DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF BUSINESS ADMINISTRATION (ENGLISH)
BUSINESS ADMINISTRATION (ENGLISH) PROGRAM
MASTER'S THESIS

MEASURING USER ACCEPTANCE OF CHATBOTS WITH TECHNOLOGY ACCEPTANCE MODEL

Can SUSAN

Supervisor
Prof. Dr. Banu DEMİREL

2025

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İZMİR 2025

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Müdür

DECLARATION

I hereby declare that this master's thesis titled as "Measuring User Acceptance of Chatbots with Technology Acceptance Model" has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with my honor.

Date
10.3.2025
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Signature

ABSTRACT

Master's Thesis

Measuring User Acceptance of Chatbots with Technology Acceptance Model

Can SUSAN

Dokuz Eylül University

Graduate School of Social Sciences

Department of Business Administration (English)

Business Administration (English) Program

Artificial intelligence has shown its effect on our lives significantly in the recent years, being a revolutionary technology that extends human-computer interaction. This technology is evolving in a way that impacts both with its impact on the daily lives of users and transforming the service methods of businesses. In this context, with the advancement of AI technologies like machine learning and natural language processing, chatbots have become more powerful and increasingly popular. Adapting to these technologies has become essential for businesses, and understanding how users in our country approach these technologies is crucial for proper positioning.

This thesis aims to explain the relationship between the acceptance of chatbots by users and the factors influencing this acceptance. For this purpose, data obtained via an online survey method was analyzed and the findings were assessed. The research found a significant and positive relationship between perceived usefulness, perceived enjoyment, and the intention to use chatbots, and a limitedly supported negative relationship between perceived risk and the intention to use chatbots. No significant relationship was observed between perceived ease of use and the intention to use chatbots, but a significant and positive relationship was found between perceived ease of use and perceived usefulness.

Keywords: Chatbot, Artificial Intelligence, Technology Acceptance Model.

ÖZET

Yüksek Lisans Tezi

Sohbet Robotlarının Kullanıcı Kabulünün Teknoloji Kabul Modeli ile Ölçümlenmesi

Can SUSAN

Dokuz Eylül Üniversitesi
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Yapay zeka son yıllarda hayatımıza adından sıklıkla söz ettirecek şekilde girmiş ve insan-bilgisayar etkileşimine olanak tanıyan devrim niteliğinde bir teknolojidir. Bu teknoloji hem kullanıcıların günlük hayatına dokunan hem de işletmelerin onlara hizmet şekil ve yöntemlerini değiştiren bir yönde ilerlemektedir. Bu bağlamda, makina öğrenmesi ve doğal dili işleme gibi yapay zeka teknolojilerinin gelişmesi ile sohbet robotları daha güçlü bir konuma gelmiş ve popülerliği artan bir kavram olmuştur. İşletmeler açısından kendilerini bu gibi teknolojilere adapte etmek elzem bir konu haline gelmiştir ve buna istinaden ülkemizde kullanıcıların bu teknolojilere nasıl yaklaştığı, doğru konumlanma adına ivedilikle anlaşılması gereken bir noktadadır.

Bu tez çalışmasında sohbet robotlarının kullanıcılar tarafından kabulü ve bunu etkileyen faktörler arasındaki ilişkinin açıklanması amaçlanmaktadır. Bu amaçla yapılmış çevrimiçi anket yöntemiyle elde edilen veriler analiz edilmiş ve bulgular değerlendirilmiştir. Araştırma sonucunda algılanan kullanışlılık, algılanan eğlence ve sohbet robotu kullanım niyeti arasında anlamlı ve pozitif bir ilişki, algılanan risk ve sohbet robotu kullanım niyeti arasında sınırlı düzeyde desteklenen negatif bir ilişki bulunmuştur. Algılanan kullanım kolaylığı ile sohbet robotu kullanım niyeti arasında anlamlı bir ilişki gözlenememiş fakat algılanan kullanım kolaylığı ile algılanan kullanışlılık arasında anlamlı ve pozitif bir ilişki saptanmıştır.

Anahtar Kelimeler: Sohbet Robotu, Yapay Zeka, Teknoloji Kabul Modeli.

MEASURING USER ACCEPTANCE OF CHATBOTS WITH TECHNOLOGY ACCEPTANCE MODEL

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INTRODUCTION

In the current era of artificial intelligence revolution, chatbot systems evolved substantially and have been increasingly offered by product and service providers. Chatbots have become more popular among users and therefore attracted more attention by businesses to enrich their communication with customers.

Thanks to the adoption rate of new technologies, chatbots are more popular to be offered by businesses within the last few years in Turkey. Prominent examples include personal digital assistants on mobile devices, customer assistants on mobile applications and voice enabled home devices. These chatbot examples are provided by several sectors such as banking, retail, transportation and education.

This study employed a holistic approach, examining a wide range of chatbot examples. The aim of this study is to explain the acceptance of chatbots by the users and factors influencing their intention. It is found that Technology Acceptance Model (TAM) involves key variables necessary to explain the relationship between users intention to use chatbots and regarding factors that have influence on it. Previous research on chatbot adoption was analyzed and independent variables; perceived usefulness, perceived ease of use, perceived enjoyment and perceived risk were decided as the explanatory items on measuring users' intention to use chatbots.

In order to establish a clear framework regarding the subject, this study is divided into three main sections. The first section will discuss artificial intelligence and chatbots, while the second section will establish a theoretical framework and examine past research. In the third section, the survey conducted for research purposes and the data obtained will be evaluated. Finally, the results related to the subject will be analyzed, and recommendations will be discussed.

CHAPTER ONE
ARTIFICIAL INTELLIGENCE AND CHATBOTS

1.1. ARTIFICIAL INTELLIGENCE (AI)

Throughout the history, workforce has seen many changes from the days of slavery to robots replacing human labor today. This spectacular change is all made possible by historical developments e.g. The Industrial Revolution and The French Revolution. The Industrial Revolution began in England and spread in 1750, was a turning point of shifting from an economy based on handcraft to machine work, manufacturing and mass production later.

Hollywood movies and science fiction have always inspired scientist because they reflect human imagination. Those works provided early insights into the concept of machines that can speak like humans, respond questions, learns on itself and acts self-autonomously. Science-fiction movies spread the idea that machines will improve so greatly and takeover their control and act independent from human command. At the moment, although we are far from a world where robots do everything, with artificial intelligence, machine learning and internet of things, humans are getting closer to that futuristic dream. On the other hand, the future of work and the role of humans in an increasingly automated society is questioned with artificial intelligence and robotics.

The term artificial intelligence was first emerged at Dartmouth Summer Research Project in 1956 organized by John McCarthy who is known to use the term first and defined it as ‘’the science and engineering of making intelligent machines’’ (Manning, 2020). The researchers at the event aimed to provide a framework for making machines exhibit intelligence and the idea propelled the field forward. John McCarthy, Marvin Minsky, Nathaniel Rochester, and Claude Shannon co-authored a proposal using the term artificial intelligence and contributed to the development of the field (Stanford, 2016: 50).

The role of artificial intelligence is taking a leap step forward influencing peoples’ daily lives as well as changing the course of workforce with the expectation of larger adoption and growth in the nearest future. AI already has a great impact on

economy and take a big pie from the investments made around globe. United States and Asia, specifically China invests in this field and are in a major and fierce competition to take the lead to be the leading authority of the AI technology and make the most benefit.

Table 1: Geographical Breakdown of AI Patents in 2024

Rank	Country	Total AI Patents (2024)	Number of Companies in Dataset	Patents per Company
1	China	12,945	523	24.8
2	United States	8,609	257	33.5
3	South Korea	1,537	43	35.7
4	Japan	1,537	41	37.5
5	Germany	784	18	43.6
6	United Kingdom	369	11	33.5
7	Netherlands	249	7	35.6
8	Sweden	243	4	60.8
9	Finland	180	1	180.0
10	Taiwan	156	11	14.2

Source: Buntz, 2024

The data at Table 1 represents that first ten months of 2024 and reflects that the competition between the two country is intense and there is a race in the number of patents registered by its companies as well. China has the lead with 12,945 total registered patents followed by United States with 8,609 registration. The third position on this list is occupied by South Korea and Japan at 1,537 registration per country. The data shows that there is a sharp difference between China, U.S. and the rest of the world.

In the near future, AI impact on economy will get deeper and there will be more impact on job creation and economics in general. As developed countries are more powerful in artificial intelligence it could create a gap between developed and

developing countries. Some big technology companies have a rich knowledge base and extensive resources in terms of artificial intelligence which may lead to monopolization and damage competitive environment (Szczepanski, 2019).

Table 2: Top Patent Owners In Genai Modes (Companies), 2014–2023

	Images/ video	Text	Speech/ voice/ music	3D image models	Molecules/ genes/ proteins	Software/code	Other modes
Tencent Holdings (China)	607	565	551	102	57	41	464
Ping An Insurance (China)	262	600	599	26	33	24	223
Baidu (China)	395	465	441	81	26	18	166
IBM (US)	101	274	168	13	37	42	132
Alibaba Group (China)	142	213	144	36	2	10	133
Samsung Electr. (Republic of Korea)	173	140	226	34	10	5	57
Alphabet/Google (US)	138	107	200	25	15	15	72
ByteDance (China)	173	82	112	21	6	7	90
Microsoft (US)	78	194	151	18	6	22	42
BBK Electronics (China)	125	58	117	12	0	4	116
Netease (China)	78	76	80	37	0	11	102
NTT (Japan)	37	100	169	11	0	3	62
Huawei (China)	104	84	72	24	1	4	102

Source: WIPO, 2024

Research made by PwC (2017) reflects that the total impact of AI is expected to be 15.7 trillion USD by 2030. Most of this gains are predicted to arise from product

upgrades and modifications and boosting consumer demand. The largest impact is awaited to come from China with 7.0 trillion USD and 26.1% of GDP followed by United States with 3.7 trillion USD and 14.5% of GDP. The corresponding number supports the idea of expected AI competition between China and U.S. to continue in the upcoming years resulting in these two countries widening the gap with others. Table 2 shows the number of patents owned by companies by AI modes and it suggests that Chinese and U.S. based companies lead in the number of registrations, specifically by three Chinese companies; Tencent Holding, Ping An Insurance and Baidu from 2014 to 2023.

1.2. AI IMPACT ON BUSINESS

Big companies in the retail industry take advantage of machine learning to apprehend customers buying patterns. Here, machine learning is used to target customers with personalized offerings based on their past buying behavior analyzing their possible needs and expectations. For example, Amazon analyze customer purchasing records and products they search to match right products to fit customer needs. Amazon also apply upsell and cross-sell strategies with machine learning offering more quality products in harmony with customers choice or advice alternative products or brand choices. (Mathur, 2019: 184)

Retail is one of the industries that use artificial intelligence to improve customer satisfaction and customer experience in a financially efficient way. Retail companies enjoy AI in many ways including understanding customers needs and expectations more competently, creating technologically enhanced stores, fast and efficient customer service and customer relationship management, payment management, personalized product recommendations, inventory optimization and route optimization in logistics (Shankar, 2018: 8)

In the supply chain, AI and robots can help in warehouse management and logistics operations. With the help of AI, accuracy of forecasting plays a significant role in understanding future demand and adjust storage accordingly for a better supply chain performance (Bala, 2012: 35). AI improves warehouse management using robots with computer vision. A company called Symbotic produces robots that can pick

packages from trucks, assess the size of box and shelf space to decide for a perfect fit and place them on the warehouse shelf autonomously (Daugherty and Wilson, 2018: 57). In 2014, Amazon bought Kiva systems and renamed it after as Amazon Robotics. In the warehouses of Amazon, these robots do the most of the physical work, load and unload shelves and replenish inventory facilitating same day delivery, which is a key customer satisfaction factor for Amazon's success (Wingfield, 2017). Machine learning can also provides more advantageous information to replenish storage from a warehouse or another branches storage calculating the distance to decide for best option (Mathur, 2019: 251)

Pricing is one of the most crucial elements of marketing mix and a bad pricing strategy can lead a product and service or a bunch of them to fail inevitably. Traditionally cost-plus pricing, price penetration, competitive positioning and value based pricing are most used techniques by marketers and nowadays with the power data and artificial intelligence, technology permits to benefit from dynamic pricing strategies, also known as predictive pricing.

Pricing is critical for the enterprises that are operating in very competitive environments such as aviation industry and electricity market where prices may change from day to day or at any moment. In such a situation artificial intelligence can help to predict prices more accurately where change is a challenge. In their study Tang & Gu (2009) explains how artificial intelligence can improve predicting electricity prices using inputs such as historical demand, historical prices and forecast demand. For a retailer, past data including factors such as manufacturers costs, labor, marketing expenses, import-export charges and advertising influence predicting the right price (Chandrashekhara et al, 2019: 364). Determining the right price at the right time is a vital and complex task requiring to be knowledgable on inner and outer variables (Elmaghraby, 2003: 1). Seasonality can be an important factor to make a pricing decision as it may involve influencing factors like day or time of the week, weather, season and competitors prices. German Retailer OTTO, partnered with Blue Yonder to enhance its pricing strategy using their price optimization solutions setting a successful connection among price changes and demand volume. Thanks to this beneficial partnership, OTTO optimized its revenue and improved sales while

decreasing product return rates by over 50% in its menswear section (Klumpp, 2019: 643).

AI has a potential of creating new ways of in-store customer experience. In 2018, retail giant Amazon opened its smart store in Seattle where there is no need for checkout and payment process. Customers download its mobile application before entering the store, create an account and QR code to be scanned. The customers just reach to shelves and pick up what they wish to purchase. Once they left the store it's automatically billed to their account. Combining AI, computer vision, deep learning, sensors and RFID readers that track customers and products, the shopping process is seamless without any waiting and human interference (Deoras, 2018).

Finance and banking is one of industries that utilize most from AI in automating many operational field. Big banks and financial institutions use AI based customer service to handle customer requests and customer complaint on the call center. Banks launch AI-powered digital assistants with partnering technology companies or using their own technology sources to provide a technology enhanced customer experience and personalized services. They use AI to assess risk profiles, detect fraud and malicious activity.

1.3. CHATBOTS

With recent major developments, artificial intelligence (AI), has more and more impact on customers daily lives. Chatbots are widely used AI based applications that facilitates mainstream adoption of artificial intelligence. The introduction of applications built with conversational agents on mobile devices helped users to meet artificial intelligence technology for several purposes beneficially (Guzman, 2019: 344). Chatbots are created with conversational interfaces that can imitate human dialogue resulting in customers to be unaware of whether they are interacting with a chatbot or a human service representative (Murtarelli et al, 2020: 927).

The chatbot is a software application, built to stimulate conversations with humans using voice methods or natural language text (xcubelabs, 2017). Another one of the few definitions for chatbots is: "A computer program, which simulates human language with the aid of a text-based dialogue system" (Zumstein & Hundertmark,

2017: 98). Neff and Nagy defines chatbots as: ‘’A category of programs that can engage users in conversations. Driven by algorithms of varying complexity, chat bots respond to users’ messages by selecting the appropriate expression from preprogrammed schemas, or in the case of emerging bots, through the use of adaptive machine learning algorithms.’’(Neff & Nagy, 2016: 4915). Shawar & Atwell (2007: 29) define chatbots as ‘’computer programs that interact with users using natural language.’’

In the literature chatbots also can be found under different names in accordance with their function, form or purpose of use; digital voice assistants (Fernandes & Oliveira, 2020), virtual agent (Ciechanowski et al., 2019), personal intelligent agent (Moussawi et al, 2020), conversational agents (Laumer et al, 2019), virtual personal assistant (Yang & Lee, 2019), e-service agent (Chung et al., 2020).

As market environment and competition grows, automated technologies are expected to be used more widely by companies (Kumar et al, 2016: 38). Technology has been a game-changer for many industries. Technological advancements can help companies to replace traditional customer-company interaction by enhancing or even substituting human agents. while facilitating the creation of enjoyable, customized, and valued service interactions (Marinova et al, 2017: 31). Chatbots are considered to be useful for many companies from different sectors. For example, companies benefit from chatbots majorly in customer service, sales and marketing and order processing operations.

Another reason for chatbots to become more popular is the new generations. In contrast to the previous, current generations are more used to technology, internet and social media. Most millennials are native to the latest technology and Generation Z is born into it. Therefore it is more important to stay up-to-date when it comes to technology and generate and keep the attention of newer generations (Jyothsna et al, 2024: 2)

The rise in the usage of chatbots regardless of featuring basic or more sophisticated artificial intelligence marked a new era for internet and social media. Chatbots generate interactions with customers in conventional channels such as online retail, customer service, data collection, marketing and advertising through a disruptive approach (Zemcik, 2019: 15).

Two modes of chatbots can be recognized as text-based and voice-based (Rese et al, 2020: 1). Through both forms, chatbots facilitate an interesting example of human-machine interaction thanks to artificial intelligence and natural language processing. Chatbot applications include voice-based digital assistants such as Amazon Alexa, Siri, Google Assistant, Cortana and text-based systems too (Sheehan et al, 2020: 14). Text-based chatbots can be built into a dedicated application or run on instant messaging platforms such as Facebook Messenger and WhatsApp. These platforms allow companies to build their chatbots in their application without the need of building an application.

Lately, chatbots are equipped with upgraded capabilities such as big data and machine learning. Combined with modern AI magic, chatbots constantly learn from user data such as conversation database, user history, user preferences, purchasing history, home ownership and location, family status and creates a model that best predicts what user might ask and how to create the best output to answer, moreover they predict user behavior and define solutions and answers accordingly (Huang & Chueh 2020: 136; Oracle: 2020).

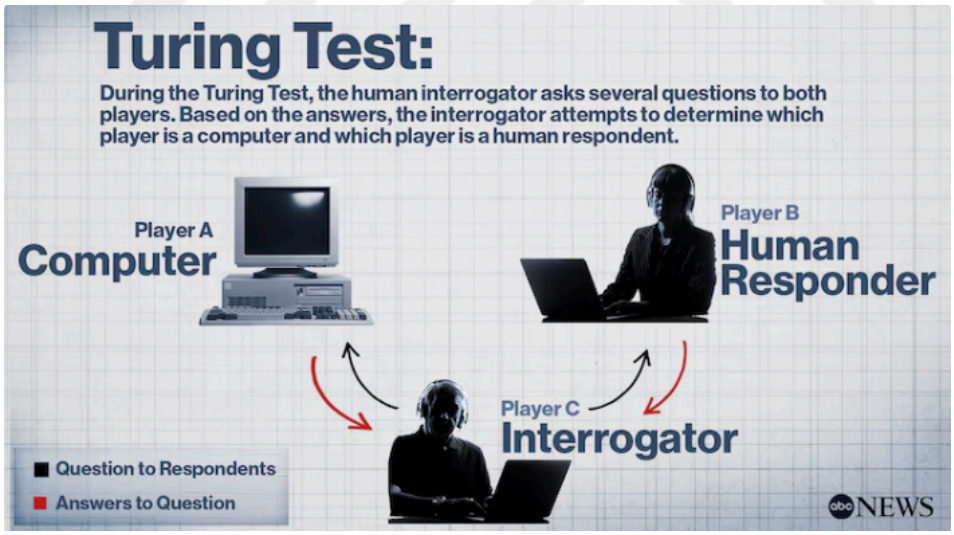
Chatbots are used for various purposes across different fields. In education, they assist students by answering questions, and supporting learning processes. In the e-commerce and retail sectors, chatbots play a crucial role by providing quick customer service, making product recommendations, and assisting with order tracking. In finance and banking, they enable users to access account information, conduct transactions, and receive financial advice while automating customer service to enhance efficiency. In general, chatbots create value for both users and service providers improving user experience and satisfaction.

Depending on the sector, chatbots may differ in the way they are built. For example, a financial chatbot should analyze customer data and suggest offers accordingly such as how to save money. On the other hand, retail chatbots are supposed to entertain customers while looking up for a longer conversation and attract their attention longer and suggest them more browsing options and cross-selling and up-selling (Przegalinska et al, 2019: 787).

1.4. CHATBOTS HISTORICAL DEVELOPMENT

In 1950, the pioneering computer scientist Alan Turing (1950) proposed the idea to test computers ability to engage in a naturel conversation with real people without letting them understand that their counterpart was in fact a computer. This concept, known as Turing Test today, was designed to stimulate natural conversation and trick people into thinking they chat to a real person. During the test, as illustrated at Figure 1, there is an interrogator and two players; a human and a computer. Based on the answer set, interrogator tries to estimate which player is computer. The Turing Test serves as a benchmark in evaluating computers ability to deploy human-like interactions. Turing's innovative idea has been considered by many scientists as a foundational contribution to scientific research and development of artificial intelligence and chatbots (Kekatos, 2023; Adamopoulou & Moussiades, 2020: 2).

Figure 1: Turing Test

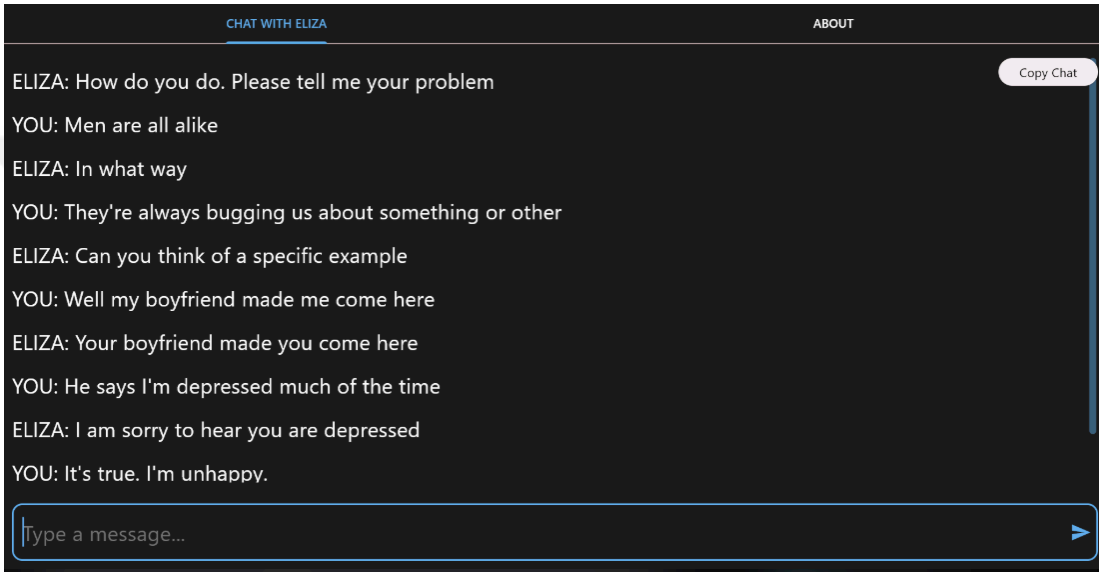


Source: Kekatos, 2023

In origin, the first chatbot ELIZA was created by Joseph Weizenbaum in 1966 at MIT Artificial Intelligence Laboratory. ELIZA was a pioneering program that benefits from a set of scripts to stimulate conversation. One of ELIZA script (Figure 2) was known as Doctor and it mimics a patient-psychotherapist conversation. Though it was limited in terms of communication capabilities, its creator was surprised by

patients who wanted to continue their therapy with ELIZA. The result of this work was Intriguing and raised significant interest in artificial intelligence field with interesting outcomes in human-machine interaction (Przegalinska et al, 2019: 786). To honor the work, developers launched an application of ELIZA in Microsoft application store as the original script is reflected in Figure 2.

Figure 2: ELIZA Script

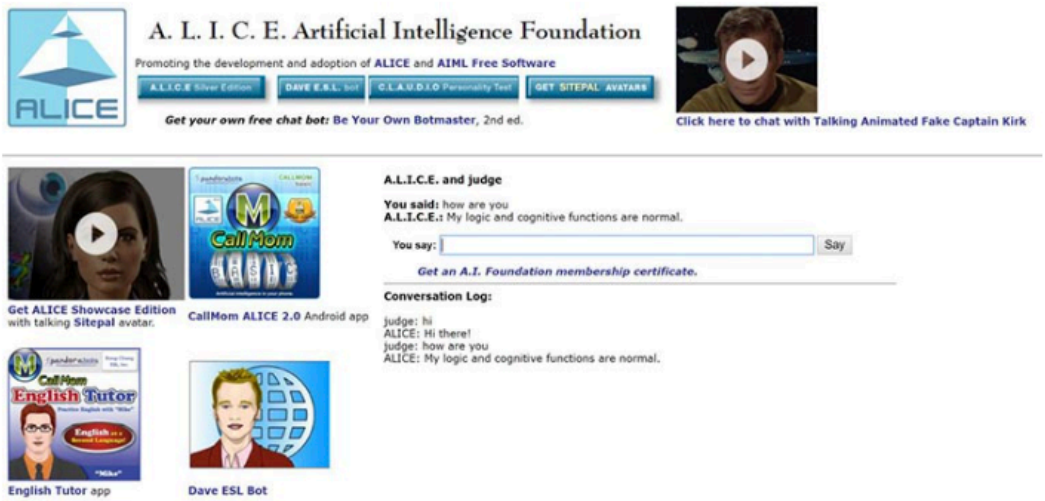


Source: Jessa, 2025

PARRY, as a more advanced chatbot compared to ELIZA, was introduced by Kenneth Mark Colby at Stanford's Psychiatry Department in 1972. Unlike ELIZA, PARRY was designed as a patient with schizophrenia. It also served as a useful tool for young psychiatrists to get more experienced with schizophrenia patients (Zemcik, 2019: 15).

Inspired by the pioneering work of ELIZA, ALICE (Figure 3) was created by Richard Wallace in 1995. Despite its innovation and improved capabilities it failed at passing the Turing Test but it was awarded with Loebner Prize, an AI competition arranged yearly (Khan & Das, 2018: 2). In the path to achieving this title, it was improved and its knowledge base was sharply larger than ELIZA, with a base of 41,000 patterns compared to 200 keywords of the counterpart (Heller, Procter, Mah, Jewell, & Cheung, 2005).

Figure 3: User Interface of ALICE



Source: Gobiet, 2024

In 2001, chatbot technology has seen a giant development with the introduction of SmarterChild which was available on platforms like Microsoft's MSN. It pioneered as an agent to help users with their daily tasks including answering questions and providing information. Its introduction was a big step forward leading to the development of advanced AI-powered digital assistants (Adamopoulou & Moussiades, 2020: 3).

In 2011, IBM's Watson with the ability of understanding natural human language, competed against the two champions Ken Jennings and Brad Rutter at a TV quiz show ''Jeopardy'' and won the title. Watson is developed and equipped with improved capabilities to serve as an AI-powered virtual assistant for businesses today. This spectacular win was an epic moment for demonstrating what AI is capable of (Gabbatt, 2011).

Figure 4: Watson Winning JEOPARDY



Source: Gabbatt, 2011

Siri, as a voice enabled digital assistant, originally was developed by Stanford Research Institute as a side Project and parented by Apple in 2011 (Khan & Das, 2018: 3). Since the introduction of iOS 5, Siri comes as a built in digital voice assistant with Apple devices across several product lines such as Apple MacBook, iPad and iPhone. Siri acts as a personal assistant enabling users to have a voice command to arrange a number of tasks such as introducing a voice-call, looking up for information, launching an application, set alarm, create reminders and sending a text massage. Siri was a turning point to get started with the trend of chatbots being added to mobile devices natively.

Additionally, instant messaging applications Telegram, WatsApp, WeChat and Slack introduced robust bot services for developers use in expanding the reach to a larger number of user with a wide variety of task completion(Khan & Das, 2018: 3). WeChat in China, excels in offering services such as ordering food, e-payments and online purchases all within the application.

In 2014, retail giant Amazon launched Alexa, a Siri-like agent acting as a personal assistant across several devices, handling request such as checking the

weather and news, commanding home-devices like lights and soundbars, ordering goods and tracking Amazon deliveries. Lately, Alexa also was placed in a wide range of Amazon products like Amazon Echo (a smart speaker) and some other smart home products.

Lately OpenAI developed prominent ChatGPT raising a great interest in chatbot usage bringing huge attention to sector as it can fluently go into conversations with users, understand complex questions, generate relevant information, human-like interaction and even entertain users at an advanced level. ChatGPT can hold long conversations, understand context in a speech adapting to follow-up questions and integrate to other platforms.

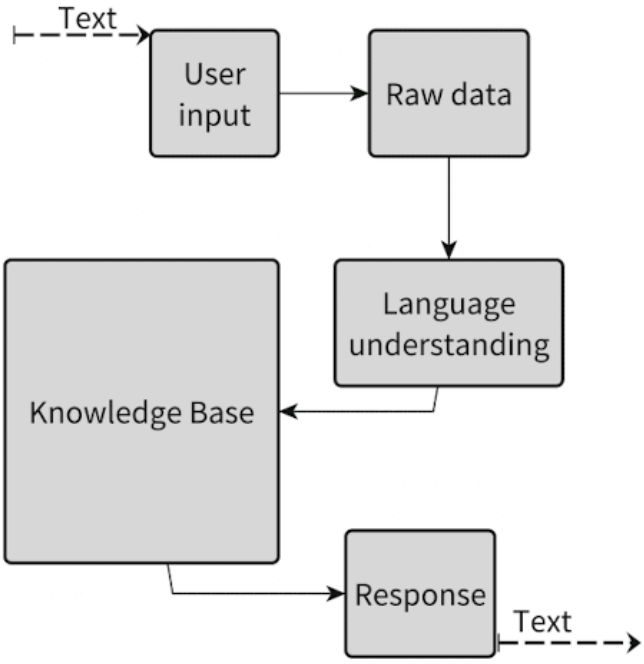
Summarizing the information above, although chatbots have a long story dating back to over fifty years, they improved significantly in a tranquil manner. Today users are not surprised by their encounter with AI chatbots as they come across them from mobile phones to even in a personal car as it has become a regular confront.

1.5. CHATBOT SYSTEMS

Chatbots can also be categorized as text and voice based chatbots with respect to their human-machine communication channel. This communication can be made built via written channels; instant messaging applications, websites, mobile application or voice based channels; mobile phones, smart speakers, laptops and a few other electronic devices.

Each chatbot may be powered by and built upon a different technology, depending on the richness of its capabilities. Yet, setting the details aside, the general working principle of a chatbot is to receive input from the user, perceive and understand it, interpret it according to its working principle, and respond to the user's query as shown at Figure 5 (Sanchez-Diaz et al, 2018: 167).

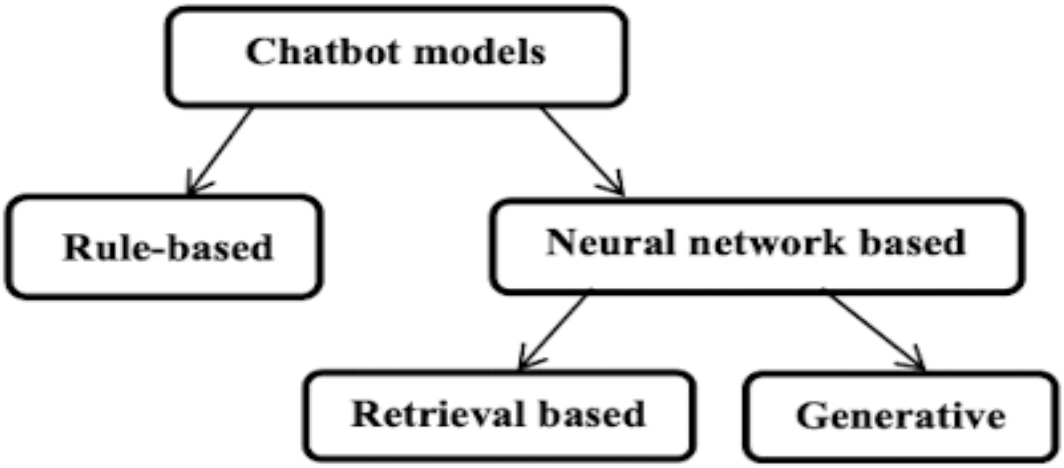
Figure 5: General Methodology For A Text-Based Chatbot



Source: Sanchez-Diaz et al, 2018: 167

Technology and programming is an evolving ecosystem and improves itself day by day. Since the launch of the first chatbot, their skills and capabilities flourished profoundly and they gain strength from several technologic approaches. The earlier chatbots were able to understand user commands where they were given simple input in a basic communication. Chatbots of today can understand complex questions and respond to humans in a context aware form. This evolution is powered by several techniques and chatbots can be classified in accordance with those approaches. As the computer science literature suggests, chatbots can be classified in two major categories which can be named as rules-based and neural network based chatbots (Agarwal and Wadhwa, 2020: 2). This classification is made as deriving from its underlying technologies fitting their method of response generation.

Figure 6: Classifcation of Chatbot Models



Source: Agarwal and Wadhwa, 2020: 2

Rule based, also called as flow-based, chatbots rely on pre-programmed conversation modules created by the developers to guide and direct user throughout the conversation between human and machine. These chatbots help users with a predefined series of questions matching them with a set of answers. They heavily rely on keywords and suggested buttons to navigate a user interaction. Whenever a user asks a question or puts a command via a text or vocal form they search their bulk of pre-set answers and find the best available answer. When given a complex question or any input that is out of their programmed context they cannot provide interaction. (Gümüş and Çark, 2021: 422).

Neural network based chatbots are considered as retrieval based and generative chatbots. Generative refers to creating new responses and retrieval refers to relying on the data set. Retrieval based chatbots, as the name suggests, retrieves a set of answers from large bulk of data using statistical methods instead of generating new responses (Almansor & Hussain, 2020: 538). Generative chatbots are context aware handle longer conversations with the ability to understand users also learn from the conversation over time. These chatbots are built with the latest technology, generative pre-trained transformer (GPT), most famous example is ChatGPT. Combining technologies like machine learning, natural language processing and natural language understanding, these chatbots can generate responses to any type of question within a

context. They generate from data as they are previously trained with large datasets already and can answer any type of question as a result (Durach & Gutierrez, 2024: 233)

1.5.1. Machine Learning

Machine learning is a subset of artificial intelligence that efforts to make computers equipped with the ability to learn by themselves. The purpose of this process is to make machines execute tasks without human intervention, improve their performance and make decisions more accurately as they are being trained by larger data pools (IBM, 2024).

Machine learning is a prominent subdomain of artificial intelligence as many businesses are already aware of the importance of implementing it to business operations. The key sectors that are heavily influenced by ML are mainly as follows:

- Healthcare
- Financial institutions (banks, fintech etc)
- Logistics and transportation
- Travel and hospitality
- Retail and e-commerce
- Supply chain
- Energy

Machine learning is applied in several key divisions of businesses as they foster decision making process in areas which involves:

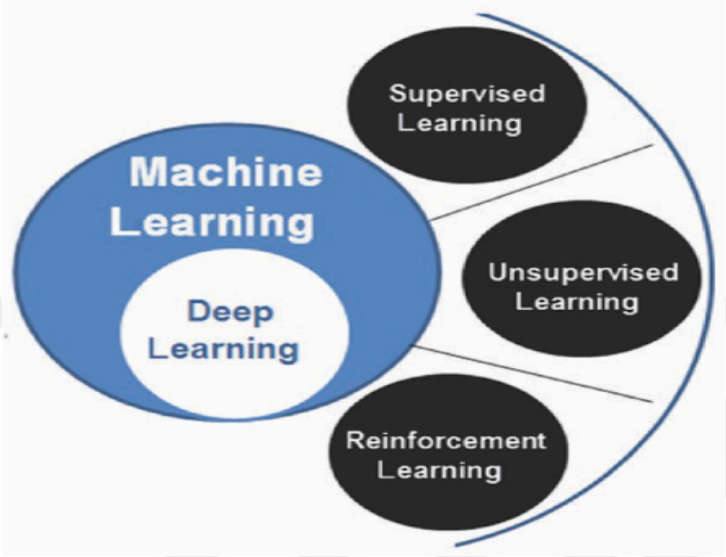
Demand and sales forecasting

- Personalized recommendation
- Price optimization
- Warehouse and inventory management

Machine learning algorithms rely on large data availability. The larger data means a better learning progress for the machine learning model. The data pools which contains any numerical information, photos, sales data, financial transactions or even maintenance records can be used for training process. Here, the aim is to educate the machine no different than a human does. The data necessary for the specific learning

model is gathered by the programmers and used on the training model. As the data given to a specific machine learning model, computer begins to use the provided data and produces the desired outcome (Brown, 2021).

Figure 7: Machine Learning



Source: Gollapudi, 2019: 12

Machine learning techniques can be addressed into three major categories; supervised leaning, reinforcement learning and unsupervised learning (Figure 7) with each carrying different approaches in order to cater the industry specific needs and expectations from the learning progress.

Supervised machine learning is a technique that uses labeled datasets to train a program. The major difference between supervised and unsupervised learning is the labelling of the data. In order to extract a meaning from the data or use it to predict an outcome, machine learning algorithm is provided with a dataset that is classified and labelled first for the training process (Alloghani et al, 2020: 4).

According to SAS (2024), reinforcement learning focuses on a regimented learning process where the program is given a set of possible actions and a goal. Through the progress, the computer gain experience with different actions and learn from them. The process forwards with adjusting the strategy accordingly until finding the best option to reach the goal.

Unsupervised learning is the training process of machines with unlabeled and unclassified data. Without setting clear learning instructions, the objective of the progression is to organize the raw data, find similar specifications, patterns and the differences. Unsupervised learning can be categorized into techniques such as clustering, dimensionality reduction, and anomaly detection (Ahmad, 2019: 162).

Deep learning is a subset of machine learning but differentiates itself in a way that it does not require human interference. Deep learning techniques facilitate the machine to learn from raw data such as image, video or text and commonly used in computer vision, chatbots and recommendation engines (Nvidia, 2024).

1.5.2 Natural Language Processing

Natural language processing is a field that brings artificial intelligence and linguistics disciplines together to provide implementation of a successful human-computer interaction. It is classified into two major parts as natural language understanding and natural language generation. In natural language understanding the message is coded by human and perceived by the computer and on the other hand the vice versa in natural language generation (Abro et al: 2023: 1523). The process of this interaction begins with receiving human language through various communication channels and converting it into understandable formant by the computer. Once the information is analyzed, this technology can help humans in a number of fields such as creating products, discover efficient solutions and in providing services (Coşkun & Kuşçu, 2021: 120)

Businesses utilize from natural language processing solutions and tools to automate business operations where it is applicable. Amazon (2024b) lists the following tasks that companies can automate using NLP technology:

- Process and analyze large text documents
- Analyze and understand customer sentiment via feedback
- Deploy chatbots to automate customer services
- Answer fact-based questions
- Develop tools to understand and extract information from text documents

Speech and voice recognition technologies allow machines to understand verbal language. Speech recognition technology enables machines to understand spoken words and convert them a text format which is an understandable format by the computer. Voice recognition is a subset of speech recognition with with the objective of identifying individuals based on voice analysis. Today many electronic devices such as televisions, mobile phones and personal computers are equipped with digital assistants powered by these technologies enabling users to enjoy a voice commanded operation. More advanced service by these assistants are provided by prominent examples including Apple's Siri, Amazon's Alexa and Google Assistant (Gollapudi, 2019: 13).

1.6. BENEFITS AND DRAWBACKS OF CHATBOTS

1.6.1. Benefits of Chatbots

In today's world, where digital products are widely integrated into the lives of users, chatbots appeared as a transformative tool for businesses as they leverage customer interaction alleviating operational burden as well as lowering operational costs. Thanks to the advanced technology of artificial intelligence, chatbots are effectively provide support, improve customer engagement and produce customer satisfaction and loyalty. As the recognition of chatbots climb among users, more businesses integrate them into their operations and ultimately reach an innovative customer experience. Chatbots can effectively manage various business processes autonomously, without the need of human interaction. This includes areas such as customer service, personalized marketing with time saving advantages and reduced labor costs (Przegalinska et al, 2019: 786)

Chatbots lure customers with their human-like capabilities such as being friendly and helpful and encourage them to share more information with them and the data acquired is usually stored in order to create a customer profile and provide more personalized services for further use (Murtarelli et al, 2020: 928). With the help other AI tools such as machine learning and predictive algorithms, this data can be used to recommend customers products and services. They can improve customer experience

using the data collected such as providing personalized services and a personalized customer experience as a result (Marr, 2018).

The last decade witnessed a booming era of instant messaging applications with increased usage rate of mobile smartphones. In light of this, messaging platforms such as WatsApp and Facebook Messenger are heavily used for communication and companies interact with their customers through such tools. These applications offer chatbots designed for corporate use, enabling instant interaction at any time of the day (Baier et al, 2018: 2). An example of this would be Facebook's feature that allows advertisers to send sponsored messages that they previously engaged with (Broeck et al, 2019: 150).

Businesses utilize from chatbots to reduce operational costs and also enjoy the ability to serve a significantly larger number of customers simultaneously (Adamopoulou & Moussiades, 2020: 1). They handle first-level customer service in a cost-efficient way providing on demand assistance (Backhaus & Awan, 2019: 342). For instance, banks and fintech companies use chatbots for user assistance as they have large number of call volumes where conversation length and efficiency matters and digital assistants intend to present fast solution to customer queries (Przegalinska et al, 2019: 787). As the digital customer agent provides faster service, customers are expected to be glad with not losing time on queue and reach products and services faster.

Chatbots provide advantages not only externally but also internally by being used for operations such as new employee onboarding. They are provided as a useful tool for employee training as being customizable and accessible on demand without resulting high costs for companies while enabling them to track employee training progress more efficiently (Casillo et al, 2020: 372). Companies can leverage from chatbots for especially consultation when employees going through mental challenges (Wang et al, 2024: 2). This indicates that organizations can utilize from chatbots for various human resources related processes.

As a consequence of the advantages above chatbots can help companies to strengthen their position in the market with obtaining competitive advantage over their rivals. With the help of digital assistants companies can analyze their customers more effectively and differentiate their products and services to gain further benefit. Thus,

chatbots can facilitate an advantage to stand out in the market and stay a step ahead of competitors when used adequately.

1.6.2. Drawbacks of Chatbots

While chatbots have a series of advantages for both users and service providers they also come with failures. A negative experience would likely result in loss of customer or potentially damage quality perception (Cai et al, 2025: 1). In case of applying a voice based chatbot such as a personal voice assistant, misunderstandings can happen via verbal communication and they may fail to complete tasks whilst content and duration of speech fail to replace human agent. (Adamopoulou & Moussiades, 2020: 3). Eventually, a poor chatbot performance may pose a threat against the brand image.

Some users may feel uncomfortable with digital assistants such as Siri and Alexa constantly operating in a command ready mode leading to privacy concerns of users. A security breach exposed vulnerabilities in the system of Amazons Alexa in 2020 and allowed hackers to access users voice history (BBC, 2020). Security and risk concerns may cause users to avoid using chatbots. A loss data could lead to a financial loss for customers and therefore the firms in a case it must be compensated by the company. Plus, technology investments may require large capital and requires effort to convince the company executives (Graham et al, 2025: 5).

In a technology context, users may resist to change their habitual way of receiving service as they tend to compare the new service with the prior. Chatbots lack emotions and cannot provide personalized service like humans and therefore mostly fail to completely replace human agents. From this perspective, users may reject certain services offered by companies and lead to dissatisfaction (Certainly, 2025).

1.7. GLOBAL CHATBOT EXAMPLES

The increasing pace of digitalization in recent years has led businesses to rethink how they enhance customer interaction and service quality. In an increasingly competitive environment, companies are adopting chatbot technologies and using

these systems as a strategic tool to meet the need for faster and more effective solutions. Due to their suitability for providing services in many different fields, many new and successful chatbot applications worldwide are rapidly increasing in number as services and productization.

ChatGPT has become the most prominent example of chatbots attracting a huge attention to AI. The tool represents the ultimate version of chatbots and exhibits what AI is capable of. As a product of OpenAI, it became publicly available on Nov 2022 and reached 100 million users within the first 2 months of launch. ChatGPT can go into long conversations, understand complex questions and learn from the user input (Marr, 2023). ChatGPT provide many functions to users including:

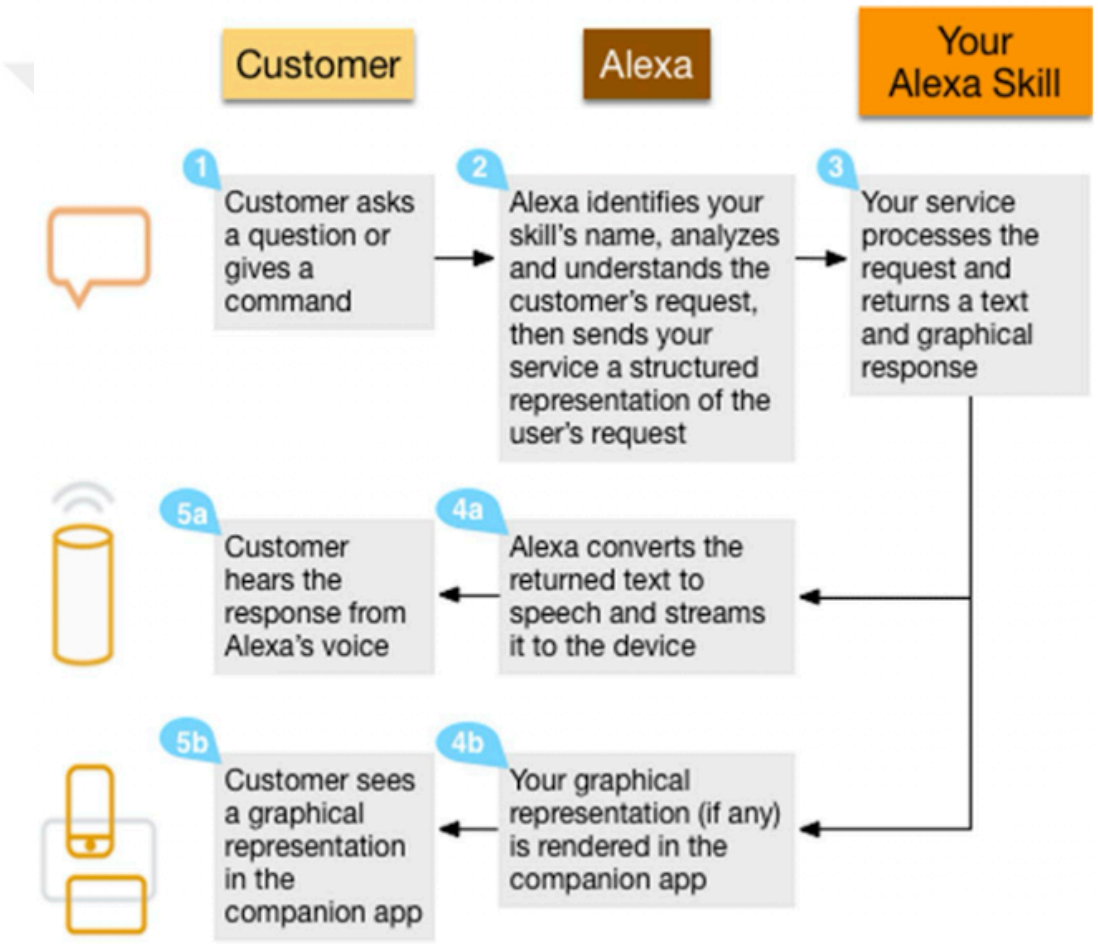
- Content creation
- Text summary
- Code Writing
- Information Search
- Translation

Bank of America launched its virtual financial assistant Erica in 2018 to step up their position in technology game. Erica offers extensive coverage of actions for customers directly within the banks mobile application thanks to its infrastructure made with natural language processing and machine learning whilst analyzing customer questions with deep understanding. Besides basic actions like checking your account balance, receive payment reminders, manage your cards and transact payments, Erica can successfully advice customers about managing their savings account with a sophisticated approach learning from their spending habits. In a circumstance where it does not understand complicated customer queries, Erica directs users to human customer agents to assure customer satisfaction (Bank of America, 2025).

The introduction of Siri was a first chance to many people to experience chatbots in a digital voice assistant form engaging artificial intelligence available for public usage (Guzman, 2019: 344). Since then, the truth about chatbots is that users are so familiar with them today such that big tech companies unveiled devices which comes with personal digital voice assistants built-in dedicated for users daily consumption. Users of HomePod can perform several actions including commanding

to device, web search, information search and answers and phone call and Echo on hand lets users to search products, manage shopping cart and track order status. Implementation of Siri to HomePod and Alexa to Amazon Echo is an opportunity to make usage of chatbots more frequent and increase awareness (Yang & Lee, 2019: 66-67). Figue 8 reflects the working principle of Alexa. Although there are some concerns about these devices are always on listening-mode, the usage of them is expected to see a larger growth in future (McLean & Frimpong, 2019: 28).

Figure 8: Alexa User Interaction Flow



Source: Amazon, 2024a

Dutch Airline company KLM is an ideal demonstration of how companies can use chatbots practically to relieve their burden of customer operations. Prior to implementing chatbots as customer assistants, KLM customer relations department

was employing 235 people having to deal with 15,000 customer query in a few languages weekly. Only in the first month of applying a simple Facebook Messenger bot , company contacted over 500,000 customers with 1.7 million messages. Then they started to cooperate with a technology company DigitalGenius, applying artificial intelligence, they were able to handle 60,000 customer questions. This chatbot can update travelers about check-in details, delays and general flight details. Almost 10% of the customer service is done without any need to redirect to human agent (Digiday, 2016).

1.8. CHATBOT APPLICATIONS IN TURKEY

Technology has a great impact on both consumers habits and companies business models. The number of organizations deploying new technologies in their business processes are in a steep increase in Turkey. AI-Powered application, chatbots, VR technology, blockchain are hot topics for all businesses and so is the situation in Turkey as well. AI-applications such as chatbots are trending these days across various industries including banking, insurance, retail, airlines, education and public services. Below, the most prominent examples of chatbot applications in Turkey are mentioned and listed as follows:

- Getir
- McDonald’s
- Garanti BBVA
- Türkiye İş Bankası Maxi
- Ministry of Education
- Turkish Airlines
- Pegasus Airlines FlyBot

Getir as an important digital retailer in Turkey provides its customers an advanced AI-powered support system Getir Support with the purpose of serving customers in a fast and efficient way through its mobile application. Thanks to this technology provided by the co-work with Cbot an innovative support system offers customers features such as checking status of order, add and remove products from their shopping carts and redeem discount codes instantly. Likewise, Getir Support

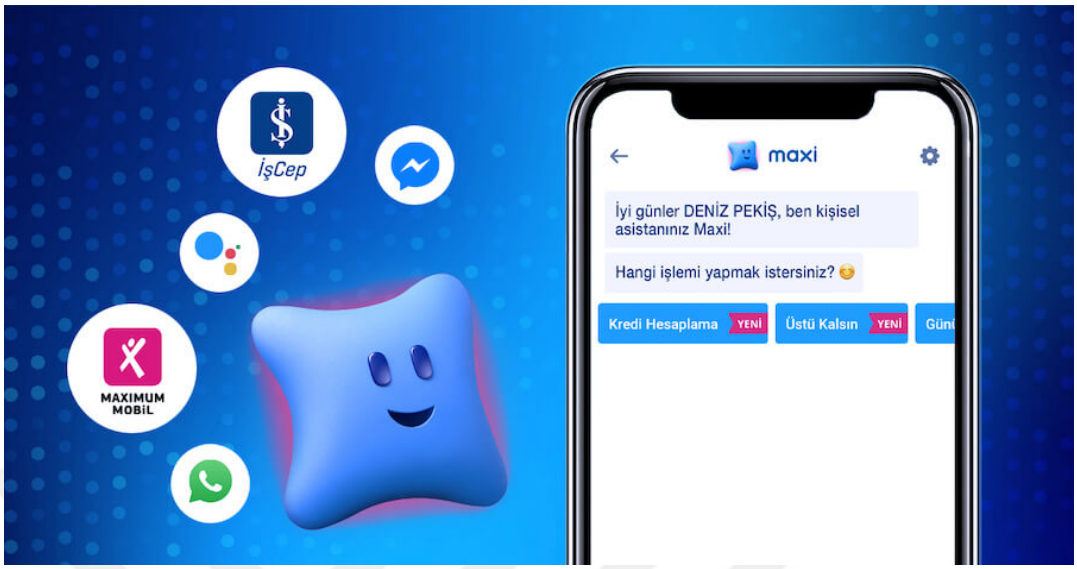
system is actively applied to its sub operations Getir Market, Getir Food and Getir Water. This system offers a fast forward, simple and efficient customer support which plays a vital role in building customer satisfaction and brand loyalty creating a real-time, enjoyable shopping experience. (CBOT, 2023a)

Fast food chain McDonald's presented İştah Hattı which is a chatbot integrated into WatsApp. The service allows the giant fast food company to contact its customers without any intervention and allow them to place and track orders, find the closest restaurant around and get information about offers anytime of the day restaurants operate. Though it is a simple chatbot provided via WatsApp, it helps to ease ordering process and differentiates the company in customer experience and customer satisfaction. (Gastronomi Dergisi, 2021).

As an outcome of Cbot and Garanti BBVA collaboration, UGI serves customers of the bank providing a seamless experience. This AI-powered chatbot can comprehend spoken language that contains natural expressions and respond correctly. These skills are built by Cbot natural language processing infrastructure and expertise in working with banking industry. UGI allows customers to realize transactions with oral expressions without the need of typing directly within the Garanti BBVA mobile application. (CBOT, 2022).

Another digital assistant example from banking industry is Maxi of Türkiye İş Bankası partnering Cbot. Maxi founded in 2017 as the first AI powered chatbot in banking sector. This chatbot offers services within İş Bankası mobile application and as well as via its website, WatsApp, Facebook and Google Assistant. (CBOT, 2025)

Figure 9: İş Bankası Maxi Digital Assistant



Source: DigitalTalks, 2021

Turkey's Ministry of Education and Cbot launched EBA Asistan to improve technology adoption with the aim of guiding teachers and students on finding answer to their questions. It is an AI powered chatbot with machine learning, constantly learn from users questions and improve response quality. Thanks to its natural language processing mechanism, this chatbot can handle questions in colloquial language. Its features include creating password, resetting password, timetable query, exam status check, conference with teachers and review the class. Especially after pandemic began in 2020, EBA Asistan had been very helpful to all parties to keep online education running. (CBOT, 2020)

In 2020, Turkish Airlines launched its chatbot application, Cargy, specifically for its subsidiary, Turkish Cargo. Cargy allows Turkish Cargo customers inquire about their shipping status, access information regarding available dates and check flights for cargo shipment through a WhatsApp number around the clock. This innovative technology is a next step for digitalization and competitive positioning of the company (Turkish Airlines, 2020).

Pegasus Airlines launched FlyBot in corporation with Cbot utilizing AI technology to handle travel inquiries and produce personalized travel recommendations. This intelligent digital assistant offers a wide range of services

including accommodation and restaurant recommendations, flight tickets complete travel itineraries. FlyBot is an important example of Pegasus' commitment to technology and innovation for a modern travel experience (CBOT, 2023b)

Many other companies like the ones mentioned above, use chatbots to lead their sales and marketing to provide services for 24/7 access with customers. Botgate, an AI-Powered chatbot solutions provider help a wide range of companies to qualify their sales. They answer customer queries without intervention and it helps to lead sales by decreasing the number of missed queries, improve lead quality and website traffic. Through API, its bots can be built into a company website or instant messaging platforms such as WhatsApp, Facebook Messenger, Skype. Customers include companies like Rixos Hotels, Shell, and Setur (Botgate, 2022).

CHAPTER TWO
TECHNOLOGY ACCEPTANCE MODEL

This section of the study aims to explain the background of the hypothetical development, models utilized, variables that are drawn based on scientific theories and the previous studies that used Technology Acceptance Model (TAM) in measuring the adoption of new technologies and specifically studies that are based on TAM in measuring the acceptance of chatbots.

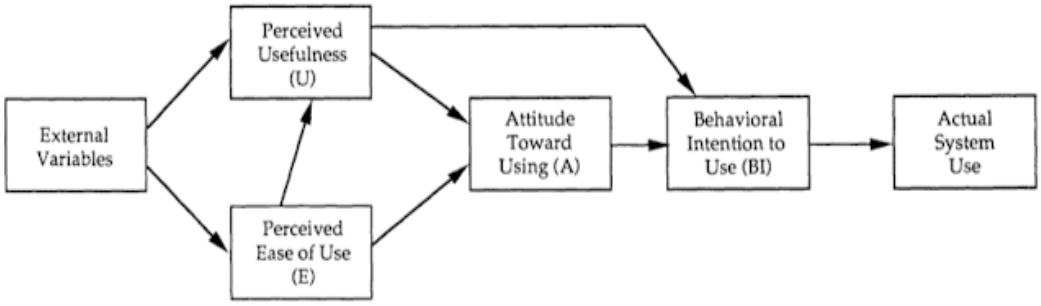
2.1. TECHNOLOGY ACCEPTANCE MODEL (TAM)

Acceptance of chatbots is a trending research field and the number of studies done in different contexts are rising lately. Many studies have been conducted in several fields such as tourism, retail, banking and finance contributing to the technology acceptance literature. TAM (Davis, 1986) is an important framework helping researchers to examine users respond to embracing new technologies effectively explaining consumer adoption across a wide variety of technology innovations (Belanche, 2019: 1414). TAM has become a leading influential model in research of Information Systems (IS) due to its ease of understanding and simple nature (King & He, 2006: 740).

Adapted from Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980), TAM was originially proposed by Davis (1986) specifically designed to test user acceptance of IS. The broad purpose of the model was to explain antecedents of accapentance of computers in general while being scientifically valid and rigorious. The primary goal of TAM was to examine how external factors influence internal beliefs, attitudes and intentions (Davis et al, 1989: 985).

TAM relies on two major particular variables in identifying behevioral intention to use of an IS which are namely perceived usefulness (PU) and perceived ease of use (PEOU). The Figure 10 illustrates the impact of external variables that are namely PU and PEOU on attitude towards using an IS and behavioral intention to use IS and actual system use as a result.

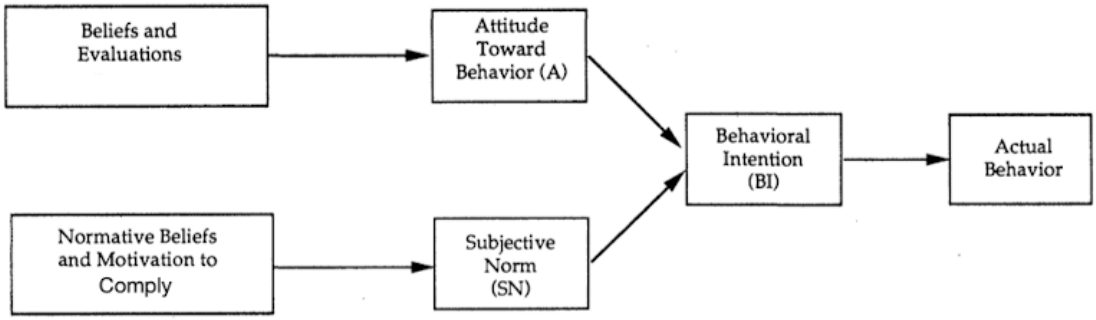
Figure 10: TAM model



Source: Davis et al, 1989: 985

TAM is derived from TRA but differs in perspective on considering drivers of behavioral intention towards a system. TAM in its original form, grounded on external variables PU and PEOU and ignores subjective norms to decide on adoption behavior which TRA suggests. TRA is a general framework that does not pinpoint beliefs that identifies a specifically given behavior.

Figure 11: TRA model



Source: Davis et al, 1989: 984

2.1.1. Perceived Usefulness

Perceived usefulness is defined as ‘’the degree to which a person believes that using a particular system would enhance his or her job performance.’’ (Davis, 1989: 320). Within the context chatbots in general, it can be referred as the degree to which using chatbot would enhance users daily tasks. As being one of the items in TAM, PU

is a vital explanatory factor of users intention to accept and adopt new technologies (Kim-Vick & Lee, 2008: 620).

As users decide to adopt a new technology depending on whether they will benefit from its features, a high number of academic research has revealed that perceived usefulness is the most signifacant determinant of technology adoption (Kulviwat et al, 2007: 1063). Individuals who recognize the potential of chatbot technology are highly likely to use it in their daily routines as they bring simplicity and comfort. As chatbots save time for consumers such as providing availability at a convenient level that traditional service channels often cannot match and offer flexibility with on-demand features, its usefulness should be acknowledged by consumers (Kasilingam, 2020).

2.1.2. Perceived Ease of Use

Along with PU, perceived ease of use is the other fundemantal variable that forms the base of TAM. Perceived ease of use is defined as "the degree to which an individual believes that using a particular technology will be free of mental effort". (Davis, 1989: 320). Studies that found in the literature, unveils that newly introduced technologies are highly probable to be accepted when the users find them easy to use. As the intention to use a new technology is directly impacted by PU and PEOU, it is also found that behavioral intention to use a system is indirectly influenced by PEOU via PU (Saade & Bahli, 2005: 318-320)

As mentioned before in this study, the number of research that is based on TAM on measuring user acceptance of new technologies non-negligible and number of citations are noteworthy. On a study conducted with 122 university students to measure intention to use of e-learning applications, Masrom (2007) found that PEOU has a significant influence on PU and PU on intention to use. However both items had only a little explanation on the attitude towards intention to use with attitudes mediator effect. Researchers suggest that this may be caused by students focus on benefits of e-learning application and therefore usefulness of the technology itself. Scherer, Siddiq and Tondeur (2019) ran a study to predict teachers intention to use digital technology

in teaching systems and they revealed that PU and. PEOU had a significant impact on intention to use technology via attitudes.

Suh and Han (2002) used TAM to understand the level of customers acceptance of internet banking considering the effect of trust. Researchers collected data from 845 participant via a survey conducted online. As expected, PU and PEOU had a significant impact on customers attitude towards online banking and intention to use it. They also found that trust was a significant independent variable to understand customers beliefs and attitude towards online banking.

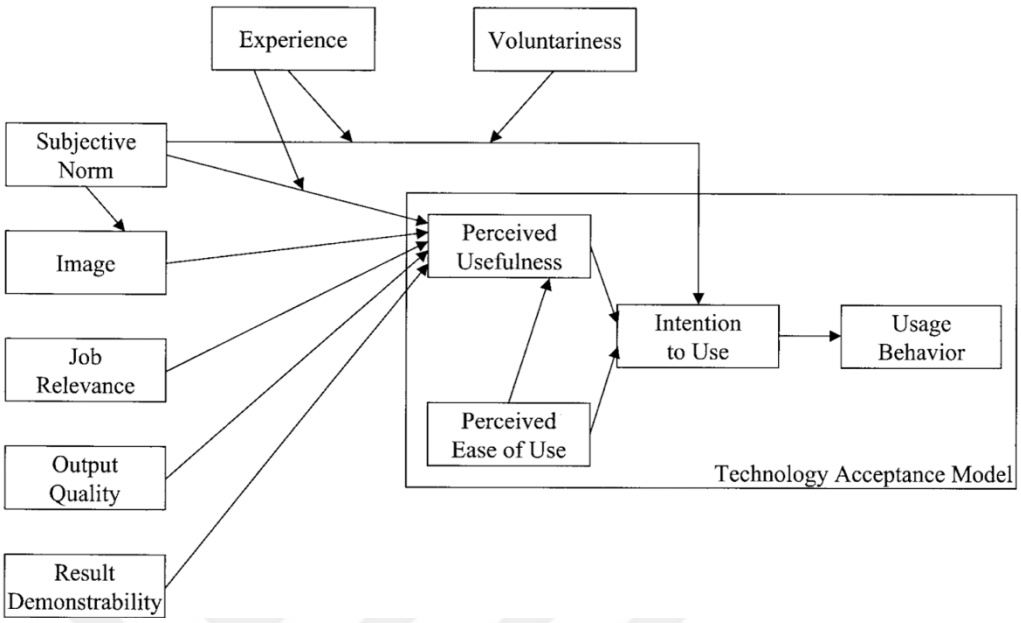
2.2. TECHNOLOGY ACCEPTANCE MODEL 2 (TAM2)

Theory of Reasoned Action posits that behavior can be predicted if a persons' belief, attitude and intention are given (Silva, 2007: 256). Davis (1989) excluded subjective norm of TRA and introduced external variables as PU and PEOU to understand attitude, behavioral intention and actual use. Since the original TAM was introduced by Davis (1989), there has been a significant gain in the literature of technology acceptance thanks to the contribution of the model.

TAM is based on external factors impact on the attitude and intention is mediated by PU and PEOU. According to TAM PU is a strong determinant of intention and PEOU is less powerful in explaining variance of intention when tested its direct effect. Venkatesh and Davis (2000) extended the study as TAM2 to provide a better understanding of determinants of external factors. They suggested that understanding the predictors of PU, since it is the strongest predictor of intention, will expose a better explanation for measuring intention.

TAM2 provides an extensive view of TAM explaining external variables of PU as subjective norm and image (social influence) and job relevance, output quality and result demonstrability (cognitive instrumental processes) along with added moderator variables experience and voluntariness (Venkatesh and Davis, 2000: 187). In original TAM subjective norm, which refers to impact of social influences of others who may be an important referrer on intention, was removed from the model. In TAM2 subjective norm is added to capture social influence and attitude is removed (Sharifzadeh et al, 2017: 89; Venkatesh and Davis, 2000: 188).

Figure 12: TAM2 Model



Source: Venkatesh and Davis, 2000: 188

Figure 12 provides a clear understanding of the extended model. Intention to use is effected by PU, PEOU and subjective norm while considering the moderator effect of experience and voluntariness between subjective norm and intention to use. PU is influenced by five elements; subjective norm, image, job relevance, output quality and result demonstrability. PU is determined by subjective norm via moderator effect of experience and as the figure demonstrates, unlike the first version of TAM, attitude is removed from the model but expended with more determinants of PU.

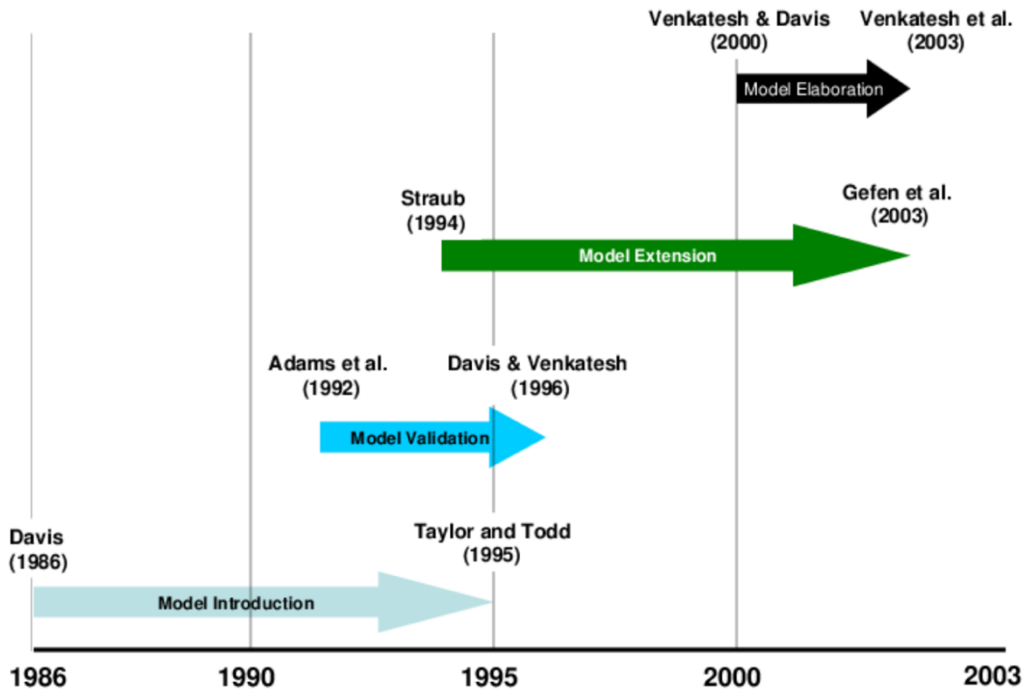
2.3. TECHNOLOGY ACCEPTANCE MODEL 3 (TAM3)

TAM and TAM2, as previously discussed, made a notable contribution to technology acceptance literature. TAM3 extends TAM2 while adding the determinants of PEOU. TAM 2 added the predictors of PU for a better understanding of intention to the original TAM, as PU is the strongest variable of intention. Over the years a number of contributors added to literature and Venkatesh (2000) explained the components of PEOU. Figure 13 reflects the development of TAM over the years prior to TAM3.

Venkatesh (2000) suggests that individuals general beliefs will create their perception of perceived ease of use. They suggest that self-efficacy, computer anxiety, computer playfulness and perception of external control are the predictors of PEOU. They also added system related items which are perceived enjoyment and objective usability to become important factors in predicting PEOU as users increase knowledge and experience with new systems (Venkatesh & Bala, 2008: 9). Along with these contributions TAM3 is suggested as it finds final model in Figure 14.

There are number of studies that utilize from the TAM3 model either partially or integrating the model with most elements. In their study, Faqih and Jaradat (2014) applied extended TAM3 model to understand the adoption of mobile commerce in Jordan. They explored that as in many other studies PU and PEOU were the strongest influencers of behavioral intention. The predictors of PU were validated strongly as image and output quality and subjective norm and determinants of PEOU as self efficacy and perceptions of external control.

Figure 13: Chronological Development of TAM Before TAM3



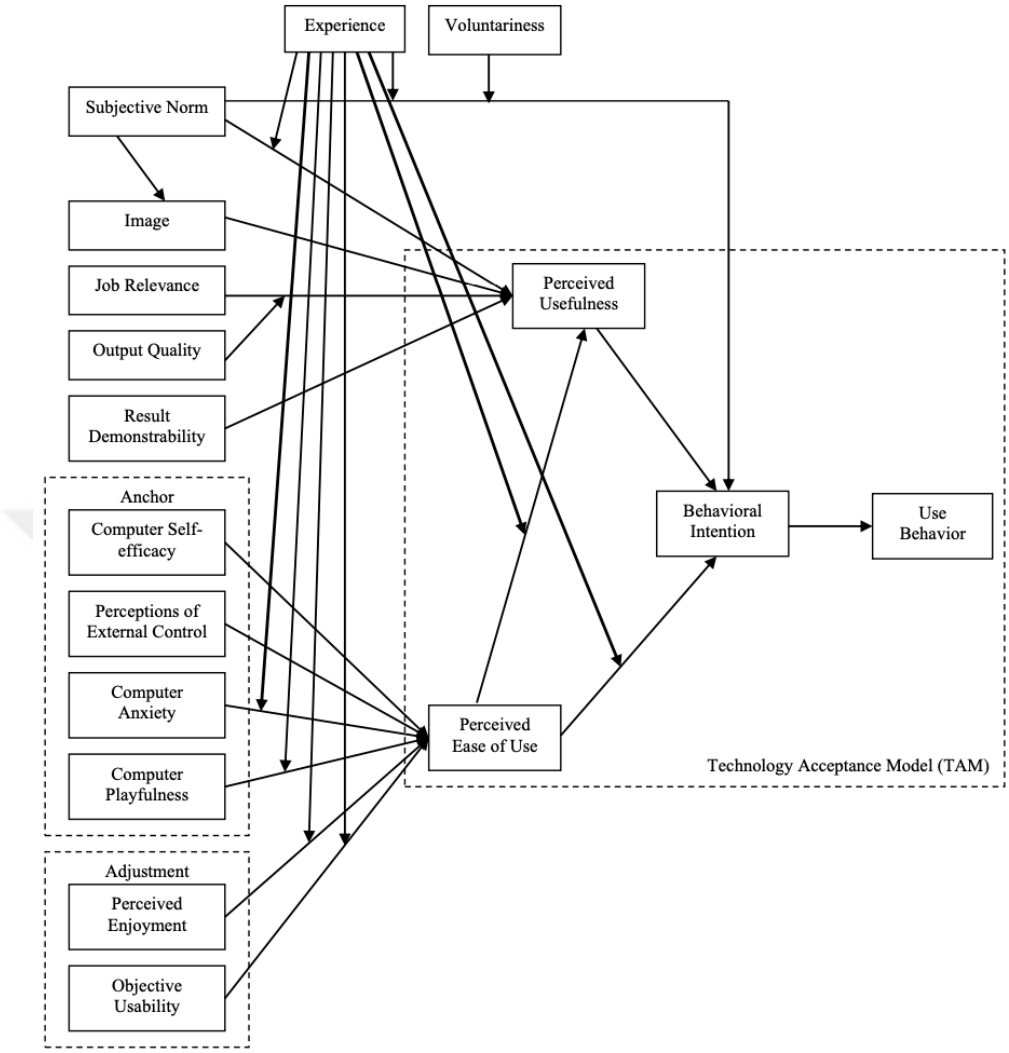
Source: Lee, Kozar, & Larsen, 2003: 755

2.3.1. Perceived Enjoyment

Perceived enjoyment (ENJ) refers to ‘’the extent to which the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated.’’ (Davis, Bagozzi, Warshaw, 1992: 1113). Motivation theorists sets two types of motivation as extrinsic and intrinsic motivation. While perceived usefulness is an example of extrinsic motivation, perceived enjoyment is an example of intrinsic motivation (Davis, Bagozzi, Warshaw, 1992: 1112).

Many studies questioned the impact of perceived enjoyment with its intrinsic utilities. Alalwan et al (2018) explored the notable impact of perceived enjoyment as its direct impact on Saudi customers intention to use mobile internet. They also found a significant relationship between ENJ and PU as customers tend to find products more useful when they think they are more enjoyable to use. In their study, Huang et al (2024), in a survey made with 380 tourists, explored that ENJ was a significant antecedent of customer satisfaction and their intention to use AI based services.

Figure 14: TAM3 Model



Source: Venkatesh and Bala, 2008

2.4. PERCEIVED RISK

TAM is centered on variables (perceived usefulness, perceived ease of use) that can be positively related to adoption of new technologies. TAM2 and TAM3 boosts the model with integrating new elements that are likely to be positively associated to acceptance. Featherman and Pavlou (2003) further develops that approach by adding an item that might be negatively linked to accaptence of technology in context of e-service adoption.

Perceived risk (PR) refers to a persons' subjective assessment of the likelihood of experiencing a loss while trying to get a desired outcome. (Pavlou and Gefen, 2004:

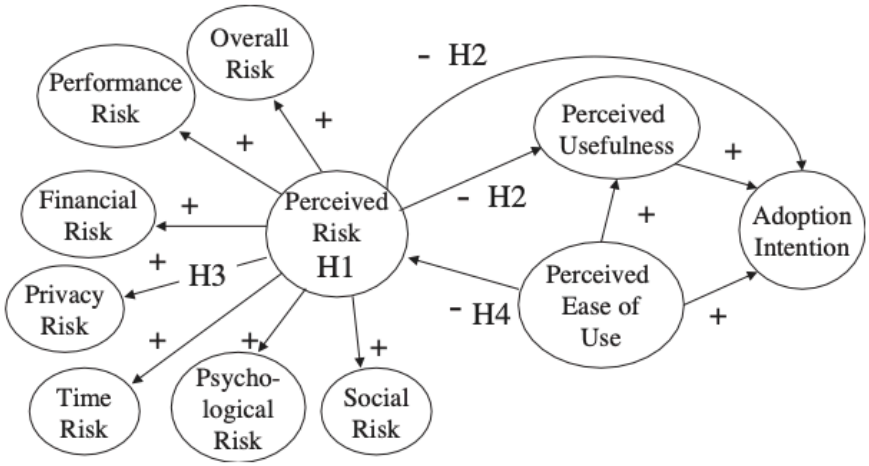
41). Perceived risk aims to explain why customers avoid online transactions. In e-commerce, risk perception of customers arise regarding the security of a given website where purchase will be made as well as including financial and privacy concerns (Sullivan & Kim, 2018: 204).

When customers initiate a transaction or get interacted in an online environment they may be exposed to internal and external factors that they perceive as risk. Featherman and Pavlou (2003) breaks down perceived risk into 7 facets that are listed an defined as below:

- Performance Risk
- Financial Risk
- Time Risk
- Psychological Risk
- Social Risk
- Privacy Risk
- Overall Risk

Performance risk is the sum of concerns with functionality according to the purpose of using a product or service. Financial risk relates to monetary consequences of a purchase or usage of a product and service. Time risk is involves the possibility of wasting time trying to utilize a product or service. Psychological risk refers to the negative psychological impact of using a product or service on ones own mind. Social risk is potential loss of social status or reputation. Privacy risk involves the leakage of personal information to the third persons without being disclosed by the owner. Overall risk is the aggregation of general dimensions that involve the previous risk factors. Featherman and Pavlou (2003) introduces their research model as visualized in Figure 15. They find that most salient items are performance risk, financial risk, privacy risk, time risk and overall risk.

Figure 15: Perceived Risk Facets Research Model



Source: Featherman and Pavlou (2003: 457)

Lee (2009) applied perceived risk factors with TAM in their study of understanding the acceptance of customers in internet banking via a survey conducted with 368 customers. The study suggests that financial risk, performance risk, privacy risk and time risk had an impact attitude towards intention to use of online banking channels. They study also suggests that performance risk has a negative determination on perceived usefulness.

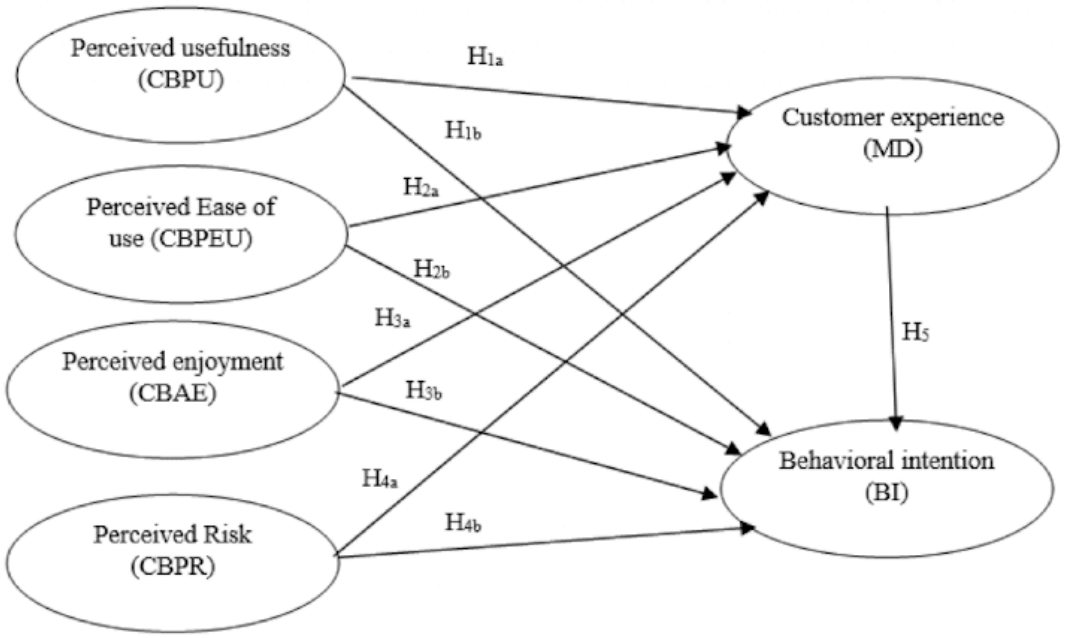
2.5. PREVIOUS RESEARCH OF CHATBOTS THAT CENTERS TECHNOLOGY ACCEPTANCE MODEL ELEMENTS

The relentless advancement of artificial intelligence technology and the visibly rapid increase in the interest from both theorists and practitioners are making this field of science popular in academic circles. Consequently, the number of studies on chatbots, as a branch of artificial intelligence, is also increasing in direct proportion to its popularity. The Technology Acceptance Model remains a robust and consistent model for measuring users' responses in terms of adopting technological advancements and gaining usage habits. So that the number of studies using this model to measure the user perspective on chatbots is quite substantial. This shows that the model is still resilient and useful. Below, we provide references to these studies and the findings they contain.

Rese et al (2020) conducted a research with 205 millennial participants in Germany to explore the adoption of a chatbot called ‘’Emma’’ offered by a German online retailer Zalando. They included perceived usefulness, perceived ease of use, perceived enjoyment and privacy risk to understand customers intention to use the specific chatbot. The study revealed that PU and ENJ were positively associated with intention to use of chatbot. However, privacy risk was found to be negatively impacting usage intention of chatbot. On the other hand PEOU had no significant impact on usage intention as participants found ‘’Emma’’ very easy to use and the construct reached the highest mean value.

In their study, Gümüş and Çark (2021) analyzed chatbot acceptance of Turkish users with 211 correspondents. Figure 16 reflects their research model and proposed hypothesis. They examined the effect of PU, PEOU, ENJ and PR on customer experience and usage intention. They explored that PU and PEOU had a significant effect on behavioral intention to use of chatbots and experience. However, they found the impact of PR insignificant on both experience and intention to use. ENJ was found to explain experience but did not influence intention to use.

Figure 16: Research Model Proposed by Gümüş and Çark (2021)



Source: Gümüş and Çark (2021: 428)

Abdalla (2024) investigated the intended use of ChatGPT by students in Palestine and their findings highlighted that the intention of adoption was positively impacted by PU and PEOU. The study also reveals the positive impact of ENJ on ChatGPT adoption.

Fernandes & Oliveira (2020) included PU and PEOU to their study as determinants of digital voice assistant adoption. They highlighted a direct relationship between PU and intention but failed to prove the same for PEOU and intention unexpectedly. Conversely, when mediated by PU, PEOU had a significant indirect impact on digital voice assistant usage intention.

Pillai et al (2020) carried out a study focused on revealing the customers shopping intention at retail stores powered by AI technologies including chatbots. The study is conducted in India with 1250 customers and the results of tested hypothesis indicate that a meaningful relationship can be explained among PU and intention, PEOU and intention, ENJ and shopping intention. The study also demonstrated that a positive influence of PEOU can be seen on PU.

Moussawi et al (2020), studied the users adoption intention of personal digital assistants such as Siri and Alexa. Their study unveiled that PU and ENJ are positively associated with intention to use these chatbots. On the other hand, the expected positive influence of PEOU on PU and intention was not supported. Researchers attribute this to chatbot systems to be perceived as simple by design and usage.

Kleine et al (2024) analyzed the usage intensity of chatbots with two studies amongs students via a survey conducted first with 72 and second with 153 individuals. They tested the impact of PU and PEOU along with other influencers and indicated that both PU and PEOU had a significant explanation to usage intensity. The study also demonstrates the mediative impact of PU between PEOU and usage. Lee (2009), Pavlou (2003) and Kasilingam (2020) on the hand highlighted the negative impact of PR on attitude and intention to use technology.

The previously referred studies discover that PU, PEOU, ENJ and PR are context related variables to understand the intention to use of chatbots in a recognized manner. Based on this view, the proposed hypothesis are to be tested in the upcoming chapter.

CHAPTER THREE
RESEARCH METHODOLOGY, RESULTS AND FINDINGS

3.1. PURPOSE OF THE RESEARCH

This thesis aimed to explore the user acceptance of chatbots, which is a trending topic with increasing number of chatbot examples and usage areas. The investigation was undertaken to understand the users' intention to use chatbots centering technology acceptance model at its core. Accordingly with the purpose of the study, the relationship between perceived usefulness, perceived ease of use, perceived enjoyment, perceived risk and intention to use are investigated with accompanying sociodemographic profiles of the participants.

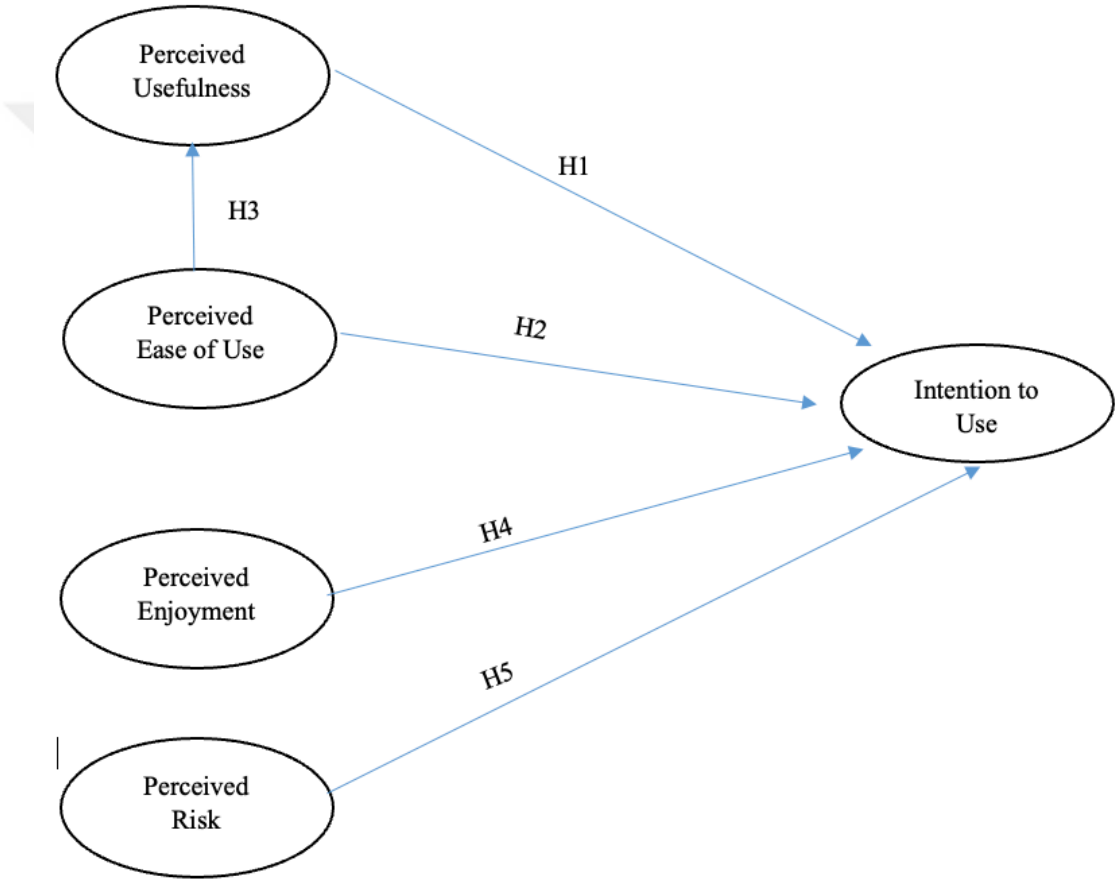
3.2. IMPORTANCE OF THE RESEARCH

In today's world, considering user interaction, the usage of chatbots is becoming increasingly common, and the variety and number of products and services in this area offered by businesses are expanding. In this context, users' perception towards chatbots are significant for businesses that wish to offer services this technology within their own operations or enhance their existing services. Especially with the advancements in artificial intelligence, chatbots have become more sophisticated, and businesses' marketing functions have turned their attention to this area. The impact of new technologies on user acceptance has been studied for a long time in various fields; however, measuring user acceptance within the framework of chatbot activities is a relatively new research topic and this research aims to examine the users approach in Turkey.

3.3. RESEARCH MODEL AND HYPOTHESIS

In order to prepare a conceptual model for the study, past literature on technology acceptance and chatbot adoption were analyzed. Based on the literature related to chatbot adoption, the following research model shown at Figure 17 was designed.

Figure 17: Research Model



Source: Compiled by the Author

In the research model, intention to use was defined as the dependent variable and perceived usefulness, perceived ease of use, perceived enjoyment and perceived risk were set as independent variables and the relationship between the dependent and independent variables were examined. Based on the findings, the following hypothesis are proposed:

H1: Perceived Usefulness (PU) has a positive impact on Intention to Use Chatbots (INT).

H2: Perceived Ease of Use (PEOU) has a positive influence on Intention to Use Chatbots (INT).

H3: Perceived Ease of Use (PEOU) has a positive impact on Perceived Usefulness of Chatbots (PU).

H4: ENJ → INT Perceived Enjoyment (ENJ) has a positive influence on Intention to Use Chatbots (INT).

H5: Perceived Risk (PR) has a negative impact on Intention to Use Chatbots (INT).

3.4. RESEARCH METHODOLOGY

3.4.1. Measurement Scales

The data necessary for the study was gathered via a questionnaire containing seven sections. In the first section of the survey participants were asked if they have heard of and used chatbots previously with yes/no questions. Also, if they used, they were asked to state the purpose of usage.

The second section of the survey contains six questions related to perceived usefulness variable designed by Davis (1989: 340). The items that form the section were based on a 7-point Likert scale ranging from completely disagree (1) to completely agree (7).

The third section is related to the perceived ease of use variable and its questions developed by Davis (1989: 340). The variable is tested with eight questions based on a 7-point Likert scale ranging from completely disagree (1) to completely agree (7).

The fourth section involves perceived enjoyment variable with questions designed by Venkatesh, Speier and Morris (2002: 307). The participants were presented with three questions to rate their answers from completely disagree (1) to completely agree (7) based on a 7-point Likert scale.

The fifth part consists of perceived risk variable with five dimensions developed by Featherman and Pavlou (2003: 470-472). 21 questions were asked in this section in total, which are composed of five dimension of perceived risk; financial risk (4 questions), performance risk (5 questions), privacy risk (3 questions), time risk (4 questions) and overall risk (5 questions), based on a 7-point Likert scale ranging from completely disagree (1) to completely agree (7).

In the sixth section three questions were asked regarding the dependant variable; intention to use. The items used were designed by Venkatesh, Thong and Xu (2012: 178) and asked based on a 7-point Likert scale ranging from completely disagree (1) to completely agree (7).

In the final section of the survey, question related to demographic profiles of the attendents were asked including age, gender, maritial status, the level of education and job sector.

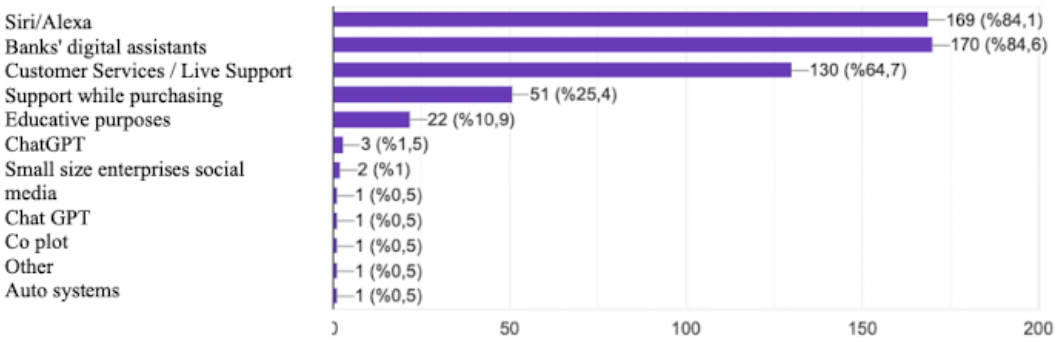
3.4.2. Data Collection and Sampling

An online survey was carried out for the data collection phase of the study and administered via Google Forms. The prepared questionnaire was applied to the online system and shared via social media platforms with the participants upon their volunteered attandence. The selected sampling approach was convenience sampling and 242 participants in total attended to the study.

3.5. DEMOGRAPHIC ANALYSIS

A total of 242 participants were reached and before begining the questionnaire they were presented with information regarding chatbots, explaining the term and reminding them the chatbot examples that they may have used previously. 41 participants stated that they did not hear of chatbots and never used them before. Therefore, their answers were not considered and the analysis were done with 201 of the respondents.

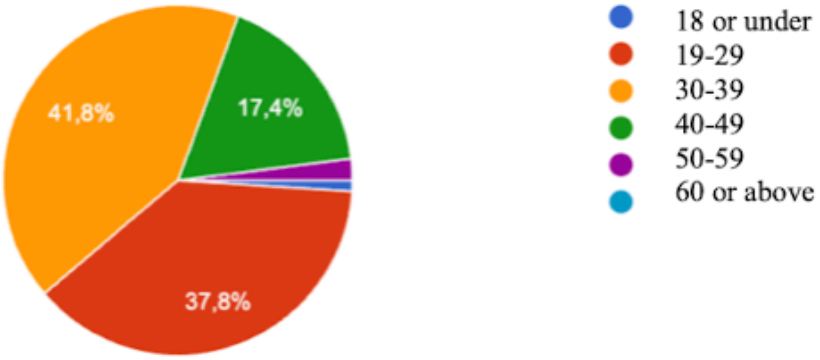
Figure 18: Type of Previous Chatbot Experience



Source: Compiled by the Author

Figure 18 illustrates the purpose of chatbot usage of respondents and it reflects that 170 participants used chatbots offered by their banking application. 169 participants had prior experience with digital assistants such Siri and Alexa. 130 were had chatbot exposure via customer support. 51 used chatbots for purchaing goods and services online and 22 stated that they used it for educational purposes. A blank space was provided for respondents to state the purpose of their use other than these, but the responses did not reflect any other purpose of use.

Figure 19: Distribution of Age

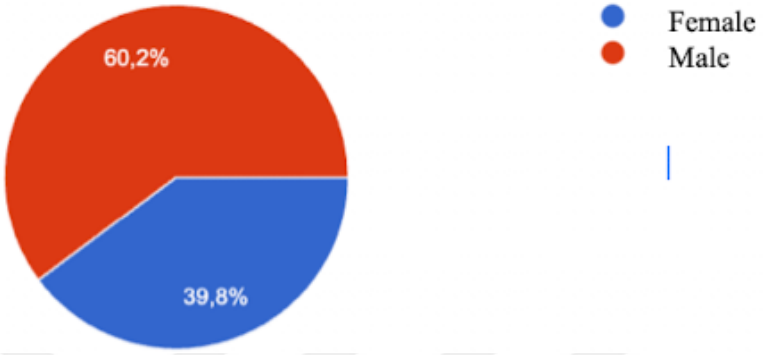


Source: Compiled by the Author

Figure 19 presents the distribution of age in percentages. The youngest respondents (18 years and under) constituted a small group of two, with only 1% of the total. 76 participants are between 19-29 age range. The participants between 30-39 are the largest group with 84 respondents. 35 participants are between 40-49 range and

4 respondents are in the range of 50-59. There were no participants above or at the age of 60.

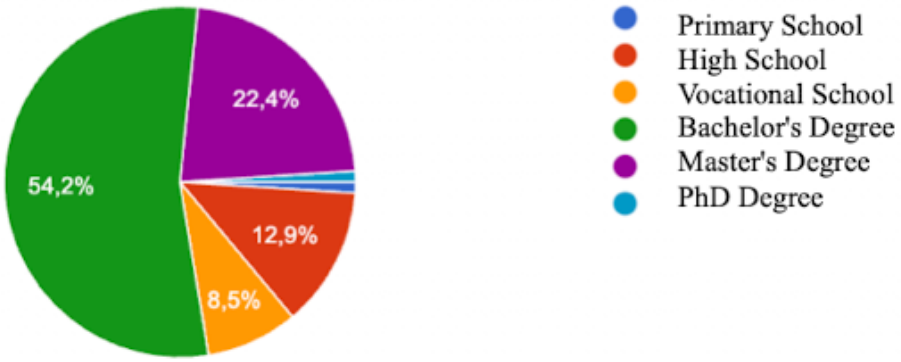
Figure 20: Distribution of Gender



Source: Compiled by the Author

Out of the 201 respondents, 121 were male and 80 were female respondent. The Figure 20 reflects the distribution in percentages.

Figure 21: Distribution of Education

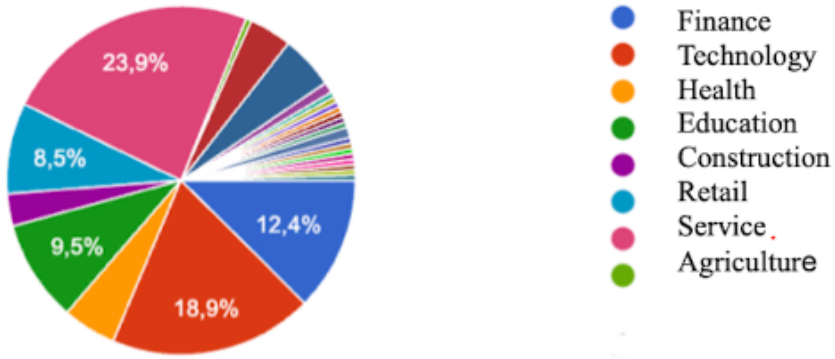


Source: Compiled by the Author

The educational profile of the 201 survey participants is largely dominated by the Bachelor's degrees holders as illustrated at Figure 21. 109 of the respondents, which is over the half of the sample, possess this level of education, indicating a strong representation of individuals with undergraduate qualifications. Master's degrees were

held by 45 respondents, while 26 participants stated that high school is their highest level of education.

Figure 22: Distribution of Job Sector



Source: Compiled by the Author

The largest group in the study with 48 participants appears to be employed in the service sector as it involves a variety of occupation. It is followed by those (38 participants) stated that they work in technology industry. And the third largest group is finance industy with 25 respondents.

3.6. DATA ANALYSIS

3.6.1 Zero-Order Correlations, Descriptive Statistics and Scale Reliabilities

The means, standard deviations, and correlations for the study variables are presented in Table 3. These descriptive statistics provide an important foundation for a better understanding of the data distribution and initial relationships among constructs prior to testing the hypothesized model. Means and standard deviations offer insights into the central tendency and variability of each construct, helping identify potential issues such as ceiling or floor effects (Tabachnick & Fidell, 2013).

Correlation analysis usually help as a preliminary test of construct relationships and provides evidence for criterion-related and construct validity, as theoretically related variables should demonstrate significant correlations in the expected directions

(Hair et al., 2019; Kline, 2015). In this study, all correlations are statistically significant at the $p < .01$ level, which suggests meaningful associations between the variables that align with theoretical expectations.

While correlations cannot establish causality, they are commonly used in early stages of model assessment to evaluate the strength and direction of linear relationships between constructs (Bryman & Cramer, 2011). These patterns help validate the conceptual model before conducting more complex analyses such as confirmatory factor analysis and structural equation modeling.

Table 3: The means, Standard Deviations And Correlations

Variable	Mean	Standard Deviation	Perceived Usefulness	Perceived Ease of Use	Perceived Enjoyment	Perceived Risk	Intention to use Chatbots
Perceived Usefulness	5.15	1.41	(0.96)				
Perceived Ease of Use	5.44	1.09	0.75	(0.88)			
Perceived Enjoyment	4.98	1.62	0.75	0.68	(0.97)		
Perceived Risk	3.76	1.33	-0.43	-0.43	-0.42	(0.97)	
Intention to use chatbots	5.15	1.62	0.73	0.64	0.73	-0.44	(0.94)

Source: Compiled by the author

Note: Cronbach's alpha coefficients for the scales are shown in parenthesis on the diagonals. All correlations are significant at $p < 0.01$. $N = 201$.

3.6.2. Test of the Measurement Model

Using the Mplus software, a confirmatory factor analysis (CFA) was performed to examine evidence for construct validity and discriminant validity for the five study variables. The respective items were used as observed indicators for all unidimensional variables except for perceived risk. For perceived risk, its 5 dimensions, rather than the 21 items, were used as indicators. This was necessary to reduce the model complexity and the number of estimated parameters relative to the sample size in order to improve model fit, as the current sample size was relatively low (Coffman and MacCallum, 2005). To account for potential non-normality in the data, MLR estimation algorithm was utilized. All covariances were freed among the five variables. The results show that all indicators loaded significantly on their respective latent factors, and the model fit was acceptable (though not outstanding) based on commonly used thresholds (Hu and Bentler, 1999) (Comparative Fit Index (CFI)=0.91, Root mean Square Error of Approximation (RMSEA) = .08, Standardized Root Mean Square Residual (SRMR) = 0.056; Chi-Square = 627.99, degrees of freedom (*df)* =265, $p < .01$) .

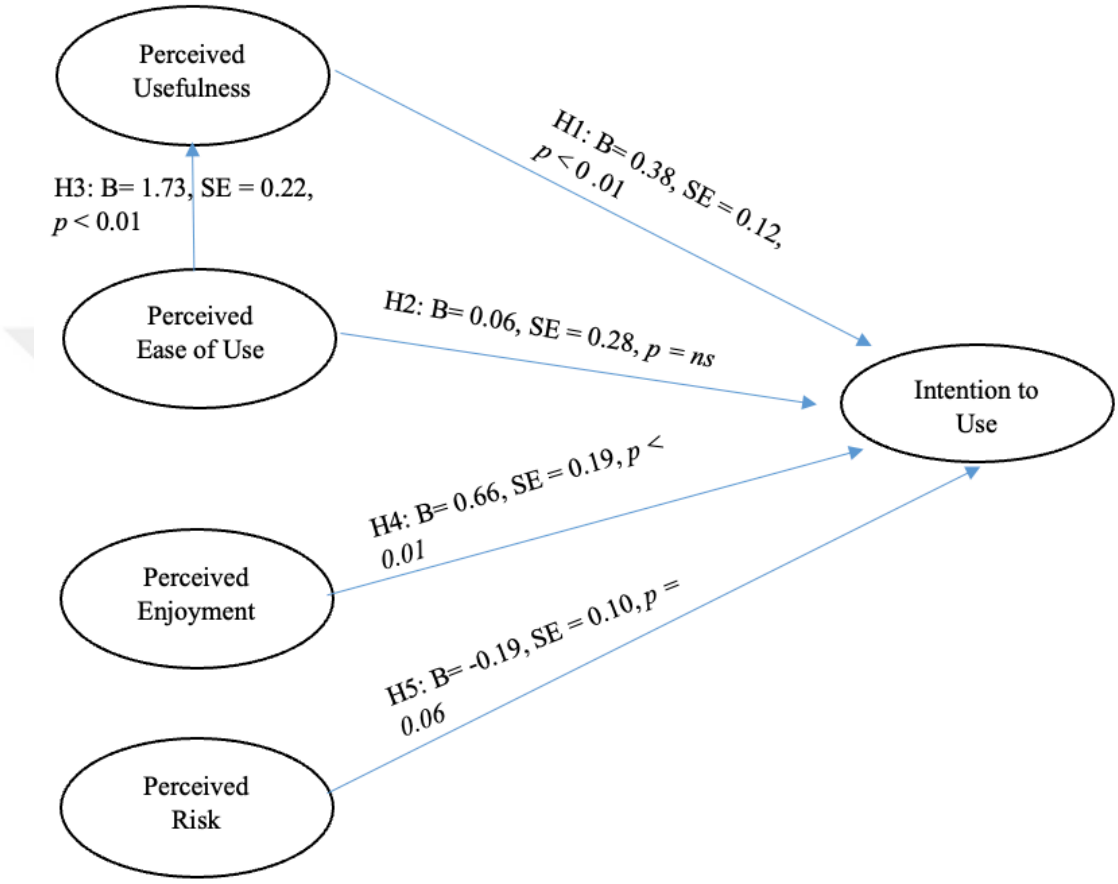
The discriminant validity was tested using the procedure recommended by Rönkkö and Cho (2022). They argue that two measures that intend to measure distinct constructs have discriminant validity if the absolute value of the correlation between these constructs after correcting for measurement error does not exceed 0.90. Following their recommendation, the variance of each latent factor was set to 1 (and all factor loadings were freed) and correlations among each latent factor was analysed in the measurement model. The absolute value of correlations ranged from 0.43 to 0.84, thus suggesting that the current measures of the five study constructs.

3.6.3. Hypothesis Tests and Results

Using a MLR algorithm and the same latent factors and observed indicators as in the CFA model, a structural model was formed to test the hypotheses. The structural model had acceptable fit to the data (CFI= 0.90, RMSEA = 0.08, SRMR = 0.06; Chi-

Square = 645.71, *df* = 267, $p < 0.01$). The beta weights for each hypothesized path and their respective standard errors are shown in Figure 23.

Figure 23: Hypothesis Results



Source: Compiled by the author

Note: B and SE refer to beta weight and standard error, respectively.

PU positively affects the intention to use of chatbots (B= 0.38, SE = 0.12, $p < 0.01$), therefore H1 is supported. PEOU has no significant impact on intention to use of chatbots (B= 0.06, SE = 0.28, p = ns), therefore H2 is not supported. However, a positive impact of PEOU on PU of chatbots was found (B= 1.73, SE = 0.22, $p < 0.01$), therefore H3 was supported. ENJ positively affects the intention to use of chatbots (B= 0.66, SE = 0.19, $p < 0.01$), therefore H4 is supported. PR negatively affects the intention to use of chatbots (B= -0.19, SE = 0.10, p = 0.06). The p value is at 0.06,

slightly higher than 0.05. Therefore H5 receives marginal support. We can conclude that there is a strong trend in the expected direction.

Although not hypothesized formally, perceived ease of use might be exerting its effect on intention to use indirectly through perceived usefulness. To test this possibility, the bootstrap procedure as recommended by Preacher and Hayes was employed. The bootstrap method is preferred in mediation analysis because it provides robust and accurate confidence intervals for indirect effects without relying on the often-violated assumption of normality, which traditional methods like the Sobel test often require (Preacher and Hayes, 2008). Accordingly, 5000 bootstrap samples were created from the data and the mediation effect (that is, indirect effect) was tested. The indirect effect was 0.66 and the 95% confidence interval was between 0.29 and 1.16. Because the confidence interval did not contain zero, the indirect effect was significant. This finding supports the possibility that perceived ease of use predicts intention to use indirectly via perceived usefulness.

CONCLUSION

Powered by the rapid developments in the artificial intelligence technology, chatbots increased their popularity among the users around the world and in Turkey. As chatbots are equipped with upgraded and increasingly sophisticated skills and containing advantages of natural language processing, users can execute a wide variety of tasks in a more efficient manner. Chatbot capabilities include many functions such as handling customer requests, assisting customers with online purchases, information retrieval and customer support. As a result of this, authorities anticipate its usage rate to raise even more in the near future. Users communicate with chatbots via text or voice, both as a matter of personal preference and because chatbots are the communication channel offered by the businesses they interact with. As companies look for ways to optimize their customer operations, chatbots help with automating customer service operations and personalized services and this indicates that people are more exposed to chatbots. In this study, almost 17% of the participants stated that they never heard of chatbots nor used them. However, a majority of the participants claimed that they have prior experience with chatbots for multiple purposes. Therefore, this study intends to understand users perceptions and motivations on adopting chatbot technology.

In this study, user acceptance of chatbots was analyzed utilizing from technology acceptance model (TAM). A generalized approach was taken when it comes to purpose of using chatbots and a corresponding sector rather than highlighting one single usage motivation. It is handled using this approach in order not to downsize the sample. Prior research, as explained previously on this study, suggested that perceived usefulness, perceived ease of use, perceived enjoyment and perceived risk are significant factors that explain the users intention to use chatbots.

Results of this study revealed that there is a positive relationship between perceived usefulness and users intention to use of chatbots. In simpler words, users who thought that using chatbots is beneficial for them, are more interested in adopting chatbots. In their prior research, Rese, Ganster and Baier (2020), Gümüş and Çark (2021), Abdalla (2024), Pillai, Sivathanu and Dwivedi (2020) also found the positive impact of perceived usefulness on intention to use of chatbots. This result is consistent

with the prior research as perceived usefulness was found to be the strongest determinant of technology adoption (Kulviwat et al, 2007: 1063).

Based on the literature review and TAM, the positive influence of perceived ease of use on intention to use was tested as users are expected to adopt new technologies more if they find them easy to use. Research findings of Suh and Han (2002), Gümüş and Çark (2021), Abdalla (2024), Kleine, Schaffernak and Lermer (2024) explained a significant impact of perceived ease of use on intention. In this research, the positive influence of perceived ease of use on intention to use of chatbots was not significant similar to the finding of Rese, Ganster and Baier (2020), Fernandes and Oliveira (2020), Moussawi, Koufaris and Benbunan-Fich (2020). As these researchers explain that this could be attributed to the users' perception of chatbots as systems that are simple to use. However, a positive relationship between perceived ease of use and perceived usefulness was validated as Davis (1989) suggested and as also found in the studies of Fernandes and Oliveira (2020) and Pillai, Sivathanu and Dwivedi (2020). Therefore, mediation analysis of perceived ease of use, perceived usefulness and intention to use can be considered in further studies as perceived ease of use might be exerting its impact on intention to use via perceived usefulness.

Results of this study indicated that perceived enjoyment has a positive influence on intention to use chatbots. Users are expected to adopt new technologies that are enjoyable and engaging to use (Venkatesh, Speier and Morris, 2002). In parallel with the results of this study, researchers previously found a positive relationship between perceived enjoyment and intention to use chatbots (Rese, Ganster and Baier, 2020; Abdalla, 2024; Pillai, Sivathanu and Dwivedi, 2020; Moussawi, Koufaris and Benbunan-Fich, 2020). This results suggest that designing systems are enjoyable to use are expected to be adopted by users.

Previous studies conducted by Lee (2009) and Pavlou (2003) indicates a significant negative impact of perceived risk on intention. On the other hand, in their study Gümüş and Çark (2021) found perceived risk to be an insignificant determinant of intention to use chatbots. In this study the findings reveal that perceived risk has a negative impact on intention to use chatbots at a 90% confidence level as p value is 0.06. Similar to this result, research made by Kasilingam (2020) reveals a negative impact of perceived risk on attitude towards chatbots highlighting the p value at 0.05,

a comparable level and indicates a significant relationship between perceived risk and intention mediated by attitude. Results may be interpreted as the level of awareness associated with risks such as security, privacy, time and performance is recognised by the users in an uptrend. The users may be becoming more knowledgeable about risk parameters related to their usage of chatbots.

To conclude, when it comes to managerial implications, this study suggests that chatbots is an important topic that businesses should carefully consider. Artificial intelligence is an everyday evolving area of computer science and as a part of it, chatbots emerging as powerful tools that businesses can utilize from. Business owners and executives should consider chatbot investment and more generally artificial intelligence to foster their operations and improve business intelligence. It should be considered to utilize this technology in handling customer services and offering personalized recommendations and benefit of time saving while building useful, simple to use and enjoyable systems. It should be taken into account that users are becoming aware of the associated risk factors and clarity regarding the concerns should be addressed with a transparent communication with users.

Limitations;

The study has several limitations. First, the data collected with a cross-sectional design since the research was done in a specifically limited timeframe. Observing the sample over extended periods and observing their attitude will provide more useful data. Second, the sample size was moderately low with 201 observable participants. Further research can be made with larger samples for a better understanding of users' intention to use chatbots. Also, when it comes to extending the research model, determinants of perceived usefulness and perceived ease of use may be added as TAM2 and TAM3 suggest.

Finally, chatbots are used with different purposes. A generalized approach was taken in this study and the purpose of use was not limited to one. Also they are offered by several sectors of businesses such as banking, food and beverage, retail and airline industry. When conducting further research, specifying the study according to both usage purpose and sector may provide more useful insights regarding the adoption of chatbots.

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APPENDIX

APPENDIX 1: Survey

1.Daha önce sohbet robotu kavramını duydunuz mu?

( ) Evet

( ) Hayır

2.Daha önce sohbet robotu kullandınız mı?

( ) Evet

( ) Hayır

3.Eğer kullandıysanız nasıl bir sohbet robotu kullandınız?

( ) Siri/Alexa vb.

( ) Bankacılık dijital asistanları

( ) Müşteri hizmetleri / Canlı Destek

( ) Ürün veya hizmet satın alma

( ) Eğitim

( ) Diğer

(Algılanan Kullanışlılık) - Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, Vol. 13, No. 3 pp. 319-340

4. Sohbet robotu kullanmak işlerimi daha hızlı halletmeme yardımcı olur

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7)Kesinlikle Katılıyorum

5. Sohbet robotu kullanırken yaptığım işteki performans genel anlamda yükselir.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

6. Sohbet robotu kullanmak üretkenliğimi arttırır.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

7. Sohbet robotu kullanmak günlük hayatımdaki etkinliğimi arttırır.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

8. Sohbet robotu kullanmak günlük işlerimi yapmayı kolaylaştırır.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

9. Sohbet robotu kullanımı günlük hayatımda fayda sağlar.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

(Algılanan Kullanım Kolaylığı) - Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, Vol. 13, No. 3 pp. 319-340

10. Sohbet robotu kullanmayı öğrenmek benim için kolaydır.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

11. Sohbet robotu kullanmak zordur.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

12. Sohbet robotu yapmasını istediğim şeyleri kolayca yapar.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

13. Sohbet robotu ile etkileşimim net ve anlaşılırdır.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

14. Sohbet robotu, onunla etkileşime girmek açısından esnektir.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

15. Sohbet robotu kullanma konusunda kolayca becerikli hale gelebilirim.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

16. Sohbet robotuna yapmasını istediğim şeyi yaptırmak zordur.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

17. Sohbet robotu kullanmak kolaydır.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum (Algılanan Eğlence) - Venkatesh, V., Speier, C., and Morris, M.G. (2002) "User Acceptance Enablers in Individual Decision Making about Technology: Toward an Integrated Model," Decision Sciences (33:2), 297-316'

18. Sohbet robotu kullanmak zevklidir.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

19. Sohbet robotu kullanma süreci keyiflidir.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

20. Sohbet robotu kullanmak eğlencelidir.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum (Algılanan Risk) - Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: a perceived risk facets perspecGve. International journal of human-computer studies, 59(4), 451-474

21. Eğer sohbet robotunu finansal amaçlarla kullanırsam para kaybedebilirim

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

22. Sohbet robotu kullanarak ödeme işlemi yapmak potansiyel dolandırıcılığa maruz kalmama sebep olabilir

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

23. Finansal amaçlar için sohbet robotu kullanmak maddi kayıp yaşamama sebep olabilir

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

24. Finansal amaçlar için sohbet robotu kullanmak işlem yaptığım hesabımı (bankacılık, online alışveriş hesabı vb) riske sokabilir

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

25. Sohbet robotu düzgün çalışmayabilir ve sorun yaratabilir.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

26. Sohbet robotuna kurulmuş güvenlik sistemi, hesabımı koruyacak kadar güçlü değildir.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

27. Sohbet robotu performansı düşük olabilir ve düzgün çalışmayabilir

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

28. Sohbet robotundan beklenen hizmet performansı göz önünde bulundurulduğunda, sohbet robotu kullanmak risklidir.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

29. Sohbet robotu performansı düşük olabilir ve eylemleri yanlış bir şekilde gerçekleştirebilir

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

30. Sohbet robotu kullanmak gizlilik üzerindeki kontrolün kaybolmasına neden olabilir.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

31. Sohbet robotu kullanmak kişisel bilgilerin izinsiz kullanılma olasılığı nedeniyle mahremiyet açısından risklidir.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

32. Sohbet robotu kullanmak internet korsanlarının hesap kontrolünü ele geçirmesine neden olabilir.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

33. Eğer sohbet robotu kullanmaya başlarsam, geleneksel bir hizmet aracına (müşteri temsilcisine aktarılma vb.) geçmek zorunda kaldığımda zaman kaybederim

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

34. Sohbet robotunun iyi çalışmaması nedeniyle ortaya çıkacak sorunları düzeltmek için çok zaman harcayarak kullanım kolaylığını kaybedebilirim

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

35. Geleneksel hizmet alma yöntemlerinden sohbet robotu kullanımına geçmek, harcadığım zaman göz önünde bulundurulduğunda risklidir.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

36. Sohbet robotunun nasıl kullanılacağını öğrenmek zaman kaybettirebileceğinden bu onları riskli kılabilir

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

37.Tüm faktörleri bir arada düşündüğümüzde, sohbet robotu kullanmak genel olarak risklidir

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

38.İşlemlerim için sohbet robotu kullanmak genel olarak risklidir

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

39. Sohbet robotu kullanımı tehlikelidir

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

40.İşlemlerim için sohbet robotu kullanmak belirsizlik yaratır

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

41. Sohbet robotu kullanmak sizi genel bir riske maruz bırakır

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum (Kullanım Niyeti) - Venkatesh, V., Thong, J.Y.L, and Xu, X. (2012), Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology, MIS Quarterly, Vol. 36, No. 1, pp. 157-178

42. Gelecekte sohbet robotu kullanma niyetim var.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

43. Günlük hayatımda hep sohbet robotu kullanmaya çalışacağım.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

44. Sıklıkla sohbet robotu kullanmaya devam etmeyi planlıyorum.

Kesinlikle Katılmıyorum (1) (2) (3) (4) (5) (6) (7) Kesinlikle Katılıyorum

45. Yaşınız

( ) 18 ve altı ( ) 19-29 ( ) 29-39 ( ) 39-49 ( ) 49-59 ( ) 59-69 ( ) 60 ve üzeri

46. Cinsiyetiniz

( ) Kadın ( ) Erkek

47. Medeni Haliniz

( ) Evli ( ) Bekar

48. Eğitimm düzeyiniz (en son aldığınız derece)

( ) İlkokul ( ) Lise ( ) Önlisans ( ) Üniversite ( ) Yüksek Lisans ( ) Doktora

49. Çalıştığınız sektör

( ) Finans ( ) Teknoloji ( ) Sağlık ( ) Eğitim ( ) İnşaat ( ) Perakende ( ) Hizmet ( ) Tarım ( ) Enerji ( ) Ulaşım ( ) Diğer