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Yifan Gai

MASTER'S THESIS

Factors that impact intention to continue using AI-based chatbots in different countries

Supervisor: **prof. dr**. Sigitas Urbonavičius

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Table of Contents

List of Tables

List of figures

INTRODUCTION

Chatbots are becoming more and more prevalent everywhere across the world. According to Eurostat (2021), in 2020, 2% of companies in the EU (with at least 10 employees) used AI-based chatbots and the use of Lithuanian companies was 9%, which was above average in the EU (7%). On the other hand, in China, chatbots are widely used in finance, telecommunications, retail, education and other fields. The size of the Chinese chatbot market increased by 94% in 2020 compared to the previous year (iResearch, 2021). With their ability to provide accurate and reliable online services, current AI agents contribute to enhanced customer satisfaction (Chung et al., 2020). AI will have internal and external impacts on organizations in a wide plethora of fields mentioned above. To be competitive, AI services need to be adopted by more customers (Kaplan & Haenlein, 2019).

In the midst of the current AI boom, the widespread global adoption of ChatGPT has highlighted its remarkable versatility and wide-ranging application in various domains (Dwivedi et al., 2023; Lund &Wang, 2023). ChatGPT will be used as the research subject in this study. Since the popularity and controversy surrounding ChatGPT, there may be individuals who are reluctant to use it. It is important to note that this study will focus exclusively on individuals who have already used ChatGPT. The objective of this study is to analyze the factors that influence the intention to continue using AI-based chatbots. The focus will be on understanding the factors that contribute to the decision of whether or not to continue using AI-based chatbots after the initial interaction.

Numerous studies have been conducted to predict the acceptance of technology. The elements of the Technology Acceptance Model (TAM) (Davis, 1989), such as perceived usefulness and perceived ease of use, have been widely recognized as important factors in chatbot usage (Park, 2010). Previous studies have also identified other factors that are related to consumers' willingness to use AI-based chatbots, including trust (Nagy et al., 2021), perceived enjoyment

(Kasilingam, 2020) and anthropomorphism (Sheehan et al., 2020; Li et al., in press). Various models have been employed to predict users' usage patterns, with some studies combining service quality dimensions and technology acceptance models (Meyer-Waarden et al., 2020). In this study, certain service quality elements will be integrated into the TAM model to further explore the factors influencing users' intention to use AI-based chatbots.

Lithuania and China are characterized by distinct cultural differences. Hofstede (2001) suggests that Chinese individuals exhibit lower levels of individualism compared to Lithuanians, which may impact the acceptance and utilization of chatbots (Fleischmann et al., 2020). The technological and economic gap between Lithuania and China may also affect chatbot users' intention to continue using AI-based chatbots. While variations in social media buying behavior (Muralidharan & Men, 2015), satisfaction with impulse purchases (Lee & Kacen, 2008), and attitudes toward journalism chatbots (Shin et al., 2022) have been observed across countries, limited research exists on cross-cultural usage in industries outside of journalism. Consequently, this study aims to explore the factors influencing AI-based chatbot continue using AI-based chatbots based on previous studies conducted in Lithuania and China.

This research utilized the Technology Acceptance Model along with service quality dimensions to examine the determinants influencing the continued use of AI-based chatbots. A survey was conducted in China and Lithuania, yielding 253 valid responses. The study is structured into four main sections. The first section provides a theoretical analysis, encompassing a review of key theories and models, crucial factors, and environmental contexts relevant to technology acceptance. The second section presents the proposed research model and hypotheses. This is followed by the third section, which involves the analysis of empirical data gathered from the survey. The final section comprises conclusions and recommendations based on the previous analysis.

The problem of this paper is what factors influence customers' intention to continue using AI-based chatbots and how these factors differ in China and Lithuania.

The aim of this paper is to examine the factors that influence customers' intention to continue using AI-based chatbots and to compare these factors between China and Lithuania.

Tasks:

1. To identify the most valuable factors influencing the intention to continue using AI-based chatbots in online platforms based on previous studies.
2. To analyze the different economic and technological background in China and Lithuania and how the background affects intention to continue using AI-based chatbots.
3. To cognize the cultural differences in China and Lithuania and understand how these differences affect intention to continue using AI-based chatbots.
4. To develop a research methodology to analyze factors that influence intention to continue using an AI-based chatbot.
5. To examine how the following factors affect intention to continue using AI-based chatbots in Lithuania and China: Perceived usefulness, perceived ease of use perceived enjoyment, perceived risks.
6. To examine how quality service dimensions (competence, reliability, tangibles and security) and anthropomorphism affect users' perception of AI-based chatbots.
7. To examine the impact of different environments in China and Lithuania on the following factors: Perceived usefulness, perceived ease of use, perceived enjoyment, perceived risks.
8. To provide conclusions and recommendations for AI-based chatbot optimization.

1. THEORETICAL ANALYSIS

1.1 Theories that impact technology acceptance

1.1.1 Diffusion of innovations theory

It often takes a process for a technology to be widely adopted in a group or society, and the diffusion of innovations theory is one of the theories to explain the process. The procedure that occurs when an innovation gradually penetrates the population of a society through specific channels is known as diffusion. Innovation, communication channels, social system, and time are the four parts of the diffusion of innovation theory.

People have different characteristics and motivations for adopting innovations, which leads to different time stages of their adoption. Adopters can be divided into innovators, early adopters, early majority, late majority, and laggards. Innovators generally love new ideas and experiences. They are more technically knowledgeable and are the ones who bring innovation to the team. But they may not be respected because of personal traits. Early adopters who are usually leaders and opinion leaders usually are respected in an organization. The attitude of early adopters towards innovation is important as their opinion can have a strong influence on team members through networking. Early majority has the intention to adopt technology, but they are not very interested in trying new things as innovators and early adopters. Whether or not a lot of people use it matters to them. It can be seen from the s-curve where the early majority adopt technology earlier than half of the population, and their behavior is also important for technology diffusion. Late majority adopt new technologies due to economic necessity or peer pressure. And the laggards are the most traditional and the last to adopt the innovation. From innovators to laggards, individuals are less and less innovative. For different people, suitable uncertainty and complexity should be different to remove the barriers of technology adoption, which can be managed in the whole process (Rogers, 1995).

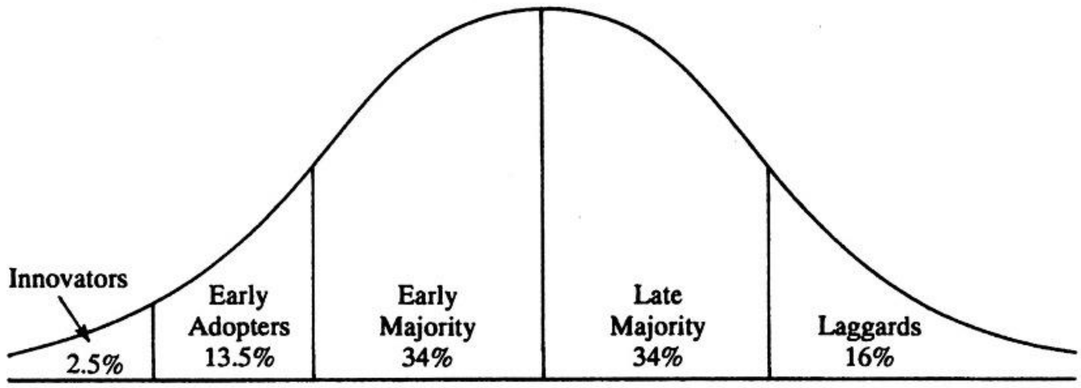


Figure 1 *Innovation Adoption Curve (Rogers, 1995)*

The innovation diffusion theory defines the significance and role of individual characteristics and social circumstances in the adoption process. This theory can help enterprises recognize and affect the adoption of new technologies (Straub, 2009), as it can assist them in identifying the stages of diffusion and tailoring their approach to different users. The notion of diffusion of innovations has been extensively applied in a range of domains, including higher education (Abrahams, 2010) and healthcare (Dearing et al., 2018).

1.1.2 Technology acceptance model (TAM)

To predict the adoption of new system, Davis (1989) developed the technology acceptance model (TAM), which combined the theory of reasoned action (TRA) model (Fishbein & Ajzen, 1977) with perceived utility and perceived ease of use. Perceived utility and perceived ease of use have an impact on technology adoption, according to the TAM model. Perceived usefulness is an individual's assessment of the usefulness of a technology, while perceived ease of use represents users’ perception of ease of use. The correlation between usefulness and attitude is significantly higher than the correlation between ease of use and attitude. Additionally, as users' experience improves, the influence of perceived ease of use on technology adoption declines (Davis et al., 1989).

TAM is a valuable and concise model that can be well applied in personal computers, software applications, e-commerce, telemedicine, e-learning and other fields (Park, 2010). However, it has received criticism for its limitations.

Firstly, TAM was developed based on a sample of researchers and students, who may be more comfortable with new technologies, in this case, the selected samples could not represent the most people (Davis et al.1989). Secondly, Perception of utility and ease of use focus more on external aspects, such as improving efficiency and saving time, while internal aspects such as enjoyment are also important in the adoption of technological products (Chtourou & Souiden, 2010). Perceived enjoyment was found to be the most important factor affecting behavioral intentions toward t-commerce (Yu et al., 2005). Thirdly, TAM does not adequately consider the influence of personality, demographic traits, and the environment on adoption behavior. Those personalities may differ because of gender, age, level of education, income, and geographic location. For example, young, educated people are more likely to be early adopters. With the current rapid economic and technological evolution, the level of support available, peer pressure, and the environment can significantly alter technology adoption. In summary, the TAM model should be tested in diverse populations and incorporate individual and environmental factors in the model.

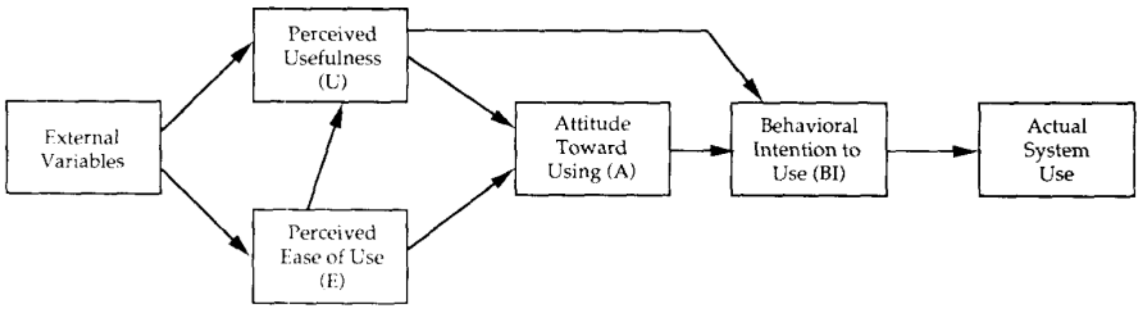


Figure 2 *Technology acceptance model (TAM) (Davis et al., 1989)*

1.1.3 Technology acceptance model 2 (TAM 2)

TAM 2 was a modification of TAM, taking into account the influence of experience and voluntariness on the adoption of technology and it also points out predictors of perceived utility such as imagery, job relevance, output quality, subjective norms and demonstrability of results. It deepens the understanding of perceived usefulness and considers the influence of environment through subjective norms and voluntariness on intention to use. TAM 2 also describes how internalization and connection with subjective norms impact perceived utility. Internalization refers to others changing a person's perception of usefulness, and identification refers to the use of innovation to improve a person's status in the work group, thereby improving a person's work performance by expanding influence (Venkatesh & Davis, 2000).

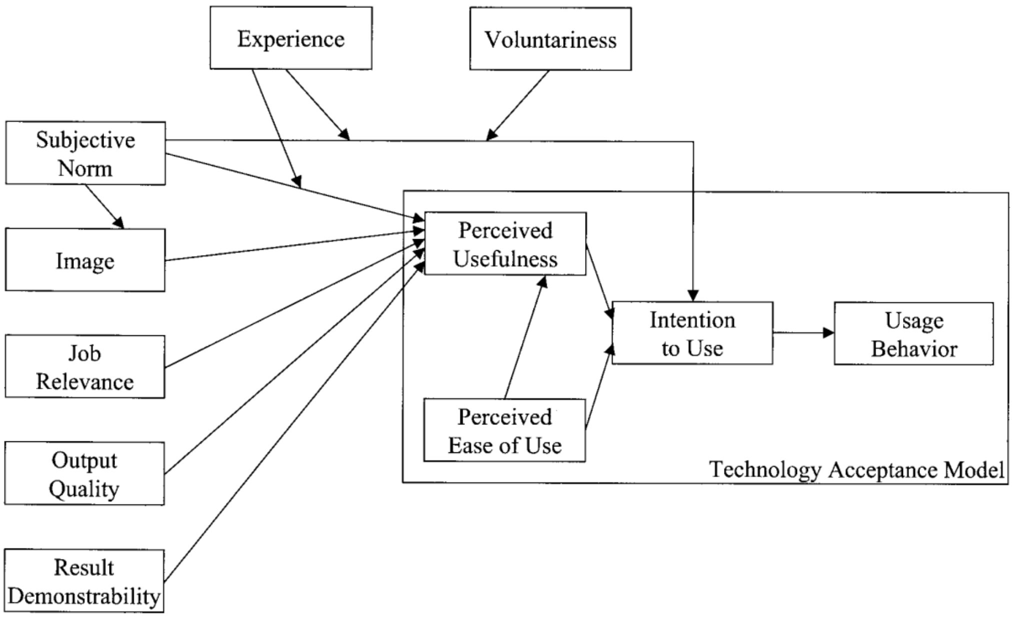


Figure 3 *Technology acceptance model 2 (TAM 2) (Venkatesh and Davis, 2000)*

1.1.4 Unified theory of acceptance and use of technology (UTAUT)

Unified Theory of Acceptance and Use of Technology (UTAUT), another modification of TAM was created. The realization that age and gender are two examples of demographic factors that can impact technology use is one of the contributions made by research in the field of technology adoption. Another important aspect is environment affects technology adoption through social influence and facilitating conditions. Figure 4 illustrates how performance expectancy, effort expectancy, social influence, and facilitating conditions all had a direct impact on the intention to use technology, whereas behavioral intention and facilitating conditions had an impact on use behavior. Additionally, four variables—age, gender, experience, and voluntariness—significantly moderated these correlations.

Although the names of the factors seem different, their definitions are similar (Jackson et al., 2013). For instance, performance expectancy essentially reflects perceived usefulness and effort expectancy relates to perceived ease of use. Furthermore, social influence can be viewed as roughly the same as subjective norms. Facilitating conditions reflect individuals' perceived support for using an innovation considering organizational and technical infrastructure aspect. The impacts of these factors on behavior are moderated by gender, age, experience. Specifically, performance expectancy has a more substantial impact on men and younger people, and both effort expectancy and social influence affect women and older people more. Besides, effort expectation is also moderated by experience, becoming less significant as experience increases. Social influence is more important in the early stage of technology acceptance and in the mandatory condition. Facilitating conditions are only relevant for older people and later stages of adoption (Venkatesh et al., 2003).

According to the findings presented by Venkatesh et al. (2003), this model is capable of accounting for 70% of the variability in the intention to use, which is better than any of the original eight models. This might be because the comprehensive demographic factors improve the predictive ability of the model (Dwivedi et al., 2020).

However, some issues were noticed. First, compared to TAM, the confirmation of UTAUT model is limited due to less used in previous literatures (Straub, 2009). Many studies of UTAUT usually only use part of the original model, such as removing moderators. Through literature review, it was shown that only about 25% of the studies adopted the UTAUT model, excluding other structures not included in the original UTAUT model (Dwivedi et al., 2019). Second, facilitating conditions might have an impact on effort expectancy. With better facilitating conditions, there are less obstacles to adopting innovations, which means less effort needed. Then, different from TAM and TAM2, the impact of effort expectancy on performance expectancy was not considered. The correlation between these 2 variables remains unclear. Finally, the usage of unfamiliar technologies may result in financial, safety, time or other losses, but the potential risks are not considered in the model.

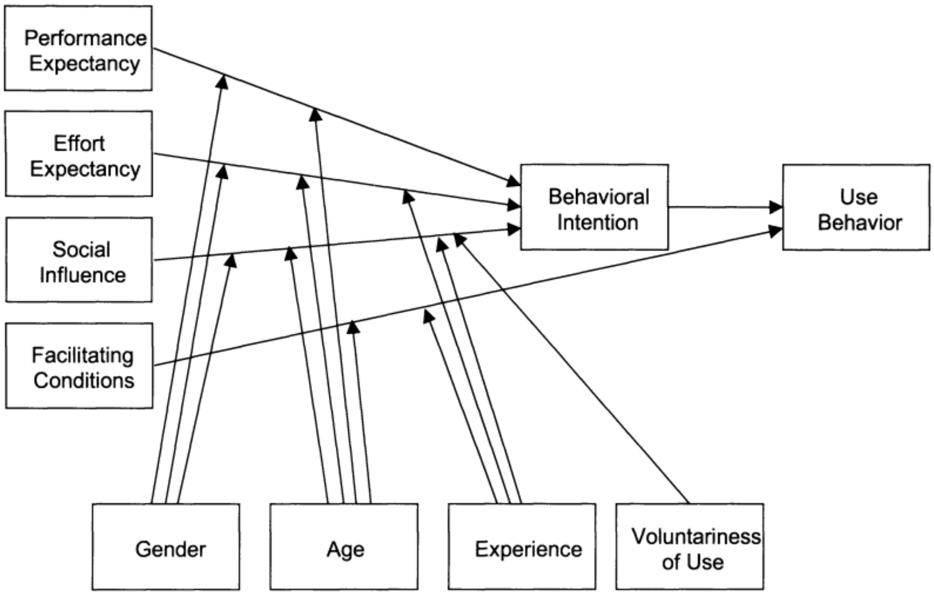


Figure 4 *Unified theory of acceptance and use of technology model (UTAUT) (Venkatesh et al., 2003)*

1.1.5 Service quality and SERVQUAL model

Parasuraman et al. (1985) conduct an extensive analysis of the factors shaping customer perceptions. According to their research, service quality can be perceived by customers across 10 dimensions: reliability, responsiveness, competence, access, courtesy, communication, credibility, security, understanding, and tangibles. However, the subsequent development of the SERVQUAL model, introduced in another paper by Parasuraman et al. (1988), consolidated these dimensions into five: tangibles, reliability, responsiveness, assurance, and empathy. The

SERVQUAL model has been commonly employed as a framework for assessing service quality.

There are studies underscore the importance of incorporating service quality dimensions into the evaluation and prediction of AI-based chatbot usage (Li et al., 2021; Meyer-Waarden et al., 2020). However, only factors that fit the unique characteristics of the chatbot in question should be selected. By considering relevant dimensions, organizations can better understand and improve service quality and adoption of AI-based chatbot products.

1.1.6 Summary

In this section, I investigated the theory of innovations diffusion and different models for predicting technology adoption, like TAM, TAM2, and UTAUT. The diffusion theory explores how groups adopt new technologies over time, and these models focus on forecasting how individuals will adopt technologies. Also, understanding the quality of providing AI-based chatbots, especially through the SERVQUAL model, is key to understanding why people adopt new technologies.

These methods provide insightful views on the adopting process of new technologies. The diffusion of innovations theory suggests that the adoption of new technologies by individuals is influenced by their personality and environment. According to TAM, perceived usefulness and perceived ease of use are the fundamental factors that can affect personal decisions on adopting a system. Antecedents of perceived usefulness the influence of one environmental factor (subjective norms) on perceived usefulness were analyzed in TAM2. Then, another environmental factor (facilitating conditions) and demographic factors (gender and age) were found to affect individual’s technological adoption.

While the diffusion of innovations theory and technology adoption models are valuable, incorporating service quality and the SERVQUAL model adds a complementary perspective.

By analyzing the quality service dimensions of the technology being adopted and how they interact with adoption factors, researchers can gain a more comprehensive understanding of the adoption process.

There are some open questions that need to be explored further to fully understand how and why people adopt new technologies. First, it is necessary to define whether the correlation between ease of use and utility exists. Second, there is a need to identify how intrinsic motivation affects technology adoption. Finally, what service quality dimensions should be selected for this study.

1.2 Technology acceptance of AI-based chatbots

1.2.1 Chatbot and the use of chatbots

Chatbots can be defined as intelligent computer programs that simulate human-like interactions and aim to assist users by answering questions, providing information, or completing tasks (Okonkwo & Ade-Ibijola, 2021). Chatbots have gained significant prominence across various domains, including finance, telecommunications, internet services, education, tourism, and healthcare (iResearch, 2021; Chocarro et al., 2021; Melián-González et al., 2021; Madhu et al., 2019; Denecke et al., 2020). The evolution of chatbots can be observed through four stages: the early stage (1960s-1990s), rule-based chatbots (2000s), natural language processing (NLP) chatbots (2010s), and deep learning chatbots (2010s-present) (Verma, 2023). Initially, chatbots were limited in their capabilities, but rule-based chatbots emerged in the 2000s, providing structured conversation support. NLP chatbots gained prominence in the 2010s, utilizing AI techniques for more sophisticated and context-aware conversations. Deep learning chatbots, such as OpenAI's ChatGPT, are currently pushing the industry forward with improved conversational abilities (Dwivedi et al., 2023).

There are numerous benefits to using chatbots, including cost reduction, 24-hour responsive service, gaining customer insights from historical conversations, increasing customer satisfaction (Winkler & Söllner, 2018; Ashfaq et al., 2020), addressing sensitive topics and providing support in mental health counseling (Denecke et al., 2020; Zamora, 2017). ChatGPT, created by OpenAI and based on deep learning and GPT (Generative Pre-training Transformer) language models, has significantly advanced chatbot technology (Dwivedi et al., 2023). The emergence of AI tools like Midjourney, New Bing and ChatGPT has broadened chatbot functionalities, benefiting both businesses and users.

Since AI-based chatbots have greatly improved their task completion abilities and are expected to greatly influence the future business landscape, the focus of this study is to analyze why people intend to keep using AI-based chatbots.

1.2.2 Previous research on chatbots

The factors used in chatbots adoption and key findings of previous studies are listed in table 22. The table shows that perceived usefulness of the TAM model has repeatedly been shown to be the most crucial factor influencing chatbot adoption, and perceived ease of use is also important (Ashfaq et al., 2020; Chocarro et al., 2021, Chuang et al.; 2016, Eeuwen, 2017, Kasilingam, 2020; Kwangsawad & Jattamart, 2022). The ease of use of a chatbot can impact how interested people are in exploring its capabilities, which in turn affects the perceived usefulness of the chatbot. This should be considered in chatbot acceptance models.

Timely customer support is needed when users are frustrated by poor communication with the chatbot. It is common that chatbots are unable to understand and deal with certain problems of customers. Ashktorab et al. (2019) found that many users did not know how to talk with chatbots and what to do when miscommunication happened, however, input keyword help and proactive fix can solve this problem. Nguyen (2019) mentioned that FAQs could improve efficiency in dealing with common situations, and as for complex cases, telephone and email channels should be provided. All the above methods of customer support can possibly improve user experience and reduce the negative impact on user intention to use. These supports allow customers to expend less effort when using the chatbot and therefore may be related to the concept of ease of use.

Perceived risk and privacy concerns were often analyzed in previous studies regarding technology adoption. Privacy concern is considered as a part of the perceived risks, and with the increase in digital marketing, privacy concerns are gaining more and more attention (Ischen et al., 2020). On online platforms, the lack of physical contact inconveniences customers, which can lead to money loss, time waste and leakage of personal information. Trust is a factor that may be closely related to perceived risk, as customers perceive fewer losses when they trust companies and brands. Perhaps for this reason, trust and perceived risk are not usually examined in the same model.

Perceived enjoyment, similar to hedonic motivation, is an important predictor of individual adoption of chatbots (Ashfaq et al., 2020; De Cicco et al., 2020; Kasilingam, 2020; Melián-González et al., 2021). Users generally have strong intention to use chatbots if they have pleasant emotions and a good experience using the chatbot. Perceived enjoyment was even found to be the most important factor in t-commerce (Yu et al., 2005), possibly because watching TV is inherently a leisure activity. Factors affecting personal use or purchase behavior are related to the overall evaluation of service or product value, so perceived enjoyment should be included.

Kasilingam (2020) found that younger, male, and more experienced individuals were more innovative, and more innovative individuals perceived less risk and more perceived pleasure, leading to more positive attitudes toward smartphone chatbots in online shopping. Some factors are important to some but not others, such as perceived usefulness and perceived risk, which only affect attitudes in men but not women. However, digital skills and age did not affect teachers' willingness to adopt chatbots (Chocarro et al., 2021). It implies that age and gender might have significant effects in technology adoption.

There is another interesting factor, anthropomorphism, that has been introduced into more and more studies. Melián-González (2021) found that anthropomorphism has significant but weak impact on intention to use chatbots. Furthermore, several studies (Han, 2021; Moussawi et al., 2021) have established that anthropomorphism indirectly affects chatbot acceptance through its impact on perceived enjoyment.

In conclusion, the most crucial elements impacting chatbot adoption are perceived utility and ease of usage. Customer support in various forms can increase users' perceptions of ease of use. Other characteristics that influence chatbot use intention include perceived risk (such as privacy issues) and perceived delight. Anthropomorphism can have an impact on chatbot adoption either directly or indirectly.

There has been an increasing interest in applying the concept of service quality to the chatbot industry. Researchers investigated how the service quality dimensions could predict the continued use of chatbots. For example, to explain why customers continue to utilize online travel services, Li et al. (2021) combined service quality variables (reliability, responsiveness, and assurance) with the expectation-confirmation model (ECM). Similarly, the variables of tangibles, competence, reliability, responsiveness, empathy, and credibility were integrated to investigate how service quality promotes intention to reuse. It implies that empathy has no effect on the desire to reuse (or continue using), but utilitarian value, as expressed by reliability and usefulness, emerged as more relevant criteria (Meyer-Waarden et al., 2020). Furthermore, this study discovered that physical aspects of AI-powered chatbot services could enhance users' perceptions of ease of use.

Based on the previous investigation, this chapter intends to examine the following elements: perceived utility, perceived ease of use, perceived enjoyment, perceived hazards, anthropomorphism, and service quality characteristics. These elements can be classified into four categories: technology elements, personal elements, service quality elements, and environmental elements. Technological factors encompass perceived usefulness and perceived ease of use. Personal factors include perceived enjoyment and perceived risks. The next section will focus on selecting the most significant service quality dimensions out of the available 10. The environmental factor, represented by the country, may be influenced by economic and technological backgrounds, as well as cultural backgrounds.

1.2.3 Factors that impact acceptance of AI-based chatbots

1.2.3.1 Technological factors

Perceived usefulness

Perceived usefulness reflects how user finds the technology useful (Davis, 1989). Usefulness of technology remains important after users gain more information and experience with the technology (Venkatesh and Davis, 2000). Many other studies have stated that perceived usefulness is significantly important in chatbot adoption (Chocarro et al., 2021; Kasilingam, 2020). Chatbots can be useful in various ways, such as providing information, improving efficiency, completing transactions, and solving other problems. For example, tourists will have stronger willingness to use chatbots will likely be more positive if a travel chatbot can help book hotels, check itinerary information, and provide destination updates, as this can save time and effort during the trip. Therefore, higher perceived usefulness may encourage the intention to continue using chatbots.

Perceived ease of use

Perceived ease of use refers to the degree to which users find it effortless to use a technology (Davis, 1989). Perceived ease of use was found to be a predictor of adopting chatbots (Chocarro et al., 2021; Kasilingam, 2020; Kwangsawad & Jattamart, 2022). Consumers are more likely to use a chatbot while shopping online if the chatbot integrates with existing applications (such as WhatsApp, Facebook, or Skype), as it requires minimal effort to add chatbot as a contact (Kasilingam, 2020). Users use chatbots more easily, and they are more likely to explore chatbot, which may have an impact on perceived usefulness. Therefore, perceived ease of use should also positively relate to behavioral intention to use AI-based chatbots.

1.2.3.2 Personal factors

Perceived enjoyment

Perceived enjoyment reflects intrinsic motivation for use the innovations. People tend to change their behavior and employ new technology if the experience is enjoyable (Teo et al., 1999). People experience excitement and anticipation when using chatbots. Perceived enjoyment positively related to users' attitudes toward chatbots (De Cicco et al., 2020; Kasilingam, 2020). Perceived enjoyment can be improved by attractive interface, personalization settings (Gkinko & Elbanna, 2022b), anthropomorphism (Han, 2021). It may also be related to personality that people may have different preferences on the same features of an AI-based chatbot. It was found that introverted customers like to communicate with chatbots using an introverted speaking style, while extroverted customers incline to communicate with chatbots using an extroverted speaking style. Matching consumers with a consistent chatbot personality can enhance consumer engagement with the chatbot, leading to increased purchases (Shumanov & Johnson, 2021). More interesting interactions with chatbots are usually associated with long interaction time in volunteer context. More interesting interactions with chatbots generally lead to increased time spent interacting with the chatbot in a voluntary context, resulting in higher perceived enjoyment and a stronger intention to use AI-based chatbots.

Perceived risks

Perceived risks encompass the user's perception of potential losses when utilizing a specific product or service (Chatterjee & Bhattacharjee, 2020). These risks can be classified into various dimensions, including time risk, financial risk, performance risk, privacy and security risk, psychological risk, physical risk, and equipment risk (Park & Tussyadiah, 2017). It is especially important to examine financial risk, performance risk, and privacy risk in the larger picture of chatbots. Performance risk means the likelihood of a product or service failure, whereas financial risk relates to the possibility of monetary losses. Concerns about the leaking of personal information are referred to as privacy risks (Kasilingam, 2020). These perceived risks significantly influence the user's attitude and indirectly impact the adoption of AI-based chatbots (Chatterjee & Bhattacharjee, 2020).

The perception of privacy risk, in particular, has a detrimental impact on the adoption of new technology (Kasilingam, 2020; Kwangsawad & Jattamart, 2022; Wang & Lin, 2017). In an online environment, concerns about personal information exposure make privacy risks a critical consideration (Kasilingam, 2020). This is because companies often use technology to gather data about customers' traits and preferences to tailor their products or services, but this could lead to privacy concerns for the customers (de Cosmo et al., 2021). For instance, it can be seen as overly intrusive when companies track customers' online activities and gather personal details like birthdays and home addresses to suggest related products (Sultan et al., 2009). The emphasis on privacy often influences usage. Customers tend to use chatbots less if they realize that chatbot platforms are accessing and collecting their personal information (Kwangsawad & Jattamart, 2022). While personalized products and services largely align with customer preferences, privacy concerns may cause people to be cautious about the use of chatbots. Therefore, when adopting AI-based chatbots, it is important to be aware of perceived risks, especially privacy risks.

Anthropomorphism

Anthropomorphism, the humanization of non-human entities and objects such as robotic computers or even animals (Bartneck et al., 2009), has been significant to driving the acceptance of chatbots (Sheehan et al., 2020). Qiu and Benbasat (2009) found that surfaces with human-like attributes (e.g., humanoid avatars and human voices) can increase users' trust and enjoyment during chatbot interactions by providing a sense of social presence, thereby increasing intention to use the chatbot.

Building on this foundation, Sheehan et al. (2020) further investigated the positive impact of anthropomorphism on chatbot adoption by comparing adoption scores for three different chatbot response types. They found that chatbot interaction styles can increase adoption by providing human-like responses such as seeking confirmation and clarification. Moussawi et al. (2021) used a scale related to the emotions and feelings experienced by users during interactions with chatbots to measure perceived anthropomorphism and found that the presence of human-like qualities in chatbots increases users' overall enjoyment and experience.

In short, anthropomorphism can improve the experience of human-computer interaction and increase the probability of adoption. Therefore, in this study, anthropomorphism is also an essential concept for the adoption of AI-based chatbots.

1.2.3.3 Service quality factors

In terms of service quality, this study identified only a few dimensions like competence, reliability, tangibles, and security as important factors that closely match the features of AI-based chatbots. While Parasuraman et al. (1985) suggested 10 dimensions including reliability, responsiveness, competence, access, courtesy, communication, credibility, security, understanding, and tangibles, not all of these may be relevant in the context of AI-based chatbots.

Competence, defined by Parasuraman et al. (1985), refers to the skills and knowledge required for effective service performance, which is directly related to the use of artificial intelligence-based chatbots and therefore was chosen. Reliability describes how the performance of a product or service is reliable. Credibility is a concept that is easily confused with reliability, emphasizing the trustworthiness and honesty of service providers. For AI-based chatbots like ChatGPT, credibility is more related to the quality of their outputs, which is the trustful outputs, and the consistent performance, as a result, reliability was chosen in this study. Security originally focused on economic losses and personal safety, but it also involves privacy issues in cyberspace (Kasilingam, 2020). According to the concepts, reliability and security may have potential impacts on users' perception of risks and trust. Tangibles mean the physical evidence which is associated with the service and have been found significant impacts in the adoption of chatbots (Meyer-Waarden et al., 2020).

As it was mentioned earlier, some service quality aspects may not be appropriate for chatbots. For instance, responsiveness may have limited effect on AI-based chatbots since chatbots can respond 24/7. Likewise, access, communication, and understanding are not suitable for chatbots because when it comes to services provided by humans, human customer assistant may not be as effective as companies who developed AI-based chatbots usually have only a handful of employees versus a large number of users.

Therefore, this study will focus on analyzing the dimensions of competence, reliability, tangibles, and security, as they are more relevant and important in the context of AI-based chatbots.

1.2.3.4 Environmental factor: country

The differences among countries can be classified into two categories: economic and technological background and cultural background.

Economic and technological background

The economic and technological background of different countries can significantly impact the adoption of new technologies like AI-based chatbots. Technological development varies among countries, and the percentage of smartphone users can serve as an indicator of this development. For instance, China exhibits high smartphone usage, with 81.1% of users utilizing mobile payments, whereas Denmark and India have lower figures of 40.9% and 37.6% respectively (de Best, 2022).

Market structure is another influential factor, with variations in the distribution of organizations across different countries. In China, a few dominant companies control a significant portion of the retail e-commerce market, accounting for 87% of the market share (Qianzhan Industry Research Institute, 2022). Conversely, in Lithuania, the top three e-commerce companies only contribute to 15% of online revenue (ecommerce DB, 2022). These market structure differences affect resource availability and risk tolerance among organizations. Larger businesses tend to have more resources and are more likely to adopt new technologies at a faster pace compared to smaller businesses (Awa et al., 2017; Kurnia et al., 2015).

Competitive pressure is another reason driving countries to adopt chatbots due to customer demands and stiff competition within the industry. Organizations, especially small and medium-sized companies, tend to use new technologies to increase their advantages in a competitive business environment (Kurnia et al., 2015).

Cultural background

Cultural background, especially the degree of individualism, is a major factor in technology adoption. In terms of individualism sores, there is a significant difference between China and Lithuania, with China scoring 20 points and Lithuania scoring 60 points (Hofstede, 2001), indicating that China has a higher degree of collectivism and Lithuania has a higher degree of individualism. The key difference between cultures lies in their priorities. In collectivist cultures, people value the needs of the group more than themselves, while individuals prioritize the needs of themselves and their immediate family over the needs of the larger group in individualistic cultures.

The educational objectives also vary across these cultures (Hofstede, 2001). While in the US, a highly individualistic, education encourages people to learn "the method to learn", which leads to the high importance of developing critical thinking. In contrast, education emphasizes teaching "how to do" in China, where memorization and practical skills are more emphasized in the education system. This variation in education could explain some cross-cultural behavior patterns in technology adoption.

Shin et al. (2022) found that attitudes towards algorithmic news differed between the US (high individualism) and the UAE (low individualism). US users are generally more critical of the algorithm process, reflecting the focus on critical thinking. On the other hand, UAE users, coming from a less individualistic background, trusted the algorithm focused on performance and usability, but were less likely to doubt the process. Furthermore, Lin et al. (2022) found that Chinese people are more likely to believe fake news because they tend to understand rather than doubt what they have been told. Besides, researchers found collectivism communities tend to encourage people to look for meanings that support existing beliefs, rather than using logic to critically assess claims.

In collectivistic cultures, relationships are prioritized over tasks, which is the opposite in individualistic cultures (Hofstede, 2001). It can be inferred that individuals in collectivist cultures may be more alert on needs of their group, while people in individualistic cultures value personal interests more than group's interests.

In summary, the economic and technological context and cultural factors may significantly influence technology adoption in different countries.

1.2.4 Summary

This section discusses the factors impacting the acceptance of AI-based chatbots, which are grouped into four categories. Technological factors, including perceived usefulness and perceived ease of use, along with personal factors such as perceived enjoyment, perceived risks, and anthropomorphism, influence chatbot acceptance. Service quality factors, including competence, reliability, tangibles, and security, are also effective in analyzing chatbot adoption. Finally, the country representing economic, technological, and cultural backgrounds, was considered in this research.

Overall, based on previous research on chatbots, this study focuses on factors that influence users' perceptions, attitudes, and intentions toward AI-based chatbots.

1.3 Impact of environmental factors on AI-based chatbot acceptance

1.3.1 Impact of economic and technological background

Different economic and technological contexts may differ users intention and behavior on chatbot adoption. Regulations, as an important element regarding global business, are shaped by a country's laws and government policies. These regulations can either promote or restrict the adoption of technologies like chatbots, and their effectiveness in influencing adoption may vary (Kurnia et al., 2015). Specific regulations may influence enterprise adoption of AI-based chatbots, thereby affecting a region's overall familiarity with chatbot technology.

Technological development represents another significant difference. Residents of a country with a higher level of technological development may have a larger portion of individuals knowledgeable and skilled in new technologies. These experienced individuals usually have a stronger willingness to use AI-based chatbots. The widespread use of mobile payments can also increase people's experience with smartphones and mobile apps, making online shopping more convenient for consumers, which can influence the adoption of AI-based chatbots.

Market structure is also worth discussing. In a highly concentrated market, where a few large companies dominate the industry and cater to a wide range of customers, these companies may be encouraged to invest in self-service technologies like chatbots to increase their efficiency and provide a more convenient customer experience. People in such markets have more interactions with chatbots and consequently develop more positive attitudes towards them. On the other hand, in a less concentrated market with a larger number of smaller competing companies, the adoption of self-service technologies like chatbots may be slower due to limited resources available to these enterprises. As discussed above, there is a high possibility that market structure influences the distribution of resources and the quality of chatbot services.

Furthermore, the pressure of competition cannot be underestimated. To maintain their competitiveness, organizations, especially small and medium-sized enterprises, are more likely to adopt certain technologies, including chatbots, when other organizations have already done so (Kurnia et al., 2015). Additionally, when organizations face business difficulties, they may be more inclined to adopt innovations as a means to seek breakthroughs (Awa et al., 2017).

In conclusion, the AI-based chatbots adoption in different countries are influenced by a range of economic and technological factors, including regulations, technological development, market structure, and competition pressure.

1.3.2 Impact of cultural background

Cultural background may influence the effects of perceived usefulness, perceived ease of use, perceived enjoyment, and perceived privacy risks on intentions to use AI-based chatbots.

Individualists may place more emphasis on whether a chatbot is easy to use. This perspective is supported by a study that found a stronger association between perceived ease of use and attitudes towards chatbots among American consumers compared to Norwegian consumers, with Norway being characterized by relatively low individualism. The relationship between perceived usefulness and intention to use was also found to differ between these two countries. These differences may be attributed to variations in individualism and perceived egalitarianism (Smith et al., 2013).

Perceived enjoyment may be related to the cultural background in the process of chatbot adoption. Lee et al. (2013) found that the level of enjoyment has a greater impact on technology adoption in America than Korea. People in individualistic cultures tend to make decisions independently by evaluating information from reliable sources and being less influenced by their social environment. Fleischmann et al. (2020) also found that individualists are more influenced by the enjoyment of using new technology, and they value new experiences. However, 7 weeks after using the new technology, only collectivism influences performance and enjoyment (Fleischmann et al., 2020). It can be inferred that cultural background moderates the relationship between perceived enjoyment and AI-based chatbot use, but the specific direction of this influence remains unclear.

Perceived privacy risk might have different impacts on individual behavior depending on the level of individualism. Hofstede (2001) suggested that Individualists place a high value on their right to privacy, while collectivists prioritize belonging to a group. In cultures that prioritize individualism, such as the US, privacy is highly valued, and individuals are more likely to protect their personal information. In collectivist cultures, like Pakistan, the welfare of the group is more important than individual privacy and individuals may be less concerned about sharing personal information. (Sultan et al., 2009). In online environments, cultural differences in values can also influence privacy concerns. For example, research has found that Chinese people tend to disclose more personal information online than Americans, possibly due to the collectivist values in Chinese culture that prioritize group interests over individual interests, while in American culture is the opposite (Li & Borah, 2018).

These differences in privacy concerns can also be observed in daily life. In China, for example, real-name authentication is required for certain products and services, such as purchasing a mobile phone card, taking a long-distance transportation, or staying in a hotel. During the COVID-19 pandemic, privacy issues in China gained widespread attention in Europe as the government implemented measures such as "health QR codes" and "tracking passes" to monitor individuals' COVID-19 test results and geospatial information. While these measures have caused some inconveniences, a high percentage of citizens believe that the government has acted in the best interests of the people (Liu & Zhao, 2021). Given the significance of perceived privacy risk among various risks, this indicates that cultural background can influence the relationship between perceived risks and the intention to use AI-based chatbots.

1.3.3 Summary

This section discusses how the environment affects the acceptance aspects of AI-based chatbots, providing insights into the economic, technological, and cultural dimensions.

At the economic and technological levels, regulations, technological advancements, market structures, and competitive pressures emerge as key determinants that support or limit the adoption of AI-based chatbots. These factors are interrelated and together shape an individual's adoption of chatbots.

Shifting the focus to the cultural dimension, constructs like individualism and collectivism significantly impact chatbot adoption. Values and priorities within these cultural frameworks can moderate the role of perceived enjoyment in technology adoption. Individualists often place great value on self-interests and the joy of using new technology. Additionally, individualistic cultures tend to emphasize individual privacy rights, whereas collectivistic cultures often prioritize group interests over individual privacy concerns. Therefore, cultural context is also cited as a key determinant in driving the adoption of AI-based chatbots.

This section highlights situational factors that influence the acceptance of AI-based chatbots. While the economic and technological aspects are very complex, especially in contrasting countries such as China and Lithuania, the most striking and enduring difference is the degree of individualism in these countries. Cultural influence is often a stable and critical factor that provides a valuable perspective on understanding complex adoption patterns in different countries.

2. RESEARCH METHODOLOGY

2.1 Purpose of the research and research model

Building upon the preceding analysis, this section aims to outline the purpose of the research and introduce the research model that will be used to investigate the factors impacting the intention to continue using ChatGPT. Furthermore, it seeks to investigate potential disparities in these factors between the regions of China and Lithuania.

Chatbot adoption has been extensively studied in order to understand the factors that influence chatbot usage and acceptance. Variations in factors and models can arise due to the diverse industries and capabilities of chatbots (Chocarro et al., 2021). The effectiveness of Technology Acceptance Model (TAM) has been consistently demonstrated in explaining user acceptance in a variety of contexts (Chocarro et al., 2021; Kasilingam, 2020). While several influential factors have been identified in the adoption of AI-based chatbots, there remains a need to explore and determine the specific dimensions of service quality that are particularly effective for AI-based chatbots and how they affect users' perception.

ChatGPT has recently emerged as an intriguing AI-based chatbot, gaining significant popularity and widespread usage among users. Its advanced capabilities position it as a potential solution for automating a significant portion of manual work in the future. (Dwivedi et al., 2023), making it necessary to reassess and modify research models previously discussed to effectively analyze and understand the adoption of these kind of AI-based chatbots. Thus, in this study, the primary focus is to examine the factors that make people continue using ChatGPT, considering its unique capabilities and characteristics. Additionally, the study aims to investigate the differences in these factors in China and Lithuania, providing insights into how cultural, technological and other variations may influence user behavior towards ChatGPT.

The research model in this study integrates multiple factors to predict customers' intention to continue using ChatGPT. Specifically, the model combines dimensions of quality service, including competence, reliability, tangibles and security, with elements of the TAM, including perceived ease of use and perceived usefulness. Additionally, extended factors like perceived risk and perceived enjoyment, anthropomorphism will be incorporated into the model. Moreover, the research model aims to compare these factors between China and Lithuania to understand potential variations in customer's attitudes and intentions across the two countries, so country will be considered as a moderator within the model.

The hypothesized relationships in the research model suggest that competence, reliability, tangibles, security and anthropomorphism can impact users' perceived usefulness, perceived ease of use, perceived risks and perceived enjoyment. These, in return, are supposed to influence users' intention to continue using. Additionally, the effects of perceived usefulness, perceived ease of use, perceived risk, and perceived enjoyment on intention to continue using ChatGPT are hypothesized to be moderated by the country variable.

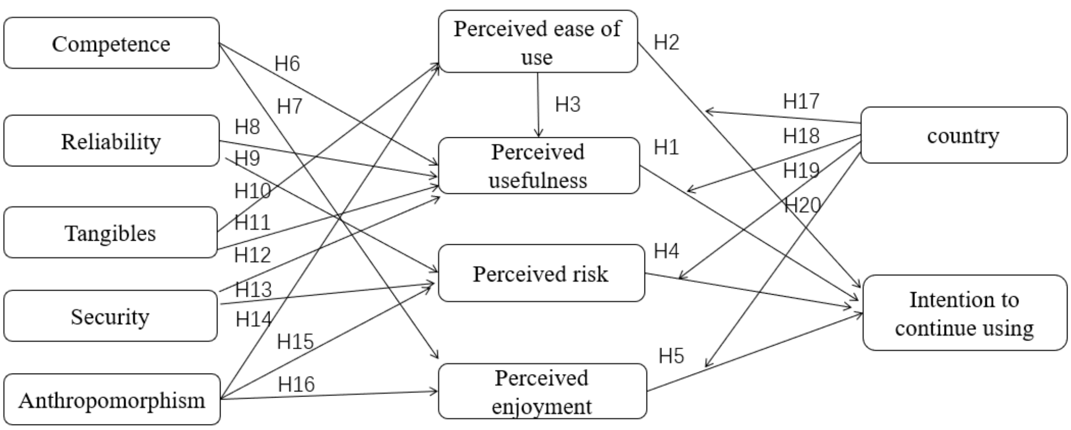


Figure 5 *Research model*

The concept of perceived usefulness and perceived ease of use has been explained previously. Perceived usefulness has been proven to have a significant effect on the intention to continue using AI-based chatbots (Ashfaq et al., 2020; Meyer-Waarden et al., 2020). Given the practical and marvelous benefits of ChatGPT, including creating comprehensive text (Thorp, 2023), facilitating a personalized teaching environment (Baidoo-Anu & Owusu Ansah, 2023), it can be inferred that users have generally positive perceptions of the usefulness of ChatGPT, consequently leading to the strong intention to use. Therefore, the following hypothesis is proposed:

H1: Perceived usefulness has a significant positive impact on the intention to continue using ChatGPT.

Previous studies have also emphasized the importance of perceived ease of use in chatbot acceptance (Chocarro et al., 2021; Kasilingam, 2020). Understandably, if users find that an AI-based chatbot requires less effort, they are more likely to continue using it. While the Technology Acceptance Model (TAM) suggests that perceived ease of use is linked to perceived usefulness, Meyer-Waarden et al. (2020) discovered that the effect of perceived ease of use on perceived usefulness may not be significant. This could be attributed to the idea that assessing the usefulness of an AI-based chatbot should prioritize factors such as its concrete functionality and reliability, rather than solely focusing on the ease-of-use aspect. However, in the case of ChatGPT, if users need to input multiple prompts to obtain the desired answer, and sometimes struggle to understand how to elicit the correct response, it may affect their perception of the usefulness of ChatGPT. Therefore, I still posit that perceived ease of use can influence the perception of usefulness. Consequently, two hypotheses are proposed:

H2: Perceived ease of use has a positive impact on the intention to continue using ChatGPT.
H3: Perceived ease of use has a positive impact on the perceived usefulness.

Several perceived risks associated with ChatGPT have emerged, potentially influencing people’s attitudes and acceptance of the system. A prominent concern is the correctness of the information generated by ChatGPT, as it has the capability to generate content seemingly out of nowhere and there are limitations in its ability to provide up-to-date information beyond 2021(Dwivedi et al., 2023). Moreover, privacy concerns have been highlighted regarding the usage of personal data in training the ChatGPT model as well as nefarious use, such as impersonation or deception through generated highly realistic synthetic text or speech（Lund &Wang, 2023). These risks may lead individuals to hesitate when considering the use of ChatGPT. Based on these considerations, the following hypothesis is put forward:

H4: Perceived risks have a negative impact on intention to continue using ChatGPT.

Various studies have provided extensive support for the importance of perceived enjoyment in determining the acceptance of chatbots (Ashfaq et al., 2020; De Cicco et al., 2020; Kasilingam, 2020). Perceived enjoyment reflects personal perception of finding something enjoyable or fun (De Cicco et al., 2020). In the ease of ChatGPT, beyond its extensive utilization, it can provide entertainment to users through recreating personalized contents and simulating historical figures or fictional characters (Thorp, 2023). This aspect enhances the user experience and encourages users to continue using ChatGPT. Thus, the following hypothesis is proposed:

H5: Perceived enjoyment has a positive impact on the intention to continue using ChatGPT.

In the context of AI-based chatbots, competence can be understood as the ability of the system to provide users with the desired answers and meet their expectations. Typically, when users perceive AI-based chatbots as competent in delivering precise and pertinent information, it enhances their perception of the technology's utility. However, Meyer-Waarden et al. (2020) made a noteworthy discovery suggesting an unexpected negative correlation between competence and the perception of usefulness. They proposed that this counterintuitive finding may be attributed to the chatbot's limited capacity to provide comprehensive responses. Given ChatGPT's standing as a more advanced AI-based chatbot, one would expect that ability and perceived usefulness should be positively related.

When users perceive AI-based chatbots as enjoyable, they typically experience a higher level of satisfaction and fulfillment, while also experiencing fewer negative emotions. Gkinko and Elbanna (2022) provide insights into the emotional experiences of individuals in the context of chatbots. They found that when users perceive the outcome of their interaction with chatbots as expected, they tend to feel happy. Conversely, users may feel frustrated when they are unable to accomplish a task through the AI-based chatbot. This suggests that the competence and effectiveness of AI-based chatbots can positively influence perceived enjoyment.

Based on the understanding, the following hypotheses are proposed:
H6: Competence has a positive impact on the perceived usefulness.
H7: Competence has a positive impact on perceived enjoyment.

The reliability of AI-based chatbots can be understood as users' perceptions of the trustworthiness of its outcomes and the consistency of its performance. Research has examined the relationship between reliability and perceived usefulness, and findings indicate that when consumers have confidence in the performance of a technology, they perceive it to be more useful (Meyer-Waarden et al., 2020).

Furthermore, reliability also plays a crucial role in reducing perceived risks. When users perceive an AI-based chatbot like ChatGPT as reliable and trustworthy, it enhances their trust and decreases their perception of risks. Previous research has consistently demonstrated the positive influence of reliability on building trust in AI-based chatbot interactions. For example, Nguyen et al. (2021) explained that high-quality information means reliable responses that reduce users' time and effort, help increase trust in AI-based chatbots, and correspondingly reduce perceived risks.

Based on these insights, two hypotheses are proposed:
H8: Reliability has a strong positive impact on the perceived usefulness.
H9: Reliability is negatively correlated with perceived risk.

Research has stated that tangibles, focusing on the attractive appearance and color of AI-based chatbots, may be related to perceived usefulness and perceived ease of use (Meyer-Waarden et al., 2020). In the context of ChatGPT, its contemporary and tech-savvy gray-black aesthetic may significantly influence people's perceptions of its usefulness and ease of use.

Based on these considerations, the following hypotheses are proposed:

H10: Tangibles have a positive impact on perceived ease of use.

H11: Tangibles have a positive impact on perceived usefulness.

Security plays an important role in shaping perception of usefulness and risks. In March 2023, ChatGPT faced a ban in Italy due to privacy concerns and worries about underage users (McCallum, 2023a). However, OpenAI promptly addressed these concerns and ensured compliance with Italian regulations. Users will now be informed about the privacy policy and undergo age verification during the registration process. Additionally, OpenAI has stated that it will provide a new mechanism for EU users to express their objection to the use of their personal data (McCallum, 2023b). This incident highlights the impact of perceived security on user behavior. When individuals perceive low levels of security in utilizing AI-based chatbots, they may perceive higher risks associated with their usage, leading to reduced adoption. Some people may choose not to use AI-based chatbots due to concerns over potential misuse of personal data, which can influence their perception of the usefulness of AI-based chatbots. Drawing from the preceding discussion, the following hypotheses can be formulated:

H12: Security has a positive impact on perceived usefulness.

H13: Security is negatively correlated with perceived risks.

Existing research offers valuable insights into how anthropomorphism shapes user perceptions and behaviors in chatbot interactions. For example, Sheehan et al. (2020), comparing chatbots with different response procedures, found that participants displayed a preference for anthropomorphic chatbots. These chatbots were perceived as easier to use, ultimately leading to a higher intention to adopt them. Consequently, anthropomorphic characteristics appear to have a positive impact on the perceived ease of use.

Moreover, Qiu and Benbasat (2009) illustrated that the inclusion of avatars and human voice-based communication in chatbot interactions can foster trust. Similarly, Ischen et al. (2020) compared the effectiveness of chatbots with human-like qualities and those with machine-like attributes. The human-like attributes resulted in greater information sharing and adherence to recommendations, indicating a higher level of trust. This increased trust is closely tied to users perceiving a higher degree of anthropomorphism, which, in turn, helps alleviate concerns associated with chatbots. Expanding on these insights, Pelau et al. (2021) asserted that human-like traits enhance the perceived level of engagement, ultimately leading to greater acceptance and trust. These findings strongly suggest the role of anthropomorphism in reducing risk perceptions.

Furthermore, Han (2021) provided further support for the impact of anthropomorphism by confirming that mobile users engaging with chatbots exhibiting human-like conversational qualities perceive anthropomorphism. This perception leads to an increased sense of chatbot social presence and a heightened level of enjoyment. Moussawi et al. (2021) bolstered these findings by highlighting a robust positive connection between anthropomorphism and perceived enjoyment.

In light of this substantial body of research, we propose the following hypotheses:

H14: Anthropomorphism has a positive impact on perceived ease of use.

H15: Anthropomorphism has a negative impact on perceived risk.

H16: Anthropomorphism has a positive impact on perceived enjoyment.

The influence of perceived usefulness on the intention to continue using technology can vary across different cultures, such as China and Lithuania, due to cultural values, prior experience, and exposure to technology. Cultural values exert a substantial influence on personal perceptions of AI-based chatbots, with collectivistic cultures potentially placing a higher value on utility compared to individualistic cultures. Studies conducted in various cultural contexts, including the US, UAE, and Japan, have highlighted differences in attitudes toward technology adoption (Shin et al., 2022a, 2022b), suggesting that the impact of perceived usefulness may be more pronounced in China, a collectivistic culture, as compared to Lithuania, which leans towards individualism.

Furthermore, an individual's prior exposure to technology significantly influences their perceptions of both usefulness and ease of use. For example, China is a technologically advanced country with a large smartphone user base and high familiarity and experience with various technologies, including chatbots (de Best, 2022). Conversely, Lithuania, with potentially fewer mobile users and a smaller market, may possess a lower level of familiarity and experience with AI-based chatbot services. Overcoming the challenges associated with adopting new technology on digital devices may prove more daunting for individuals with limited prior experience. Consequently, the impact of perceived ease of use on the intention to continue using such technology may be more pronounced.

Moreover, Im et al. (2011) pointed out that people in cultures characterized by individualism tend to make more independent decisions. Therefore, the influence of effort expectancy on behavioral intention should be more prominent in societies with a strong emphasis on individualism, and their data analysis supported this hypothesis. Effort expectancy, a key construct within the UTAUT framework, represents an individual's perceived ease of use or the level of effort they expect to exert when using a particular technology.

Based on these insights, we propose two hypotheses:

H17: The impact of perceived ease of use on the intention to continue using technology is stronger in Lithuania than in China.

H18: The impact of perceived usefulness on the intention to continue using technology is stronger in China than in Lithuania. Based on these insights, two hypotheses are proposed:

Cultural disparities can result in distinct perceptions of privacy risks associated with AI-based chatbots. According to Hofstede (2001), individuals in collectivistic cultures may be more inclined to share personal information if they perceive it as advantageous for the group or society, whereas those in individualistic cultures tend to prioritize safeguarding their individual privacy. This phenomenon has been supported by prior research (Li & Borah, 2018; Sultan et al., 2009). Consequently, it can be inferred that the influence of privacy concerns on technology acceptance is more pronounced in individualistic cultures, such as Lithuania, compared to collectivistic cultures, like China.

Additionally, as mentioned above, China's significant advancements in smart and digital technologies may result in the public becoming more familiar with and comfortable with AI-based chatbots. This level of familiarity can potentially mitigate the perceived risks associated with AI chatbots and reduce their impact on usage intentions. Conversely, Lithuania may have a stronger perception of risk, leading to lower intention to use.

Considering the marked cultural variations in privacy attitudes and differing levels of familiarity with digital technologies between the two countries, it is reasonable to conclude that the impact of perceived risk on the intention to continue using AI-based chatbots will vary significantly between Lithuania and China.

Based on the considerations, a hypothesis is proposed:
H19: The impact of perceived risk on intention to continue using is stronger in Lithuania than in China.

The impact of perceived enjoyment on intention to continue using AI-based chatbots may vary between Lithuania and China due to cultural differences in individualism and the influence of social environments on decision-making. Individualistic cultures, such as the United States, tend to prioritize independent decision-making and value new experiences (Lee et al., 2013; Fleischmann et al., 2020). Individualists are more influenced by the enjoyment of using new technology and tend to value the novelty and excitement it brings (Fleischmann et al., 2020).

In contrast, collectivist cultures like China may place less emphasis on individual enjoyment and more importance on group interests and social influences in decision-making. Individuals in collectivist cultures may be less driven by personal enjoyment and more influenced by social norms and the opinions of others when it comes to adopting new technologies like AI-based chatbots (Lee et al., 2013).

Therefore, it can be inferred that the impact of perceived enjoyment on intention to continue using AI-based chatbots is likely to be stronger in Lithuania than in China. Individuals in Lithuania may value the personal enjoyment and novel experiences offered by AI-based chatbot interactions to a greater extent, leading to a stronger intention to continue using AI-based chatbots based on the perceived enjoyment they derive from using them.

Thus, a hypothesis is proposed:
H20: The impact of perceived enjoyment on intention to continue using is stronger in Lithuania than in China.

2.2 Data collection method and instrument

In many research studies focusing on the adoption of chatbots, a structured questionnaire has been widely used (Kwangsawad and Jattamart, 2022; Meyer-Waarden et al, 2020; Trivedi, 2019). ChatGPT will be used as the AI-based chatbot model in this research. Although ChatGPT is not officially available in China owing to the country's "Great Firewall," some Chinese have found a means to access it by purchasing foreign ChatGPT accounts on Chinese e-commerce sites (Cheng, 2023). Because it is more difficult for Chinese users to utilize ChatGPT, the questionnaire was based on prior ChatGPT experience. I distributed the questionnaire on WJX.cn in China and Facebook in Lithuania to collect data on the experience of using ChatGPT. The original questionnaire is in English, however, it was distributed in Chinese and Lithuanian.

The questionnaire is based on service quality aspects and Technology Acceptance Model (TAM) ideas. It is broken into two sections: the first collects general information about the respondents, such as gender, age and ChatGPT experience. The second portion focuses on factors influencing respondents' perceptions of ChatGPT. The perception-related factors include competence, reliability, tangibles, security, anthropomorphism, perceived usefulness, perceived ease of use, perceived risks, perceived enjoyment, and intention to continue using. Respondents will be asked to score their level of agreement with statements on a 7-point scale ranging from "strongly disagree" to "strongly agree."

The survey begins with an initial question: "Have you used ChatGPT?" This question serves the purpose of ensuring that only individuals with firsthand experience of ChatGPT participate in the survey. The scales used to measure tangibles, competence and reliability of ChatGPT are adapted from the study conducted by Meyer-Waarden et al. (2020). Meyer-Walden's study highlights the importance of attractive appearance in online services through the variable tangibles.

As mentioned earlier, ChatGPT's competence lies in its ability and knowledge. As a large language model (LLM), ChatGPT can generate sophisticated content that can be utilized for various tasks, including writing and engaging in conversations for different purposes (van Dis et al., 2023). Furthermore, ChatGPT is known for its quick responses and ability to save user’s time. Therefore, assessing its competence can be effectively done through descriptions related to responsiveness, efficiency, meeting user needs, and successfully completing tasks.

According to Dwivedi et al. (2023), ChatGPT users place importance on obtaining useful and accurate information, as well as achieving positive outcomes. These factors significantly contribute to establishing trust in the reliability of ChatGPT's outputs and ensuring consistent performance. To assess these aspects of reliability, the questions from the study conducted by Meyer-Waarden et al. (2020) were specifically selected as they align with the user's expectations regarding the reliability of ChatGPT.

The questions related to security in ChatGPT are drawn from the research conducted by Noor et al. (2022). Addressing security concerns in online services is crucial, as they often involve electronic transactions that may lead to potential financial losses and the exposure of personal data， as highlighted by Alshurideh (2022). Therefore, the scales employed to assess security in ChatGPT focus on measuring the potential risks associated with privacy breaches.

The metrics used to measure perceived usefulness in this study are derived from Ashfaq et al. (2020), which reported a composite reliability of 0.926 for the scales measuring perceived usefulness. Likewise, the perceived ease of use scale was taken from this study.

To assess perceived enjoyment, I have adapted questions from a questionnaire developed by Oghuma et al. (2016). Meanwhile, the intention to continue using ChatGPT is measured using scales adopted from Li & Wang (2023), comprising four items with a reliability score of 0.93. Finally, the scale for perceived risks is constructed based on studies by Chatterjee & Bhattacharjee (2020), addressing concerns such as receiving incorrect answers and privacy issues. These concerns have been frequently mentioned in relation to the use of ChatGPT (Dwivedi et al., 2023; McCallum, 2023a; McCallum, 2023b; van Dis et al., 2023). The questionnaire questions and their sources are listed in Table 23.

2.3 Research sample size and structure

This study will specifically target individuals who have utilized ChatGPT and belong to either the Chinese or Lithuanian population. Referring to the data presented in Table 1 concerning research sampling methods, previous studies typically involved respondent counts ranging from 146 to 400, with an average of 288 respondents. The objective of the questionnaire is to collect a minimum of 200 valid responses, with a preference for achieving a balanced distribution between the two countries. Given the distinct websites commonly used in these two countries, respondents will be categorized based on their country of origin. The Lithuanian form was created using Google Forms, and the Chinese form was created using WJX.cn. The sampling method will be convenience sampling, and two forms will be distributed to the target population.

Table 1 *Comparable research sampling method*

No.	Author	Type of questionnaire	Sampling	Number of respondents
1	Li et al. (2021)	Online questionnaire	Non-probability	295
2	Meyer-Waarden et al. (2020)	Online questionnaire	Non-probability	146
3	Chocarro et al. (2021)	Email, online questionnaire	Non-probability	225
4	Kwangsawad & Jattamart (2022)	Online questionnaire	Non-probability	401
5	Ashfaq et al. (2020)	Online questionnaire	Non-probability	370
6	Melián-González et al. (2021)	Online questionnaire	Non-probability	476
7	Trivedi, (2019)	Online questionnaire	Non-probability	258
8	Kasilingam (2020)	Using chatbot, online questionnaire	Non-probability	350
9	Sheehan et al. (2020)	Using chatbot, online survey	Non-probability	190
10	Lei et al. (2021)	Online questionnaire	Non-probability	400
11	Lee et al. (2020)	Laboratory experiment, questionnaire	Non-probability	64
Average				288

2.4 Summary

This chapter delineates a well-structured plan for exploring the factors influencing users' intentions to persist in using AI-based chatbots, with a specific focus on the globally popular chatbot ChatGPT. The research model hypothesizes that competence, reliability, tangibles, security, and anthropomorphism impact perceived usefulness, perceived ease of use, perceived risks, and perceived enjoyment of users, subsequently influencing their intention to continue usage. A total of twenty-two hypotheses were formulated to guide the study.

To align with the research objectives, a structured questionnaire was employed for data collection, emphasizing users' experiences with ChatGPT. This questionnaire was intended for distribution in both China and Lithuania, using convenience sampling, with a targeted minimum sample size of 200 responses. This approach ensures a comprehensive understanding of user perspectives across diverse cultural contexts.

3. THE ANALYSIS OF THE EMPIRICAL DATA

3.1 Data Analysis

3.1.1 Descriptive statistics

A total of 310 responses were gathered from China and Lithuania, with 175 responses from China and 135 from Lithuania. The first question in the survey was "Have you used ChatGPT in the past 6 months". To align with the focus of my study on the experience of using ChatGPT, only participants who responded "Yes" to this question were included as target respondents. Out of the collected responses, 253 were deemed valid for the study, comprising 152 from Chinese participants and 101 from Lithuanian participants.

Table 2 presents the demographic profile of the survey participants. In terms of gender distribution, 34.4% are men and 65.6% are women. The majority of respondents were of Chinese nationality, accounting for 60.1% of the sample, which exceeded the proportion of Lithuanian respondents at 39.9%.

Furthermore, a significant proportion of participants belonged to the age group of under 27 years old, with 37.2% being younger than 23, 29.6% falling between the ages of 23 and 26, and 33.2% being older than 26 years. These findings are consistent with Thormundsson's (2023) statistics, which highlight that ChatGPT enjoys the highest usage among individuals aged 18 to 34 globally, constituting 65.52% of its user base. Thormundsson's (2023) report also highlights a gender disparity, showing a predominance of male users of ChatGPT. Interestingly, this contrasts with this study, where female participants demonstrated higher activity levels.

Table 2 *Demographic data for respondents*

	Frequency	Percent
Number of respondents	253	100

Gender	Man	87	34.4
	Woman	166	65.6
Nationality	Chinese	152	60.1
	Lithuanian	101	39.9
Age	Young than 23 years old	94	37.2
	23~26 years old	75	29.6
	Older than 26 years old	84	33.2

3.1.2 Reliability analysis

The results of this study indicate a strong internal consistency among the scale items used, as evidenced by Cronbach's Alpha values exceeding the 0.6 benchmark for all factors (See table 23). This is particularly notable in the case of the scales measuring Competence, Reliability, Tangibles, Security, Anthropomorphism, Perceived Usefulness, Perceived Ease of Use, Perceived Enjoyment, and Intention to Continue Using, all of which show Cronbach's Alpha values exceed 0.8. Such high values underscore the considerable reliability of these factors within the scale. On the other hand, the scale assessing Perceived risk initially presented a lower reliability, with Cronbach's Alpha of 0.611. Interestingly, removing the item "I believe content generated by ChatGPT is not always correct" resulted in a slight increase in reliability scores, from 0.611 to 0.614. Therefore, the number of items for Perceived risk was changed from 4 to 3 items as shown in table 23.

3.1.3 Additional analysis

Data of all variables are presented in Table 3 in the order of Variability from highest to lowest. The mean value for all factors lies within the range of 3.68 to 5.55. Notably, the highest recorded score for intention to continue using stands at 5.55. This implies that, despite some levels of dissatisfaction, respondents remain inclined to continue using ChatGPT. The standard deviation and variance are moderate, showing that while there is some difference in users' intentions, the overall trend is very positive. The second highest mean value was for perceived usefulness. A high mean with moderate variability indicates that while most users find ChatGPT useful, there is still a range in how strongly they feel about its usefulness.

Security exhibits the lowest mean (3.68), alongside the highest variance (2.29). This suggests that users' perceptions of security display considerable variability, reflecting a pronounced level of concern among participants. The results for perceived risk are similar to the result of security. The second highest variability is in anthropomorphism, indicating a wide range of opinions on the anthropomorphic properties of ChatGPT. Competence has one of the lower standard deviations and variance, indicating that users' perceptions of ChatGPT's competence are more consistent and generally positive. Users generally agree on the ease of use of ChatGPT and reliability, as indicated by high means and relatively low variance on the factors perceived ease of use and reliability. High means accompanied by moderate variabilities are observed in Perceived Enjoyment and Tangibles. This indicates that, while the majority of users rate tangible aspects highly and perceive significant enjoyment, there is some degree of variation in how users perceive these aspects.

Table 3 *Descriptive statistics for analyzed factors*

Factors	Mean	Std. Deviation	Variance
Security	3.6789	1.51198	2.286
Anthropomorphism	4.3887	1.22817	1.508
Perceived risk	4.3333	1.21716	1.481
Intention to continue using	5.5534	1.09884	1.207
Perceived Enjoyment	5.1014	1.09181	1.192
Perceived Usefulness	5.4417	1.08531	1.178
Tangibles	4.9249	1.08179	1.170
Perceived ease of use	5.2095	1.04824	1.099
Reliability	5.2095	1.01799	1.036
Competence	5.2783	0.98837	0.977
Valid N	253		

The Independent Samples t-test was conducted comparing Chinese group and Lithuanian group. Table 4 reveals that for certain variables, namely Anthropomorphism, Competence, Perceived Usefulness, and Perceived Enjoyment, there are statistically significant differences between Chinese and Lithuanian participants' perceptions. Chinese rated these aspects more favorably on average, highlighting a particularly positive reception towards ChatGPT's anthropomorphic attributes, its competence in handling tasks, its overall usefulness, and the enjoyment derived from interacting with it.

No statistically significant differences were found between the two nationalities in their perceptions of Tangibility, Reliability, Perceived Risk, Security, and Perceived Ease of Use. This indicates a broad consensus among Chinese and Lithuanian participants regarding tangibility (aesthetic aspects), reliability, perceived risk, security in terms of personal information protection and perceived ease of use.

Security is a notable aspect where, despite general concerns around personal information in digital interactions, both groups have similar perceptions, which did not differ significantly. This could be because interactions with ChatGPT typically do not involve sensitive personal data handling or financial transactions, which are common areas of security concerns in other online services.

The Chinese participants' higher scores for Perceived Usefulness and Enjoyment suggest that ChatGPT may align well with their preferences or needs in technology use, possibly indicating greater acceptance of ChatGPT within the Chinese digital landscape. The absence of a notable discrepancy in security perception underscores a potentially universal trust in ChatGPT's ability to handle user data responsibly, irrespective of cultural or national context.

Table 4 *Descriptive statistics comparison of analytical factors between China and Lithuania*

Variable	**Nationality**	**N**	**Mean**	**SD**	**Sig.**
Tangible	Chinese	152	4.83	1.04	0.186
	Lithuanian	101	5.07	1.13	
Anthropomorphism	Chinese	152	4.72	1.03	0.001
	Lithuanian	101	3.88	1.33	
Competence	Chinese	152	5.46	0.87	0.014
	Lithuanian	101	5.01	1.09	
Reliability	Chinese	152	5.27	0.94	0.108
	Lithuanian	101	5.11	1.12	
Perceived risk	Chinese	152	4.42	1.19	0.596
	Lithuanian	101	4.20	1.26	
Security	Chinese	152	3.46	1.50	0.989
	Lithuanian	101	4.01	1.47	
Perceived Usefulness	Chinese	152	5.60	0.92	0.006
	Lithuanian	101	5.21	1.26	
Perceived ease of use	Chinese	152	5.21	0.96	0.051
	Lithuanian	101	5.21	1.18	
Perceived Enjoyment	Chinese	152	5.35	0.93	0.006
	Lithuanian	101	4.73	1.21	
Intention to continue using	Chinese	152	5.77	0.94	0.009
	Lithuanian	101	5.22	1.24	

3.2 Tests of hypotheses

As depicted in Table 5, three key predictors significantly influence the intention to continue using ChatGPT: perceived usefulness, perceived risks, and perceived enjoyment (Adjusted R2= 0.653, F=119.357, $p < .001$). Notably, perceived ease of use does not exhibit a statistically significant relationship with the intention to continue using ChatGPT. H2 is thus rejected. Furthermore, significant positive impacts are supported that perceived usefulness and perceived enjoyment on the intention to continue using ChatGPT, while perceived risks are supported to have a negative impact on the intention to continue using ChatGPT. Therefore, H1, H4, and H5 are supported.

Table 5 *Regression statistic of Intention to continue using*

Model Summary					
R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig.
.811[a]	0.658	0.653	0.64765	119.357	<.001[b]

Coefficients[a]					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.344	0.283		4.744	0.000
Perceived ease of use	0.042	0.055	0.040	0.754	0.452
Perceived Usefulness	0.436	0.061	0.430	7.095	0.000
Perceived Risks	-0.095	0.034	-0.106	-2.810	0.005
Perceived Enjoyment	0.399	0.056	0.396	7.178	0.000
a. Dependent Variable: Intention to continue using					

The model proves its effectiveness with both tangibles and anthropomorphism significantly impact perceived ease of use (Adjusted R^2=0.215, F = 35.444, p < 0.001). Both tangibles and anthropomorphism contribute positively to perceived ease of use, and the coefficient for anthropomorphism stands out as particularly significant. As a result, hypotheses H11 and H14 find strong support.

Table 6 *Regression statistics of perceived ease of use*

Model Summary					
R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig.
.470a	0.221	0.215	0.92893	35.444	<.001b
Coefficients[a]					

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	2.976	0.294		10.118	0.000
Tangible	0.174	0.059	0.180	2.944	0.004
Anthropomorphism	0.313	0.052	0.367	6.005	0.000
a. Dependent Variable: Perceived ease of use					

The concept of perceived usefulness can be effectively explained with an adjusted R-square value of 0.657, primarily influenced by three factors: competence, reliability, and perceived ease of use. Among these, competence emerges as the most impactful factor on perceived usefulness. Following competence, perceived ease of use also plays a significant role in determining perceived usefulness. Although the impact of reliability is relatively small compared to other factors, its impact is positive, as hypothesized. On the other hand, the effects of tangible and security factors on perceived ease of use are insignificant. Consequently, this analysis lends support to hypotheses H3, H6, and H8, while hypotheses H10 and H12 are rejected.

Table 7 *Regression statistics of perceived usefulness*

Model Summary					
R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig.
.815a	0.664	0.657	0.63564	97.529	<.001b

Coefficients[a]					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.329	0.253		1.301	0.194
Competence	0.451	0.072	0.411	6.222	0.000
Reliability	0.191	0.071	0.179	2.677	0.008
Tangible	0.035	0.043	0.034	0.801	0.424

Security	-0.058	0.030	-0.081	-1.937	0.054
Perceived ease of use	0.343	0.052	0.331	6.555	0.000
a. Dependent Variable: Perceived usefulness					

Table 8 suggests that reliability has a negative impact on perceived risk, while security has a positive influence, although both effects are relatively modest. Consequently, H9 is supported, and H13 is rejected. However, in this model, anthropomorphism does not exhibit a significant impact on perceived risk, leading to the rejection of H15. It is important to emphasize that this model explains only a small portion of the variance in perceived usefulness, as the R-squared is 0.223 and the adjusted R-squared is 0.038. The low reliability of the perceived risk scale may have contributed to the rejection of H13 and H15.

Table 8 *Regression statistics of perceived risk*

Model Summary					
R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig.
.223a	0.050	0.038	1.19374	4.329	.005b

Coefficients[a]					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	4.865	0.398		12.214	0.000
Reliability	-0.278	0.091	-0.233	-3.057	0.002
Security	0.118	0.056	0.146	2.109	0.036
Anthropomorphism	0.111	0.079	0.112	1.399	0.163
a. Dependent Variable: Perceived risk					

The model summary in table 9 shows a high degree of explanatory power (adjusted R^2=0.455), which implies a strong correlation between the predictors and the dependent variable, perceived enjoyment. Both competence and anthropomorphism are significant predictors of perceived enjoyment, and both are positively correlated. Therefore, H7 and H16 are supported.

Table 9 *Regression statistics of enjoyment*

Model Summary							
R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig.		
.678a	0.459	0.455	0.80590	106.261	<.001b		
Coefficients[a]							
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.		
	B	Std. Error	Beta				
(Constant)	1.314	0.278		4.734	0.000		
Competence	0.465	0.063	0.421	7.405	0.000		
Anthropomorphism	0.303	0.051	0.341	6.001	0.000		
a. Dependent Variable: Perceived enjoyment							

Table 10 displays the outcomes of a multiple regression analysis. Among the hypotheses that were investigated, H1, H3, H4, H5, H6, H7, H8, H9, H10, H14, and H15 have received support, suggesting substantial relationships among the examined variables. On the contrary, H2, H11, H12, and H16 have not gained support. Additionally, the correlation in H13 is statistically significant, but its directional effect contradicts the initial hypothesis, leading to the rejection of H13.

Within the framework of the Technology Acceptance Model, it becomes evident that perceived usefulness and perceived enjoyment play pivotal roles as the most influential factors directly affecting the intention to maintain usage of an AI-based chatbot. Additionally, when we delve into the realm of quality factors and anthropomorphism, it becomes clear that competence stands out as the primary factor contributing to both perceived enjoyment and perceived usefulness. Furthermore, anthropomorphism was observed to significantly impact both perceived usefulness and ease of use, underlining its significance in the model. Both competence and anthropomorphism emerged as robust indicators within the acceptance model.

Moreover, perceived enjoyment was seen to have a substantial impact on the intention to continue using ChatGPT, highlighting the significance of the hedonic aspect in the adoption of AI-based chatbots.

Table 10 *Result of research model 1*

No.	Independent variable	Dependent variable	β	p	Result
H1	PU	ITCU	0.43	<0.001	Accepted
H2	PEOU	ITCU	0.04	0.452	Rejected
H3	PEOU	PU	0.331	<0.001	Accepted
H4	PR	ITCU	-0.106	0.005	Accepted
H5	PEnj	ITCU	0.396	<0.001	Accepted
H6	Comp	PU	0.411	<0.001	Accepted
H7	Comp	PEnj	0.421	<0.001	Accepted
H8	Rel	PU	0.179	0.008	Accepted
H9	Rel	PR	-0.233	0.002	Accepted
H10	Tang	PEOU	0.18	0.004	Accepted
H11	Tang	PU	0.034	0.424	Rejected
H12	Sec	PU	-0.081	0.054	Rejected
H13	Sec	PR	0.146	0.036	Rejected
H14	Anthr	PEOU	0.367	<0.001	Accepted
H15	Anthr	PR	0.112	0.163	Rejected
H16	Anthr	PEnj	0.341	<0.001	Accepted

Table 11 reveals that nationality significantly moderates the relationship between perceived ease of use and the intention to continue using a service, as indicated by a model with a significant p-value of 0. The scatter plot underscores this finding, with Lithuanians demonstrating a steeper regression line (slope = 0.7207) compared to Chinese (slope = 0.5055), indicating that for Lithuanians, as perceived ease of use increases, so does their intention to continue using the service to a greater extent than for Chinese nationals.

Table 11 *Moderation statistics of nationality 1*

Model summary			
R	R Square	F	p
0.6429	0.4133	58.4613	0
Test(s) of highest order unconditional interaction(s)			

	R2-chng	F	p
PEOU*Nation	0.0105	4.474	0.0354
Conditional effects			
Nationality	Effect	t	p
Chinese	0.5055	7.0162	0
Lithuanian	0.7207	10.0266	0

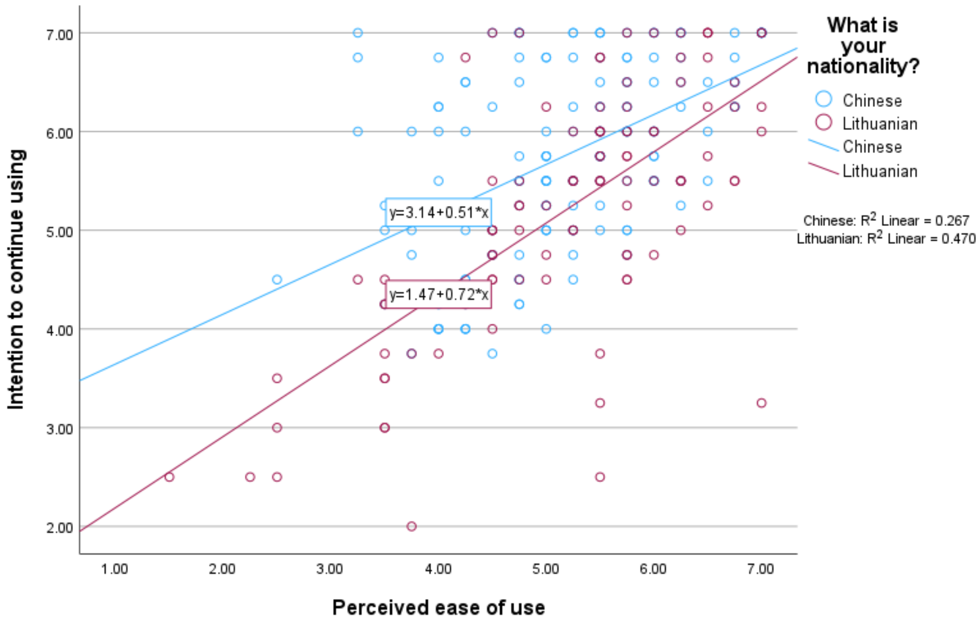


Figure 6 *The moderating effect of nationality*

The statistical analysis demonstrates that nationality does not substantially modify the relationship between perceived usefulness and the intention to continue using ChatGPT (F=.1232, p=0.7259). Consequently, H18, H19, and H20 are rejected.

The statistical analysis reveals that nationality does not have a significant impact on the relationship between perceived usefulness and the intention to continue using (F=0.1232, p=0.7259). Similarly, nationality does not appear to influence the relationship between perceived risk and the intention to continue using (F=1.6860, p=0.1963). In the last case, with an even lower F-value of 0.0006 and a p-value of 0.9802, it is highly likely that any observed correlation is simply a result of chance rather than a systematic influence. Therefore, it can be concluded that nationality does not play a role in the relationship between perceived enjoyment and the intention to continue using.

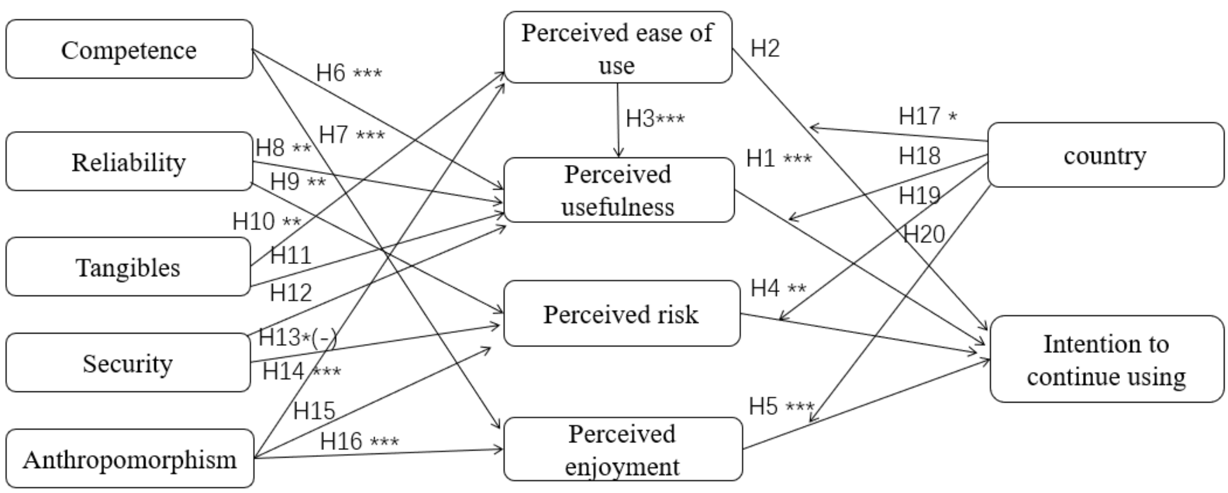
Table 12 *Moderation statistics of nationality 2*

	R2-chng	F	df1	df2	p
PU*Nation	.0002	.1232	1.0000	249.0000	.7259
PR* Nation	.0061	1.6860	1.0000	249.0000	.1953
PENJ*Nation	.0000	.0006	1.0000	249.0000	.9802

In summary, the moderation effect between perceived ease of use and intention to continue using is statistically significant, while the remaining moderation effects, as indicated in Table 13, are found to be insignificant. The results for all hypotheses can be found in Table 24 and are visually depicted in Figure 7.

Table 13 *Result of research model 2*

No.	Independent variable	Dependent variable	Moderator	F	p	Result
H17	PEOU	ITCU	Country	4.474	0.0354	Accepte d
H18	PU	ITCU	Country	0.1232	0.7259	Rejected
H19	PR	ITCU	Country	1.686	0.1953	Rejected
H20	PENJ	ITCU	Country	0.0006	0.9802	Rejected



(No *: not significant; * p<0.05; ** p<0.01; ***p<0.001; -: Not supported)

Figure 7 *Result of structural model*

3.3 Additional calculations

Two additional analyses have been conducted. The first aimed to explore the potential impact of gender disparity, while the second sought to investigate differences between China and Lithuania.

Firstly, as indicated in Table 2, 65.6% of the respondents are female. Previous research by Kasilingam (2020) suggested that gender might significantly influence technology adoption. To assess the potential impact of gender disparity on this research outcomes, we included gender as a variable in this research model. The statistical analysis presented in Tables 14 to 18 indicates that gender did not demonstrate a significant influence on the correlations examined previously, as all p-values associated with gender exceeded the threshold of 0.05. Therefore, we can confidently conclude that gender disparity did not have a discernible impact on the research findings, and the results remained consistent despite variations in gender distribution among the respondents.

Table 14 *Regression statistic of Intention to continue using (gender is included)*

Coefficients[a] (Intention to continue using)					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.345	0.316		4.249	0.000
Your gender	0.000	0.086	0.000	-0.005	0.996
Perceived ease of use	0.042	0.055	0.040	0.752	0.453
Perceived Usefulness	0.436	0.062	0.430	7.074	0.000
Perceived Risk	-0.095	0.034	-0.106	-2.798	0.006
Perceived	0.399	0.056	0.396	7.156	0.000

Enjoyment					
a. Dependent Variable: Intention to continue using					

Table 15 *Regression statistic of Perceived ease of use (gender is included)*

Coefficients[a] (Perceived ease of use)					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	3.114	0.371		8.403	0.000
Your gender	-0.076	0.124	-0.035	-0.614	0.540
Tangible	0.169	0.060	0.175	2.832	0.005
Anthropomorphism	0.316	0.052	0.370	6.028	0.000
a. Dependent Variable: Perceived ease of use					

Table 16 *Regression statistic of Perceived usefulness (gender is included)*

Coefficients[a] (Perceived usefulness)					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.39	0.298		1.308	0.192
Your gender	-0.033	0.086	-0.015	-0.388	0.698
Competence	0.452	0.073	0.412	6.222	<.001
Reliability	0.191	0.071	0.179	2.674	0.008
Tangible	0.034	0.043	0.034	0.776	0.439
Security	-0.06	0.031	-0.084	-1.971	0.05
Perceived ease of use	0.342	0.052	0.331	6.541	<.001
a. Dependent Variable: Perceived usefulness					

Table 17 *Regression statistic of Perceived risk (gender is included)*

Coefficients[a] (Perceived risk)					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.

	B	Std. Error	Beta		
(Constant)	4.472	0.490		9.123	0.000
Your gender	0.223	0.163	0.087	1.369	0.172
Reliability	-0.274	0.091	-0.229	-3.011	0.003
Security	0.136	0.057	0.169	2.373	0.018
Anthropomorphism	0.096	0.080	0.097	1.198	0.232
a. Dependent Variable: Perceived risk					

Table 18 *Regression statistic of Perceived enjoyment (gender is included)*

Coefficients[a] (Perceived enjoyment)					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.542	0.326		4.722	0.000
Your gender	-0.141	0.107	-0.061	-1.319	0.188
Competence	0.464	0.063	0.420	7.399	0.000
Anthropomorphism	0.306	0.051	0.344	6.054	0.000
a. Dependent Variable: Perceived enjoyment					

The second calculation was done by selecting data according to country. The result as it showed in table 19~21. The regression models for intention to continue using for both countries indicate that the model is slightly more predictive for Lithuanian respondents with an adjusted R2 of 0.648 compared to Chinese respondents with an adjusted R2 of 0.625. The model explains a significant portion of the variance in the intention to continue using ChatGPT for both groups but is more effective for Lithuanian users.

For Chinese respondents, perceived ease of use did not significantly influence intention to continue using ChatGPT, while for Lithuanian respondents it was an important factor, suggesting that ease of use is more critical for Lithuanians in their decision to continue using ChatGPT.

Perceived usefulness emerged as a significant influencer in both countries, underscoring its general importance in the decision to keep using ChatGPT. Notably, stronger beta values in China imply a more pronounced effect of perceived usefulness on Chinese users' intentions, aligning with previous findings that performance and usability are more emphasized in collectivist cultures than in individualistic ones (Shin et al., 2022a; 2022b).

Perceived risk has negative influence on the intention to continue using ChatGPT in both countries, indicating that higher perceived risks may deter continued use. Perceived enjoyment positively correlates with the intention to continue using ChatGPT, which holds true across both cultural contexts. Comparing the beta values, it can be deduced that the relationship between perceived risk and the intention to continue using ChatGPT is stronger among Lithuanians than among Chinese users. Conversely, the correlation between perceived enjoyment and behavioral intention is stronger among Chinese users compared to Lithuanians.

Therefore, the model is valid in both countries, yet the differences in the significance and strength of its predictors highlight that cultural variations may play a role in influencing user acceptance and the continued use of technology.

Table 19 *Additional statistics for Chinese respondents*

Model Summary (China)					
R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig.
.797a	0.635	0.625	0.57311	64.039	<.001b

Coefficients[a] (China)					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.511	0.359		4.205	0.000
Perceived ease of use	-0.042	0.068	-0.043	-0.621	0.535
Perceived Usefulness	0.486	0.079	0.479	6.165	0.000
Perceived Risks	-0.081	0.040	-0.102	-2.036	0.044

Perceived Enjoyment	0.397	0.081	0.393	4.886	0.000
a. Dependent Variable: Intention to continue using					

Table 20 *Additional statistics for Lithuanian respondents*

Model Summary (Lithuania)					
R	R Square	Adjusted R Square	Std. Error of the Estimate	F	Sig.
.814a	0.662	0.648	0.73526	46.979	<.001b

Coefficients[a] (Lithuania)					
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	1.279	0.473		2.703	0.008
Perceived ease of use	0.212	0.099	0.202	2.151	0.034
Perceived Usefulness	0.318	0.101	0.323	3.139	0.002
Perceived Risks	-0.123	0.060	-0.125	-2.047	0.043
Perceived Enjoyment	0.360	0.085	0.352	4.234	0.000
a. Dependent Variable: Intention to continue using					

Table 21 *Additional statistics for hypotheses H1, H2, H4, H5*

No.	Independent variable	Dependent variable	Select cases	β	p	Result
H1	PU	ITCU	All	0.43	0	Accepted
			China	0.479	0	Accepted
			Lithuania	0.101	0.002	Accepted
H2	PEOU	ITCU	All	0.04	0.452	Rejected
			China	-0.043	0.535	Rejected
			Lithuania	0.202	0.034	Accepted
H4	PR	ITCU	All	-0.106	0.005	Accepted
			China	-0.102	0.044	Accepted
			Lithuania	0.06	0.043	Accepted
H5	PEnj	ITCU	All	0.396	0	Accepted
			China	0.393	0	Accepted

			Lithuania	0.36	0	Accepted

This section of the study disclosed that gender exerted no notable influence on the research outcomes, underscoring its limited relevance to technology adoption. Moreover, the disparities in the significance of various factors between the two countries emphasize the importance of accounting for cultural dynamics in shaping technology acceptance.

3.4 Discussion on findings

The data analysis has shown significant findings in terms of the factors influencing user intentions.

Firstly, the result of data analysis confirmed the fundamental principles of the Technology Acceptance Model (TAM), showing the positive impact of perceived usefulness on the intention to use AI-based chatbots and positive impact of perceived ease of use in shaping perceived usefulness. These findings are consistent with prior research, highlighting the significant roles of perceived ease of use and perceived usefulness in chatbot adoption (Ashfaq et al., 2020; Chocarro et al., 2021; Kasilingam, 2020). However, it is worth noting that my analysis shows that perceived ease of use has no clear influence on intention to continue using ChatGPT, unlike the results of most other studies.

Furthermore, this research highlights the positive effect of perceived enjoyment on the intention to continue using ChatGPT, aligning with previous studies (Ashfaq et al., 2020; De Cicco et al., 2020; Kasilingam, 2020). This suggests that users who feel pleasure from their interactions with ChatGPT are more likely to express an intention to continue using it.

Additionally, the data analysis supports earlier research on perceived risk (Kasilingam, 2020; Kwangsawad & Jattamart, 2022; Wang & Lin, 2017), indicating that a high perceptions of risk have a negative impact on chatbot adoption. When users perceive ChatGPT to be risky, it may prevent them from adopting or continuing to use the chatbot.

There are a limited number of studies that effectively integrate service quality dimensions with the Technology Acceptance Model (TAM). Therefore, some correlations are indirectly inferred based on previous research and logical reasoning.

Several findings are in alignment with the results of Meyer-Waarden et al. (2020); for instance, tangibles have a substantial impact on perceived ease of use, and reliability significantly influences perceived usefulness. However, there are also differences. Notably, the impact of tangibles on perceived usefulness was deemed insignificant in a previous study, but it holds significance in this study. This discrepancy may be attributed to ChatGPT's robust and consistent perception of utility, which appears to be less influenced by the aesthetics of its interface. Another contrasting observation is that competence significantly affects perceived usefulness in this study, while it was deemed insignificant in a previous study, possibly indicating the advanced development of ChatGPT.

As with other correlations, our hypotheses have both consistency and bias. As hypothesized, competence indeed demonstrates a positive impact on perceived enjoyment. Additionally, reliability exhibits a negative correlation with perceived risk. However, the lack of a significant impact of security on perceived usefulness contradicts previous analyzes based on existing research. This result suggests that factors related to perceived safety concerning privacy, fraud, and personal information may not substantially influence users' perceptions of ChatGPT's utility. Surprisingly, security has a positive effect on perceived risk, implying that higher perception of security for personal data protection is associated with increased perceived risks, which may seem counterintuitive. This indicates that privacy concerns alone may not significantly reduce perceived risks. However, other aspects, such as potential errors and incompetence in ChatGPT responses, may lead to higher perceived risks.

Moving on to the aspect of anthropomorphism, the result of data processing confirms its positive impact on perceived ease of use, consistent with the previous studies (Han, 2021; Moussawi et al., 2021; Qiu & Benbasat, 2009; Sheehan et al., 2020). These studies have all suggested that human-like traits are associated with a higher level of trust (Ischen et al., 2020; Pelau et al., 2021; Qiu & Benbasat, 2009). Increased trust, in turn, tends to reduce the perceived risk among users. However, anthropomorphism was found to have no effect on perceived risk, which may be due to the lower reliability score of the perceived risk scale used in my study and small sample size.

In the comparative analysis between Chinese and Lithuanian users of ChatGPT, a notable cultural variation emerges. Chinese participants exhibited a higher perception of ChatGPT's usefulness and enjoyment compared to Lithuanian participants, leading to a higher intention to continuous use.

Regarding the moderation effects concerning the nationality on the relationship between perceived ease of use and the intention to continue using ChatGPT, a moderation effect was observed, echoing the findings of Im et al. (2011). The lack of a significant effect of perceived ease of use on behavioral intentions was initially inconsistent with most previous studies, therefore, the country-specific regression analyzes were conducted to further investigate.

This additional analysis shows the differences between the two countries: in Lithuania, perceived ease of use has a significant effect on the intention to continue using ChatGPT, suggesting that ease of interaction with the chatbot is a critical factor for Lithuanians. However, in China, this influence is not significant. This deviation from the traditional Technology Acceptance Model (TAM) may be associated with ChatGPT's unique standing in China. Despite not being officially supported in China (OpenAI, 2024), ChatGPT has still gained considerable popularity, frequently discussed and shared on Chinese social media. This trend suggests that Chinese users accessing ChatGPT are likely more adventurous and open to new technologies, thereby diminishing the importance of ease of use in their decision to continue using the platform. Kasilingam (2020) found that customers have higher levels of innovation and are more inclined to try new technologies. Therefore, for these Chinese users, the innovative and novel aspects of ChatGPT may surpass traditional ease-of-use considerations.

Furthermore, in China, perceived usefulness is a more significant factor in determining continued usage. This supports the findings of Shin et al. (2022a, 2022b), which highlight the importance of practical benefits in technologies within collectivist cultures. In this case, the usefulness of the technology is often the main reason for its adoption. This insight is crucial, as it points to the utility of technology being a more pivotal consideration in collectivist societies, shaping how technologies like ChatGPT are adopted and integrated into daily use.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

In summary, this study provides a detailed exploration of technology adoption theory, including the diffusion of innovative theories and models, such as TAM, TAM2, and UTAUT, in the context of AI-based chatbots. A rigorous analysis of the literature provides the basis for understanding common factors that influence technology acceptance and for investigating the unique economic, technological, and cultural landscapes of China and Lithuania. This study employs an enhanced technology acceptance model incorporating service quality dimensions and personification to examine ChatGPT usage patterns in the two countries.

Based on the theoretical analysis, four key conclusions have been drawn.

1. Drawing from previous research, this study incorporates a range of crucial factors into the research model. These factors encompass perceived usefulness, perceived ease of use, perceived enjoyment, perceived risks, anthropomorphism, competence, reliability, tangibles, and security. They are all considered to analyze their collective impact on the acceptance of AI-based chatbots.

2. TAM, a cornerstone model in technology acceptance, underscores the significance of perceived usefulness and perceived ease of use. Additionally, perceived enjoyment and perceived risk were extended in this study as essential factors. By integrating these quality dimensions, an enriched and comprehensive perspective on technology adoption emerges.

3. The adoption of technology within diverse countries is subject to a confluence of economic, technological, and cultural factors. China and Lithuania, being notably distinct nations, exhibit varying economic and technological backgrounds, which include differences in technological development, market structures, and competitive pressures. The degree of individualism, a key aspect of cultural backgrounds, substantially shapes opinions and behaviors in technology adoption.

4. Cultural background plays an integral role in molding the influence of perceived usefulness, perceived ease of use, perceived enjoyment, and perceived privacy risk on the intention to use AI-based chatbots. In highly individualistic societies, there is a tendency to place personal convenience and self-interest at the forefront, which can potentially influence the impact of factors like perceived ease of use, perceived enjoyment, and concerns about privacy affect in technology adoption.

The empirical analysis has led to eight key conclusions.

1. The analysis revealed the significant importance of perceived usefulness, enjoyment, competence, and anthropomorphism in influencing the intention to continue using AI-based chatbots. Notably, perceived usefulness and perceived enjoyment had a direct impact on the intention to continue using these chatbots, while competence and anthropomorphism indirectly influenced behavioral intention.

2. Perceived usefulness is the primary driver of user acceptance, closely followed by perceived enjoyment. This highlights the significance of both utility and entertainment in shaping the

adoption of AI-based chatbots.

3. Competence shaped users' perceptions of usefulness and enjoyment. This finding suggests that the capabilities of AI-based chatbots contribute not only to their utility but also enhance the overall user experience.

4. Anthropomorphism has great impacts on perceived ease of use and enjoyment. This underscores the importance of incorporating human-like features into AI-based chatbots. Interestingly, there is no significant correlation between anthropomorphism and perceived risk, potentially attributed to the limitations of the perceived risk scale or sample size.

5. Reliability emerged as another critical service quality dimension, positively affecting perceptions of usefulness and mitigating perceived risks. This highlights the imperative need to enhance the reliability of chatbots to bolster their acceptance.

6. On the other hand, tangibles, particularly aesthetics, did not significantly impact perceived usefulness. Nevertheless, they retained importance in terms of perceived ease of use. Therefore, attention to design elements such as text style, color, and overall appearance of AI-based chatbots should not be underestimated.

7. Security concerns, surprisingly, displayed no substantial influence on perceived usefulness. This suggests that, in the context of using ChatGPT, users' perceptions of utility are not notably swayed by privacy and personal data concerns. However, this outcome may differ in contexts involving different chatbots.

8. Lastly, the cross-cultural analysis revealed distinct preferences: In Lithuania, perceived ease of use held greater influence, while in China, perceived usefulness significantly impacted the intention to continue using AI-based chatbots. This divergence suggests that

individualistic cultures may prioritize ease of use, whereas collectivistic cultures may place greater emphasis on utility.

Recommendations

This study's findings provide crucial recommendations to accelerate AI-based chatbot adoption across various industries. Startups specializing in AI and chatbot technology, major e-commerce platforms, and social media networks are particularly poised to benefit from these strategies. These insights are also invaluable for Customer Service Software Providers, enabling them to refine chatbot interactions, especially in markets with diverse cultural backgrounds. Furthermore, global enterprises such as Microsoft, Alibaba, eBay, Apple, and Samsung can leverage these recommendations to effectively manage cross-cultural challenges in their international operations.

1. Promote Utility and Practical Benefits

Emphasize the use of AI-based chatbots in marketing campaigns. Due to the pivotal role of perceived usefulness in user acceptance, marketing strategies should concentrate on showcasing the practical benefits and utility of AI-based chatbots. This approach is particularly relevant in collectivist cultures where the practical value of technology is highly esteemed.

2. Enhance competence of AI-based chatbots

Recognizing the significant impact of perceived competence on improving perceptions of usefulness and enjoyment, management efforts should be dedicated to enhancing the functionality of AI-based chatbots and user-centered design. Regular updates and feature enhancements, guided by user feedback, are essential in maintaining a high level of capabilities.

3. Prioritize reliability to mitigate perceived risks

It is recommended to cultivate trust through reliable functionality and providing high-quality information. This requires ensuring that AI-based chatbots provide accurate, timely and consistent responses, thereby reducing perceived risk and increasing user confidence.

4. Incorporate Human-like Features

Given the influence of anthropomorphism on user acceptance, incorporating human-like elements in chatbots, such as natural language processing and empathetic responses, can improve user experience. This requires investment in advanced AI technologies to make AI-based chatbots more relevant and engaging. Consider incorporating marketing campaigns that highlight the empathy and emotion that AI-based chatbots display during interactions with users.

5. Tailor Strategies for Cultural Differences

To tailor strategies for cultural differences in technology adoption, it's essential to align with the specific needs of various cultures. In individualistic cultures, the focus should be on the ease of use and personal benefits, highlighting how chatbots simplify individual tasks and enhance user autonomy. Marketing in these cultures should illustrate these personal advantages. In contrast, for collectivistic cultures, it's important to emphasize the utility, demonstrating how chatbots play a role in group coordination and community efficiency. This approach ensures higher engagement with chatbots across different cultural landscapes.

Limitation and future research

While this study has made valuable contributions, it is important to acknowledge its limitations. Future research should address these limitations to enhance the robustness of our findings and provide a more comprehensive understanding of user acceptance in e-commerce environments.

1. Sample Size Limitation:

One of the limitations is the limited sample size. To bolster the reliability and generalizability of our findings, it is imperative to replicate this study with a larger sample size. This extension will allow us to investigate whether our results hold in a broader context.

2. Perceived Risk Scale Reliability

Another limitation pertains to the relatively low reliability of the adapted scale for perceived risk. In future research endeavors, it is essential to explore alternative measurement scales for perceived risk and conduct an in-depth analysis of their correlations within the acceptance model.

3. Expanding Evaluation of Product interface design

While my study primarily focuses on the attractiveness of the product interface within the tangibles scale, it is noteworthy that other aspects of product page design, such as secondary menus and examples, wield significant influence. Future research should delve deeper into various facets of product page design to gain a comprehensive understanding of their impact on user behavior and acceptance. This broader investigation will yield valuable insights for enhancing the design of online platforms and elevating user experiences.

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Factors that impact intention to continue using AI-based chatbots in different countries

Yifan Gai

Master Thesis

Supervisor: prof.dr. Sigitas Urbonavičius

Programme: Marketing and Integrated Communication
Faculty of Economics and Business Administration, Vilnius University

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SUMMARY

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This thesis delves into the determinants influencing the continued use of AI-based chatbots, with a specific focus on comparing user attitudes in China and Lithuania. This comparison aims to shed light on how cultural contexts shape technology adoption and user behavior. The thesis is structured into four key sections: a review of relevant literature, a description of research methodology, an analysis of research results, and a final section offering conclusions and recommendations.

The literature review section critically examines various technology acceptance theories and models, focusing on service quality and key influencing factors. It also discusses the integration of technology adoption model with service quality dimensions, providing a thorough analysis of AI-based chatbots adoption.

In the empirical research section, the study involved distributing surveys to users in China and Lithuania, resulting in 253 valid responses for detailed analysis. This part of the research emphasizes key factors and the cultural differences in the adoption of AI-based chatbots. It particularly showcases the effective combination of service quality aspects and

anthropomorphism within the framework of the Technology Acceptance Model (TAM). The findings indicate that perceived usefulness and enjoyment are substantial determinants influencing the users' intention to continue using AI-based chatbots. Competence emerges as a critical factor enhancing both perceived usefulness and enjoyment. Additionally, anthropomorphism has predominant influence on perceived ease of use and enjoyment, highlighting the significance of embedding human-like features in adoption of users. Regarding the cultural differences, the study points out that perceived ease of use is an important factor in Lithuania but not in China. Moreover, perceived usefulness has a more obvious impact on Chinese users' usage intentions than Lithuanians.

The study concludes with a comprehensive summary of key findings from the literature and empirical research. The conclusion also presents a strategic roadmap for the development and marketing of future AI-based chatbots. This roadmap includes targeted strategies designed to enhance chatbot adoption both globally and within culturally diverse environments, addressing the unique needs and preferences identified in various regions.

ANNEXES

Annexe 1

Table 22 *Previous studies*

Article	Domain	Factors	Findings
Ashfaq et al., 2020	Chatbots in open domain	Perceived usefulness, perceived ease of use, perceived enjoyment, information quality, service quality, need for interaction with a service employee	The need to interact with service employee moderates the correlations among perceived usefulness, perceived ease of use, perceived enjoyment, and user satisfaction. Information quality and service quality are key factors of satisfaction.
Chatterjee & Bhattacharjee, 2020	AI in higher education	Performance expectancy, effort expectancy, facilitating conditions, perceived risk	Perceived risk and effort expectancy have significant effects on users' attitudes to AI adoption. Facilitating conditions have significant impacts on effort expectancy and attitudes.
Chen et al., 2021	Chatbots in e-retailing	Usability, responsiveness, customer personality	The usability of chatbots significantly affects the extrinsic value of customer experience. While the responsiveness affects the intrinsic value of customer experience. Customer personality moderates the relationship between chatbot usability and the extrinsic value of the customer experience.
Chocarro et al., 2021	Chatbots in education	Perceived usefulness, perceived ease of use, use of social language	Chatbots that use formal language will be more accepted than those that use social language. There are two possible reasons: the Uncanny Valley theory, and the professional characteristics of teachers.
Chuang et	Fintech	Perceived usefulness,	Customer attitudes towards using

al., 2016	service	perceived ease of use, brand and service (trust)	fintech services are the most important factor in predicting usage.
De Cicco et al., 2020	Chatbots in e-retailing	Interaction style, avatar, social presence, trust, perceived enjoyment	Social-oriented conversations can increase users' social presence. Social presence increases user trust and perceived enjoyment, leading to more positive attitudes toward using chatbots online.
Eeuwen, 2017	Mobile messenger chatbots	Perceived usefulness, perceived ease of use, compatibility, internet privacy concern, attitude towards mobile advertisement	Compatibility, the extent to a mobile messenger chatbot aligns with existing values, past experiences, and user needs, is the strongest predictor of attitude.
Ischen et al., 2020	Chatbots in digital communication environment	Human-like chatbots vs. machine-like chatbot, privacy concerns, information discloses	Less privacy concerns, higher information discloses, more positive attitudes, and higher recommendation adherence were found in the interactions with human-like chatbots than machine-like chatbots.
Kasilingam, 2020	Chatbots in mobile shopping applications	Perceived usefulness, perceived ease of use, perceived enjoyment, price consciousness, perceived risk, personal innovativeness, age, gender, and experience	Perceived usefulness, perceived ease of use, perceived enjoyment, price consciousness, perceived risk, and personal innovativeness directly influence the attitude. Age, gender, and experience moderate those correlations.
Kwangsawad & Jattamart, 2022	Chatbots in community-enterprise customer	Perceived usefulness, perceived ease of use, perceived convenience, perceived information quality, technology anxiety, privacy risk	Perceived information quality has a significant positive effect on attitude, while technology anxiety and perceived privacy risk have negative effects on attitude. Perceived usefulness, perceived ease of use, and perceived

	service		convenience only have an impact on user attitudes in the early stages of use.
Li et al., 2021	AI-based chatbot in online travel agencies	Service quality dimensions (Understandability, reliability, responsiveness, assurance, interactivity), technology anxiety, confirmation, satisfaction, use continuance	The service quality factors of understandability, reliability, assurance, and interactivity have a positive influence on confirmation. Confirmation, in turn, positively affects satisfaction, which subsequently influences the intention to continue using the service.
Melián-González et al., 2021	Chatbots in tourism	Performance expectancy, social influence, hedonic motivation, habit, inconvenience, anthropomorphism, perceived innovativeness, attitudes to self-service technologies	Performance expectancy, social influence, hedonic motivation, habit, inconvenience, and anthropomorphism have a direct impact on chatbot usage intentions. Perceived innovativeness affects attitudes to self-service technologies, indirectly affects chatbot use intentions
Meyer-Waarden et al. (2020)	AI-based chatbot in airline industry	Service quality dimensions (Tangibles, competence, reliability, responsiveness, empathy, credibility), perceived usefulness, perceived ease of use, trust, intention to reuse	Reliability and perceived usefulness are the most important criteria influencing the intention to reuse a chatbot. Tangible elements play an important role in improving perceived ease of use.
Sheehan et al., 2020	Chatbots in open domain	Anthropomorphism, need for human interaction, Error-free Chatbot vs. Clarification	Clarification in communication is one way to make up for a chatbot's lack of intelligence. Anthropomorphism was more positively associated with

		Chatbot vs. Error Chatbot	adoption when the need for human interaction was higher.
Toader et al., 2019	Chatbots in open domain	Anthropomorphic design clues, chatbots' error, perceived competence, social presence, trust	Highly anthropomorphic female chatbots drives more positive customer behaviors than male chatbots, even when they make mistakes.
Trivedi, 2019	Chatbots in banking	System quality, information quality, service quality, perceived risk	Timely response, user-friendly and reliable system, relevant and accurate information provided, empathetic conversations and professional service support contribute to the good customer experience while perceived risks reduce the impacts of the above characteristics on customer experience

Annexe 2

Table 23 *Scales of measurement and sources*

Factors and citations	**Items of scales**	**Cronbach's Alpha**
Tangibles Meyer-Waarden et al. (2020)	1. ChatGPT has an attractive text style. 2. ChatGPT has attractive website colours. 3. ChatGPT has an attractive appearance in general.	0.833
Anthropomorphism Noor et al. (2022)	1. ChatGPT has humanlike features. 2. ChatGPT has personality. 3. ChatGPT gradually gets to know me. 4. ChatGPT is able to behave like a human. 5. ChatGPT responds in ways that are personalized. 6. ChatGPT is able to communicate like a human.	0.861
Competence Meyer-Waarden et al. (2020)	1. ChatGPT is efficient. 2. ChatGPT is thorough. 3. ChatGPT meets my needs. 4. ChatGPT performs as I expected.	0.877

	5. ChatGPT competently handles my request.	
Reliability Meyer-Waarden et al. (2020)	1. ChatGPT is useful. 2. ChatGPT is reliable. 3. ChatGPT gives useful information. 4. ChatGPT gives real information.	0.834
Perceived risk Chatterjee & Bhattacharjee (2020)	1. Application of ChatGPT for my purposes is confusing. 2. I shall not prefer to use ChatGPT for professional purposes. 3. Use of ChatGPT for completing tasks is risky.	0.614
Security Noor et al. (2022)	1. There is no risk of loss associated with disclosing personal information to ChatGPT. 2. I feel secure in providing sensitive information to ChatGPT. 3. I believe that the information ChatGPT has about me is protected. 4. I trust that my personal information with ChatGPT will not be misused.	0.903
Perceived usefulness Ashfaq et al. (2020)	1. I find ChatGPT useful in my daily life. 2. Using ChatGPT helps me to accomplish things more quickly. 3. Using ChatGPT increases my productivity. 4. Using the ChatGPT helps me to perform many things more conveniently.	0.893
Perceived ease of use Ashfaq et al. (2020)	1. My interaction with ChatGPT is clear and understandable. 2. Interaction with the ChatGPT does not require a lot of mental effort. 3. It is easy to get the result I want with ChatGPT. 4. I find ChatGPT to be easy to use.	0.831
Perceived enjoyment Oghuma et al.	1. I have fun interacting with ChatGPT. 2. Using ChatGPT provides me with a lot of enjoyment.	0.812

(2016)	3. I enjoy using ChatGPT.	
Intention to continue using Li & Wang (2023)	1. I would like to continue interacting with ChatGPT. 2. I would like to continue accepting services from ChatGPT. 3. I intend to continue using ChatGPT than using alternative means. 4. It is likely that I will continue using ChatGPT in the future.	0.896

Annexe 3

Questionnaire design

Section 1

Page 1 ChatGPT User Experience Survey
We are eager to understand your perceptions of ChatGPT. We genuinely appreciate your time and would be grateful if you could take a few moments to complete the following questionnaire. Please rate each statement on a 7-point Likert scale

Page 2 Let's start with some general information!	
How old are you?	______ Years old
Gender	Male / Female
Have you used ChatGPT?	Yes / No

Section 2

Each page (pages 3 through 7) contains the following statements:

There are no right or wrong answers. We genuinely appreciate your opinion and request you to provide feedback for each statement on a scale from 1 to 7, where 1 signifies "strongly disagree" and 7 indicates "strongly agree".

Page 3 To start with, we would like to know your general impressions about ChatGPT	
ChatGPT has an attractive text style.	Score 1-7
ChatGPT has attractive website colours.	Score 1-7
ChatGPT has an attractive appearance in general.	Score 1-7
ChatGPT has humanlike features.	Score 1-7
ChatGPT has personality.	Score 1-7
ChatGPT gradually gets to know me.	Score 1-7
ChatGPT is able to behave like a human.	Score 1-7
ChatGPT responds in ways that are personalized.	Score 1-7
ChatGPT is able to communicate like a human.	Score 1-7
Page 4 Let's talk about the practical side of ChatGPT.	
ChatGPT is efficient.	Score 1-7
ChatGPT is thorough.	Score 1-7
ChatGPT meets my needs.	Score 1-7
ChatGPT performs as I expected.	Score 1-7
ChatGPT competently handles my request.	Score 1-7
ChatGPT is useful.	Score 1-7
ChatGPT is reliable.	Score 1-7
ChatGPT gives useful information.	Score 1-7
ChatGPT gives real information.	Score 1-7
Page 5 We want to address any concerns you may have about ChatGPT.	
I believe content generated by ChatGPT is not always correct.（The result of this question was removed after reliability analysis)	Score 1-7
Application of ChatGPT for my purposes is confusing.	Score 1-7
I shall not prefer to use ChatGPT for professional purposes.	Score 1-7
Use of ChatGPT for completing tasks is risky.	Score 1-7
There is no risk of loss associated with disclosing personal information to ChatGPT.	Score 1-7
I feel secure in providing sensitive information to ChatGPT.	Score 1-7
I believe that the information ChatGPT has about me is protected.	Score 1-7
I trust that my personal information with	Score 1-7

ChatGPT will not be misused.	
Page 6 We would love to know your overall evaluation of ChatGPT	
I find ChatGPT useful in my daily life.	Score 1-7
Using ChatGPT helps me to accomplish things more quickly.	Score 1-7
Using ChatGPT increases my productivity.	Score 1-7
Using the ChatGPT helps me to perform many things more conveniently.	Score 1-7
My interaction with ChatGPT is clear and understandable.	Score 1-7
Interaction with the ChatGPT does not require a lot of mental effort.	Score 1-7
It is easy to get the result I want with ChatGPT.	Score 1-7
I find ChatGPT to be easy to use.	Score 1-7
Page 7 How do you like ChatGPT and what are your plans for using it?	
I have fun interacting with ChatGPT.	Score 1-7
Using ChatGPT provides me with a lot of enjoyment.	Score 1-7
I enjoy using ChatGPT.	Score 1-7
Given the opportunity, I will use ChatGPT.	Score 1-7
I am likely to use ChatGPT in the near future.	Score 1-7
I am willing to use ChatGPT in the near future.	Score 1-7
I intend to use ChatGPT when the opportunity arises.	Score 1-7

Page 8	We appreciate your feedback and suggestions. Thank you for your participation!

Annexe 4

Table 24 *The result of all hypotheses*

No.	Independent variable	Dependent variable	Result
H1	PU	ITCU	Accepted
H2	PEOU	ITCU	Rejected
H3	PEOU	PU	Accepted
H4	PR	ITCU	Accepted
H5	PEnj	ITCU	Accepted
H6	Comp	PU	Accepted
H7	Comp	PEnj	Accepted
H8	Rel	PU	Accepted
H9	Rel	PR	Accepted
H10	Tang	PEOU	Accepted
H11	Tang	PU	Rejected
H12	Sec	PU	Rejected
H13	Sec	PR	Rejected
H14	Anthr	PEOU	Accepted
H15	Anthr	PR	Rejected
H16	Anthr	PEnj	Accepted
H17	PEOU	ITCU (Moderator: Country)	Accepted
H18	PU	ITCU (Moderator: Country)	Rejected
H19	PR	ITCU (Moderator: Country)	Rejected
H20	PENJ	ITCU (Moderator: Country)	Rejected