	11.8
	No	529	88.2

In the study, basic statistics regarding the variables defined as consumer behavior in the model were determined and given in table 4.16. Online Banking activities show a high level of engagement, with mean values ranging between 0.86 and 0.17, and a notable overall mean of 0.45, suggesting strong consumer participation especially in money transfers and bill payments. Conversely, online Shopping and customer service behaviors display significantly lower mean values, all under 0.2, indicating less frequent usage among consumers. For online shopping, technology products lead with the highest mean of 0.11, yet this is still considered low, reflecting limited consumer interaction in purchasing technology, ready wear, and other items online. Similarly, in customer service, the highest mean value is 0.11 for telecommunication services, which is low, followed by even lower engagement in tourism, education, and health services. These trends reveal a discrepancy between frequent online banking and less frequent shopping or service-related online interactions, possibly due to varying levels of trust, necessity, or satisfaction with online experiences across these sectors. This suggests opportunities for businesses to enhance online shopping and customer service platforms to increase consumer engagement and satisfaction.

Table 4.16. The level of (Consumer Behavior)

Statements (Consumer Behavior)	Mean	Std. Deviation	Rank	Level
Money Transfer	0.86	0.35	1	High
Paying bills	0.72	0.45	2	High
foreign exchange buying / selling	0.28	0.45	3	Low
loan request	0.20	0.40	4	Low
Stok, Coin buying selling	0.17	0.38	5	Low
Online Banking	**0.45**	**0.25**		**Medium**
Technology	0.11	0.31	1	**Low**
Ready_Wear	0.05	0.22	2	**Low**
Household_appliances	0.05	0.22	2	**Low**
Accessories	0.05	0.22	2	**Low**
Furniture_Decoration	0.04	0.20	5	**Low**
Online_shopping	**0.06**	**0.17**		**Low**
Telecommunication	0.11	0.31	1	**Low**
Tourism_Services	0.09	0.28	2	**Low**
Education_Services	0.08	0.26	3	**Low**
Health_Services	0.06	0.23	4	**Low**
Customer_service	**0.08**	**0.20**		**Low**
Consumer Behavior (Total)	**0.20**	**0.13**		**Low**

0 – 0.33 Low, 0.34 – 0.67 Medium, 0.68 – 1.00 High

4.6. Comparison Analysis for Independent Variables.

Table 4.17 shows the mean and standard deviation values of how the factors are distributed across generations. The average attitude values of Generation Z, which has been exposed to technology since birth, were found to be higher in all factors compared to other generations. The statistical significance of this difference was also tested. A significant difference was found between generations in the One-Way ANOVA test (Table 4.17).

Table 4.17. Basic statistical indicators of factors in generations

		N	Mean	Std. Deviation
Tech_savvy	Z	227	3.40	0.84
	Y	256	3.05	0.87
	X	109	3.02	0.75
	Total	592	3.18	0.85
Excited, decision maker	Z	227	3.44	0.77
	Y	256	3.19	0.81
	X	109	3.12	0.71
	Total	592	3.28	0.79
Tech_skeptical	Z	227	3.25	0.82
	Y	256	3.11	0.76
	X	109	3.12	0.66
	Total	592	3.17	0.77
Open_minded	Z	227	4.14	0.80
	Y	256	4.18	0.87
	X	109	3.82	1.01
	Total	592	4.10	0.88
Metaverse_Factor	Z	227	3.68	0.75
	Y	256	3.37	0.80
	X	109	3.24	0.73
	Total	592	3.46	0.79

The results showed that there were a statistically significant differences in the level of chatbot usage (Tech Savvy, Decision Maker, Open-minded) and Chatbots Usage in Metaverse world according to the Consumer Generation, F values = (12.551, 8.932, 7.011, 15.852) respectively, which these values are significant at the level of 0.05 and to show the source of differences in the level of Chatbots Usage and Chatbots Usage in Metaverse world according to the Consumer Generation, the study has used Scheffe-test for post-Hoch Multiple Comparison as shown in Table 4.19. While the results showed that there were no statistically significant differences in the level of (Tech skeptical) factor according to the consumer generation.

Table 4.18. Differences in the level of chatbot usage between generation

		Sum of Squares	df	Mean Square	F	Sig.
Tech_savvy_F1	Between Groups	17.637	2	8.818	12.551	.000*
	Within Groups	413.834	589	.703		
	Total	431.471	591			
Excited_ decision Maker F2	Between Groups	10.776	2	5.388	8.932	.000*
	Within Groups	355.300	589	.603		
	Total	366.076	591			
Tech_skeptical_F3	Between Groups	2.699	2	1.349	2.307	.100
	Within Groups	344.534	589	.585		
	Total	347.233	591			
Open_minded_F4	Between Groups	10.727	2	5.364	7.011	.001*
	Within Groups	450.590	589	.765		
	Total	461.318	591			
Metaverse_Factor	Between Groups	18.771	2	9.386	15.852	.000*
	Within Groups	348.743	589	.592		
	Total	367.515	591			

*: Significant at level of (0.05)

Scheffe test results in table 4.19 showed that the variance in the level of Tech savvy, Excited decision makers, and Chatbots in the Metaverse world were in favor of the Z generation, while the Open-minded level was in favor of Y followed by Z generations. According to Belen et al., (2021) users over 45 exhibited higher degrees of concern.

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Table 4.19. Scheffe test

Dependent Variable	Age	Age	Mean Difference	Sig.
Tech_savvy_F1	Z	Y	.34605*	.000
		X	.37396*	.001
	Y	Z	-.34605-*	.000
		X	.02791	.959
	X	Z	-.37396-*	.001
		Y	-.02791-	.959
Excited Decision makers F2	Z	Y	.24895*	.002
		X	.32516*	.002
	Y	Z	-.24895-*	.002
		X	.07622	.692
	X	Z	-.32516-*	.002
		Y	-.07622-	.692
Open_minded_F4	Z	Y	-.03456-	.910
		X	.32666*	.006
	Y	Z	.03456	.910
		X	.36122*	.002
	X	Z	-.32666-*	.006
		Y	-.36122-*	.002
Metaverse_Factor	Z	Y	.31387*	.000
		X	.44528*	.000
	Y	Z	-.31387-*	.000
		X	.13141	.329
	X	Z	-.44528-*	.000
		Y	-.13141-	.329

There are statistically significant differences in the level of Chatbots Usage and Chatbots Usage in Metaverse world according to the educational level. The results in table 4.20 showed that there were apparent differences between Means values in the level of Chatbots Usage and Chatbots Usage in Metaverse world according to the educational level, and to show the statistically significant differences, One-Way ANOVA test was used as shown in table 4.21.

Table 4.20. Chatbots and Chatbots usage in metaverse world and education

		N	Mean	Std. Deviation
Tech_savvy	Primary School	8	3.07	0.35
	Middle School	11	3.26	0.51
	High School	245	3.33	0.85
	Bachelor’s degree	289	3.10	0.82
	inception	47	2.89	1.02
	Total	600	3.18	0.85
Excited, decision maker	Primary School	8	3.45	0.37
	Middle School	11	3.34	0.64
	High School	245	3.42	0.80
	Bachelor’s degree	289	3.18	0.75
	inception	47	3.10	0.91
	Total	600	3.28	0.78
Tech_skeptical_F3	Primary School	8	3.21	0.33
	Middle School	11	3.12	0.51
	High School	245	3.30	0.80
	Bachelor’s degree	289	3.10	0.76
	inception	47	2.95	0.64
	Total	600	3.17	0.77
Open_minded_F4	Primary School	8	3.31	1.10
	Middle School	11	3.73	0.85
	High School	245	4.12	0.80
	Bachelor’s degree	289	4.04	0.93
	inception	47	4.51	0.76
	Total	600	4.10	0.88
Metaverse_Factor	Primary School	8	3.00	0.00
	Middle School	11	3.27	0.74
	High School	245	3.58	0.81
	Bachelor’s degree	289	3.40	0.75
	inception	47	3.34	0.85
	Total	600	3.46	0.79

The results showed that there were a statistically significant differences in the level of Chatbots Usage (Tech Savvy, Enthusiastic decision, Tech skeptical and Open minded) and Chatbots Usage in Metaverse world according to the educational level, F values (4.190, 3.898, 3.205, 5.183) respectively, which these values are significant at level of 0.05 and to show the source of differences in the level of Chatbots Usage and Chatbots Usage in Metaverse world according to the educational level, the study has used Scheffe-test for post-Hoch Multiple Comparison as shown in table 4.22.

While the results showed that there were statistically significant differences in the level of (Metaverse factor) according to the educational level, F value = 3.072, and it's not significant at the level of 0.05 and shows the source of the variance in Mean values, the study has used Scheffe test as following. In a study conducted on the use of smart tourism technologies, it was determined that the level of education showed a significant difference (Turdubaeva and Kızanlıklı, 2022).

Table 4.21. Chatbots and Chatbots usage in metaverse world and education-ANOVA test

		Sum of Squares	df	Mean Square	F	Sig.
Tech_savvy_F1	Between Groups	11.905	4	2.976	4.190	.002*
	Within Groups	422.668	595	.710		
	Total	434.573	599			
Excited, decision maker	Between Groups	9.411	4	2.353	3.898	.004*
	Within Groups	359.135	595	.604		
	Total	368.546	599			
Tech_skeptical_F3	Between Groups	7.397	4	1.849	3.205	.013*
	Within Groups	343.305	595	.577		
	Total	350.701	599			
Open_minded_F4	Between Groups	15.599	4	3.900	5.183	.000*
	Within Groups	447.641	595	.752		
	Total	463.240	599			
Metaverse_Factor	Between Groups	7.476	4	1.869	3.072	.016*
	Within Groups	362.027	595	.608		
	Total	369.503	599			

Scheffe test results in table 4.22 showed that the variance in the level of Tech savvy, Excited decision, Tech skeptical and Chatbots in the Metaverse world was in favor of high school, and the level of open-minded was in favor of a inception, then the variance was in favor of high school, followed by the bachelor’s degree.

Table 4.22. Scheffe test

Dependent Variable	Qualification	Qualification	Mean Difference	Sig.
Tech_savvy	Primary School	Middle School	-.19628-	.616
		High School	-.26429-	.383
		Bachelor’s degree	-.02713-	.928
		Inception	.17843	.580
	Middle School	Primary School	.19628	.616
		High School	-.06800-	.794
		Bachelor’s degree	.16915	.514
		Inception	.37471	.185

Dependent Variable	Qualification	Qualification	Mean Difference	Sig.
	High School	Primary School	.26429	.383
		Middle School	.06800	.794
		Bachelor’s degree	.23715*	.001
		Inception	.44272*	.001
	Bachelor’s degree	Primary School	.02713	.928
		Middle School	-.16915-	.514
		High School	-.23715-*	.001
		inception	.20556	.121
	Inception	Primary School	-.17843-	.580
		Middle School	-.37471-	.185
		High School	-.44272-*	.001
		Bachelor’s degree	-.20556-	.121
Excited, decision maker	Primary School	Middle School	.11222	.756
		High School	.03476	.901
		Bachelor’s degree	.27319	.327
		Inception	.35472	.233
	Middle School	Primary School	-.11222-	.756
		High School	-.07746-	.746
		Bachelor’s degree	.16098	.500
		Inception	.24250	.352
	High School	Primary School	-.03476-	.901
		Middle School	.07746	.746
		Bachelor’s degree	.23844*	.000
		Inception	.31996*	.010
	Bachelor’s degree	Primary School	-.27319-	.327
		Middle School	-.16098-	.500
		High School	-.23844-*	.000
		Inception	.08153	.505
	Inception	Primary School	-.35472-	.233
		Middle School	-.24250-	.352
		High School	-.31996-*	.010
		Bachelor’s degree	-.08153-	.505
Tech_skeptical	Primary School	Middle School	.09740	.783
		High School	-.08192-	.764
		Bachelor’s degree	.11048	.685
		Inception	.25988	.371
	Middle School	Primary School	-.09740-	.783
		High School	-.17933-	.444
		Bachelor’s degree	.01308	.955
		Inception	.16248	.523
	High School	Primary School	.08192	.764
		Middle School	.17933	.444
		Bachelor’s degree	.19240*	.004
		Inception	.34180*	.005
	Bachelor’s degree	Primary School	-.11048-	.685
		Middle School	-.01308-	.955
		High School	-.19240-*	.004
		Inception	.14940	.212
	Inception	Primary School	-.25988-	.371
		Middle School	-.16248-	.523

Dependent Variable	Qualification	Qualification	Mean Difference	Sig.
		High School	-.34180-*	.005
		Bachelor's degree	-.14940-	.212
Open_minded	Primary School	Middle School	-.41477-	.304
		High School	-.81199-*	.009
		Bachelor's degree	-.72729-*	.020
		Inception	-1.19814-*	.000
	Middle School	Primary School	.41477	.304
		High School	-.39722-	.138
		Bachelor's degree	-.31252-	.241
		Inception	-.78337-*	.007
	High School	Primary School	.81199*	.009
		Middle School	.39722	.138
		Bachelor's degree	.08470	.261
		Inception	-.38615-*	.005
	Bachelor's degree	Primary School	.72729*	.020
		Middle School	.31252	.241
		High School	-.08470-	.261
		Inception	-.47085-*	.001
	Inception	Primary School	1.19814*	.000
		Middle School	.78337*	.007
		High School	.38615*	.005
		Bachelor's degree	.47085*	.001
Metaverse_Factor	Primary School	Middle School	-.27273-	.452
		High School	-.58204-*	.038
		Bachelor's degree	-.39827-	.155
		Inception	-.34255-	.251
	Middle School	Primary School	.27273	.452
		High School	-.30931-	.199
		Bachelor's degree	-.12554-	.601
		Inception	-.06983-	.789
	High School	Primary School	.58204*	.038
		Middle School	.30931	.199
		Bachelor's degree	.18377*	.007
		Inception	.23949	.054
	Bachelor's degree	Primary School	.39827	.155
		Middle School	.12554	.601
		High School	-.18377-*	.007
		Inception	.05572	.650
	Inception	Primary School	.34255	.251
		Middle School	.06983	.789
		High School	-.23949-	.054
		Bachelor's degree	-.05572-	.650

The study has used descriptive analysis and Independent Samples T-test to show the statistically significant differences in the level of Chatbots Usage and Chatbots Usage in Metaverse world according to the gender. And the results of Independent Samples T-test showed that there were a statistically significant differences in the level of Tech Savvy according to gender T value =

-2.422 with significant level 0.016 and its less than 0.05 and the variance was in favor of male. There were no statistically significant differences in the level of excited, decision maker, Tech skeptical, open-minded, and metaverse factor according to the gender t values were of (-1.554 -, 0.465, 0.663, -1.117-) respectively, and these values not significant at the level of 0.05 as shown in table 4.23.

Table 4.23. Chatbots usage and chatbots usage in metaverse world and gender-T Test

	Gender	N	Mean	Std. Deviation	T value	Df	Sig.
Tech savvy	Female	260	3.08	0.86	-2.422-	598	.016*
	Male	340	3.25	0.84			
Exciting Decision maker	Gender	260	3.22	0.79	-1.554-	598	.121
	Female	340	3.32	0.78			
Tech skeptical	Gender	260	3.19	0.73	.465	598	.642
	Female	340	3.16	0.79			
Open minded	Gender	260	4.12	0.89	.663	598	.507
	Female	340	4.08	0.87			
Metaverse Factor	Gender	260	3.42	0.84	-1.117-	598	.264
	Female	340	3.49	0.74			

The study has used descriptive analysis and Independent Samples T-test to show the statistically significant differences in the level of chatbot usage and chatbot usage in the Metaverse world according to marital status. And the results of the Independent Samples T-test showed that there were statistically significant differences in the level of Tech Savvy, Exciting Decision Maker, and Metaverse factor according to gender T values = (-3.305, -2.393, -3.771) with significant level less than 0.05 and the variance was in favor of Single. There are no statistically significant differences in the level of Tech skeptical and minded according to the Marital Status (t) values -0.821 and -1.768, respectively, and these values are not significant at the level of 0.05 as shown in table 4.24.

Table 4.24. Chatbots usage and chatbots usage in metaverse world and marital status-T Test

	Marital status	N	Mean	Std. Deviation	T value	Df	Sig.
Tech-savvy	Married	223	3.03	0.79	-3.305-	598	.001*
	Single	377	3.27	0.87			
Exciting Decision maker	Married	223	3.18	0.76	-2.393-	598	.017*
	Single	377	3.34	0.79			
Tech skeptical	Married	223	3.14	0.67	-.821-	598	.412
	Single	377	3.19	0.81			
Open minded	Married	223	4.01	0.93	-1.768-	598	.078
	Single	377	4.14	0.84			
Metaverse Factor	Married	223	3.31	0.72	-3.771-	598	.000*
	Single	377	3.55	0.81			

There are no statistically significant differences in the level of Chatbots Usage and Chatbots Usage in Metaverse world according to the monthly income. The results in the table 4.25 showed that there were apparent differences between means values in the level of Chatbots Usage and Chatbots Usage in Metaverse world according to the monthly income and to show the statistically significant differences; One-Way ANOVA test was used (Table 4.26).

Table 4.25. Chatbots and Chatbots Usage in Metaverse world and Income

		N	Mean	Std. Deviation
Tech_savvy	less than 15000 TL	289	3.3709	.81641
	15001 - 30000 TL	125	3.1062	.89153
	30001- 45000 TL	119	2.9832	.81052
	more than 45000 TL	67	2.8331	.80392
	Total	600	3.1788	.85176
Excited, decision maker	less than 15000 TL	289	3.4183	.76629
	15001 - 30000 TL	125	3.2560	.81038
	30001- 45000 TL	119	3.1218	.75553
	more than 45000 TL	67	2.9869	.74179
	Total	600	3.2775	.78439
Tech_skeptical	less than 15000 TL	289	3.2739	.77582
	15001 - 30000 TL	125	3.0994	.81849
	30001- 45000 TL	119	3.0924	.67714
	more than 45000 TL	67	3.0128	.71849
	Total	600	3.1724	.76517
Open_minded	less than 15000 TL	289	4.1228	.85369
	15001 - 30000 TL	125	4.2240	.83872
	30001- 45000 TL	119	3.9034	.89556
	more than 45000 TL	67	4.0821	.99086
	Total	600	4.0958	.87941
Metaverse_Factor	less than 15000 TL	289	3.6021	.74176
	15001 - 30000 TL	125	3.3856	.86544
	30001- 45000 TL	119	3.3151	.76807
	more than 45000 TL	67	3.2552	.74596
	Total	600	3.4613	.78541

The results showed that there were statistically significant differences in the level of Chatbots Usage (Tech Savvy, Enthusiastic decision, Tech Skeptical, Open minded) and Chatbots Usage in the Metaverse world according to the monthly income (Table 4.26).

Table 4.26. Chatbots and Chatbots Usage in Metaverse world and Income- ANOVA test

		Sum of Squares	df	Mean Square	F	Sig.
Tech_savvy_F1	Between Groups	23.881	3	7.960	11.552	.000*
	Within Groups	410.692	596	.689		
	Total	434.573	599			
Excited, decision maker	Between Groups	14.323	3	4.774	8.033	.000*
	Within Groups	354.223	596	.594		
	Total	368.546	599			
Tech_skeptical_F3	Between Groups	6.108	3	2.036	3.521	.015*
	Within Groups	344.594	596	.578		
	Total	350.701	599			
Open_minded_F4	Between Groups	6.685	3	2.228	2.909	.034*
	Within Groups	456.554	596	.766		
	Total	463.240	599			
Metaverse_Factor	Between Groups	11.832	3	3.944	6.572	.000*
	Within Groups	357.671	596	.600		
	Total	369.503	599			

*: Significant at a level of (0.05)

Scheffe test results in Table 4.27 showed that the variance in the level of Tech savvy, Excited decision makers, Tech Skeptical and Metaverse world were in favor of monthly income (less than 15.000 TL, and the variance of (Open Minded) was in favor of monthly income 15.001 – 30.000 TL.

Table 4.27. Scheffe test

Dependent Variable	Monthly_Income	Monthly_Income	Mean Difference	Sig.
Tech_savvy_F1	less than 15000 TL	15001 - 30000 TL	.26469*	.003
		30001- 45000 TL	.38768*	.000
		more than 45000 TL	.53776*	.000
	15001 - 30000 TL	less than 15000 TL	-.26469-*	.003
		30001- 45000 TL	.12299	.248
		more than 45000 TL	.27307*	.030
	30001- 45000 TL	less than 15000 TL	-.38768-*	.000
		15001 - 30000 TL	-.12299-	.248
		more than 45000 TL	.15009	.237
	more than 45000 TL	less than 15000 TL	-.53776-*	.000
		15001 - 30000 TL	-.27307-*	.030
		30001- 45000 TL	-.15009-	.237

Dependent Variable	Monthly_Income	Monthly_Income	Mean Difference	Sig.
Excited, decision maker	less than 15000 TL	15001 - 30000 TL	.16225*	.050
		30001- 45000 TL	.29640*	.000
		more than 45000 TL	.43131*	.000
	15001 - 30000 TL	less than 15000 TL	-.16225-*	.050
		30001- 45000 TL	.13415	.175
		more than 45000 TL	.26906*	.022
	30001- 45000 TL	less than 15000 TL	-.29640-*	.000
		15001 - 30000 TL	-.13415-	.175
		more than 45000 TL	.13491	.252
	more than 45000 TL	less than 15000 TL	-.43131-*	.000
		15001 - 30000 TL	-.26906-*	.022
		30001- 45000 TL	-.13491-	.252
Tech_skeptical_F3	less than 15000 TL	15001 - 30000 TL	.17442*	.033
		30001- 45000 TL	.18141*	.029
		more than 45000 TL	.26106*	.012
	15001 - 30000 TL	less than 15000 TL	-.17442-*	.033
		30001- 45000 TL	.00699	.943
		more than 45000 TL	.08664	.452
	30001- 45000 TL	less than 15000 TL	-.18141-*	.029
		15001 - 30000 TL	-.00699-	.943
		more than 45000 TL	.07964	.493
	more than 45000 TL	less than 15000 TL	-.26106-*	.012
		15001 - 30000 TL	-.08664-	.452
		30001- 45000 TL	-.07964-	.493
Open_minded_F4	less than 15000 TL	15001 - 30000 TL	-.10116-	.281
		30001- 45000 TL	.21948*	.022
		more than 45000 TL	.04075	.731
	15001 - 30000 TL	less than 15000 TL	.10116	.281
		30001- 45000 TL	.32064*	.004
		more than 45000 TL	.14191	.285
	30001- 45000 TL	less than 15000 TL	-.21948-*	.022
		15001 - 30000 TL	-.32064-*	.004
		more than 45000 TL	-.17873-	.182
	more than 45000 TL	less than 15000 TL	-.04075-	.731
		15001 - 30000 TL	-.14191-	.285
		30001- 45000 TL	.17873	.182
Metaverse_Factor	less than 15000 TL	15001 - 30000 TL	.21648*	.009
		30001- 45000 TL	.28695*	.001
		more than 45000 TL	.34685*	.001
	15001 - 30000 TL	less than 15000 TL	-.21648-*	.009
		30001- 45000 TL	.07047	.478
		more than 45000 TL	.13038	.267
	30001- 45000 TL	less than 15000 TL	-.28695-*	.001
		15001 - 30000 TL	-.07047-	.478
		more than 45000 TL	.05990	.613
	more than 45000 TL	less than 15.000 TL	-.34685-*	.001
		15.001 – 30.000 TL	-.13038-	.267
		30.001- 45.000 TL	-.05990-	.613

To interpret the previous results, the study has conducted a Crosstabulation test for the monthly income with the generation, the results from table 4.28 showed that the most participants were at monthly income less than 15.000 TL and its direct relationship with Z generation.

Table 4.28. Cross table age and income

Generation	less than 15000 TL	15001 - 30000 TL	30001- 45000 TL	more than 45000 TL	Total
Z	208	14	3	2	227
Y	68	83	63	42	256
X	9	26	51	23	109
Baby boomers	4	2	2	0	8
Total	289	125	119	67	600

The results in table (4.29) showed that there was a clear difference between means values in the level of Chatbots Usage and Chatbots Usage in the Metaverse world according to the employment, and to show the statistically significant differences, a One-Way ANOVA test was used.

Table 4.29. Chatbots and Chatbots usage in metaverse world and employment

		N	Mean	Std. Deviation
Tech_savvy_F1	Full time	323	2.9797	.81746
	Part time	30	3.4515	.91860
	Retried	8	3.3409	.69362
	Unemployed	239	3.4081	.82947
	Total	600	3.1788	.85176
Excited, decision maker	Full time	323	3.1227	.75515
	Part time	30	3.5875	.79948
	Retried	8	3.3594	.69577
	Unemployed	239	3.4451	.78217
	Total	600	3.2775	.78439
Tech_skeptical_F3	Full time	323	3.0650	.71580
	Part time	30	3.4381	.88217
	Retried	8	3.5714	.58654
	Unemployed	239	3.2708	.79735
	Total	600	3.1724	.76517
Open_minded_F4	Full time	323	4.0635	.93988
	Part time	30	4.2000	.70221
	Retried	8	4.1250	.58248
	Unemployed	239	4.1255	.82308
	Total	600	4.0958	.87941
Metaverse_Factor	Full time	323	3.3170	.75998
	Part time	30	3.5700	.94765
	Retried	8	3.1875	.56930
	Unemployed	239	3.6519	.76383
	Total	600	3.4613	.78541

In the Table (4.30), the results shows that there were statistically significant differences in the level of Chatbots Usage (Tech Savvy, Enthusiastic decision, Tech Skeptical) and Chatbots Usage in Metaverse world according to the employment, (F) values = (13.583, 9.839, 5.489, 9.203) respectively, which these values are significant at level of 0.05 and to show the source of differences in the level of Chatbots Usage and Chatbots Usage in Metaverse world according to the employment, the study has used Scheffe-test for post-Hoch Multiple Comparison as shown in table (4.31) below and the variance between Means values according to the factors was in favor of part-time followed by unemployed.

Table 4.30. Chatbots and Chatbots usage in metaverse world and employment - ANOVA Test

		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Tech_savvy_F1	Between Groups	27.812	3	9.271	13.583	.000*
	Within Groups	406.761	596	.682		
	Total	434.573	599			
Excited, decision maker	Between Groups	17.391	3	5.797	9.839	.000*
	Within Groups	351.155	596	.589		
	Total	368.546	599			
Tech_skeptical_F3	Between Groups	9.429	3	3.143	5.489	.001*
	Within Groups	341.272	596	.573		
	Total	350.701	599			
Open_minded_F4	Between Groups	.881	3	.294	.379	.768
	Within Groups	462.358	596	.776		
	Total	463.240	599			
Metaverse_Factor	Between Groups	16.358	3	5.453	9.203	.000*
	Within Groups	353.145	596	.593		
	Total	369.503	599			

Table 4.31. Scheffe test

Dependent Variable	Employment_Status	Employment_Status	Mean Difference	Sig.
Tech_savvy	Full time	Part time	-.47178-*	.003
		Retried	-.36117-	.222
		Unemployed	-.42840-*	.000
	Part time	Full time	.47178*	.003
		Retried	.11061	.737
		Unemployed	.04338	.786
	Retried	Full time	.36117	.222
		Part time	-.11061-	.737
		Unemployed	-.06723-	.821
	Unemployed	Full time	.42840*	.000
		Part time	-.04338-	.786
		Retried	.06723	.821
Excited, decision maker	Full time	Part time	-.46482-*	.002
		Retried	-.23670-	.389
		Unemployed	-.32241-*	.000
	Part time	Full time	.46482*	.002
		Retried	.22812	.455
		Unemployed	.14242	.339
	Retried	Full time	.23670	.389
		Part time	-.22812-	.455
		Unemployed	-.08571-	.756
	Unemployed	Full time	.32241*	.000
		Part time	-.14242-	.339
		Retried	.08571	.756
Tech_skeptical	Full time	Part time	-.37308-*	.010
		Retried	-.50641-	.062
		Unemployed	-.20576-*	.002
	Part time	Full time	.37308*	.010
		Retried	-.13333-	.658
		Unemployed	.16732	.254
	Retried	Full time	.50641	.062
		Part time	.13333	.658
		Unemployed	.30066	.269
	Unemployed	Full time	.20576*	.002
		Part time	-.16732-	.254
		Retried	-.30066-	.269
Metaverse_Factor	Full time	Part time	-.25297-	.086
		Retried	.12953	.638
		Unemployed	-.33485-*	.000
	Part time	Full time	.25297	.086
		Retried	.38250	.212
		Unemployed	-.08188-	.583
	Retried	Full time	-.12953-	.638
		Part time	-.38250-	.212
		Unemployed	-.46438-	.094
	Unemployed	Full time	.33485*	.000
		Part time	.08188	.583
		Retried	.46438	.094

There are no statistically significant differences in the level of Chatbots Usage and Chatbots Usage in Metaverse world according to the Occupation type. To answer this question, the study has used descriptive analysis and the One-Way ANOVA test to show the statistically significant differences in the level of Chatbots Usage and Chatbots Usage in the Metaverse world according to the occupation type as following. The results in Table (4.32) showed that there were apparent differences between Means values in the level of Chatbots Usage and Chatbots Usage in Metaverse world according to the Occupation type, and to show the statistically significant differences, One-Way ANOVA test was used.

Table 4.32. Chatbots and Chatbots Usage in Metaverse world and occupation

		N	Mean	Std. Deviation
Tech_savvy_F1	Blue Color	31	2.98	0.74
	Operator	38	3.23	0.59
	White Color	262	3.01	0.87
	student	237	3.38	0.88
	other	32	3.16	0.46
	Total	600	3.18	0.85
Excited, decision maker	Blue Color	31	3.17	0.71
	Operator	38	3.21	0.53
	White Color	262	3.13	0.81
	student	237	3.47	0.78
	other	32	3.29	0.64
	Total	600	3.28	0.78
Tech_skeptical_F3	Blue Color	31	3.17	0.59
	Operator	38	3.14	0.64
	White Color	262	3.06	0.74
	student	237	3.31	0.83
	other	32	3.12	0.61
	Total	600	3.17	0.77
Open_minded_F4	Blue Color	31	4.03	0.94
	Operator	38	3.82	0.90
	White Color	262	4.10	0.93
	student	237	4.16	0.82
	other	32	4.00	0.80
	Total	600	4.10	0.88
Metaverse_Factor	Blue Color	31	3.08	0.64
	Operator	38	3.34	0.71
	White Color	262	3.35	0.79
	student	237	3.68	0.78
	other	32	3.27	0.58
	Total	600	3.46	0.79

From the table 4.33, the results showed that there were statistically significant differences in the level of Chatbots Usage (Tech Savvy, Enthusiastic decision, Tech Skeptical) and Chatbots Usage in the Metaverse world according to the Occupation type, (F) values = (6.476, 6.158, 3.227, 8.742) respectively, which these values are significant at level of 0.05 and to show the source of differences in the level of Chatbots Usage and Chatbots Usage in Metaverse world according to the Occupation type, the study has used Scheffe-test for post-Hoch Multiple Comparison as shown in table (4.34) below. While the results showed that there were no statistically significant differences in the level of (Open Minded) factor according to the Occupation type, (F) value = 0.232 and it was not significant at a level of 0.05 and the variance between Means values if found, but it is not significant.

Table 4.33. Chatbots and Chatbots Usage in Metaverse world and occupation- ANOVA Test

		Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Tech_savvy_F1	Between Groups	18.129	4	4.532	6.476	.000*
	Within Groups	416.444	595	.700		
	Total	434.573	599			
Excited, decision maker	Between Groups	14.650	4	3.662	6.158	.000*
	Within Groups	353.896	595	.595		
	Total	368.546	599			
Tech_skeptical_F3	Between Groups	7.447	4	1.862	3.227	.012*
	Within Groups	343.254	595	.577		
	Total	350.701	599			
Open_minded_F4	Between Groups	4.325	4	1.081	1.402	.232
	Within Groups	458.915	595	.771		
	Total	463.240	599			
Metaverse_Factor	Between Groups	20.511	4	5.128	8.742	.000*
	Within Groups	348.992	595	.587		
	Total	369.503	599			

*: Significant at a level of (0.05)

Scheffe test results in Table (4.34) showed that the variance in the level of Tech savvy, Excited decision makers, Tech Skeptical, and chatbots in the Metaverse world were in favor of students.

Table 4.34. Scheffe test

Dependent Variable	Occupation_type	Occupation_type	Mean Difference	Sig.
Tech_savvy_F1	Blue Color	Operator	-.25019-	.822
		White Color	-.03510-	1.000
		student	-.40181-	.178
		other	-.17678-	.951
	Operator	Blue Color	.25019	.822
		White Color	.21509	.700
		student	-.15162-	.898
		other	.07342	.998
	White Color	Blue Color	.03510	1.000
		Operator	-.21509-	.700
		student	-.36671-*	.000
		other	-.14168-	.936
	student	Blue Color	.40181	.178
		Operator	.15162	.898
		White Color	.36671*	.000
		other	.22503	.728
	other	Blue Color	.17678	.951
		Operator	-.07342-	.998
		White Color	.14168	.936
		student	-.22503-	.728
Excited, decision maker	Blue Color	Operator	-.04849-	.999
		White Color	.03603	1.000
		student	-.29987-	.388
		other	-.11983-	.984
	Operator	Blue Color	.04849	.999
		White Color	.08452	.983
		student	-.25137-	.482
		other	-.07134-	.997
	White Color	Blue Color	-.03603-	1.000
		Operator	-.08452-	.983
		student	-.33590-*	.000
		other	-.15586-	.884
	student	Blue Color	.29987	.388
		Operator	.25137	.482
		White Color	.33590*	.000
		other	.18003	.820
	other	Blue Color	.11983	.984
		Operator	.07134	.997
		White Color	.15586	.884
		student	-.18003-	.820
Tech_skeptical_F3	Blue Color	Operator	.02304	1.000
		White Color	.10265	.973
		student	-.13971-	.920
		other	.04536	1.000

Dependent Variable	Occupation_type	Occupation_type	Mean Difference	Sig.
	Operator	Blue Color	-.02304-	1.000
		White Color	.07961	.985
		student	-.16275-	.826
		other	.02232	1.000
	White Color	Blue Color	-.10265-	.973
		Operator	-.07961-	.985
		student	-.24236-*	.014
		other	-.05729-	.997
	student	Blue Color	.13971	.920
		Operator	.16275	.826
		White Color	.24236*	.014
		other	.18507	.795
	other	Blue Color	-.04536-	1.000
		Operator	-.02232-	1.000
		White Color	.05729	.997
		student	-.18507-	.795
Metaverse_Factor	Blue Color	Operator	-.25942-	.743
		White Color	-.27487-	.468
		student	-.60022-*	.002
		other	-.19446-	.907
	Operator	Blue Color	.25942	.743
		White Color	-.01545-	1.000
		student	-.34080-	.167
		other	.06497	.998
	White Color	Blue Color	.27487	.468
		Operator	.01545	1.000
		student	-.32535-*	.000
		other	.08042	.989
	student	Blue Color	.60022*	.002
		Operator	.34080	.167
		White Color	.32535*	.000
		other	.40576	.096
	other	Blue Color	.19446	.907
		Operator	-.06497-	.998
		White Color	-.08042-	.989
		student	-.40576-	.096

The Crosstabulation test was used to illustrate the attitude toward the occupation type Chatbot usage from the sample of the study, and the results showed that most Chatbot usage was in favor of the student participants which were 85.7%, indicating most using Chatbot were from the young students in the community in their daily life (table 4.35).

Table 4.35. Occupation and age crosstabulation

			Age			Total
			Z	Y	X	
	Blue Color	Count	3	21	7	31
		% within Occupation_type	9.7	67.7	22.6	100.0
	Operator	Count	4	23	11	38
		% within Occupation_type	10.5	60.5	28.9	100.0
	White Color	Count	12	166	81	259
		% within Occupation_type	4.6	64.1	31.3	100.0
	student	Count	203	34	0	237
		% within Occupation_type	85.7	14.3	0.0	100.0
	other	Count	5	12	10	27
		% within Occupation_type	18.5	44.4	37.0	100.0
Total		Count	227	256	109	592
		%within Occupation_type	38.3	43.2	18.4	100.0

4.7. Comparison Analysis for Dependent Variables

The study has used descriptive analysis and One-Way ANOVA to show the statistically significant differences in the level of consumer behavior according to the generation for the participants as follows. The results in Table (4.36) showed that there were apparent differences between Means values in the level of consumer behavior according to the generation, and to show the statistically significant differences, the One-Way ANOVA test.

Table 4.36. Descriptive analysis

	N	Mean	Std. Deviation
Z	227	0.167	0.130
Y	256	0.224	0.137
X	109	0.196	0.123
Total	592	0.197	0.134

From the One Way-ANOVA test, the results showed that there were statistically significant differences in the level of consumer behavior according to the generation of the participants (F) value = 11.257 and its significance at a level of 0.05. and to show the source of the differences, the study has used the Scheffe test which the results are shown in Table (4.37) below.

Table 4. 37 One-Way ANOVA The level of consumer behavior according to the Generation

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.392	2	.196	11.257	.000
Within Groups	10.267	589	.017		
Total	10.659	591			

The Scheffe test showed that the variance in the level of consumer behavior was in favor of (Y) Generation participants Category, as shown in table 4.38.

Table 4.38. Scheffe test for multiple Comparison

Age	Age	Mean Difference	Sig.
Z	Y	-.05710-*	.000
	X	-.02915-	.167
Y	Z	.05710*	.000
	X	.02795	.181
X	Z	.02915	.167
	Y	-.02795-	.181

The study has used descriptive analysis, One-Way ANOVA, and independent samples t-test to show the statistically significant differences in the level of consumer behavior according to education level. The results in Table 4.39 showed that there were apparent differences between means values in the level of consumer behavior according to the education level, and to show the statistically significant differences, a One-Way ANOVA test was used.

Table 4.39. The level of Consumer behavior according to the educational level

	N	Mean	Std. Deviation
Primary School	8	.0250	.03450
Middle School	10	.1417	.14746
High School	242	.1804	.14349
Bachelor's degree	286	.2137	.12457
Inception	46	.2254	.11742
Total	592	.1972	.13430

From table (4.40), the results showed that there were statistically significant differences in the level of consumer behavior according to the education level of the participants (F) value = 6.473, and it is significant at a level of 0.05. To show the source of the differences, the study has used the Scheffe test.

Table 4.40. Consumer behavior and educational level-ANOVA Test

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.450	4	.113	6.473	.000
Within Groups	10.209	587	.017		
Total	10.659	591			

Scheffe test in Table 4.41 showed that the variance in the level of consumer behavior was in favor of a inception, then for bachelor's degree and followed by the high school education.

Table 4.41. Scheffe test

Qualification	Qualification	Mean Difference	Sig.
Primary School	Middle School	-.11667-	.482
	High School	-.15544-*	.030
	Bachelor's degree	-.18869-*	.003
	Inception	-.20036-*	.004
Middle School	Primary School	.11667	.482
	High School	-.03877-	.934
	Bachelor's degree	-.07203-	.578
	Inception	-.08370-	.508
High School	Primary School	.15544*	.030
	Middle School	.03877	.934
	Bachelor's degree	-.03325-	.082
	Inception	-.04492-	.345
Bachelor's degree	Primary School	.18869*	.003
	Middle School	.07203	.578
	High School	.03325	.082
	Inception	-.01167-	.989
Inception	Primary School	.20036*	.004
	Middle School	.08370	.508
	High School	.04492	.345
	Bachelor's degree	.01167	.989

The independent samples T-test showed that there were statistically significant differences in the level of consumer behavior according to gender, (t) value = 2.978, which is significant at the level of 0.05, and the variance was in favor of females independent samples T-test showed that there were statistically significant differences in the level of consumer behavior according to the gender, (t) value = 2.978 which is effective at the level of 0.05 and the variance was in favor of female.

Table 4.42. Consumer behavior and gender-t test

	Gender	N	Mean	Std. Deviation	T value	Df	Sig.
consumer behavior	Female	256	.2160	.13534	2.978	590	0.003*
	Male	336	.1830	.13193			

There are no statistically significant differences in the level of consumer behavior according to the Marital status. The results of the independent samples T-test showed that there were no statistically significant differences in the level of consumer behavior according to the marital status, (t) value = 1.184, which is not significant at the level of 0.05 and the variance between mean values if found, but it's not significant.

Table 4.43. Consumer behavior and marital status.

	Marital Status	N	Mean	Std. Deviation	T value	Df	Sig.
consumer behavior	Married	215	.2059	.12135	1.184	590	.237
	Single	377	.1923	.14107			

Another sub hypothesis is “there are no statistically significant differences in the level of consumer behavior according to the monthly income”. The results in Table 4.44 showed that there were apparent differences between means values in the level of consumer behavior according to the monthly income, and to show the statistically significant differences, a One-Way ANOVA test was used.

Table 4.44. Consumer behavior and income

	N	Mean	Std. Deviation
less than 15000 TL	285	.1753	.13989
15001 - 30000 TL	123	.2099	.12118
30001- 45000 TL	117	.2232	.11765
more than 45000 TL	67	.2219	.14712
Total	592	.1972	.13430

From the One Way-ANOVA test, the results showed that there were statistically significant differences in the level of consumer behavior according to the monthly income of the participants F value = 5.215 and its significant at the level of 0.05. To show the source of the differences, the study has used the Scheffe test, and its results are shown in Table 4.45 below.

Table 4. 45 Consumer behavior and income-ANOVA test

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.276	3	.092	5.215	.001*
Within Groups	10.383	588	.018		
Total	10.659	591			

Scheffe test in Table (4.46) showed that the variance in the level of consumer behavior was in favor of monthly income 30001- 45000TL followed by more than 45000 TL but it's not significant with other categories.

Table 4.46. Scheffe test

Monthly_Income	Monthly_Income	Mean Difference	Sig.
less than 15000 TL	15001 - 30000 TL	-.03457-	.122
	30001- 45000 TL	-.04790-*	.014
	more than 45000 TL	-.04657-	.085
15001 - 30000 TL	less than 15000 TL	.03457	.122
	30001- 45000 TL	-.01333-	.896
	more than 45000 TL	-.01200-	.950
30001- 45000 TL	less than 15000 TL	.04790*	.014
	15001 - 30000 TL	.01333	.896
	more than 45000 TL	.00133	1.000
more than 45000 TL	less than 15000 TL	.04657	.085
	15001 - 30000 TL	.01200	.950
	30001- 45000 TL	-.00133-	1.000

The results in table 4.47 showed that there were apparent differences between means values in the level of consumer behavior according to the employment status, and to show the statistically significant differences, a One-Way ANOVA test was used.

Table 4.47. Consumer behavior and employment status

	N	Mean	Std. Deviation	Maximum
Full time	321	.2163	.12424	.73
Part time	29	.2431	.16953	.87
Retried	3	.1778	.07698	.27
Unemployed	239	.1663	.13745	.80
Total	592	.1972	.13430	.87

From the One Way-ANOVA test, the results showed that there were statistically significant differences in the level of consumer behavior according to the employment status of the participants F value = 7.787, and its significant at level of 0.05 as shown in table 4.48. And, to show the source of the differences, the study has used the Scheffe test that the variance in the level of consumer behavior was in favor of the employment status category of part-time and followed by full-time.

Table 4.48. Consumer behavior and employment status-ANOVA test

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.407	3	.136	7.787	.000*
Within Groups	10.252	588	.017		
Total	10.659	591			

Table 4.49. Scheffe test

Employment_Status	Employment_Status	Mean Difference	Sig.
Full time	Part time	-.02680-	.778
	Retried	.03853	.969
	Unemployed	.04999*	.000
Part time	Full time	.02680	.778
	Retried	.06533	.881
	Unemployed	.07679*	.034
Retried	Full time	-.03853-	.969
	Part time	-.06533-	.881
	Unemployed	.01146	.999
Unemployed	Full time	-.04999-*	.000
	Part time	-.07679-*	.034
	Retried	-.01146-	.999

There were apparent differences between means values in the level of consumer behavior according to the occupation, and to show the statistically significant differences, a One-Way ANOVA test was used. The results showed that there were statistically significant differences in the level of consumer behavior according to the job type of the participants F value = 7.141 and its significant at a level of 0.05. To show the source of the differences, the study has used the Scheffe test.

Table 4.50. Consumer behavior and occupation

	N	**Mean**	**Std. Deviation**
Blue Color	31	.1978	.13627
Operator	38	.1689	.13101
White Color	259	.2292	.12439
student	237	.1707	.13883
other	27	.1623	.12890
Total	592	.1972	.13430

Table 4.51. Consumer behavior and occupation- ANOVA test

	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Between Groups	.495	4	.124	7.141	.000*
Within Groups	10.165	587	.017		
Total	10.659	591			

Scheffe test in table (4.52) showed that the variance in the level of consumer behavior was in favor of White Color.

Table 4.52. Scheffe test

Occupation	Occupation	Mean Difference	Sig.
Blue Color	Operator	.02899	.934
	White Color	-.03137-	.814
	student	.02710	.884
	other	.03550	.902
Operator	Blue Color	-.02899-	.934
	White Color	-.06036-	.139
	student	-.00189-	1.000
	other	.00651	1.000
White Color	Blue Color	.03137	.814
	Operator	.06036	.139
	student	.05847*	.000
	other	.06687	.178
student	Blue Color	-.02710-	.884
	Operator	.00189	1.000
	White Color	-.05847-*	.000
	other	.00840	.999
other	Blue Color	-.03550-	.902
	Operator	-.00651-	1.000
	White Color	-.06687-	.178
	student	-.00840-	.999

The study has used the Pearson Correlation test to show the relationship between using chatbots and the usage area online shopping according to products, banking operation, etc., reflecting the consumer behavior toward online shopping as shown in Table 4.53 below.

The results showed that there was no statistically significant relationship between (Tech savvy, Excited, decision maker, Tech Skeptical, Metaverse Factor, and Consumer behavior; (R) Correlation values were not significant at the level of 0.05. That assures acceptance of the null hypothesis for these variables.

The results showed that there was a statistically significant relationship between (Open Minded) and (Consumer behavior) (R) value = 0.082 with a significant level of 0.044, which is less than the significant level of 0.05 that assure rejection of null hypothesis and acceptance alternative which stipulated (There is significant relationship between using chatbots (Open

Minded) and the usage area (online shopping according to products, banking operation, etc. reflect the consumer behavior toward the online shopping.

Table 4. 53 Pearson Correlation Test

Consumer_behavior		
Tech_savvy_F1	Pearson Correlation	-.037-
	Sig. (2-tailed)	.364
	N	600
Excited, decision maker	Pearson Correlation	-.017-
	Sig. (2-tailed)	.679
	N	600
Tech_skeptical_F3	Pearson Correlation	-.060-
	Sig. (2-tailed)	.141
	N	600
Open_minded_F4	Pearson Correlation	.082*
	Sig. (2-tailed)	.044
	N	600
Metaverse_Factor	Pearson Correlation	.044
	Sig. (2-tailed)	.284
	N	600

*: Significant at a level of (0.05).

4.7.1. Hypothesis Testing Results

To investigate the Chatbots and Chatbots in the Metaverse Usage Difference Among Generations (X, Y, Z), three hypotheses were formulated and tested using appropriate statistical methods. The following sections present the hypotheses, the statistical tests applied, and the outcomes of these tests and table 4.54 shows. The analysis was conducted using various statistical tests to determine if there were significant differences based on the specified factors.

Table 4.54. The results of hypotheses

Hypothesis	Description	Result (Accepted/Rejected)	Statistical Test Applied
H1	There are no statistically significant differences in the level of Chatbot usage according to the Generation (X, Y, and Z).	Rejected.	**Descriptive analysis** **One-Way ANOVA**, p-value significance at the level (0.005) **Scheffe-test,** α -value significance at the level (0.005)
H2	There are no statistically significant differences in the level of Chatbot usage and Chatbot usage in the metaverse world according to sociodemographic factors (educational, Gender, Marital status, Monthly Income, Employment, and Job type).	Partially accepted.	**Descriptive analysis** **One-Way ANOVA**, p-value significance at the level (0.005) **Scheffe-test,** α -value significance at the level (0.005) **Independent Samples T-test** p-value significance at the level (0.005)
H3	There are no statistically significant differences in the type of consumer behaviour according to sociodemographic factors (educational level, Gender, Marital status, Monthly Income, Employment, and Job type).	Partially accepted.	**Descriptive analysis** **One-Way ANOVA**, p-value significance at the level (0.005) **Scheffe-test,** α -value significance at the level (0.005) **Independent Samples T-test** p-value significance at the level (0.005)

5. CONCLUSION

The study results showed that the level of (Tech savvy, Innovated, and Efficient) was medium level, and the statement stipulated, "Chatbots make it easier for me to review products) ranked first with medium level. This result may be due to the allowance of Chatbots to answer their inquiries about products, and it provides comfort and ease for the buyers; they can search for the products and services they need quickly and conveniently obtain them without the need to leave home or office, as well as getting access to a lot of information about the products such as their types, specifications, quality, and prices so individuals can choose the products they may want and meets their needs.

Even "e-shopping is faster using chatbots" came to a medium level. As well, this is because Chatbots make online shopping faster and more efficient, Chatbots provide instant responses to customer inquiries and assist in navigating the websites, speeding up the product search process and offer personalized recommendations based on customer preferences, enhancing the shopping experience, and accelerating purchasing decisions. Additionally, chatbots can handle administrative functions such as tracking shipments and managing returns and are available around the clock, and this result Our results are consistent with (Kasilingam, 2020; Zhang et al., 2020; Cicco et al., 2021).

Likewise, The findings of the study showed that (Excited, Decision-maker, and Customer-Centric Influencers) were also of a medium level from the participants perspectives, and the statement " Chatbots can easily recognize our picture" came in the first class with medium level and it's due to the customers feeling a sense of enthusiasm and engagement due to the advanced features of chatbots, such as their ability to recognize images, voices, and unique writing styles. This high-tech interaction, combined with the chatbots' practical assistance in making rational decisions and solving specific problems like technical support, significantly enhances the customer experience.

Additionally, Chatbots as an AI advanced technology is a wonderful and attract individuals enthusiastically, and the services they provide cannot be ignored in light of the continuous and many needs individuals have, and it’s agreed with (Winkler and Sollner, 2018)

On the other hand, the Tech-skeptical and worry about Chatbots were of a medium level, and it may be due to the discomfort with the impersonal nature of chatbots, as they often need help to understand and effectively respond to complex human problems fully. This limitation creates frustration and anxiety, especially when seeking specific goods or services. Additionally, using such technologies raises significant privacy concerns, leading to apprehension about over-reliance on chatbots in daily life. The desire for chatbots to have emotional intelligence reflects a need for more human-like interaction, highlighting the gap between current technological capabilities and the complex nuances of human communication and emotions. These results agree (Belen et al., 2021, Denecli, Yıldız and Deneçli, 2022).

While the results showed that (Open-minded and tech-adaptable) were at a high level, and it can lead to creativity when using chatbot technology, as this greatly helps in working on research, going beyond the limits of limited thinking, and even going beyond knowledge and the possibility of obtaining data and information, which benefits the user in a way that opens his horizons. Scientific and cognitive until the individual has a massive bank of information that helps him in his daily life and secures his needs. These results agree with (Araujo, 2018; Chatterjee et al., 2021; Jiménez-Barreto et al. 2021; Gkinko and Elbanna, 2022).

Conversely, individuals who use chatbot technology have a high level of acceptance of emerging technologies because of their influential role in helping individuals and employing them in a way that ensures successful searches and easy access to information through what chatbot technology offers, which has become one of the necessities of life in our days.

In the Metaverse, 3D chatbots are poised to revolutionize e-shopping by providing unique, immersive experiences. They offer valuable guidance and enrich the shopping process with visual and meaningful recommendations. These advancements are not only anticipated to make online shopping more satisfying and engaging compared to traditional methods but also safer, especially in preventing inappropriate purchases by children. While businesses are encouraged to develop their online stores in this virtual environment, users are excited and apprehensive about transitioning to this new form of shopping. The potential for a more secure and enjoyable shopping experience in the Metaverse is intriguing and, for some, daunting; these results align with (Xie et al., 2023) even though his study applied in a different dimension (education). This is due to the unique and interactive experience that chatbots add to the Metaverse world.

The study results are helpful for consumers as they provide insights into current trends in online banking behavior. Understanding the proportion of consumers using online banking for different services (like bill payments, foreign exchange, stock trading, and loan requests) helps identify areas of growing consumer engagement and potential gaps in service usage. This information can guide banks to enhance their online offerings and tailoring their services to meet consumer needs better. These findings can inform consumers about common practices and services they might not be utilizing, encouraging more informed financial decisions; these results agreed with the results per (Juniper Research, 2017, Eren, 2021)

However, the responses of participants regarding the use of chatbot technologies indicated that younger age groups, particularly Generation Z, show greater engagement in using this technology and this finding is attributed to the upbringing of this generation, which involved extensive computer, and mobile use and interaction with numerous websites. Their familiarity with navigating through various online platforms easily results from their broad experience in this domain. Generation Z, often referred to as the internet and technology generation, possesses unique skills and expertise in these areas, a trait that is less evident in older age groups from previous generations. Their upbringing in a tech-savvy environment has equipped them with distinct capabilities in using and interacting with digital technologies like chatbots, distinguishing them from older generations (X and Y), and these results agreed with (Xueming et al., 2019)

Also, the study findings reveal that there's a higher inclination towards using chatbot technologies among individuals studying at the high school level across various aspects, except for the open-mindedness aspect. In this regard, individuals with a master's degree showed a greater tendency, indicating a higher awareness of their use of chatbots. This is attributed to these individuals, typically belonging to Generation Y or X, known for their advanced level of awareness and perception. On the other hand, high school students, who predominantly fall into Generation Z, exhibit numerous motivations and inclinations, including a strong enthusiasm for using chatbots. This interest is closely linked to their age group, reflecting the characteristic tech engagement of Generation Z that agreed with the study (Statista, 2020; Hürriyet Daily News, 2020).

According to the results, this study revealed it was observed that the use of chatbots was equal among both males and females across all aspects of the study, except for the aspect of inclination towards technology and its innovations, where a clear preference was noted among males. These findings suggest that the desire to use chatbots is not confined to a specific gender, as the world of the internet and the services it provides cater extensively to both genders, fulfilling their needs and attracting both males and females. However, the greater orientation towards technology among males can be attributed to differences in technological interests and preferences and patterns of use and applications. Generally, our results partially agreed with (Kasilingam, 2020).

The findings show that singles individuals may use chatbots more than married ones due to having more free time, fewer family commitments, and lifestyles more aligned with technological trends. They might be more open to adopting new technologies and find chatbots useful for fulfilling social needs and maintaining privacy. These general trends can vary widely among individuals based on personal and cultural factors.

And the study found that chatbot usage was higher among individuals with incomes less than 15000 Turkish Lira, and, his trend can be attributed to the fact that this group primarily consists of younger individuals, most of whom are students belonging to Generation Z. To corroborate these findings, a cross-sectional test was conducted, which revealed that the inclination to use chatbots was more pronounced in this demographic. This higher usage among them may also be linked to their limited personal income and the lack of significant financial responsibilities within their families, also, Individuals with lower incomes may be more price-sensitive and more likely to use chatbots as it is free service.

The study's results indicated that part-time employees use chatbot technology more than others, primarily due to the ample time available to them. This is attributed to their limited working hours, which allow them the leisure time to spend on chatbot technology. The nature of part-time work, with its reduced hours, provides these employees with the opportunity to engage more with such technologies, possibly for personal interests, socializing, or even for further enhancing their professional skills. This trend highlights how work schedules and job demands can influence individuals' engagement with new technologies.

It was revealed that students among the study's sample exhibited the most remarkable inclination towards using chatbot technology. Notably, this group predominantly consisted of students from Generation Z. This finding was confirmed after conducting a crosstab test, which substantiated their higher usage of chatbot technology. As mentioned earlier, students who have sufficient time are more inclined to utilize and explore the various features of chatbot technology. Their engagement is facilitated by their available time, which allows them to delve into what this technology can offer, fulfilling their interests and needs in the process. This trend underscores the significant role of chatbots in catering to the technological curiosity and requirements of younger generations, particularly students who are keen on exploring new digital tools and platforms, this also, agreed with study of (Statista, 2020; Hürriyet Daily News, 2020).

It's noted that the influence on consumer behavior was more significant among Generation Y, who are typically employed and have a sufficient income that allows them to participate in electronic payments. This generation is also characterized by owning bank accounts and having the capability to make online payments or online shopping. Moreover, many in this group have families and tend to fulfill their children's desires to interact with various online platforms and make purchases from them.

This suggests that Generation Y financial capabilities, along with their familial responsibilities, greatly influence their consumer behavior, particularly in the realm of digital transactions and online shopping. Their ability to engage in e-commerce is not just for personal needs but also extends to meeting the demands and interests of their family members, especially children., however, as (Kamran, et al. 2021) found in his results reveal that perceived enjoyment and intelligence of AI tools positively influence user attitudes towards them, which means having chatbots in Metaverse may attract the Turkish consumer.
On the other hand, the study found that individuals with inception exhibited a higher influence level on consumer behavior. This trend could be associated with Generation Y. As previously analyzed, those people typically have their own jobs and independent income, granting them complete autonomy in behaviors related to dealing with online shopping platforms.

It was observed that females exhibited more pronounced consumer behaviour compared to males. This could be attributed to females seeking to fulfil their desires through what they see in online marketing, which tends to attract females more than males.
This difference in consumer behaviour might stem from various factors, including targeted marketing strategies that appeal more to female interests and preferences, Additionally, the

online shopping environment, which often emphasizes products and services that traditionally appeal to females, could play a significant role in this observed behavior.

The influence of digital marketing and its ability to cater to specific demographics is a key factor in shaping consumer behaviors and preferences in the digital era. And this result agrees with (Kasilingam, 2020).

The study found that marital status had no significant impact on consumer behaviour, with equal levels observed among married and single individuals. This result can be attributed to the fact that the desires for purchasing, online shopping, and even electronic payment are extensively blended among a broad segment of society. This blending makes consumer behaviour a shared characteristic that does not show bias towards one social status over another.

Essentially, the inclination towards e-shopping transcends marital status, indicating that such behaviours are uniformly distributed across different social states. This uniformity suggests that factors driving online consumer behaviour are more universally applicable, regardless of whether individuals are married or single.

Regarding consumer behaviour in relation to different monthly income levels, it was found that individuals with higher incomes tend to e-shop and purchase more; a higher income enables people to buy with greater ease, coupled with having bank accounts that are consistently well-funded.

This financial freedom does not restrict the individual but rather provides a broad scope for e-shopping, purchasing, and engaging in online payments. This reflects the relationship between financial capability and the propensity to participate actively in online consumer activities.
Similarly, to how the use of chatbot technology varies by occupation type, the study found a similar trend in consumer behaviour favouring those in part-time employment; this result can also be attributed to the fact that individuals working limited hours have more time to dedicate to online shopping, which satisfies their desires and offers a convenient form of shopping that fits well into their leisure time. This indicates that part-time workers, due to their more flexible schedules and potentially more free time, are likely to engage more in activities like online shopping, making the most of their time outside work. This trend underscores the influence of work schedules on consumer behavior, especially in the context of digital consumerism.

Finally, the study's analysis of consumer behaviour differences based on job type revealed that the 'White Collar' category tends to engage more in e-shopping in general; this preference can be attributed to the distinct social characteristics of this group. Individuals in this category often feel the need to present themselves well, whether at home, work or in social settings with friends. Social status plays a significant role in shaping one's identity and in efforts to enhance it through activities associated with this group, who consider themselves a distinguished segment of society. This reflects how socio-professional identity influences consumption patterns, with white-collar workers often seeking to maintain or enhance their social standing through their consumer choices.

These results demonstrate that consumer behavior is linked primarily to the open-minded factor rather than other factors. This outcome could be attributed to psychological and social factors, not technical ones; technical factors are merely tools that can be utilized based on an individual's inclinations and open-mindedness toward what they need or don't need.

Here, individuals can control their actions and emotions toward what they desire to own personally or for their or their family's needs,

Consumer behavior is tied to the extent of an individual's emotional engagement, enabling them to determine their needs accurately. Possessing technical skills does not play as significant a role in consumer behavior as does (Open Minded) to accept emerging technologies or follow specific applications that may cause financial strain or irresponsible behavior, and this is agreed with (Gkinko and Elbanna, A., 2022).

All of this diminishes the role of chatbot technology in consumer behavior while encouraging mental control, openness, and the use of insights and experience when engaging in consumption through online shopping websites.

LIMITATIONS

1. The sample limitation: it should be conducted on a larger scale that reflects the population well and the X, Y, and Z generations.
2. The trend in Technologies Changing toward the evolution of chatbot technology and AI causes findings might need to be updated quickly.
3. The study relies on self-reported data; there may be biases in how participants perceive and report their interactions with chatbots because the data was Self-Reporting
4. As data and privacy are important factors, the different generations might have varying levels of concern regarding data privacy and security when interacting with chatbots, which could impact their willingness to engage.
5. The study might not account perfectly for cultural or regional differences within generations, which can significantly impact consumer behavior and interaction with technology.
6. Variability in technical savvy, particularly among older generations

RECOMMENDATIONS

1. It would be useful to develop chatbots with tailored interaction styles and content that cater to the unique preferences and needs of each generation. For example, simpler, more direct interactions for Generation X and more engaging, multimedia-rich experiences for Millennials and Gen Z.
2. Implement capacity-building programs and educational initiatives focused on older generations to increase their comfort and proficiency with chatbot technology.
3. It is important that the chatbots should be designed with robust security features.
4. We should stay abreast of emerging trends and technologies in AI and chatbots to continually adapt and update the chatbot experience, keeping it relevant for all generations, especially the tech-savvy younger ones.
5. For younger generations, integrating chatbot functionalities into platforms they frequently use, like social media or gaming apps, to increase accessibility and engagement.
6. It will be useful to design chatbots that can interact in multiple languages and understand cultural nuances, catering to the diverse backgrounds within each generational cohort.
7. Service enterprises are recommended to reimagine their customer engagement strategies to enhance the overall customer experience by incorporating chatbots can play a crucial role in this transformation.

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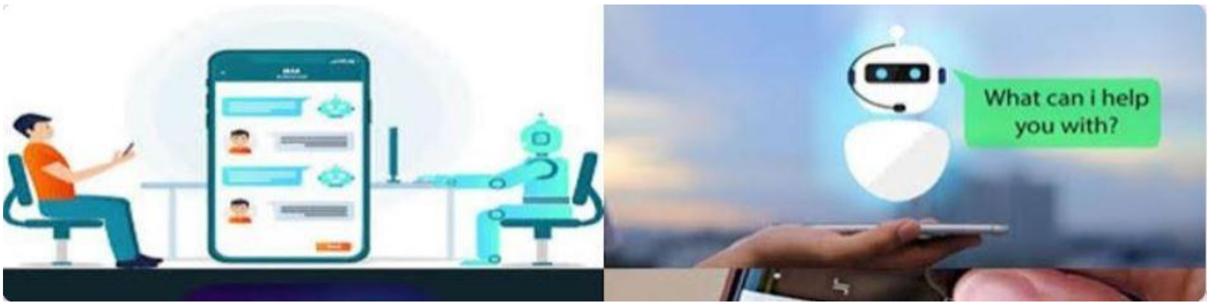
APPENDICES

Appendix A

Survey Form

CHATBOTS AND CHATBOTS IN THE METAVERSE USAGE DIFFERENCE AMONG GENERATIONS (X, Y, Z)

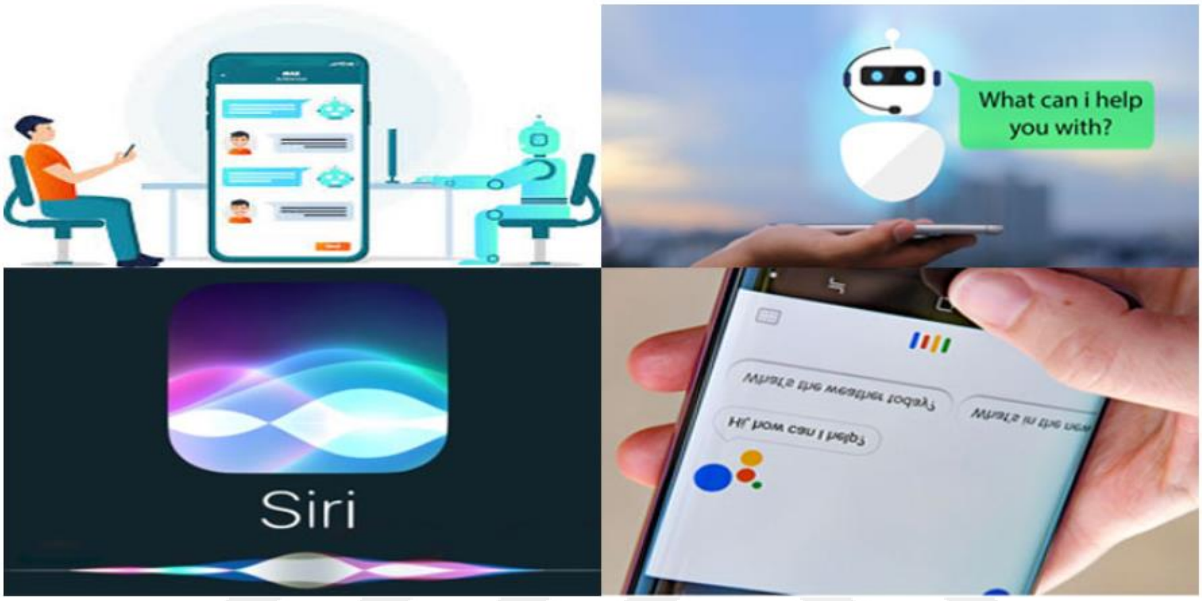


Consent text - Chat Robot

We invite you to the research/survey titled "The effect of the use of chat robots on consumer behavior" conducted by Celile Özçiçek Dölekoğlu and Muhammad Aboush. Before deciding whether to participate in this research/survey study, you need to know why and how the research will be conducted and the possible benefits and discomforts this research will bring to volunteer participants. Therefore, it is of great importance to read and understand this form. If there are things you do not understand or are not clear to you, or if you would like more information, please ask us. Participating in the research/survey is completely voluntary. Do not be under anyone's pressure or suggestion when answering the questions on the forms given to you. The information obtained from these forms will be used solely for research purposes and your information will be kept strictly confidential. In addition, this information will not be shared with any institution or person and will be anonymized or destroyed depending on its nature when the study is completed. You have the right not to participate in the study or to withdraw from the study at any time. In both cases, there will be absolutely no penalty or loss of benefits to which you are entitled." In addition, pictures, video and audio recordings, identity, contact information and financial information, group memberships, family information, health information, interview evaluation reports, survey forms, etc. All your information containing personal data, including personal data, will not be shared with any institution or person due to the Personal Data Protection Law No. 6698, and will not be shared with any institution or person when the working period ends (pictures, video and voice recordings, identity, contact information and financial information, group memberships, family information, health "All information, including information, interview evaluation reports, survey forms) will be destroyed in written and electronic form."

If you agree to participate in the survey, continue. Thanks for your participation.

Chatbot



1. I approve of participating in the survey.

a) Yes b) No

Section 1: Socio-demographic information

1. Gender

a) Female b) Male c)I do not want to specify.

2. Marital status

a) Married b) Single c) I do not want to specify.

3. What is your job?

4. Age

a) Under 24 b)25 – 40 c)41 – 56 d) 57 – 66

5. What is your employment status?

a) Full-time b) Part-time c) Retired d) unemployed

6. Last graduated school (Educational level)

7. primary school b)middle school c)high school d) bachelor's degree e) inception

8. Could you please indicate your monthly income?

a) <15000TL b)15001-30000TL c) 30001- 45000TL d)>45000TL

9. **Who/where do you get the most help when making purchasing decisions for the following product groups? (you can choose more than one)**

	chatbot	Friend	Family members/relatives	Sales Representative	blogger /Influencer	I don't get help.	Reviews on sales sites
ready-to-wear							
Technology							
Household appliances							
Accessory							
furniture/decoration							
Tourism services							
Health Service							
Educational services							
Telecommunication							
banking finance							

10. **Have you done online banking this year?**
 a) Yes b) No

If the answer **Yes,** then go to question 10 then continue **or if No** go directly to 11

11. **If yes, which of the following steps did you take?**

Money transfer	
Paying bills	
Foreign exchange buying/selling	
Stock, coin buying/selling	
loan request	
Other	

12. **How many hours a day are you active on the internet?...............**

13. **What are you most interested in when you are active on the Internet?**

Browsing and purchasing on shopping sites	
research, homework	
Follow financial markets	
Movies, music, games, etc. entertainment	
social platforms	
Other	

14. Which of the following does chatbot mean to you?

It is an artificial intelligence application that provides personalized service	
It is an easy communication tool	
It is a social media application	
It is an online chat program	
Other	

Chatbots are artificial intelligence-based robots designed to better understand human communication, whether written or verbal, and to communicate with people in the same natural language they use, which should be perceived by people as if they were real service representatives. In other words, it is an unmanned communication tool.

15. When was the last time you shopped online for yourself or your family?

less than a month	
between 2 months	
Between 2-4 months	
Between 4-6 months	
more than 6 months	

16. Did you use a chatbot for your last e-shopping?

a) Yes b) No

17. Which platform do you prefer most for your e-commerce shopping?

Telephone	
Computer	
Tablet	

18. What are the important criteria for you when choosing an e-shopping website? Please select your top 3 preferences.

Delivery time	
Product variety	
Payment options	
Easy return	
Technological innovations	
Reliability	
Other	

19. Carefully read the following statements in the table below, determine to what extent you see the behavior in each item, and select the appropriate option. Please turn your phone sideways if you are answering on a mobile phone.

(5: Strongly agree, 4: Agree, 3: neutral/undecided, 2: Disagree, 1: Strongly disagree)

	5	4	3	2	1
1. Chatbots can provide more benefits than customer service agents					
2. Chatbots can easily recognize our voice					
3. Chatbots can easily recognize our picture					
4. I'm worried from using chatbots					
5. Chatbots are a fascinating technology					
6. Chatbots have changed online shopping habits and online service style					
7. Chatbot saves money for companies					
8. The chatbot has the capacity to solve many problems simultaneously and instantly					
9. Chatbot is more empathetic than customer representative					
10.Chatbot's advice is more reliable than customer representative's					
11.Chatbots like Microsoft chatbot can always support you to solve your laptop problem					
12.Chatbots have a huge impact on our personal and family lives					
13.Chatbots help us choose our needs rationally					
14.Chatbots can easily recognize us based on our sentences or the way we write.					
15.Chatbot creates anxiety in finding the correct goods and services					
16.Chatbot can provide more accurate information than a customer representative					
17.The chatbot helps us choose goods and services based on our already known preferences					
18.The lifeless interlocutor annoys me					
19.If you have read this statement, please select I am undecided.					
20.Chatbots must be able to react emotionally					
21.Chatbots are skilled at finding innovative solutions to problems					
22.E-Shopping is faster using chatbots					
23.Chatbots make it easier for me to review products					
24.Chatbots etc. Technologies increase my privacy concerns					
25.I can't explain my problem to chatbots					
26.having a conversation with chatbots is fun and enjoyable					
27.Chatbots give me new information					
28.Chatbots can offer me products and services that I cannot find from another brand.					
29.Chatbots handle my returns and exchanges without any problems					
30.Using chatbots is satisfying					
31.Chatbots are like a fun game in the free time					
32.If you have read this statement, please select I Strongly Agree.					
33.I am open to innovations					
34.I am successful and willing to use technology					

35.I worry that our lives will increasingly be ruled by chatbots					
36.I can talk to chatbots easily because I know they are not human.					

20. **In which field do you use chatbots the most? (please indicate your top three preferences)**

Banking-finance	
e-commerce	
Telecommunications	
Health	
transportation	
Education	
public services	
Tourism	
Other	

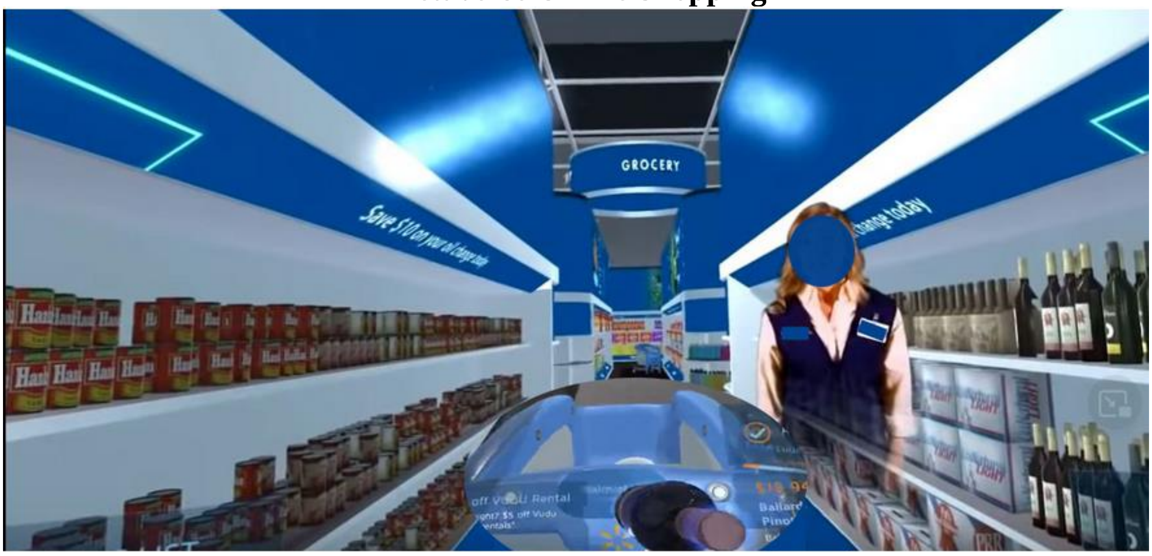
Chatbots in the Metaverse

Imagine yourself trying to use online shopping in the Metaverse world while virtually wandering around a shopping mall or a grocery store to buy your daily household needs. Suddenly, your digital assistant, your Chatbot assistant, appears before you in 3D, talks to you, tries to help you and reminds you of items you forgot to buy, or gives you advice by stating the price, expiration date or product features.

21. Do you know or have you heard of the Metaverse?

a) Yes b) No

Metaverse Online Shopping



22. Look at the photo and answer the questions below.
(5: Strongly agree, 4: Agree, 3: neutral/undecided, 2: Disagree, 1: Strongly disagree)

	5	**4**	**3**	**2**	**1**
1. Chatbots offer a different experience in the Metaverse world					
2. Chatbots on Metaverse are helpful and add value to your shopping experience					
3. Businesses should develop their online shopping stores in the Metaverse environment					
4. Chatbots in the Metaverse can guide us, help us					
5. Chatbots within the Metaverse provide visual and meaningful recommendations and prevent children from purchasing age-inappropriate products.					
6. I'm excited to try Chatbots for online shopping within the Metaverse					
7. It seems scary for me to go through this experience					
8. I think it is more satisfying than classic online shopping.					
9. Metaverse will be very useful as they can advise us on online stores					
10. I believe it will provide safe shopping opportunity					

Thanks for participating.