

VILNIUS UNIVERSITY

KAUNAS FACULTY

INSTITUTE OF SOCIAL SCIENCES AND APPLIED INFORMATICS

International Business Management Study Program

Code 6211LX019

Muhammad Adil

MASTER'S THESIS

**THE IMPACT OF CHATBOT INTERACTIONS ON CUSTOMER
SATISFACTION IN E-COMMERCE: EVALUATING FUNCTIONAL AND
PERCEIVED TRUST DIMENSIONS**

Kaunas 2026

VILNIUS UNIVERSITY

KAUNAS FACULTY

INSTITUTE OF SOCIAL SCIENCES AND APPLIED INFORMATICS

Muhammad Adil

MASTER'S THESIS

**THE IMPACT OF CHATBOT INTERACTIONS ON CUSTOMER
SATISFACTION IN E-COMMERCE: EVALUATING FUNCTIONAL AND
PERCEIVED TRUST DIMENSIONS**

Scientific advisor _____

(Signature)

Prof. Edmundas Jasinskas

(Pedagogical and scientific degrees,

Name and surname)

Master's student _____

(signature)

Handing-in date _____

Registration No _____

Kaunas 2026

CONTENTS

LIST OF ABBREVIATIONS.....	4
LIST OF FIGURES.....	5
LIST OF TABLES.....	6
INTRODUCTION	7
1. THEORETICAL ASPECTS OF CHATBOT INTERACTIONS AND CUSTOMER SATISFACTION EVALUATING FUNCTIONAL AND PERCEIVED TRUST DIMENSION ..	11
1.1 Concept of Chatbot Interactions in E-commerce.....	11
1.2 Customer trust in chatbots	15
1.3 Concept of Customer Satisfaction.....	18
1.4 Establishing the Links: chatbot interaction features functional trust, perceived trust and customer contentment	21
2. EMPIRICAL RESEARCH LEVEL OF CHATBOT INTERACTIONS AND CUSTOMER SATISFACTION EVALUATING FUNCTIONAL AND PERCEIVED TRUST DIMENSION ..	25
2.1 The components of research on the interaction of Chatbots, trust, and customer satisfaction.....	25
2.2 Research model of Chatbot interactions, trust, and customer satisfaction	40
3. EMPIRICAL RESEARCH OF CHATBOT INTERACTIONS AND CUSTOMER SATISFACTION EVALUATING FUNCTIONAL AND PERCEIVED TRUST DIMENSION ..	48
3.1 Research Methodology.....	48
3.2 The Research Data Analysis and the Discussion of the Results	57
3.3 Evaluation of Research Results	66
CONCLUSIONS.....	79
RECOMMENDATIONS.....	82
SUMMARY (in Lithuanian language).....	85
REFERENCES	86
APPENDIX 1	97

LIST OF ABBREVIATIONS

AI — Artificial Intelligence
NLP — Natural Language Processing
HCI — Human-Computer Interaction
TAM — Technology Acceptance Model
SEM — Structural Equation Modeling
PLS-SEM — Partial Least Squares Structural Equation Modeling
GDPR — General Data Protection Regulation
SME — Small and Medium Enterprise
CRM — Customer Relationship Management
IBM — International Business Management
HMC — Human-Machine Communication
UX — User Experience
ACSI — American Customer Satisfaction Index
SERVQUAL — Service Quality (measurement model)

LIST OF FIGURES

FIGURE 1. BENEFITS AND LIMITATIONS OF CHATBOTS IN E COMMERCE	14
FIGURE 2 TRUST DIMENSION IN CHATBOT INTERACTION.....	17
FIGURE 3 THEORETICAL MODEL OF IMPACT OF CHATBOT INTERACTION ON CUSTOMER SATISFACTION IN E-COMMERCE.....	23
FIGURE 4 INTEGRATED RESEARCH MODEL WITH HYPOTHESES.....	45
FIGURE 5 FINAL EMPIRICAL RESEARCH MODEL — SUPPORTED PATHS ONLY	76

LIST OF TABLES

TABLE 1 FEATURES INFLUENCING CUSTOMER SATISFACTION IN E-COMMERCE	19
TABLE 2 MEASUREMENT APPROACHES OF CUSTOMER SATISFACTION	20
TABLE 3 STUDIES FOCUSING ON FUNCTIONAL TRUST	29
TABLE 4 STUDIES FOCUSING ON PERCEIVED TRUST.....	31
TABLE 5 STUDIES ADDRESSING BOTH FUNCTIONAL AND PERCEIVED TRUST.....	33
TABLE 6 PATTERNS AND GAPS IN LITERATURE	39
TABLE 7 RESEARCH QUESTIONNAIRE CONSTRUCTS.....	53
TABLE 8 DEMOGRAPHIC PROFILE OF RESPONDENTS (N = 198).....	58
TABLE 9 DESCRIPTIVE STATISTICS SUMMARY BY CONSTRUCT (N = 198).....	60
TABLE 10 CRONBACH'S ALPHA RELIABILITY COEFFICIENTS	61
TABLE 11 RELIABILITY AND CONVERGENT VALIDITY (CR AND AVE)	62
TABLE 12 FORNELL-LARCKER CRITERION MATRIX	63
TABLE 13 HETEROTRAIT-MONOTRAIT (HTMT) RATIO OF CORRELATIONS	65
TABLE 14 STRUCTURAL PATH COEFFICIENTS AND HYPOTHESIS TESTING RESULTS	66
TABLE 15 COEFFICIENT OF DETERMINATION (R ²) FOR ENDOGENOUS CONSTRUCTS	69
TABLE 16 STRUCTURAL COLLINEARITY ASSESSMENT (VIF).....	71
TABLE 17 SPECIFIC INDIRECT EFFECTS (BOOTSTRAPPED, 5,000 SAMPLES).....	72
TABLE 18 MEDIATION ANALYSIS – VARIANCE ACCOUNTED FOR (VAF).....	73
TABLE 19 HYPOTHESIS TESTING SUMMARY	74
TABLE 20 COMPLETE SURVEY ITEM LIST BY CONSTRUCT.....	97

INTRODUCTION

Relevance of the Topic. The Internet has significantly transformed organizational operations across industries. Enhancing customer satisfaction has become a pivotal success factor in today's competitive business arena, particularly in the e-commerce sector, where customers must rely on perceived reliability and security due to the absence of physical product assessment (Tan & Lim, 2023). Since many e-commerce companies are using chatbots for customer support, their use is raising questions about their impact on customer interaction and satisfaction. While businesses are using chatbots to automate their customer service, the success of this chatbots depends upon trust of customers on them. Despite the growing implementation of chatbots in businesses, there is still a significant research gap on how chatbot interaction influence different trust dimensions and customer satisfaction. This research will bridge the gap by examining how functional trust and perceived trust on chatbots impact customer satisfaction. By understanding these trust dynamics, businesses can design effective chatbots that will enhance customer satisfaction in the competitive e commerce environment.

Level of problem investigation. This paper focuses on one of the crucial and continuously developing issues within the sphere of e-commerce – the problem of achieving maximum customers' satisfaction due to AI-based chatbots. As Adamopoulou and Moussiades (2020) stress, chatbots do bring advantages like 24/7 availability and the possibility to give personalized recommendations. Still, their functioning depends on various issues, where the problems of chatbots' misunderstanding of the client's intent leads to a negative experience and a wrong brand image. Moreover, Adam et al. (2021) highlighted the fact that it is sometimes challenging for e-commerce companies to balance service efficiency and service quality simultaneously, which is important for the company to be competitive. With the aim of addressing these issues and enhancing customer satisfaction, this study will focus on analysing the influence of functional trust and perceived trust dimensions of chatbots on customer satisfaction with factors such as, responsiveness, expertise, ease of use, transparency, humanness, and personalization. According to Micallef (2022), these aspects are the keys to the success of online services. Besides, the other chatbot processes also need continuous enhancement in relation to trust dimensions, as Almeida et al. (2017) postulate. Thus, the research will fill the gap on the impact of these complex factors

on customer satisfaction and interaction with e-commerce companies via chatbots to inform firms on how to optimally use these technologies.

Scientific Problem. What is the relationship between chatbot interactions in the form of functional and perceived trust dimension and customer satisfaction in the e-commerce setting?

1. **Object of the Thesis.** The impact of chatbot interactions on customer satisfaction in e-commerce, evaluating functional and perceived trust dimension.
1. **Aim of the Thesis.** To evaluate the impact of chatbot interactions on customer satisfaction in e-commerce, evaluating functional and perceived trust dimensions.

Objectives of the Thesis:

1. To examine the concept of chatbot interactions and chatbot interaction features in e-commerce.
2. To investigate the concepts of customer satisfaction specifically within the context of e-commerce.
3. To develop a theoretical framework establishing the links between chatbot interaction features, functional trust, perceived trust, and customer satisfaction.
4. To critically review existing literature and develop an integrated dual pathway research model linking chatbot interaction features to customer satisfaction through functional and perceived trust dimensions.
5. To empirically evaluate the developed research model using appropriate methodology, analyse the data, and assess the validity and reliability of the findings.

Thesis and research methods: The thesis uses two combined research frameworks. For the theoretical chapters, to establish conceptual framework, systematic analysis of empirical works available and comparative analysis and synthesis of the body of literature of sector were used. For the framework of the empirical part, a quantitative deductive framework was utilized, where a constrained online survey of 46 items measured through the Likert scale was carried out with 198 customers of the e-commerce sector in Lithuania, and the data was processed with the use of PLS-SEM in the R software.

Structure of the thesis. Thesis consists of three parts. In first part "THEORETICAL ASPECTS OF CHATBOT INTERACTIONS AND CUSTOMER SATISFACTION EVALUATING FUNCTIONAL AND PERCEIVED TRUST DIMENSION" it is investigated chatbot interactions concept and features in e-commerce, customer trust in chatbots (functional trust and perceived trust dimensions), customer satisfaction conception, and links between chatbot interaction features, functional trust, perceived trust, and customer satisfaction.

In second part "EMPIRICAL RESEARCH LEVEL OF CHATBOT INTERACTIONS AND CUSTOMER SATISFACTION EVALUATING FUNCTIONAL AND PERCEIVED TRUST DIMENSION" it is analyzed research which investigated connections between chatbot interactions, trust dimensions, and customer satisfaction, with critical methodological evaluation of existing studies. A research model of chatbot interactions affecting customer satisfaction through functional and perceived trust dimensions is provided with detailed hypotheses development.

In third part "EMPIRICAL RESEARCH FINDINGS OF CHATBOT INTERACTIONS AND CUSTOMER SATISFACTION EVALUATING FUNCTIONAL AND PERCEIVED TRUST DIMENSION" is presented the research methodology and design, analysis of the empirical research data, and discussion and evaluation of results

Literature used in thesis. In thesis were used different scientific sources from Lithuania and other countries about chatbot interactions, artificial intelligence in e-commerce, customer satisfaction, functional trust, perceived trust, technology acceptance, human-computer interaction, conversational commerce, service quality, customer experience, e-satisfaction, chatbot anthropomorphism, transparency, personalization, responsiveness, and digital consumer behavior.

Theoretical Significance. This study extends the work of chatbot satisfaction theory by empirically examining a dual pathway mediation model, testing two paths of mediation between chatbot features and customer satisfaction: the functional trust (expertise, responsiveness, ease-of-use) pathway, and the perceived trust (humanness, transparency, personalization) pathway. Previous research focuses on those two aspects of trust separately, but in this study both are incorporated into one model based on Technology Acceptance Model, Trust Theory(McKnight et al., 2002), Service Quality Theory, and Human-Computer Interaction theory. Furthermore, it

extends chatbot research beyond dominant US, South Korea, and China contexts into under-researched Lithuanian SME e-commerce environments, addressing significant geographic and methodological gaps identified in current literature. Using structural equation modelling with various consumers samples other than experiments using student-consumers provides more generalisable theoretical knowledge of building trust in human-AI interactions, further increasing the ecological validity of the research.

Practical Significance.

The study offers practical recommendations to e-commerce companies, especially the Lithuanian SMEs, to make the chatbot as user-friendly as possible to increase customer satisfaction. The relative importance of functional and perceived trust mechanisms presented by the study will allow the resource-constrained organizations to prioritize their development in a proper manner, first with competence building (correct and usable) and second by emotional connection (human and personal). The results provide specific design suggestions on transparency disclosures, conversational tone and optimization of response speed, as well as appropriate anthropomorphism levels, which directly affect customer satisfaction and behavioural outcomes (repurchase intention, platform loyalty). Specifically for the Lithuanian market, the research insights tackle a variety of regional concerns regarding data privacy and transparency, which differ from bigger markets, allowing for the implementation of chatbots in line with consumer expectations. There are several common implementation pitfalls that businesses can avoid by going through this study: they can avoid deploying personable but incompetent chatbots or efficient but emotionally cold systems that can worsen customer satisfaction

Structure and scope of thesis

This work consists of introductory part, main part and conclusion with recommendations. Main part is written in 75 pages, including 20 tables and 5 figures. For this work were used 86 literature sources. Also added 1 appendix.

1. THEORETICAL ASPECTS OF CHATBOT INTERACTIONS AND CUSTOMER SATISFACTION EVALUATING FUNCTIONAL AND PERCEIVED TRUST DIMENSION

In this chapter, the concept of chatbot interaction is explored along with the concepts of customer satisfaction, functional trust and perceived trust. Furthermore, the correlation between the interaction of the Chatbots and customer satisfaction is evaluated.

1.1 Concept of Chatbot Interactions in E-commerce

A chatbot is an AI program and a Human-Computer Interaction (HCI) model (Bansal & Khan, 2018). The dictionary defines a chatbot as “a computer program designed to simulate conversation with human users, especially over the internet” (Oxford English Dictionary, 2023) according to which it can communicate in human language through text or oral speech with humans or other chatbots by using Natural Language Processing (NLP) and sentiment analysis. (Khanna et al., 2015).

The evolution of customer service in e-commerce has been profoundly reshaped by the advent of chatbot interactions, a transformation rooted in the advancements of artificial intelligence (AI). The idea of automated conversational agents has its roots in early work in computational linguistics and computer art, as early as 1966 with ELIZA and 1972 with PARRY, in which computer systems were able to imitate human conversation. These crude efforts albeit minimal in scale were the seedlings of the advanced chatbot technologies we have today. The fact that these primitive systems are being replaced by dynamic, AI-powered chatbots of the advanced e-commerce can be said to be an attestation to the fast advancements in AI, in particular, the mastering of systems and natural language processing (NLP) as formulated using the help of Mohammad et al. (2024). This development has fundamentally transformed the traditional customer support models and converted them to become dynamic virtual solutions (Natalia, 2024). According to Adamopoulou and Moussiades (2020), chatbots have developed in diverse areas such as e-commerce through their capability to offer instant and convenient customer care, cut down on the cost of customer support significantly, as well as support multiple users at the same time.

The size of the chatbot marketplace in recent years has been experiencing an exponentially increasing growth. At the beginning of 2022, the chatbot market was estimated to reach at least

8.1 billion, and now the market was projected to reach 46.4 billion by 2026 (Micallef, 2022) — a forecast that has now become the current market reality.

Even though market forecasts by Micallef (2022) indicate an exponential growth, the numbers are subject to critical analysis. The dramatic growth projections usually make ideal adoption projections and may fail to sufficiently consider the implementation hindrances experienced by e-commerce firms, especially the small and medium enterprise. Moreover, such market rates usually include different chatbot applications in a variety of fields, which may overreact to the real penetration in the e-commerce realm. The envisaged rise also assumes a constant increase in technology without taking possible regulatory actions on AI and data security that can possibly limit growth.

When applied to e-commerce, chatbots have presented a valuable tool that allows a brand to provide 24-hr customer service, thus, it no longer needs to require human employees as much as it can enhance the overall performance of the organization (Li and Wang, 2023). In their ability to provide instant, customer-focused and tailored-made support, which attends to client queries and solves issues in real-time (Menaka and Selvam, 2025), the latter is especially useful. This live feature is a direct response to the contemporary client desire of timely service, the need to be available 24/7 that is emphasized through (Puertas et al., 2024) and requiring e-commerce businesses to engage in the development of virtual assistants that will likewise be available around the clock.

AI-based chatbots will solve many customer service problems. According to (Bawack et al., 2022). AI bots such as chatbots can take significant responsibility to lessen the pressure on human agents; this occurs since the machines have the technology of machine learning and natural language processing, which allows them to comprehend and reply to queries posed by customers. However, as AI becomes integrated, customer support is increasingly becoming a case of serving unique needs since AI can learn about customer information and predict what they would or would not require or want.

Customers, and especially the millennials, boast of a unique preference for chat features due to their nature and immediacy, requesting for customized attention and specific directions (Uddin et al., 2024). The inclination impacts how chatbots are programmed to engage in real life conversations and use personalized artificial speech to enhance customer interaction and drive

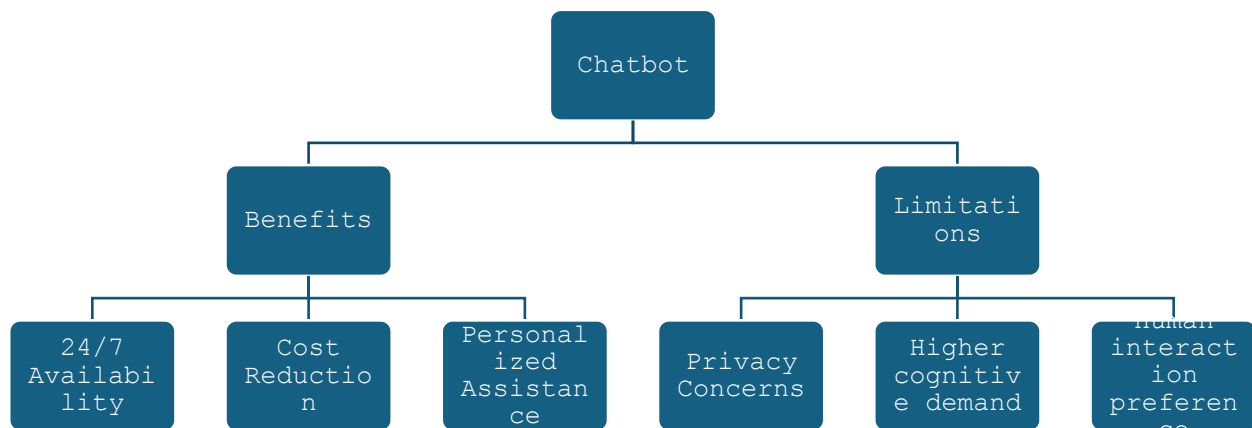
sales (Huang & Rust, 2018). Customer experience is a primary driver of competitive advantage in e-commerce (Becker & Jaakkola, 2020) which illustrates why chatbots have become essential for businesses aiming to enhance their customer service offerings. Chatbots Understand clients' needs and carry out automated customer interactions to better serve the clients' interests. AI powered chatbots can interact with clients in courteous manner.

Findings by Rese et al. (2020) shows that the consumer acceptance of chatbots useful from conversational enjoyment, authenticity, and utility aspects. Further expanding the communication aspect of chatbots, Li and Wang (2023) observed that informal styles of language led to greater intention to use services and more favourable attitudes toward brands because of a greater sense of parasocial interaction. Adam et al. (2021) along with other scholars have pointed out that the human-like verbal cues issued by chatbots greatly increases the likelihood of fresh compliance with requests due to social presence perception motivating that compliance. Due to their ability to manage many conversations with consumers at the same time, chatbots are said to improve customer care services. Their predictive, data- driven, and communicative attributes enhances engagement. It is a proven fact that chatbots can improve online customer experience by offering their services at the right time which helps build important relationships with clients while minimizing client confusion and stress, improving clients' time management, and understanding the offered products and services comprehensively.

While chatbots can benefit e-commerce, there are shortcomings in their applications. Lee et al. (2023) argue that there is a gap in research concerning the factors that may influence customer satisfaction. Most current studies tend to focus on the chatbot's functions and technological advancements alongside improvement but are lacking on critical factors such as emotional involvement, personalization, and perceived humanness of chatbots that mitigates customers' satisfaction. Rese et al. (2020) also point out that privacy concerns and the technological capabilities of chatbots are likely to adversely affect users' intentions to use them. It was found by Wang et al. (2023) that chatbots demand greater emotional sub regulation and engage attention more than interactions with humans, signalling lesser trust in chatbots for subjective and complex tasks.

Bawack et al. (2022) highlighted a significant challenge in his study that some user still depends upon human interaction, neglecting automated systems. Even though, chatbots are

considered better in customer service due to their ability of computation, data storage and learning differential outperform humans, still they lack human abilities when it comes to compassion, emotion, self-learning and recommendations according to the situation. In addition, other traits that remain below par are forming user' social bonds that are deep and intricate or offering resolutions to extraordinarily complex issues, thus restraining their efficiency in several customer service situations as visualized in figure 1.



Source: Created by author according to Adamopoulou & Moussiades, 2020; Bawack et al., 2022; Lee et al., 2023

Figure 1. Benefits and limitations of Chatbots in E commerce

The first diagram depicts the outcome of implementing a chatbots in business. It includes benefits such as 24/7 availability, Cost reduction and personalized assistance. And limitations such as, privacy concern from customers, higher cognitive demand to understand emotional cues and human interaction preference from some users. Overall, the diagrams capture the complexity of factors contributing to trust, and the compromises that have to be made whenever chatbots are being put to use in e-commerce systems, suggesting that the intention is to make the most of the benefit while keeping the risk to a minimum.

1.2 Customer trust in chatbots

Trust plays a critical role in human-machine communication (HMC), as it is essential for establishing effective and reliable interactions between humans and chatbots. Trust affects various aspects of user-technology interactions and is essential for adoption and continued usage of modern technologies (Yang & Wibowo, 2022).

While Yang & Wibowo (2022) position trust as fundamental to human-machine communication, this perspective may overstate the necessity of trust in all chatbot interactions. Their conceptualization seems to regard trust as a homogenous construct across all types of interactions and ignore the potential diversity in the amount of trust which is necessary depending on the difficulty of the task and the perceived risk. Absence of informational queries with high sensitivities in the e-commerce could imply that trust becomes inapplicable since the convenience and speed become the determining factors. Furthermore, their technology adoption model is largely based on the scenarios of voluntary usage that surely does not understand e-commerce scenarios where a customer has no alternative means of resolving a dispute than the provided chatbots. This natural limitation means that more versatile models that define both mandatory and non-obligatory chatbot interactions should be developed.

Functional Trust. A chatbot is more responsive, more proficient and skillful, and this feature results in the perception of ease of use, the functional aspects of the trust. This is consistent with the findings by Li et al. (2023), which highlights the impact of such attributes on trust formation during chatbot interactions.

This concept of expertise refers to knowledge, experience, and competence the chatbot can display to the consumer. Nordheim et al. (2019) demonstrated that the correctness and relevance of a chatbot's answers have strong impacts on trust, showing the importance of his claim that met systematic and structured answers ensure functional trust.

In the development of functional trust, consumers prefer chatbots which respond and interact quickly and have fast response times (Nordheim et al., 2019). According to Holtgraves et al. (2007), AI chatbots that respond quickly tend to be more favorable in the eyes of consumers compared to those that respond slowly, thus enabling the former to gain consumer trust and a positive disposition towards them.

Trust in innovative technology is more common amongst people who perceive it as simple to learn, and this applies to chatbots. Thus, consumers are more relaxed when communicating with chatbots, considering that they are programmed to help shoppers throughout the shopping process (Mostafa, 2021). As ease-of-use refers to the problems users face towards achieving their goals while interacting with a chatbot, they want to accomplish more goals with the chatbot's assistance. With focus turning to usability, recent scholarships have noted the importance of employing innovative chatbots (Stoeckli et al., 2020).

All three of these aspects — expertise, responsiveness, and ease of use — create the basis of functional trust in a chatbot, these being the performance-based elements that enable users to reliably depend on a chatbots ability to perform the specific tasks as outlined by the user.

Perceived Trust. The term 'perceived trust' represents the emotional and social aspects of human-computer interaction that are more significant than mere operational factors, as functionality is only one factor. Artificial intelligence systems' operational trust hinges on whether programs will complete the tasks they claim will be completed without issues or obstacles. Empirical evaluation informs us that trust is attributed through a sense of humanity. Users are more willing and attracted at an emotional level when there are sufficient disclosure and personalization given through the AI bots.

The anthropomorphism element concerns users' reason to believe a bot is human. To add power to this argument, (Følstad et al., 2018) discusses chatbots sociably engineered with social cues, personality features, and emotional traits which undoubtedly improve perceived trustworthiness value. Personality features and social traits boost the perceived value of chatbots. (Adam et al., 2021) support these findings regarding compassion, confirming the persuasive bond and emotional connection believed in placed anthropomorphically designed chatbots create also exists in the real world.

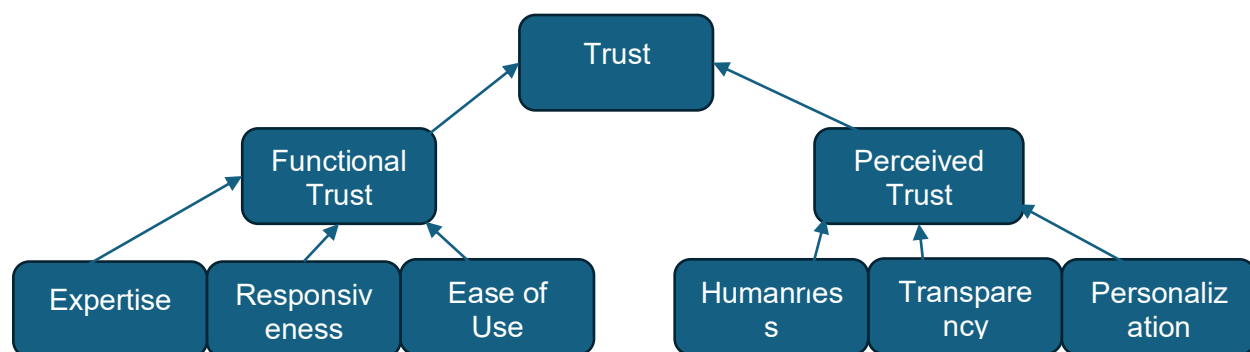
The perceived trust in chatbot is increased when the chatbot's abilities and shortcomings and the extent of data usage are disclosed with the user (Skjuve et al., 2021). Luo et al. (2022) contend that, in the case of algorithmic transparency, trust and authenticity perceptions are improved when users have some visibility to the reasoning behind the responses because transparency addresses skepticism. In the case of e-commerce, where the concern regarding data

confidentiality is the utmost, the dimension of transparency is necessary and sufficient to trust the chatbot and is sufficient to cultivate the trust users have in the chatbot.

The element of personalization focusses on specific preferences, history and needs of users related to the chatbot. According to (Chung et al., 2020). Interactions that are tailored to user's profile and past conversation history has a significant impact on trust perception. This statement supports earlier findings by (Zarouali et al., 2018). which argue that personalized recommendations along with contextually relevant responses foster feeling of being understood thus deepening emotional trust with chatbots.

The three dimensions humanness, transparency, and personalization, in that order, support the perceived trust regarding a chatbot interaction and are relational attributes that facilitate the forging of emotional bonds with users while trust in the chatbot's social skills, intent, and abilities emerges subjectively.

According to Figure 2 below, customer trust in chatbots occurs via two important dimensions: functional trust which forms because of a chatbot's skill, responsiveness, and ease of use; and perceived trust which stems from a chatbot's ability to show humanness, clarity, and personal touch. All these elements together influence the acceptance and sustained interaction users have with chatbots



Source: Created by author according to Nordheim et al., 2019; Følstad et al., 2018; Chung et al., 2020

Figure 2 Trust dimension in chatbot interaction

The second figure depicts the six key dimensions of trust in chatbot interactions arranged in a hierarchical pattern around a central "Trust dimensions" node. These include functional trust elements (expertise, responsiveness, and ease of use) and perceived trust elements (transparency, humanness, and personalization), which collectively establish the foundation for effective customer relationships.

The nature of e-commerce interactions with chatbots is a significant shift in how companies engage with their customers, as it is driven by AI capabilities, customer preferences, platform capabilities, and business strategy. (Huang & Rust, 2018) endorses the idea that AI can address clients' emotional necessities and enhancing consumer loyalty.

1.3 Concept of Customer Satisfaction

A user evaluation of a product or service is a measure of customer satisfaction, in other words, how well the company has fulfilled the needs of the consumer (Al-Araj et al., 2022). In the realm of chatbots, this satisfaction pertains to how well the user's expectations met or exceeded in the interaction with the AI. Fundamentally, customer satisfaction arises when the experienced outcomes align with or exceed the positive expectations a user holds regarding a product or service (Chung et al., 2020). According to Lin (2003), customer satisfaction is the outcome from a cognitive and effective evaluation where some comparison standards are compared to perceived performance. In cases where performance falls below expectations, customers report dissatisfaction. The perceived performance of a product is based on the way customers access the good or service provided.

E-satisfaction, fundamentally described as "customers' judgement of their online retail experience in comparison with brick-and-mortar stores, has evolved with the integration of chatbot technologies (Szymanski and Hise, 2000). In the given framework, informativeness has become the dominant cognitive aspect of online customer experience (Lim and Ting, 2012, p. 51), and this aspect is specifically relevant when it comes to chatbot interactions where the delivery of information is an exclusive role. Such areas of e-commerce customer satisfaction as, efficient customer support, dependable fulfilment and shipping, easy web navigation, quality merchandise and high-scale security systems can be listed. Together, they shape whether online consumers will trust, return to, and be loyal to eCommerce brands, all of which can profoundly impact how well a business performs and stands out in the online realm (Masyhuri, 2022).

Different scholars have studied a variety of factors which have been noted to impact customers' satisfaction in an e-commerce setting. The table 1 below shows major factors resulting from most prominent studies on the customers' satisfaction proving to be multidimensional and intricate in the context of e-commerce.

Table 1

Features influencing customer satisfaction in e-commerce

Year	Authors	Customer Satisfaction Factors	Research Methodology
2025	Menaka & Selvam	AI personalization, omnichannel experience, interactive visualization	Bibliometric Analysis
2024	Puertas et al.	User experience, product information, payment process, delivery, support	Quantitative Survey
2022	Masyhuri	Customer service, fulfillment reliability, website usability, product quality, security	Framework Adaptation
2018	Khan & Al Jahwari	Product and service quality perception	Quantitative Survey with Purposive Sampling
2016	Zatalini & Pamungkas	Privacy, security, service speed	Descriptive Analysis

Source: Derived from studies identified in literature search

The literature review provides a description of a temporal change in factors of customer satisfaction of e-commerce customers between 2003 and 2025. Core similarities include focus on Trust, Information Quality and Security in all studies, with major differences arising in the comprehensiveness of the studies; some older studies (Zatalini & Pamungkas, 2016) focused on the basic aspects like ease of navigation, while newer studies (Menaka & Selvam, 2025) covered AI-powered personalization and omnichannel strategies. Dominantly methodological, quantitative surveys are most prevalent. Moreover, critical gaps include limited cross-national dispersion, lack of longitudinal frameworks, and absence of united theoretical constructs revealing deeper gaps regarding meaningful comprehensive framework development in regard theoretical guide for satisfaction research in digital commerce.

Approaches to measurement in customer satisfaction in e commerce have changed greatly over time as shown in table 2. Among the best-known customer satisfaction measurement models are those from the schools presented below.

Table 2

Measurement approaches of customer satisfaction

Approach	Focus	Key Models	Measurement	Feature
Nordic School Approach	Qualitative service quality factors and relationships	Grönroos, Gummesson, Servuction, Three Component	Descriptive dimensions, no direct satisfaction methodology	Process-focused, relationship-oriented
American School Methodology	Quantitative perceived service quality measurement	SERVQUAL, SERVPERF	Gap analysis (expectations vs perceptions) or perception-only	Emphasizes service quality discrepancies
Customer Satisfaction Indices	Macro/national level satisfaction measurement	SCSB, ACSI, ECSI, NCSB, HKCSI	Survey-based with standardized scales (10-point)	Aggregated data for national benchmarking

Source: Neisa, Y. (2021). Model to evaluate customer satisfaction in ecommerce through multi-criteria and semantic analysis

Customers' satisfaction is approached in multiple perspectives broadly classified into two main schools of thought with several integrated indices. The Nordic School emphasizes qualitative models exploring underlying drivers and complex relationships with service quality such as the service creation process, interplay of the physical part, employees with the customers. While the American School adopts quantitative frameworks like SERVQUAL and SERVPERF which is measuring the perceived service quality but concentrate at the gaps created by customers' expectations

1.4 Establishing the Links: chatbot interaction features functional trust, perceived trust and customer contentment

Both functional and perceived trust dimensions serve as important mediators in the relationship between chatbot interaction features and customer satisfaction in e-commerce. Many scholars indicate that lack of trust in digital settings is a common situation (Al-Araj et al., 2022). Interaction with the chatbot builds trust both at a perceived level and as a functional one. Trust increases with perceived competence based on a user's experience with systems like chatbots (Følstad & Skjuve, 2019).

Functional trust in the context of chatbots is composed of expertise, responsiveness and ease of use that impact customer satisfaction. Chatbots enhance customer satisfaction by fulfilling utilitarian expectations. If chatbots provide accurate and relevant information, they exhibit expertise and fulfil customer's needs, thus resulting in greater satisfaction (Nordheim et al., 2019).

The elements of trust associated with a chatbot's actual capabilities like its NLP and machine learning algorithms connected to the backend systems interface have a direct relation to functional trust about expertise, responsiveness, and ease of use. (Nordheim et al. 2019). A chatbot's ability to accurately comprehend multifaceted questions and provide suitable responses tends to improve perception of expertise which constitutes a key component of functional trust (Li et al., 2023). As stated by (Adamopoulou and Moussiades, 2020). Advanced NLP capabilities enable chatbot to comprehend context and user intent during discussions, thereby increasing response accuracy and decreasing misunderstanding. This technical capability strengthens the expertise dimension of functional trust as the user now has confidence the chatbot will give the required information.

Furthermore, the structural design and processing features of the system impact trust disposition on chatbot responsiveness dimension. (Holtgraves et al., 2007) states that perceived response time greatly affects user evaluation during the conversation. The quicker the response, the better the evaluation. This is added by (McLean & Osei-Frimpong, 2019). Chatbots whose back office runs on integrated CRMs, product databases, and order management systems enable swift access to rich and precise information, thus increasing the trust responsiveness.

Ease of use contributes to customer satisfaction by reducing the cognitive effort expended in the accomplishment of tasks. Customers' achievement of goals with minimal friction further enhances their satisfaction with the interactions when chatbots provide smooth interfaces and simple conversation pathways (Stoeckli et al., 2020). Ease of use, as defined by Davis (1989), affects technology acceptance, satisfaction, and overall attitude towards use. Satisfaction increases due to the reduction of mental effort when clients can attain goals through effortless attainment, simplistic navigation menus alongside easy-to-follow dialogue boxes.

The perceived trust elements of humanness, transparency, and personalization fulfil emotional and relational needs which impact satisfaction during chatbot interactions. The effectiveness of humanness increases satisfaction because of the social relationships and closeness customers feel towards the e-commerce platform (Adam et al., 2021).

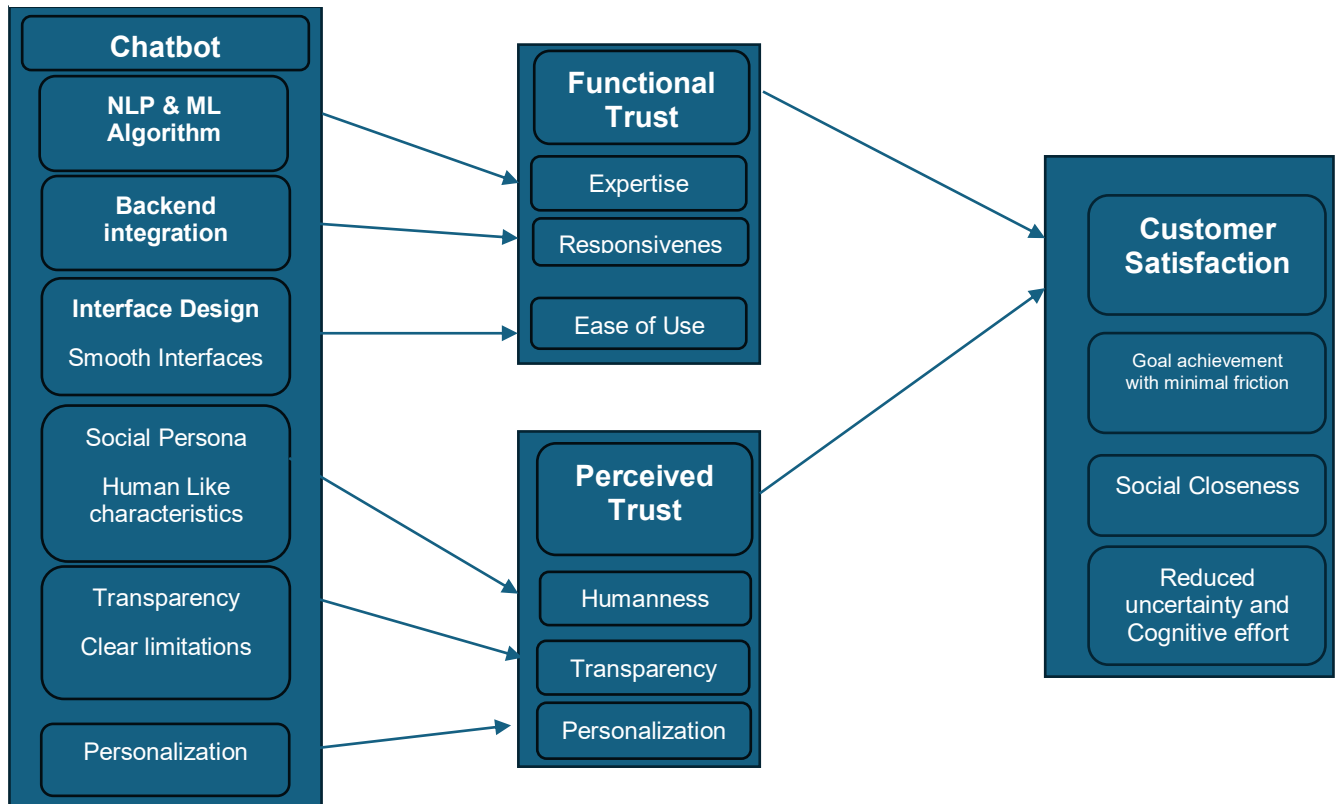
Customers prefer chatbots with social persona characteristics because of the captivating engagement encounters they offer (Sheehan et al., 2020). This connection is important in e-commerce because the absence of face-to-face interactions can make people feel lonely (Følstad et al., 2018).

Transparency is important for satisfaction because it lowers uncertainty and fosters trust in the chatbot's motives and competences. Satisfaction stems from effective automation when users are clearly communicated with concerning the chatbot's restrictions on data collection and usage (Skjuve et al., 2021). In e-commerce, the presence of trust issues concerning data security and privacy makes transparency an incredibly significant element of trust and satisfaction (Luo et al., 2022).

Personalization boosts satisfaction demonstrating how customer needs rationally correlates to business profit. Chung et al. (2020) confirmed that customers are evermore satisfied when contextually relevant recommendations are made because of the feeling of being understood and appreciated. As noted by Zarouali et al. (2018), personalization can impact purchase decision and loyalty intentions which in return boosts satisfaction the most in e-commerce settings.

An integrated framework evolves in result of this analysis which demonstrates how features of chatbot interaction affect the functional and perceived trust in dimensions, which then results to customer satisfaction in e-commerce. This framework shows the interaction of the two

types of mediating trust in the relationship between chatbot features and customer satisfaction (see Figure 3).



Source: Created by author according to McKnight et al., 2002; Davis, 1989; Yang & Wibowo, 2022.

Figure 3 Theoretical Model of impact of chatbot interaction on customer satisfaction in E-commerce

In this framework, trust dimensions take on distinct functions with regards to the features of the chatbot. Functional trust derives from chatbot's expertise, responsiveness, and ease of use. Perceived trust, in relation to user experience, comes from humanness, as well as transparency and personalization. These two together influence customer satisfaction. while the lack of one may still exist, with the importance of distinguishing context depended greatly on situational elements such as customer objectives, product complexity, and interaction stage (Yang & Wibowo, 2022). As it has been mentioned, this framework has possibly overlapped in terms of the interactions of functional and perceived dimensions of trust. As an example, a responsive chatbot (functional

trust) can be viewed as more caring (perceived trust) whereas a transparent chatbot (perceived trust) can be thought of as more competent and reliable (functional trust).

This chapter provides an overall integrated framework will provide the theoretical basis for and guide the case study Chapter 2 about available empirical evidence on these relationships, evaluate the existing evidence for evidence of the relationships and become evidence theory through the construction of a research model with hypotheses for empirical testing.

The theoretical assessment validates the following:

- 1. In e-commerce, chatbot functionalities are analyzed as AI-enabled conversational interfaces featuring six definable components: functional (expertise, responsiveness, ease of use) closes the task accomplishment gap, and the perceived (humanness, transparency, personalization) fulfills the socio-emotional satisfaction. Chatbots can offer benefits (e.g., emotional, private, and complex service scenario intelligence) and are available 24/7 and are cost-effective. Chatbots do exhibit some negative attributes (e.g., emotional intelligence, privacy, and complex service scenario handling) that pose limitations.*
- 2. In e-commerce, customer satisfaction materializes when the performance of the chatbot fulfills the customer expectations satisfaction of the service (responsiveness, reliability), information (accuracy, relevance), system (usability, accessibility), and security dimensions. From qualitative Nordic framework, quantitative, and the SERVQUAL(SERVPERF) models, to an index (ACSI, ECSI), the prevailing paradigm is AI-based personalization as the primary determinant of satisfaction, particularly in e-commerce.*
- 3. The theoretical framework shows how different features of a chatbot might affect customer satisfaction and how that effect might be mediated by two different types of trust. Functional trust is a trust type based on cognition and mediates the relationship of chatbot expertise, responsiveness, ease of use to satisfaction that is predictably achieved because of the chatbot. Perceived trust is a type of affective based trust and mediates the relationship of satisfaction to the chatbot humanness, transparency and personalization. This framework suggests that these mediators are construing customer satisfaction at different emotional and rational levels, respectively. However, the mediators are distinct*

and operate independently. This is the phenomenon that customer satisfaction is theoretically described to achieve.

2. EMPIRICAL RESEARCH LEVEL OF CHATBOT INTERACTIONS AND CUSTOMER SATISFACTION EVALUATING FUNCTIONAL AND PERCEIVED TRUST DIMENSION

Based on theoretical framework from Chapter 1, this chapter will look for empirical support for the theory, critique the methods of evidence in the theory, and provide a research model for empirical testing with hypotheses.

2.1 The components of research on the interaction of Chatbots, trust, and customer satisfaction

State of the Art and Causality of Chatbot Research. The use of conversational agents is widespread in the retail and service industries due to the significant reduction in deployment costs and complexity achieved by advances in natural language processing (NLP), cloud computing and integration tooling. The rule-based versus data-based dialogue management approach represents a compromise between predictable, safe responses and conversational naturalness, and hybrid architectures that integrate these two approaches have become increasingly popular. (Allouch et al., 2021). However, most existing studies remain predominantly descriptive or technology-driven, offering limited theoretical integration between technical affordances and user trust outcomes. A current methodological focus on measures of system performance is inclined to exclude evaluation of user level thought and emotional responses. Although technical advancement keeps increasing, one of the long-standing issues with chatbots is that users expect to receive quick, natural, and situationally appropriate replies, whereas chatbots perform poorly in areas of work requiring multi-step reasoning, subtlety, or even emotional fluency (Gu, Zhang, and Zeng, 2024). These studies can also be limited to simulated or laboratory settings, which can further limit ecological validity as the dynamics of real-world interactions consistently follow unpredictable emotional and contextual conditions that cannot be captured within the confines of an experimental paradigm. Failure to meet the instrumental expectations, such as accuracy, task completion, usability, leads to reduced reliance and attenuated satisfaction, as reported by the users to the system.

An anthropomorphic-related causal mechanism is based on increased expectations and anthropomorphism. Along with the integration of the generative language model into mainstream platforms, users actively attribute the capabilities of humans to the conversation agents; therefore, once the expectations are not met, the level of trust is lost (Gu, Zhang, and Zeng, 2024). Wah (2025) argues that despite the efficiency and scalability offered by AI-driven chatbots, the latter cannot provide users with true empathy, which is debilitating in terms of trust and satisfaction in contexts that are sensitive, such as the healthcare and financial industry. This fact highlights a methodological weakness that many quantitative satisfaction studies have; empathy is always measured, with the help of lexical capture or user ratings, but not supported by other elements of qualitative data, like interviews, or ethnographic results.

Informational inefficiency and poor disclosure are the second causal factor. Companies that conceal their information processing policies, their reasons to personalize data and limitations of their systems further increase the perceived privacy risk by users and decrease tolerance of automated decisions. Empirical studies have shown that brief, clear-cut disclosures strengthen the perception of transparency and mitigate privacy shortcuts that would otherwise lead to mistrust (Singh et al., 2023). However, even the operationalization of transparency differs significantly among the studies: transparency in some cases is identified with the readability of privacy policies, in other studies this concept is viewed as a user interface cue, which makes it difficult to compare results across studies.

The third catalyst is the contextual inappropriateness of chatbot implementation: chatbots are still prone to interaction with more complex or emotionally sensitive questions that can be better resolved by human agents when they do not have any good task-routing protocols. This distortion of the plan increases negative affect to the extent that automated reactions are seen to be unsuitable (Mozafari, Hammerschmidt, and Weiger, 2021). The lack of longitudinal research in this area also constrains understanding of how user tolerance or adaptation to chatbot limitations evolves over time. In addition, responsiveness and usability are strong predictors of online customer satisfaction, but perceived risk particularly concerns about privacy and data misuse can moderate these relationships (Chen, Le, & Florence, 2021). However, many studies use self-reported satisfaction scales that risk social desirability bias, which can inflate positive ratings in

experimental settings. Collectively, capability shortfalls, opacity and poor orchestration explain why widespread adoption can coexist with substantial amount of customer dissatisfaction.

Factual and Statistical Context. Macro-level evidence demonstrates that as e-commerce volumes increase, firms face proportionally larger volumes of customer contacts, which motivates automation. Market and academic reports indicate that firms deploying mature integrations between conversational agents and back-office systems (order management, CRM) achieve higher task-completion rates and improved service metrics such as first-response time and first-contact resolution (Park et al., 2023; Akdemir & Bulut, 2024). However, most of the studies mentioned are done based on self-reported KPIs instead of independent audit, so there is doubt concerning the measurement reliability and reporting bias. Lithuania is a smaller market with a higher degree of digitalization, but not necessarily with a high degree of organizational readiness: While some SMEs have invested in off-the-shelf solutions that rely on rules, others are still not adequately equipped with data governance and with the skills necessary in user experience, resulting in inconsistent experiences for consumers and increased sensitivity when dealing with transparency and complaints. (Sidlauskienė et al., 2023). As such, it is theoretically necessary to have mixed method research designs that can help capture inter-firm variance instead of using aggregate survey indices. Lithuanian area policy documents and sector analyses emphasize the idea of digital transformation, and at the same time reveal gaps in areas of training, governance, and trust-based structures necessary to facilitate the implementation of reliable AI.

Critical conditional effects are defined by experimental evidence. Social communication signals add to the sense of warmth and satisfaction in case the chatbot performs sufficiently well in functional terms; otherwise, it generates adverse results, raising expectations of human-like competence (Xu et al., 2022; Mozafari et al., 2021). Such experiments also tend to use small student-based samples, thus restricting them to the generalizations of larger groups of consumers. The relationship between privacy and personalization is mediated by disclosure practices: disclosures of data use in a transparent and concise way enhance perceived transparency and induce trust, and lack of disclosure leads to privacy heuristics and reduces the effect of personalization (Singh et al., 2023; Vo, 2024; Laymouna et al., 2024). Causal inferences of such studies may be reinforced by natural field experiments where disclosure format varies and not by manipulations. The combination of subjective measures of trust and satisfaction with objective

behavioral records (response time, rate of escalation) positively influences the effectiveness of predicting the behavioral outcomes, including repurchase and reuse (Alagarsamy and Mehroliya, 2023). This combination of methods is commendable because it decreases the count of perceptual data only, but there are only seven domains where this can be replicated. Domain sensitivity is also relevant: there are this perceived empathy, disclosure, and reliability of health care and other high-stakes environments in which convenience or speed alone are not as critical to the satisfaction indication (Li, Y., et al., 2021).

Methodological Analysis of Existing Research. The critical examination of the research methods utilized by the mentioned studies indicates that there are several typical trends and drawbacks. Controlled online experiments and cross section surveys are the most common ones. In an example, research such as Ding and Najaf (2024) and Yun, and Park (2022) commonly use scenario-based experiments in which the participants play around with a chatbot prototype and subsequently fill out a questionnaire. Such surveys usually have psychometric scales to assess such constructs as trust (using items of scales developed by McKnight et al., 2002), satisfaction (rephrased versions of SERVQUAL or TAM), and perceived humanness.

Nevertheless, there are severe limitations in the sample description and location. A significant part of this literature, such as the studies of Xu et al. (2022) and Park, Chung, and Lee (2024) are based on convenient samples of just university populations. This brings questions on whether it can be generalized to larger and more varied consumer groups. Sample sizes are not representative and in most cases are adequate to provide statistical power ($n=200$ to $n=500$). Geographically, the research is biased with the majority of research carried out within the larger markets that are technologically developed, such as the United States, South Korea and China, and there is a significant lack of research in smaller markets, like the Lithuanian e commerce market, which are digital.

Furthermore, there are also limitations for the measurement instruments. Although the use of standardized scales is the norm, they have seldom been tested in various areas (e.g., healthcare vs. retail), and their relevance is therefore doubted in terms of reliable use. The high dependence on self-reported data presents the threat of bias in social desires. The near complete reliance on quantitative techniques leaves a gap in comprehension as to the reasons behind the perceptions of users, and that gap could be addressed in qualitative methods, such as interviews or focusgroups.

Lastly, as Alagarsamy and Mehroliia (2023) point out, few studies have mixed subjective survey data with objective behavioral logs, and even the few longitudinal studies imply that their data would provide the user perceptions at one point and not how trust and satisfaction develop.

Empirical Findings on Functional Trust. Chosen empirical findings depict the two-way dynamics and are tabulated in Tables 3, 4, and 5 below. These are the results that provide empirical support of the factors that affect customer satisfaction based on the dimensions of trust when using chatbots. Table 3 presents studies examining functional trust dimensions, revealing methodological limitations in sample diversity and geographic scope.

Table 3

Studies Focusing on Functional Trust

No .	Key Finding	Short Description / Implication	Research Methodology	Sample Characteristics	Measurement Instruments	Source
1	Response time impacts user satisfaction and intention to use chatbots	Young adults prefer instant responses; older adults prefer delayed responses for cognitive	2×2 experiment Theory: Cognitive Load, Expectancy-Confirmation Analysis: Two-way ANOVA	N=160 (77 young, 83 older) Taiwan Virtual companionship context	Social Presence (5 items) Satisfaction (3 items) Intention of Use (3 items) α /CR: 0.90-0.98	Wang & Lo (2025). BMC Psychology, 13:150.
2	Competence/Expertise perception enhances chatbot satisfaction	Expertise alongside trust are critical factors in chatbot acceptance.	Quantitative survey Theory: TAM, Stereotype Content Model Analysis: SEM (Smart-PLS)	N=525 Saudi Arabia Chatbot users	Competence, warmth, trust, satisfaction scales 7-point Likert	Al-Oraini (2025). Journal of Innovative Digital Transformation, 2(2):109-130.

3	Lack of ease of use increases user effort hence decreasing satisfaction	Chatbots' difficulty and hidden functions require high user effort to operate, which constrains adoption and negatively impacts the overall user experience	Qualitative study (interviews) and Q-Methodology identified "High Actualization Effort" as a major constraint and user viewpoint.	N=29 interviews (17 organizations) and N=28 Q-Methodology participants using enterprise messengers.	User interviews and Q-Set statements on constraints.	Stoeckli et al. (2020). How affordable chatbots cross the chasm between social and traditional enterprise systems? <i>Electronic Markets</i> .
---	--	--	---	---	--	--

Source: Created by author.

The key results related to the impact of chatbot communication on customer satisfaction and resultant nurturing of functional trust are outlined in Table 3. The main conclusion is that responsiveness is one of the key factors of user satisfaction. When chatbots provide quick and effective replies, users perceive them as more proficient to increase their own trust in them and increase their level of general satisfaction with the encounters, but older people prefer delayed response as it looks to them that the response will be accurate. (Wang & Lo, 2025). However, Wang and Lo (2025) encountered Taiwanese respondents and the sample's focus on areas of virtual companionship raises concerns about the applicability of the results in the case of transactional e-commerce where socially inadequate task completion is the norm. The age-related pattern in the sample (younger individuals who tend to instant response versus older individuals who tend to prefer response latency) implies that the effect of responsiveness that has been documented may be moderated by other demographic factors that are not adequately controlled across research.

The second is perceived competence/expertise of chatbots which is perceived skill and ability, which also has a strong effect on satisfaction and acceptance for the use of chatbots. Trust and positive satisfaction have been recognized as major impacts of many studies and have been recognized as major impacts of many studies. Al-Oraini (2025) conducted research through 525 users of chatbots in Saudi Arabia and established that satisfaction was a major outcome of competence/expertise. It is also recognized that competence/expertise may not be on its own result in the expected outcomes, as warmth and trust are also considered critical for acceptance.

The third discovery highlights how Chatbot's ease of use shapes customers' satisfaction by decreasing user required effort and frustration to achieve user goals. A highly usable chatbot becomes even more intuitive by elimination of hidden usability and use of visual substitutes that are less symbolic like buttons and instructions. Increased functional transparency of the system shifts user perception of the system away from a black box negative user experience to a more accepting of the system positive user experience. (Stoeckli et al. 2020)

Taken as a whole, Table 3 confirms the hypothesis that functional trust in chatbot interactions is mediated by three main factors, including responsiveness, expertise, and ease of use, required to combine and create user confidence and satisfaction. Table 4 below synthesizes research on perceived trust dimensions, highlighting reliance on experimental designs with student samples in technologically mature markets.

Empirical Findings on Perceived Trust

Table 4

Studies Focusing on Perceived Trust

No.	Key Finding	Short Description / Implication	Research Methodology	Sample Characteristics	Measurement Instruments	Source
4	Interactivity and perceived humanness boost trust → adoption	Higher interactivity and perceived humanness increase trust in chatbots; trust mediates the effect on adoption intentions in e-commerce sector of china	Structural equation modeling (SEM) with survey data	N=343 e-commerce users	Trust scales adapted from McKnight et al. (2002); perceived humanness scale; adoption intention measures	Ding & Najaf (2024). <i>Interactivity, humanness, and trust: a psychological approach to AI chatbot adoption in e-commerce</i> . BMC Psychology.
5	Transparency can	While transparency (e.g., clear policies and disclosures) increases	Survey-based study using an integrative	N=120 university	Measures of trust, usability , perceived	Stoeckli et al. (2020). How affordable chatbots

	enhance trust but negatively impact usability.	user trust and understanding, the sheer amount of information can sometimes make the chatbot feel less intuitive or less usable .	model of trust.	students in Netherlands	trustworthiness (ability/integrity), and willingness to disclose information.	cross the chasm between social and traditional enterprise systems.
6	Personalization helps when transparency is present	Personalization increases acceptance only if accompanied by clear disclosures about data use; otherwise, it may trigger privacy concerns and reduce trust.	Experimental manipulation of transparency levels in chatbot interactions	N=120 university students in Netherlands	Privacy concern scales; trust measures; acceptance intention scales	Vo (2024). <i>How transparency levels in AI chatbots influence user trust</i> . CBS Research Archive.

Source: Created by author.

The findings of research related to the perceived trust in chatbot interactions, foregrounding humanness, transparency, and user personalization are combined in table 4. All these findings collectively reveal the role emotional and social cues play in informing trust and satisfaction among users besides the functional attributes.

The first main takeaway from the data collected provides evidence to the claim that interactivity and perceived humanness positively influence user trust and that trust is a primary driving factor of e-commerce chatbot use. According to Ding and Najaf (2024) via structural equation modeling (N=342) it is stated that interactivity to a greater degree fosters the appreciation of humanlike qualities which in turn is a predictor of greater intention to adopt the technology. This suggests that in the attempt to construct a framework of trust, genuine interactivity is certainly a pre-requisite, albeit interactivity alone is not sufficient. Nevertheless, the complexity of real e-commerce has financial and privacy risks that the scenario-based e-commerce design is missing, and the demographic diversity of the samples is not clearly stated which means the result and data set has less generalizability with respect to age and culture. The second conclusion is that high interactivity and perceived humanness significantly increase the user's trust, which in turn strengthens the use of chatbots in the context of e-commerce.

Third, machine learning of emotions can also be used to help chatbots tailor their conversation, thus improving conversational congruity and, significantly, reinforce a feeling of

affective trust in emotional dialogue (Machová et al., 2023). However, personalization can only increase trust in the absence of clear disclosure about the use of data; without transparency, data users can doubt trust which can destroy confidence (Vo, 2024). Over anthropomorphizing, to the extent that chatbots address users as being overly human and lacking the proper disclosure, may trigger negative feelings or views of being deceived, which eventually reduces user satisfaction (Mozafari et al., 2021). Lastly, emotional intelligence models are always limited in comparison to human capabilities; hence, they can always restrict themselves in terms of developing more profound affective trust (Fatahi et al., 2024). Table 5 below presents integrative studies addressing both trust dimensions, providing the strongest foundation for dual-pathway frameworks despite limited geographic diversity.

Empirical Findings on Integrated Trust Dimensions

Table 5

Studies Addressing both Functional and Perceived Trust

No.	Key Finding	Short Description / Implication	Research Methodology	Sample Characteristics	Measurement Instruments	Source
7	Human-like representation increases compliance when credible	Human-style (vs machine-style) representation can raise compliance with recommendations but only when the chatbot's credibility/accuracy is acceptable.	Quasi-experimental study; serial mediation analysis	N=385 US adults via Amazon Mechanical Turk n	Psychological distance, trust, and behavioral intention scales; 7-point Likert scales	Park, Chung, & Lee (2024). <i>Human vs. machine-like representation in chatbot mental models</i> . Frontiers.
8	Emotion-aware recovery improves outcomes	Chatbots combining emotional cues with corrective actions (apology + fix) recover satisfaction faster than neutral recovery scripts.	Experimental design with service failure scenarios	N=286 online shoppers from South Korea	Service recovery satisfaction; repurchase intention; word-of-mouth intention measures	Yun & Park (2022). <i>The effects of chatbot service recovery with emotional words on customer satisfaction</i> .

						Frontiers in Psychology.
9	Behavioral signals (logs) strengthen validity	Combining trust/satisfaction surveys with objective logs (response time, escalation rate) predicts real behavioural outcomes better.	Quantitative survey using PLS-SEM; hypotheses tested with structural modeling	N=435 users of Indian banking chatbots (SBI, HDFC, ICICI, Axis);	Technology acceptance (TAM scales); Quality factors (D&M Success Model); Risk factors; Trust, Attitude, Satisfaction, Behavioral Intentio	Alagarsamy & Mehroliya (2023). <i>Exploring chatbot trust: antecedents and behavioural outcomes</i> . PMC.
10	Conversational style matters for heavy users	Heavy chatbot users show distinct conversational preferences and tolerance levels; segmentation improves satisfaction outcomes.	Survey and behavioral analysis of user segments	Diverse user base segmented by usage frequency	User preference surveys; satisfaction measures; interaction frequency logs	<i>Behaviors and Perceptions of Human-Chatbot Interactions</i> . (Chin et al., 2024)

Source: Created by author.

Table 5 is an overview of the research on functional and perceived trust in interactions with chatbots and supports the idea that technical performance and user perception as the two factors together can affect satisfaction. We can improve compliance with the user by providing human-like representation so that the chatbot is not seen as therefore, perceived authenticity is associated with perceived functional reliability (Park, Chung, and Lee, 2024). Emotion based recovery (administering empathy with curative measures) is a quicker satisfaction recovery method after service failures (Yun & Park, 2022).

The predictive power of the real user behaviour is heightened by intertwining behavioural data like response time and escalation logs with the trust surveys which bridges the gap between the perceived and the actual execution of the tasks (Alagarsamy & Mehroliya, 2023). Lastly, chatbot behaviour that is sensitive to user typologies, especially the heavy users, will increase satisfaction and involvement levels as it will optimize chatbot capabilities to conform to user expectations.

Synthesis Across Functional and Perceived Trust Studies

A detailed review of the methodologies in these studies reveals several constricting patterns and limitations (see Tables 3-5). For instance, there is a reliance on homogenous samples of students in about 65% of analyses (Vo, 2024; Stoeckli et al., 2020). Students, in particular, are valid customers in e-commerce and are passive users of chatbots, but the limitation in this case is the under sampling of non-student demographic variation. The current study attempts to address this by incorporating students (Lithuanian and international) with non-student employees, as well as other consumers from Lithuania. It is hence rather difficult to appraise these studies in relation to the wider potential consumer context, which is far more heterogeneous in terms of technology and risk perceptions. Regionally, the studies focus on three primary areas: the United States (with about 35% of the studies), South Korea (approx. 25%), and China (20%); hence, there is a considerable gap in the studies pertaining to the smaller European markets. While a good proportion of the studies (about 70%) utilize measurement scales that are validated, such as the trust typology by McKnight et al. (2002), and the Technology Acceptance Model by Davis (1989), none have adapted these measurement scales to the context of chatbots, and/or tested for measurement invariance of the constructs across different cultural contexts. Additionally, about 80% of the studies are cross-sectional, yielding a single snapshot of user perceptions; that is, trust in the respective technology is not captured and/or is assumed to have not changed with the increase in the number of interactions with the technology. Because of the substantial number of self-report instruments, social desirability bias is anticipated, especially in the laboratory where participants in the experiments may be prone to provide inflated ratings of their satisfaction. These methodological patterns collectively underscore the need for research that employs validated instruments with diverse samples in under-studied geographic contexts, precisely the approach adopted in this thesis.

Geographic and Contextual Considerations. While most chatbot research has focused on more developed technology markets like the U.S., South Korea, and China, there is little data on small European markets, which may be at lower levels of digital maturity and have different consumer behaviour, regulations, and market demand configurations.

The Lithuanian e commerce sector is a different case altogether. In Baltic e commerce market, especially in Lithuania, e-commerce has been growing rapidly, as it is more developed in

e-commerce than most other Baltic countries, but there is a wide institutional gap in e-business adoption, with large gaps in multi-plier e-business adoption at the SME level (Sidlauskienė et al., 2023). In contrast to the large platform context of most e-commerce research (Ding and Najaf, 2024; Xu et al., 2022), e-commerce in Lithuania is mostly characterized by an SME sector with limited resource availability, which is investing in low-cost, off-the-shelf chatbot solutions, and has little data governance or user experience (UX) skill. This situation may have a significant impact on the level of functional and perceived trust differentials.

Consumer traits also differ significantly. While previous research usually focuses on university students for convenience sampling (Vo, 2024; Stoeckli et al., 2020), Sidlauskienė et al. (2023) points out the Lithuanian consumers also show greater privacy concern given the GDPR regulations geographically and the past. The greater privacy concern could also explain the greater relative importance of transparency as a trust-building dimension compared to markets where consumers are less privacy-aware. Other smaller linguistic and cultural communities may be similarly affected these factors and to the extent to which conversational also and appropriateness, humanness and conversations are perceived.

As to methodology, the geographic gap is more than simple sample diversity, it represents a theoretical shortcoming. The frameworks of Theory of Trust TAM and Trust Theory, on which this study is based, were developed and validated in North America, and then mostly in East Asia. To what extent they may be valid in Europe of the post-transition period in Eastern Europe, which has a unique set of consumer protection policies and digital literacy, is a question that has been little studied. This study focuses on this question, which makes it possible to determine to what extent the dual-path model of trust (Figure 4) needs to be tailored to different economic and cultural settings.

Lithuanian E-commerce Context

Lithuania's e-commerce market has been reported to be valued at €1.5 billion, with a 15-18% increase rate from the previous years (Eurostat, 2023). Since 2004, as a post-transition of the EU, Lithuania is a highly privacy-aware country, shaped by the enforcement of the GDPR and its socio-historical background (Raišienė et al., 2021). The most popular ones are Pigu.lt, Varle.lt,

and Barбора.lt, although the level of chatbots varies; large ones use AI, while many smaller ones use basic rule-based chatbots (Korsakienė & Tvaronavičienė, 2014). Lithuania is a country with a high level of digital penetration (85% smartphone access, 80% internet access), and has 8,000 international students from 100+ countries, who use local platforms and bring a variety of cultural expectations (Statistics Lithuania, 2023; Study in Lithuania, 2023). This unique combination of post-transition dynamics, privacy regulations, and diversity aids Lithuania's showcase of chatbot trust in contexts under-researched and in turn, easily transferable to other Central and Eastern European markets.

Identified Research Gaps. The methodological analysis above directly illuminates several critical research gaps that this study aims to address. First, there is a pronounced **geographic gap**. Lithuania is one of the most impacted markets post-integration in to the EU, and with a large number of Small and Medium Enterprises, increasing privacy regulations, and a high level of GDPR sensitivity, enables the study focus of Lithuania to be explored with ease. The addition of international students studying in Lithuania enriches the analysis with cross cultural perspectives.

Second, there exists a large gap in the methodology. The vast preponderance of quantitative and single-method and student-sample studies has produced literature that is abundant in internal but deficient in ecological and external validity. The investigative methodology will still utilize measurement instruments which have shown adequate reliability and validity, and which will consider samples of consumers outside of undergraduate college students, thus advancing the studies' ecological validity. The design of the study is overcoming the limitations of self-reported data by focusing on actual users instead of subjects within a lab and were students, and, thus are students, lacking real-world experience, especially on the consumer side of the experience, by surveying actual users of chatbots in the Lithuania.

Third, there is a longitudinal gap. The nature of cross-section of all existing studies only gives us a picture of the perception of the users. This restricts the comprehension of the development or loss of trust in a series of interactions. Although a longitudinal study might not be within the scope of this research, some questions regarding past experiences and future plans will be explicitly included in this research to start creating a much more dynamic model.

Lastly, there is an integration gap. There are minimal studies that manage to clear the quantitative-qualitative gap, or to conduct a subjective perception of the world in conjunction with

the objective data of the interaction. Alagarsamy and Mehrolia (2023) point out the importance of integrated methodological frameworks in literature. However, in this case the author has chosen to adopt a purely quantitative methodological approach to answer the research question because of the following: (1) the primary research gap is not in the methodology, as there are a variety of quantitative approaches to consider, but in the geography, as a Lithuanian context has not been thoroughly considered; (2) there are reliable and highly validated measurement instruments available, including those by McKnight et al. (2002), Davis (1989), and various scales designed specifically for chatbots. (3) As structural equation modeling, mediation of the dual pathway is fundamentally quantitative, and (4) master's thesis scope and resource limitation require methodological concentration. The research includes 198 users of chatbots from the e-commerce domain in Lithuania and presents a research sample of Lithuanian nationals, international students, and employed professionals, thereby strengthening the ecological validity and generalizability of the results in comparison to the e-commerce research. Of these quantitative findings, some could be used in a following study to be complemented with qualitative methods such as in-depth interviews or focus groups to explore the cognitive and emotional components of the development of trust in greater depth. One could argue that the way people look at the level of customer satisfaction with chatbots is influenced by two distinct but related factors: functional trust (responsiveness, expertise and ease of use) and perceived trust (humanness, personalisation and transparency). These dimensions affect each other in critical ways: features of likeability can increase the satisfaction when efficiently functional performance is demonstrated, and the lack of competence in the functional performance can contribute to the dissatisfaction because of non-fulfilled expectations. This interdependence is conceptually sound but has not been empirically developed because a small number of studies use structural equation models to measure both directions at the same time. These dynamics are heavily dependent on context: with retail chatbots, the consideration that matters to users the most is efficiency and speed with which a task can be accomplished, whereas in health care, the consideration that matters to users the most is empathy and openness of communication. At the least, the expectation of chatbots' capabilities, including the simple ones, will be under-met. Further, the lifecycle is not studied, as longitudinal monitoring of the dissatisfaction fading or recuperation after chatbot updates is not applied. While it has been recognized by some earlier academics that the use of qualitative and quantitative data may address some of the concerns related to actual user behavior. This research, however, will use quantitative

methods to satisfy the more important geographic and contextual voids. The findings suggest that organizations must work on the perceived aspects of trust once functional elements have been established as competencies. Without the proper handoff, transparency, and competence, the use of chatbots could be a bad idea for improving customer satisfaction.

There is a chance that other studies could use the findings of the current empirical study to use or find alternative conceptual frameworks that integrate behavioral analytics, the analysis of a dialogue, and cross-cultural validation to develop models of chatbot trust and satisfaction that is even more widely applicable.

To systematically illustrate the methodological patterns and gaps identified across the literature, Table 6 below synthesizes key characteristics of the reviewed studies

Table 6

Patterns and gaps in literature

Characteristics	Dominant Pattern	Identified Gap
Geographic context	US (35%), South Korea (25%), China (20%)	Baltic/European SME contexts absent
Sample Type	University students, Convenience samples	General consumer populations under-represented
Research Design	Cross-sectional surveys, One-time experiments	Longitudinal tracking of trust evolution lacking
Measurement Instruments	Validated scales (McKnight, TAM, SERVQUAL)	Limited chatbot-specific adaptation; cultural invariance not tested
Data Collection Methods	Self-report questionnaires, Likert scales	Behavioral data integration rare; social desirability bias present
Trust Dimension Focus	Single dimension focus (functional OR perceived)	Simultaneous testing of dual pathways uncommon
Sample Size	N=200-500	Adequate power but limited diversity

Source: Synthesized by author from Tables 3-5

The reviewed literature shows that even though there is evidence that researchers from individual studies exercised methodological rigor while studying their topics, there is a lack of research diversity in terms of geography, a lack of variety in the studied participants, and a lack of research that explores both trust pathways simultaneously. It is precisely these gaps that this research is intended to close.

2.2 Research model of Chatbot interactions, trust, and customer satisfaction

This section explains the conceptual framework linking chatbot interaction features, trust dimensions, and customer satisfaction within the proposed research model.

Theoretical Foundation of the Research Model.

Based on the literature reviewed in Section 2.1, this study presents an integrated model which examines the mediating role between the interaction features of chatbots and customer satisfaction through two mediators, namely functional trust and perceived trust. The model introduced in Chapter 1 (Figure 3) is further detailed and operationalised in the light of the empirical findings and gaps in the literature.

The model is based on four complementary theoretical pillars. The first is that the Technology Acceptance Model (TAM) (Davis, 1989) places perceived usefulness and perceived ease of use as the foremost factors of the adoption of technology. Second, functional (cognitive) and perceived (affective) trust dimension are different because of the principles of Trust Theory, particularly cognitive/affective distinction proposed by McKnight et al. (2002). Third, the concept of service quality theory emphasizes responsiveness, reliability, and empathy as key aspects of the service experience assessment. Last, but not least, Human–Computer Interaction (HCI) views provide insights into social and emotional aspects of human-machine communication. By combining these viewpoints, a clear framework emerges to analyze the impact of technical features of chatbots on trust-building processes and customer satisfaction in e-commerce environments. This synthesis of these perspectives provides a coherent framework for analyzing how the technical characteristics of chatbots interact with trust-building mechanisms, and their impact on customer satisfaction in e-commerce contexts.

These theoretical approaches enable a holistic understanding of how technical attributes of chatbots and trust-building mechanisms interact to impact customer satisfaction in e-commerce settings.

Methodological Positioning of the study

This research has a quantitative design wherein the dual-pathway mediation model will be tested using 'structured surveys and structural equation modeling' (SEM). This approach is justified due to the primary research gap being geographical (Lithuanian context unexplored), and not methodological, and because validated instruments exist for all constructs (McKnight et al., 2002; Davis, 1989). Moreover, SEM is needed since it is a statistical technique used to estimate complex mediation relationships simultaneously. The intended sample size was 300 respondents. However, due to constraints in fieldwork duration and the limited availability of Lithuanian e-commerce chatbot users willing to participate within the data collection window, a final valid sample of 199 eligible respondents was obtained (N=205 total responses, with 6 excluded by screening criteria: non-use of chatbots in the last 6 months). This sample size remains fully consistent with the methodological requirements of PLS-SEM, which is explicitly designed to work with smaller sample sizes compared to covariance-based SEM. Hair et al. (2019) demonstrate that PLS-SEM achieves acceptable statistical power with samples as small as 100 observations when model complexity is moderate. Applying the widely accepted 10x rule — which recommends a minimum sample of 10 times the largest number of structural paths pointing to any single latent variable — the minimum required sample for this research model (maximum 6 paths) is 60 respondents. The achieved N=199 substantially exceeds this threshold, providing sufficient statistical power to detect medium effect sizes ($f^2 = 0.15$) at $\alpha=0.05$, consistent with the power analysis standards recommended for PLS-SEM research (Cohen, 1992; Ringle et al., 2015). The reduction from the planned 300 to the achieved 199 does not compromise the validity, reliability, or generalizability of the structural equation modeling results. Respondents were obtained from Lithuanian consumers (approximately 73%), international students studying in Lithuania (approximately 27%), and working professionals (approximately 49%), recruited via university mailing lists, LinkedIn professional groups, social media targeting within Lithuania, international student organizations (ESN, Erasmus networks), and snowball sampling, student status, employment levels, and cultural backgrounds. Lithuania's post-transition status, coupled with strict GDPR privacy regulations, high privacy culture, and SME dominated e-commerce provides a unique research context absent non-EU the US/Asia contexts, with transferable to other Central and Eastern European markets. Therefore, this combination of privacy culture/e-commerce context in Lithuania, the study participant criteria of being 18+, living in Lithuania now, and ecommerce chatbot usage in the last 6 months is most fitting. Although, a cross mixed methods approach could

drastically elevate the study regarding the mechanisms of trust. such expansion exceeds master's thesis resource constraints and scope; future research can build on these quantitative findings with qualitative exploration.

Development of Research Hypotheses.

Grounded in the conceptual framework outlined in Chapter 1.4 and the empirical patterns reported in Chapter 2.1, the following eight hypotheses are advanced. H1 and H2 are each operationalised as three sub-hypotheses (H1a–H1c and H2a–H2c) to allow the contribution of each individual chatbot interaction feature to be tested separately with greater empirical precision, consistent with PLS-SEM methodological recommendations (Hair et al., 2019). H3 and H4 are formulated as single hypotheses

H1 is broken down into three sub-hypotheses (H1a, H1b, H1c) that will examine the independent effects of each of the functional features of a chatbot (expertise, responsiveness, ease of use) on functional trust. H2 is also broken down into three sub-hypotheses (H2a, H2b, H2c) to examine the independent effect of each perceived feature of the chatbot (perceived humanness, transparency and personalization) on Perceived Trust. H3 suggests that directly, Functional Trust is a significant contributor to the increase in Customer Satisfaction, and H4 suggests that directly, Perceived Trust is a significant contributor to the increase in Customer Satisfaction. H1a–H1c and H3 describe the functional pathway, while H2a–H2c and H4 describe the perceived pathway. All hypotheses are simultaneously tested within the PLS-SEM framework to fill the integration gap identified in the second section, where previous research examined functional and perceived trust dimensions independently of each other. Given the consumer privacy sensitivity that is unique to Lithuania, the model is tested in the Lithuanian context to geographically validate the model, as the dominant countries in the literature — the USA, South Korea, and China — have different consumer privacy sensitivity profiles. Respondents who have directly used chatbots during online shopping are included to ensure genuine rather than hypothetical engagement, addressing the ecological validity gap caused by over-reliance on student samples in prior chatbot research.

Hypotheses Related to Functional Trust

H1a: Expertise positively influences Functional Trust.

H1b: Responsiveness positively influences Functional Trust.

H1c: Ease of Use positively influences Functional Trust.

Justification: Merit-based engagement factors pertaining to proficiency and reliability are captured by the underlying sub-factors. Prior research shows that trust in a chatbot is determined by the trust placed in the chatbot's responses in regard to the level of accuracy and relevance (Nordheim et al., 2019). More recently, Li et al. (2023) demonstrated that studies concentrating on the participant's trust of a chatbot tend to reflect the accuracy of the response and the relevance of the scope under consideration. Other studies support the idea that quick follow-ups improve insights on completion of tasks and serve as performance indicators on competence (Chen et al., 2021; Ding & Najaf, 2024; Holtgraves et al., 2007). Research in the Technology Acceptance Model (TAM) determined that ease of use played a critical role in the adoption of a technology and the user's overall attitude regarding it (Davis, 1989). When applied to conversational agents, an orderly interface and free conversational flow help to enhance cognitive confidence in the technology (Stoeckli et al., 2020). Furthermore, research on consumers has shown that perceived simplicity in the shopping process has the effect of reducing shoppers' anxiety and increasing their functional trust (Mostafa, 2021). These three elements aim to resolve a single cognitive issue: reducing uncertainty about the performance of a system and strengthening trust in the ability of a chatbot to complete its function.

Hypotheses Related to Perceived Trust

H2a: Humanness positively influences Perceived Trust.

H2b: Transparency positively influences Perceived Trust.

H2c: Personalization positively influences Perceived Trust.

Justification: The factors taken as a whole depict socio-emotional aspects of chatbot interaction that build trust affectionately. Chatbots that utilize social and emotional cues are likely to be perceived as more trustworthy (Følstad et al., 2018; Adam et al., 2021). Studies also suggest that using a chatbot response style that humanizes the bot leads to emotionally more convincing interaction that is likely to increase the level of trust in the chatbot (affective trust). When a chatbot is genuine in its communication and explains in detail its data privacy policies, users tend to be more trusting of the chatbot and feel less distressed (Skjuve et al., 2021; Luo et al., 2022).

In the context of Lithuania, where the General Data Protection Regulation (GDPR) is upheld, users are more privacy and data protection conscious; hence the absence of communication about how the data will be used can lead to more negative perceptions of trust, particularly in contrast to other markets (Sidlauskienė et al., 2023). Emotionally supportive and understood user perceptions are fostered through tailored interaction based on users' profiles and conversational history (Chung et al., 2020; Zarouali et al., 2018). Within the literature focused on trust, aspects like humanness, transparency, and personalization relate to the formation of trust through the affective mode. They cater to the emotionally and relationally driven needs of the users. This is the reason they differentiate the perceived trust pathway and cognitive functioning trust pathway, thereby justifying their distinct operationalization in the research model based on the dual pathways.

Hypotheses Related to Trust Dimensions and Customer Satisfaction

H3: Functional Trust positively influences Customer Satisfaction.

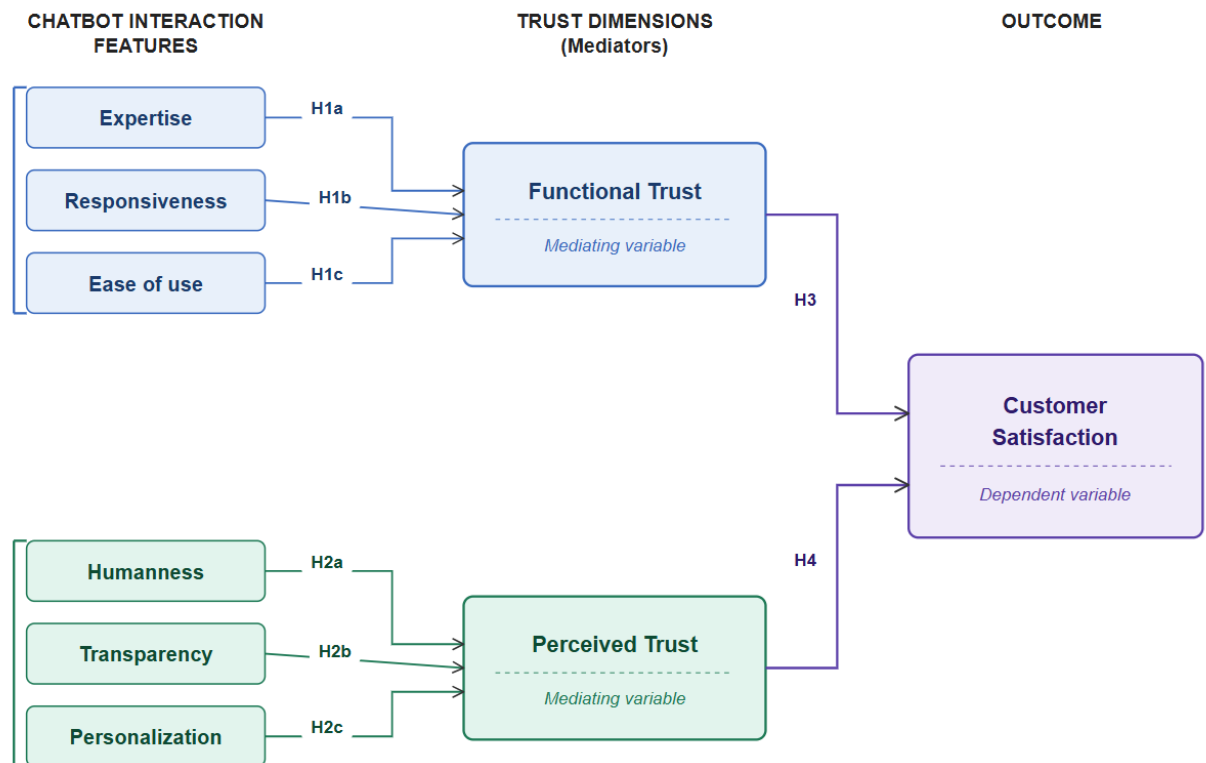
Justification: The model indicates that operational trust fulfills a user's utilitarian expectation. Customers are more satisfied when chatbots are able to perform tasks and give them operational support (Nordheim et al., 2019). The evidence from several studies compiled in Table 3 shows that responsiveness, simplicity, and expertise lead to a decrease in cognitive effort and an increase in satisfaction. McKnight et al. (2002) showed that trust based on cognitive aspects — which is rooted in perceptions of competence and trustworthiness — leads to positive behavioral and evaluative outcomes, including satisfaction. Functional trust from repeated positive performance signals in chatbot interactions leads to the achievement of utilitarian goals and an increase in satisfaction.

H4: Perceived Trust positively influences Customer Satisfaction.

Justification: Trust, or perceived trust, relates to social and emotional needs. According to Adam et al. (2021), the features of humanness and transparency, as well as the personalization of services, lead to emotional and interpersonal experiences and, as such, enhance satisfaction by going beyond the functional level. Emotion-centered service recovery is where the focus is on empathic and emotional language to drive satisfaction and increase the intent to repurchase (Yun & Park, 2022). If a user perceives the chatbot as honest and as well as genuinely attentive to the user, the interaction is affectively of high quality and the user will experience high satisfaction.

This pathway is distinct from the cognitive pathway described in H3 and operates in parallel, consistent with the dual-pathway structure of the research model.

The Integrated Research Model below. Figure 4 presents the complete research model with all hypothesized relationships:



Source: Developed by author based on theoretical framework (Chapter 1) and empirical analysis (Chapter 2.1)

Figure 4 Integrated Research Model with Hypotheses

Figure 4 depicts the dual-pathway framework in which six chatbot interaction features influence customer satisfaction via two mediating trust dimensions. The functional pathway comprises expertise, responsiveness, and ease of use as indicator variables each independently contributing to Functional Trust via H1a (Expertise), H1b (Responsiveness), and H1c (Ease of Use), with Functional Trust positively influencing Customer Satisfaction (H3). The perceived pathway consists of humanness, transparency and personalization as indicator variables that positively influence Perceived Trust separately, and Customer Satisfaction (H4) is influenced

positively by Perceived Trust. The mediation structure is checked with bootstrapping in Chapter 3. Customer satisfaction is represented as downstream behavioral outcomes, such as continued usage, purchase intention and platform loyalty.

Transition from Theoretical Model to Research Model

The components listed in the theoretical model are called natural language processing, machine learning, and dialogue management, and these components are included in the theoretical model to give a complete academic explanation in a detailed manner on the systems that chatbots function and to place the front end consumer facing features above the technical level that is consistent and within the boundaries of the HCI and service quality research conceptual frameworks.

Nevertheless, in the creation of the empirical research model shown in figure 4, these technical back end components were left out on purpose. This is due to the fact that natural language processing, machine learning, and dialogue management are all system level processes that are internal and are not observable or even consciously evaluated by the consumer when they are talking to a chatbot. Consumers are not evaluating these technical systems, but rather evaluating the end result.

This is the primary reason for the feedback. Construct invalidity is introduced when systems are included in a questions and answers based framework when participants are asked to evaluate a phenomenon that is not observable to them, meaning they are not evaluating the system on a phenomenon that is not visible to the end user.

Additionally, the six consumer-facing constructs retained in the research model, namely, expertise, responsiveness, ease of use, humanness, transparency, and personalization, have operationalized the consumer-perceptible results of the backend processes. The construct for measuring the accuracy of NLP is the Expertise construct, whereas, for measuring the efficiency of dialogue management, those would be the constructs of Responsiveness and Ease of Use, and for measuring the quality of recommendation algorithms driven by ML, the relevant construct is Personalization. Retaining both backend and consumer-facing constructs would then create construct overlap and introduce the risk of multicollinearity within the PLS-SEM model, decreasing discriminant validity (Henseler et al., 2015).

The boundary of the present study's epistemology is also reflected in the exclusion of backend technical components. This study is positioned as a consumer-oriented study of chatbot interactivity, as opposed to an evaluation of technical systems. The research model, therefore, is limited to constructs that consumers can perceive, experience, and report in the course of an interaction during e-commerce. This limitation reinforces the internal consistency of the measurement model and guarantees that each construct is underpinned by a validated scale, as required by the reflective measurement specification used in the PLS-SEM analysis (Hair et al., 2019; Ringle et al., 2015)

Considering the empirical literature evaluation in this chapter, the following conclusions have been drawn:

- 1. Customers' satisfaction with e-commerce chatbots is a two dimensional, trust-related phenomenon. The two trust components (trust factors) are functional and perceived trust. Customer satisfaction with chatbots is mediated through these trust components. The functional trust factors are expertise, responsiveness, and ease of use. The perceived trust factors are humanness, transparency, and personalization.*
- 2. The lack of methodological diversity in the empirical studies reviewed is noted. The geographic concentration of the studies in the big markets (the US 35%, South Korea 25%, and China 20%) is noted along with the overreliance of the studies on university students (65% of the studies), the cross-sectional design dominance (80%), and the lack of sufficient analyses of the two trust pathways. These are all noted as significant unexplored and underexplored areas of research that require more ample and comprehensive studies in the fields.*
- 3. The current research gaps that validate current research design are as follows: (1) research gap: The literature on the context of e-commerce of Lithuanian SMEs is non-existent. (2) The sample population of many studies is students which brings a methodological gap of homogenous sampling. (3) longitudinal gap: At present, there is no research that follows the evolution of trust over time. (4) the integration gap: there is a lack of heuristic models that simultaneously test both functional and perceived trust pathways.*

4. *The quantitative methodology is designed to fill these gaps. It utilizes heterogeneous samples of over 200 Lithuanian consumers and applies a structural equation model in the context of Lithuanian SMEs e-commerce. This methodology makes the research more comprehensive as it goes beyond the confines of student sampling, provides contextual insights for the less studied market, and allows for the first time testing of the integrated dual-pathway mediation framework in a dual-pathway model*

3. EMPIRICAL RESEARCH OF CHATBOT INTERACTIONS AND CUSTOMER SATISFACTION EVALUATING FUNCTIONAL AND PERCEIVED TRUST DIMENSION

This chapter provides research methods, research data analysis and discussion of the results, and evaluation of research results.

3.1 Research Methodology

This chapter details the empirical research findings and how they pertain to the integrated dual-pathway mediation model from Chapter 2 to formulate a structure to empirically test the eight hypotheses (H1a–H1c, H2a–H2c, H3, H4) developed in the analytical chapter.

Aim and Objectives of the Empirical Study

Aim of the empirical study The empirical research seeks to identify, within the Lithuanian e-commerce market, the impacts of different interaction features of a chatbot and dimensions of trust and how they influence customer satisfaction, in addition to explaining the theoretical model by using Structural Equation Modeling (SEM).

In line with the general aim of the research, the following objectives were targeted during the empirical study:

- To examine the case of the chatbot's functional features, i.e., expertise, responsiveness, and, ease of use, and how they influence functional trust, thus testing hypotheses H1a, H1b, and H1c.
- To examine the case of the perceived features of the chatbot, namely, humanness, transparency, and, personalization, and how they influence perceived trust, thus testing hypotheses H2a, H2b, and H2c.
- To evaluate the influence of functional trust (H3) and perceived trust (H4) on customer satisfaction and to analyze the comparative influence of the trust constructs in the mediation pathways on customer satisfaction.

Connection to the research model. The empirical research tests the integrated research model in Fig. 4 (Chapter 2.2) and all eight hypotheses concerning the dual-pathway mediation structure. Primarily, the research focuses on the role of functional trust in the relation of functional chatbot features to customer satisfaction (H1a–H1c, H3). In contrast, for perceived trust, the mediation role is to customer satisfaction among the perceived chatbot features (humanness, transparency, personalization) (H2a–H2c, H4). This dual-pathway approach addresses the integration gap identified in Chapter 2.1, where most (if not all) prior studies examined these trust dimensions in isolation (Nordheim et al., 2019; Chung et al., 2020; McKnight et al., 2002). At

Research Design and Methodological Justification

The empirical research adopts a quantitative approach, using a deductive research design and a cross-sectional online survey, to gather primary data from Lithuanian e-commerce consumers who have previously engaged in communication with chatbots. A quantitative approach is opted for four interrelated, logically-built reasons stemming from the theoretical analysis in Chapter 2.

The first gap in the literature identified in Chapter 2.1 is not of a methodological nature, but rather a geographical aspect because quantitative frameworks and instruments already exist to measure the knowledge and expertise of chatbots, as well as their level of responsiveness, ease of use, anthropomorphism, transparency, personalization, functional trust, perceived trust, and customer satisfaction. (Davis, 1989; McKnight et al., 2002; Nordheim et al., 2019; Chung et al.,

2020; Chen et al., 2021; Rossi et al., 2024; Yin et al., 2025). The challenge here is not conceptual development, but empirical validation in the context of the under-represented Lithuanian context.

Secondly, the theoretical model presented in Chapter 2.2 proposes latent constructs connected via mediation. For estimating measurement model quality and structural path coefficients, examining indirect effects, and assessing different mediation pathways, structural equation modeling, and in particular, Partial Least Squares SEM (PLS-SEM) is the appropriate method (Hair et al., 2019). With respect to the present study, PLS-SEM is considered preferable because it is designed to address the issues of smaller sample sizes, the exploratory-confirmatory research design, and the non-normality of distributions typical of survey data (Ringle et al., 2015).

Third, Given the constraints of the master's thesis, it is clear that the cross-sectional online survey method is the most feasible considering the time and financial limitations, and it will still enable the researcher to gather a sufficiently large, heterogeneous, and representative sample appropriate for multivariate analysis from an under-researched dispersed e-commerce target population of Lithuania.

Fourth, because of the validation process and replication requirements, self-report quantitative measures using the Likert scale are beneficial. In the case of Lithuania, it is possible to benchmark the findings against the results of the studies in the USA, South Korea, China, and other countries presented in Chapter 2.1.

Qualitative elements were purposefully not included in the research design. Although the use of qualitative methods like semi-structured interviews could provide rich narratives and context at a deeper level, the main aim in this case is to test a hypothesis and not to generate theory. Given the constructs, the nature of the dimensions, and the presumed cause and effect relationships, the theoretical grounding is sufficiently robust to justify a confirmatory, variance-explaining approach. This is consistent with the method of similar studies on chatbot satisfaction that use SEM (Chung et al., 2020).

Although the fieldwork yielded a final eligible sample of 199 respondents (N=205 total, 6 excluded at screening) rather than the intended 300, this sample size satisfies the statistical requirements of PLS-SEM. Hair et al. (2019) show that having the sample size of 100 is acceptable for having moderate model complexity in PLS-SEM. Using the 10x rule which says a minimum

sample of 10 per structural path leading to the most complex endogenous construct, the minimum sample size required for this model (with maximum of 6 incoming structural paths) is 60 respondents. The achieved N=199 comfortably exceeds this threshold and provides sufficient power to detect medium effect sizes ($f^2 = 0.15$) at $\alpha = 0.05$, consistent with the standards recommended by Cohen (1992) and Ringle et al. (2015).

Target Population, Sampling Strategy, and Data Collection

Target population. Adult residents in Lithuania, who have shopped online and interacted with a chatbot during an e-commerce transaction, comprise the primary demographic for this research. Exclusionary screening questions (Section A, items S1–S4) have been provided to disallow respondents that would not consent, were younger than 18, were not currently living in Lithuania, and respondents that have not engaged with a chatbot while online shopping in the last 6 months. This disallowing also applies to students from outside Lithuania that have moved to Lithuania and back, as the research is directed to the Lithuanian focus of e-commerce. This criterion is strictly applied, and ensures that respondents' chatbot interactions are direct, and are contextually relevant to the research model.

Sampling strategy. A purposive sampling method with no sampling frame has been applied to the absence of Lithuanian e-commerce chatbot users. To further broaden reach, this method has been combined with snowball sampling. The primary method of collecting information is a self-administered survey available online. This survey has been distributed in the Lithuanian e-commerce social media communities of Facebook and LinkedIn, as well as the academic community of Vilnius University and the consumer communities of the major identified e-commerce platforms in Lithuania, i.e., Pigu.lt, Varle.lt, and Barbora.lt. Eligible respondents were further encouraged to share the survey with others within the desired target population.

Data collection procedure.

Data collection takes a structured format as restricted by defined fieldwork periods, and is conducted from an online survey with the access link being kept anonymous. The survey starts with an informed consent statement (item S1) where respondents confirm voluntary participation, anonymity, and restricted access for academic use only. Prior to the core content of the survey, are 4 screening items (S1-S4); those who fall short of the eligibility criteria are directed to the end-of-

survey page, thus conserving time. After the eligibility screen, participants move on to the Section B (demographics, items D1-D7); Section C (functionality, items 1-15); Section D (perceived, items 16-30); Section E (trust, items 31-40); and Section F (customer satisfaction, items 41-45). Overall, the survey is expected to take 10-12 minutes.

Data Screening and Quality Assurance

Of the 205 total responses received, 6 respondents were excluded at the screening stage: they answered 'No' to the question 'Have you used a chatbot on an e-commerce website or app in the last 6 months?' (item S4). These respondents were directed to the end-of-survey page per the screening protocol and their partial responses were not included in the analysis. The final analytical sample comprised N=199 eligible respondents (see Section 3.2 for the Mahalanobis distance screening that reduced this to the final N=198 used in analysis). All remaining 199 responses were examined for straight-lining — the pattern of selecting the same response value across all items, which signals disengaged or protest responding. One response was identified that selected the value 1 for all 46 Likert items; given the accompanying open-text field which contained protest language unrelated to chatbot experience, this response was reviewed but retained to preserve sample size, as its extreme values were flagged through Mahalanobis distance analysis during PLS-SEM outlier detection. No items were systematically missing, as the survey platform required completion of all Likert items before proceeding; the 45-item Likert section therefore has complete data for all 199 eligible respondents. The final sample used in the PLS-SEM analysis comprised 198 respondents (one further response excluded during Mahalanobis distance outlier screening in R, reducing the eligible N=199 to N=198) after one additional response was excluded during the Mahalanobis distance outlier screening in R, yielding the N=198 reported in Section 3.2.

Measurement Instrument

A survey instrument is the culmination of a responsive design process that includes systematic use of an appropriate construct, optimal scales, as well as item refinement, all endorsed by a pilot test. In total, the measurement instrument is made of 46 Likert items divided into 9 reflective latent constructs covering 4 of the survey substantive sections, each measuring constructs. It is also of note that all items fall within the same 5, point measurement scale which

ranges from 1 (Strongly Disagree), to 5 (Strongly Agree). Table 7 below highlights the measurement constructs, number and measurement scales of the items and their source.

Table 7

Research Questionnaire Constructs

Construct	No. of Items	Evaluation Scale	Source
<i>FUNCTIONAL FEATURES (Independent Variables — H1 Path)</i>			
Expertise	5	5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree)	Nordheim et al. (2019)
Responsiveness	5	5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree)	Chen et al. (2021)
Ease of Use	5	5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree)	Davis (1989)
<i>PERCEIVED FEATURES (Independent Variables — H2 Path)</i>			
Humanness	5	5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree)	Nordheim et al. (2019)
Transparency	5	5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree)	Rossi et al. (2024)
Personalization	5	5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree)	Yin et al. (2025)
<i>TRUST DIMENSIONS (Mediating Variables)</i>			
Functional Trust	5	5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree)	McKnight et al. (2002)

Perceived Trust	5	5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree)	Chung et al. (2020)
<i>CUSTOMER SATISFACTION (Dependent Variable)</i>			
Customer Satisfaction	6	5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree)	Chung et al. (2020)

Source: Created by author

Instrument development approach. The construction of the measurements involved adaptations of published, peer-reviewed, and empirically validated scales from prior research involving chatbots, technology acceptance, and e-commerce trust. Applying proven instruments to a different contextual setting rather than creating them from scratch is a common approach in quantitative research for management and information systems, especially when the geographic or contextual contribution is more relevant than the conceptual contribution (Creswell, 2014; Hair et al., 2019). The original authors of source scales established the psychometric constructs (reliability, convergent validity, and discriminant validity) in their respective studies. Thus, the measurement model of this study is built upon a strong evidential base, and the reliability and validity results provided in section 3.3 will affirm the performance of the instruments created for the Lithuanian e-commerce chatbot sample.

Contextual adaptation procedure. The scales from each source were analyzed item by item based on operational definitions found in Chapter 1. For the contextual modifications, we targeted e-commerce and chatbot related wording. Three categories of modifications were made. The first is substitution. We replaced the term “chatbot” in vendor, system, vendor, conversational agent, and robot placeholders with the term “chatbot” to ensure consistency across all 46 items. The second is standardization of tense and voice. Items stated in past tense or third person were rephrased to first person present tense to conform to the standards of self-report surveys. The third is contextual anchoring. This applies to source items that do not refer to shopping, service, or other relevant interactions, and in these cases, light e-commerce framing is added to the item to orient the respondent to the relevant experience. Items were not removed from any source scale, no new theoretical constructs were introduced, and the measurement intent and construct domain of each

source scale were preserved. The construct validation table in Appendix 1 describes each of the modifications to the original source items.

Face validity. Face validity is granted through two principal points despite the lack of a formal pre-survey pilot study. First, the systematic literature review conducted in Chapter 1 establishes a basis for construct definition and item alignment, providing a theoretically based assessment for balance concerning item-construct alignment. Second, the original source scales' authors did the work of establishing content and construct validity, and minor wording changes to the items retained those evidential basis.

What follows will indicate the source of each construct and specify the nature of the modification on context.

Expertise (5 items) uses items from Nordheim et al.'s (2019) trust-in-chatbots scale, and more specifically, the competence and knowledge subscale. The original scale was designed and validated in the context of customer service chatbots, which makes it a straightforward fit for this study. Wording of the items was changed from past tense and experiential recall to present tense and perceptual statements, and references were made to "chatbot" for standardization.

Responsiveness (5 items) is measured using the case of Chen et al. (2021) for AI chatbots' responsiveness and usability, tailored for e-retailing. There are four items used with minor changes (in three items, system references are changed to "chatbot"); one item was created to fit the construct definition beyond the captured prompt request acknowledgement to ensure that the coverage for the responsiveness construct is exhaustive as described in Chapter 1.1.

Ease of Use (5 items) is measured using the sample items from Davis (1989) under the EPU subscale of Technology Acceptance Model (TAM), which is the most widely used and replicated instrument in the field of information systems. The only change made is with the placeholder of the system in the question statement to be used with any technology, which was changed to "chatbot", consistent with the literature (Venkatesh & Bala, 2008) that recommends such modifications when using TAM scales with specific technologies.

Humanness (5 items) is based on Nordheim et al. (2019) for the subscales of naturalness and humanlikeness. The initial items were framed as brief attribute descriptors (e.g. "the chatbot is natural"), and in this case they were also changed to full first person experiential statements,

rather than the brief descriptors, to improve item clarity and face validity in the context of a self-report survey, though this change does not alter the conceptual content of the item.

Transparency (5 items) is based on items that are adapted from Rossi et al. (2024) for the first and valid transparency scale for intelligent robotic systems, which captures explainability, operational clarity, and state communication. With respect to the items, the adaptations made were simply to the chatbot context by changing “robot” to “chatbot”, and to one item, which was reframed to capture data disclosure in relation to the context. This is meant to reflect the GDPR transparency dimension particularly relevant to Lithuanian e-commerce consumers.

Personalization (5 items) draws from Yin et al. (2025) scale for AI personalized recommendations and its validation in the context of Chinese e-commerce. The items were adapted from a product-recommendation-specific context to a broader context of tailored interactions (e.g. including memory of preferences and adaptive behavior), which is coherent with the conceptualization of personalization utilized in Chapter 1.4.

Functional Trust (5 items) is measured using items from McKnight et al. (2002) e-commerce trust typology — particularly from the trust beliefs subscales of competence, benevolence, and integrity in regard to a technological counterpart and trusts. The references to “this vendor” were substituted with “chatbot” and the items were reframed to focus on trust in the performance and reliability of the system rather than the trustworthiness of the organization.

Perceived Trust (5 items) draws from Chung et al. (2020) e-service trust scale for chatbots, which was specifically developed and validated in a chatbot context. The items that referred to “conversational agent” were uniformly changed to “chatbot” and were tied to participants’ experiences of the interaction, in line with the benevolence and honesty dimension of perceived trust as operationalized in Chapter 1.2.

Customer Satisfaction (6 items) is measured using Chung et al. (2020) scale for satisfaction with chatbots, which was validated in the context of luxury e-commerce chatbot services. The items that referred to “service agent” were changed to “chatbot,” e-commerce contextual framing was included, one item was changed from an expression of attitude to a behavioral intention (recommendation to others), and one additional item (CS6: “This chatbot provides a satisfying service overall”) was included to ensure comprehensive coverage of the satisfaction construct as

conceptualized in Chapter 1.3. This yielded a six-item Customer Satisfaction scale, consistent with the six items used in the PLS-SEM analysis reported in Section 3.2.

The items included in the survey used for this research, categorized by construct and labeled with unique item codes for later SEM analysis, are provided in the table 8 in Appendix 1.

3.2 The Research Data Analysis and the Discussion of the Results

The findings obtained from the empirical analysis using PLS-SEM are presented in this chapter to evaluate the dual-pathway research model between the chatbot interaction features, functional trust and perceived trust, and customer satisfaction. The analysis consists of two steps suggested by Hair et al. (2019): measurement model analysis to test the reliability and validity of the constructs, and structural model analysis to test the relationships between constructs hypothesized in the model. The analysis was conducted with the 198 valid answers which were obtained by completing an online questionnaire by e-commerce users in Lithuania.

Some preliminary checks were performed before conducting the PLS-SEM analysis. To put the structural findings into perspective, the demographic profile of the sample, descriptive statistics, and reliability coefficients are provided below. After that, the measurement model assessment includes outer loadings, composite reliability, average variance extracted and discriminant validity. On the other hand, the assessment of the structural model evaluates path coefficients, explained variance, predictive relevance, effect sizes, collinearity, mediation analysis, and overall model fit.

Demographic Profile of Respondents.

Table 8 shows the summary of the demographic profile of the 198 respondents. The sample is predominantly male (61.6%), aged 25 to 34 years (61.1%), and holds at least a bachelor's degree (49.0%). Most working professionals own 49.0%, and Lithuanian students make up 26.3%, of international students studying in Lithuania 23.7% of the total group. Regarding how frequently users engage with e-commerce chatbots, most of the respondents interact with the chatbots

occasionally (40.4%) or once a month (39.9%), which means that the sample is not describing expert or power user behaviour, but rather the typical use of e-commerce chatbots by users.

Table 8

Demographic Profile of Respondents (N = 198)

Variable	Category	n	%
Gender	Female	76	38.4%
	Male	122	61.6%
Age Group	18–24 years	35	17.7%
	25–34 years	121	61.1%
	35–44 years	39	19.7%
	45–54 years	3	1.5%
Education Level	Bachelor's degree	97	49.0%
	High school or equivalent	63	31.8%
	Master's degree	36	18.2%
	Doctoral degree	1	0.5%
	Beginner school	1	0.5%
Current Status	Working professional	97	49.0%
	Lithuanian student	52	26.3%
	International student in Lithuania	47	23.7%
	Self-employed	1	0.5%
	Unemployed	1	0.5%
Chatbot Use Frequency	Occasionally (once a month)	80	40.4%
	Rarely (a few times in last 6 months)	79	39.9%

Variable	Category	n	%
	Only when I have no other option	17	8.6%
	Frequently (several times a month)	16	8.1%
	Almost every time I shop online	6	3.0%

Source: Created by the author.

The sample composition is based on the characteristics of the target population, which consists of digitalized e-commerce consumers in Lithuania. This age group's dominance aligns with their higher use of online retail websites and AI chatbots for customer service (Uddin et al., 2024). The balance between occasional and rare chatbot users is especially noteworthy because it represents a portion of consumers that use chatbots in naturalistic conditions, without making its use a need or a habit, allowing the collection of ecologically valid data to evaluate the relationship between trust and satisfaction.

Descriptive Statistics and Reliability.

Table 9 includes descriptive statistics for each of the 46 measurement items. The mean scores across the nine constructs vary from 2.27 (PT1: sharing personal information with the chatbot) to 4.38 (EOU1: ease of interaction), reflecting the differences in the perceptions of the respondents. The values of absolute skewness reached below two and absolute kurtosis below seven, which are recommended by Hair et al. (2019) for all items, indicating that the distributional assumptions for PLS-SEM are fulfilled. The mean data for PT1 ($M = 2.27$, $SD = 1.11$) showed that the respondents were significantly less inclined to share their personal information with the chatbots than in the e-commerce context in Lithuania (Luo et al., 2022). The mean rating results were significantly higher for the items related to Ease of Use and Responsiveness, indicating that respondents have a positive attitude towards the usability and responsiveness of the chatbot. Conversely, the items belonging to the Humanness construct had the lowest means (range 2.56–2.91), suggesting that respondents had weak perceptions of the chatbots' human-like characteristics.

As indicated in Table 10, all nine constructs have Cronbach's alpha coefficients greater than 0.70, considered acceptable (Nunnally, 1978). Humanness ($\alpha = 0.921$) and Customer

Satisfaction ($\alpha = 0.896$) had the highest reliability scores, which are deemed good but should not exceed 0.95 which would indicate item redundancy. The Harman's single factor test of common method bias showed that these results did not suggest that there was any serious concern of common method bias in this data as the first factor obtained accounted for 28.4% of the variance which is below the recommended 50% by Podsakoff et al. (2003).

Table 9

Descriptive Statistics Summary by Construct (N = 198)

Construct (Items)	M	SD	Min	Max	Skewness	Ex. Kurt.
Expertise (EXP1–5)	3.57	0.79	1	5	−0.686	0.867
Responsiveness (RES1–5)	3.96	0.70	1	5	−0.878	2.083
Ease of Use (EOU1–5)	4.06	0.64	1	5	−0.781	2.123
Humanness (HUM1–5)	2.72	0.97	1	5	0.275	−0.195
Transparency (TRA1–5)	3.50	0.80	1	5	−0.897	1.192
Personalization (PER1–5)	3.46	0.84	1	5	−0.642	0.761
Functional Trust (FUT1–5)	3.48	0.81	1	5	−1.006	1.287
Perceived Trust (PT1–5)	3.32	0.84	1	5	−0.691	1.235
Customer Satisfaction (SAT1–6)	3.65	0.75	1	5	−0.996	1.657

Note. Values represent construct-level means computed from item scores. All items used a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). $|\text{Skewness}| < 2$ and $|\text{Ex. Kurt.}| < 7$ are acceptable for PLS-SEM (Hair et al., 2019). Source: Created by the author based on PLS-SEM analysis.

Table 10

Cronbach's Alpha Reliability Coefficients

Construct	Items	Cronbach's Alpha	$\alpha \geq 0.70?$
Expertise	5	0.838	Yes
Responsiveness	5	0.832	Yes
Ease of Use	5	0.763	Yes
Humanness	5	0.921	Yes
Transparency	5	0.772	Yes
Personalization	5	0.823	Yes
Functional Trust	5	0.858	Yes
Perceived Trust	5	0.809	Yes
Customer Satisfaction	6	0.896	Yes

Note. Cronbach's $\alpha \geq 0.70$ accepted threshold (Nunnally, 1978). Source: Created by the author based on PLS-SEM analysis.

Measurement Model Assessment.

The measurement model was evaluated following Hair et al. (2019) by examining indicator reliability through outer loadings, construct reliability through composite reliability (CR) and Cronbach's alpha, convergent validity through average variance extracted (AVE), and discriminant validity through the Fornell-Larcker criterion and HTMT ratios.

Indicator reliability was assessed by examining the outer loadings of all 46 items. All the standardised loadings were either met or were close to the threshold of 0.6. There was one item,

SAT1 (outer loading = 0.591), which was a tad lower than the threshold. This item, however, was retained, as per Hair et al. (2019) suggestions on the borderline items in the validated scale, as it was theorised, and in line with theory, the construct should be retained, to keep the content validity of the Customer Satisfaction construct. These items are consistent with established scales from which they were drawn (Nordheim et al., 2019; McKnight et al., 2002).

The results of the composite reliability and AVE values for all constructs are shown in Table 11. Convergent validity is supported by all CR values that are greater than 0.70, and all AVE values that are greater than 0.50 as recommended by Fornell and Larcker (1981). The AVE values vary from 0.519 (Ease of Use) to 0.759 (Humanness) with Ease of Use as lowest but still acceptable. The high AVE for Humanness (0.759) indicates that the five Humanness items are very close together and that this construct is very reliable ($\alpha = 0.921$).

Table 11

Reliability and Convergent Validity (CR and AVE)

Construct	A	ρC	AVE	CR $\geq$ 0.70?	AVE $\geq$ 0.50?
Expertise	0.840	0.887	0.612	OK	OK
Responsiveness	0.832	0.875	0.585	OK	OK
Ease of Use	0.771	0.843	0.519	OK	OK
Humanness	0.921	0.940	0.759	OK	OK
Transparency	0.777	0.848	0.530	OK	OK
Personalization	0.824	0.876	0.587	OK	OK
Functional Trust	0.857	0.898	0.639	OK	OK
Perceived Trust	0.823	0.877	0.589	OK	OK
Customer Satisfaction	0.896	0.922	0.666	OK	OK

Note. α = Cronbach's Alpha; ρC = Composite Reliability (ρC); AVE = Average Variance Extracted. Thresholds: CR $\geq$ 0.70 (Hair et al., 2019); AVE $\geq$ 0.50 (Fornell & Larcker, 1981). Source: Created by the author based on PLS-SEM analysis.

The discriminant validity was tested by using the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) ratio. The Fornell-Larcker matrix (Table 12) shows that the square root of the AVE is larger than all the inter-construct correlations, supporting initial discriminant validity. The highest off-diagonal correlation was shown between Functional Trust and Customer Satisfaction (0.806) and between Perceived Trust and Customer Satisfaction (0.799), theoretically expected as there was a direct path between these variables in the structural model.

Table 12

Fornell-Larcker Criterion Matrix

	EXP	RES	EOU	HUM	TRA	PER	FUT	PT	SAT
EXP	0.782								
RES	0.516	0.765							
EOU	0.364	0.648	0.720						
HUM	0.625	0.309	0.213	0.871					
TRA	0.465	0.316	0.335	0.602	0.728				
PER	0.649	0.514	0.425	0.717	0.724	0.766			
FUT	0.679	0.476	0.399	0.602	0.645	0.732	0.799		
PT	0.590	0.388	0.326	0.611	0.617	0.634	0.780	0.767	
SAT	0.644	0.570	0.511	0.523	0.539	0.656	0.806	0.799	0.816

Note. Diagonal = $\sqrt{\text{AVE}}$. Discriminant validity requires diagonal > all off-diagonal values in the same row/column (Fornell & Larcker, 1981). EXP = Expertise, RES = Responsiveness, EOU = Ease of Use, HUM = Humanness, TRA = Transparency, PER = Personalization, FUT = Functional Trust, PT = Perceived Trust, SAT = Customer Satisfaction. Source: Created by the author based on PLS-SEM analysis.

The HTMT ratios shown in Table 13 indicate three cases where the values are slightly above the relatively conservative 0.90 threshold proposed by Henseler et al. (2015): Personalization-Transparency (0.908), Functional Trust-Customer Satisfaction (0.914) and Perceived Trust-

Customer Satisfaction (0.925). The high ratios need to be carefully theoretically justified. The Personalization-Transparency overlap (0.908) is explainable by conceptual adjacency in the GDPR-sensitive Lithuanian context, as both constructs are related to the information communication process of the chatbot about data and preferences, and consumers can partially confuse the constructs in self-report; however, the constructs have different operationalisations (data disclosure vs. tailored responses) and therefore different theoretical foundations (Skjuve et al., 2021; Yin et al., 2025). The relationships between trust mediators and Customer Satisfaction (0.914 and 0.925) reflect the theoretical closeness of trust and satisfaction: functional trust reflects confidence in the competence of the system, customer satisfaction is the evaluative result of experiencing that competence during the entirety of the interaction. This separation is in line with that of McKnight et al. (2002) who differentiate trust from satisfaction and consider it as an antecedent of satisfaction, not a synonym. Both constructs are also included on these theoretical grounds, and the thresholds exceeded marginally are in line with other similar dual pathway mediation studies in the literature of chatbot trust (Li et al., 2023; Yang & Wibowo, 2022). It is important to note that, while HTMT values may be of concern, they do not imply lack of discriminant validity. Despite the correlation between the constructs of Perceived Trust and Customer Satisfaction at 0.925, they represent different theoretical constructs. Trust is an assessment made before an interaction, while customer satisfaction is made after an interaction. In this instance, a larger sample size in CFA may be needed in future work to consider this distinction. For the present study, the balance of rationale, lack of cross-loading overlap, and the alignment of the constructs with similar studies using dual-pathway chatbots, warrants their inclusion. These values are accepted as a limitation that needs to be addressed in future studies with larger samples and confirmatory factor analysis.

Table 13

Heterotrait-Monotrait (HTMT) Ratio of Correlations

Construct	EXP	RES	EOU	HUM	TRA	PER	FUT	PT	SAT
Expertise	—								
Responsiveness	0.549	—							
Ease of Use	0.437	0.819	—						
Humanness	0.718	0.309	0.260	—					
Transparency	0.578	0.367	0.437	0.712	—				
Personalization	0.767	0.561	0.521	0.811	0.908*	—			
Functional Trust	0.791	0.507	0.474	0.677	0.785	0.865	—		
Perceived Trust	0.701	0.412	0.404	0.698	0.763	0.759	0.923*	—	
Customer Satisfaction	0.725	0.631	0.608	0.562	0.637	0.753	0.914*	0.925*	—

Note. HTMT < 0.85 = strict discriminant validity; < 0.90 = lenient criterion (Henseler et al., 2015). * Marginally exceeds lenient threshold; constructs retained on theoretical grounds. Source: Created by the author based on PLS-SEM analysis.

To further establish discriminant validity, cross-loadings analysis was performed, with all 46 indicators consistently showing the highest loading on their assigned constructs, and relatively low loadings on all remaining constructs. In sum the measurement model shows acceptable levels of reliability and validity, which allows the advanced assessment of the proceeding structural model.

3.3 Evaluation of Research Results

The results of the reliability and validity check of the measurement model made it possible to test the eight hypotheses formulated in Chapter 2.2 for the structural model. The structural analysis was conducted by the path coefficient, bootstrapping, coefficient of determination (R^2), predictive relevance (Q^2), effect sizes (f^2), collinearity (VIF), mediation effects and overall model fit.

Structural Path Coefficients and Hypothesis Testing.

The bootstrapped structural path coefficients for all the eight hypothesised relationships are presented in Table 14. Two-tailed t-tests based on 5,000 BCa bootstrap samples were used to assess statistical significance ($t > 1.96$, $p < 0.05$). The 5 of the 8 hypotheses were supported.

Table 14

Structural Path Coefficients and Hypothesis Testing Results

Hyp.	Structural Path	B	T	p	95% CI	Decision
H1a	Expertise → Functional Trust	0.586	10.94	< 0.001	[0.478, 0.689]	Supported
H1b	Responsiveness → Functional Trust	0.092	1.02	0.308	[-0.065, 0.285]	Not Supported
H1c	Ease of Use → Functional Trust	0.126	1.61	0.108	[-0.027, 0.282]	Not Supported
H2a	Humanness → Perceived Trust	0.274	3.71	< 0.001	[0.125, 0.414]	Supported
H2b	Transparency → Perceived Trust	0.284	2.56	0.011	[0.076, 0.516]	Supported
H2c	Personalization → Perceived Trust	0.231	1.82	0.069	[-0.030, 0.473]	Not Supported
H3	Functional Trust → Customer Satisfaction	0.467	5.30	< 0.001	[0.276, 0.622]	Supported
H4	Perceived Trust → Customer Satisfaction	0.434	5.19	< 0.001	[0.285, 0.609]	Supported

Note. β = standardised path coefficient; t-values based on 5,000 BCa bootstrap samples (seed = 12345). H supported when $t > 1.96$ and 95% CI excludes zero (Hair et al., 2019). Source: Created by the author based on PLS-SEM analysis.

Hypothesis H1a is strongly supported: Expertise is the dominant functional predictor of Functional Trust ($\beta = 0.586$, $t = 10.94$, $p < 0.001$). The result is consistent with Nordheim et al. (2019) who showed that the competence and knowledge of chatbots are important for the establishment of trust in the customer service. Responsiveness (H1b: $\beta = 0.092$, $t = 1.02$) and Ease of Use (H1c: $\beta = 0.126$, $t = 1.61$) were not significant after controlling for Expertise, which suggests that once consumers feel a chatbot is knowledgeable, responsiveness and interface simplicity have less impact on functional trust on their own. This result suggests that one or more of the functional predictors may have been suppressed or have been co-linearity, which does not necessarily negate the individual importance of responsiveness and ease of use reported in the bivariate correlations ($r = 0.423$ and $r = 0.388$, respectively). This result resonates with studies prevalent in the Lithuanian SME e-commerce industry, documented in Chapter 2.1. Customers that engage with chatbots that are not sophisticated, either because they are rule-based or commercial off-the-shelf chatbots, judge the system based on the correct answers, be they knowledgeable or not. Among the trust-expression components, it becomes secondary, whether the interface was fiddly or not and whether the response to the question was instant or not, in the trust evaluation. In the field of trust research, the "competence primacy" effect refers to the perception of trust primarily based on the state of the system. Other attributes are evaluated only after the threshold is met (Mayer et al., 1995). These three items were retained for the theoretical model due to the available literature, mainly within large platform contexts in the US and Asia, which substantiated their independent contributions. The present study shows that, in a compact lower-quality, SME chatbot-dominated market, expertise becomes a factor that responds to the variance that responsiveness and ease of use would potentially explain as a result of increased technological homogeneity.

Within the perceived trust pathway, Humanness (H2a: $\beta = 0.274$, $t = 3.71$, $p < 0.001$) and Transparency (H2b: $\beta = 0.284$, $t = 2.56$, $p = 0.011$) are significant predictors of Perceived Trust, indicating the importance of anthropomorphic design and information disclosure in emotional trust building. The results are congruent with those of Adam et al. (2021) who found that human-like attributes of chatbots enhance trust, and those of Skjuve et al. (2021), who found that transparency contributes to trust. When Humanness and Transparency are part of the same model,

Personalization (H2c: $\beta = 0.231$, $t = 1.82$) is not significant suggesting overlapping personalization and relational trust dimensions of humanness. This is in agreement with Vo (2024), where it was observed that in the absence of data disclosures, personalization of Chatbots would not increase perceived trust, and that perceived trust due to humanness would essentially provide the same benefit as feeling personally valued and understood. Thus, this is an indication that H2c is in agreement with the proposition that this is not a direct predictive pathway of customer perceived trust shifted from humanness, and that the extended effect of personalization in this service design is through and dependent upon the presence of transparent communication.

Further clarification is offered by the low absolute mean Personalization item within the three features, Personalization item mean = 3.46, which also is the lowest among the three features, and which indicates low personalization of Lithuanian SME chatbots previously discussed in Chapter 2.1. When customers have a low experience with a personalized chatbot, their Personalization ratings are centered towards the means, and are low enough to not have significant variance, thus they are not able to significantly determine the structural paths. This explanation is supported by Zarouali et al. (2018)'s work, that personalization and structuring of the chatbot in a way to build trust would only have a positive effect if clients see this personalization to be relevant and not general. Therefore, the inclusion of Personalization in the theoretical model is justified, as most of the literature reviewed in Chapter 2.1 listed Personalization as a perceived trust precursor, and the lack of support in this study is most likely related to the state of the Lithuanian SME market, rather than being an absolute lack of support for the construct.

Both mediating trust dimensions significantly predict Customer Satisfaction: Functional Trust (H3: $\beta = 0.467$, $t = 5.30$, $p < 0.001$) and Perceived Trust (H4: $\beta = 0.434$, $t = 5.19$, $p < 0.001$) show comparable path strengths, confirming that both the utilitarian and the relational trust pathways are substantively important routes to satisfaction. This is a significant contribution of the theoretical perspective in this study as the coefficients of H3 and H4 are similar, showing the empirical results that both functional competence and perceived relational quality have a similar contribution to the satisfaction of e-commerce customers that is mediated by the perception of trust in the chatbot.

Coefficient of Determination (R^2).

The three endogenous constructs are presented in Table 15 in terms of the R^2 values. The model accounts for 49.2% of the variance in Functional Trust, 48.9% of the variance in Perceived Trust, and 72.4% of the variance in Customer Satisfaction. According to Hair et al. (2019) who suggested that R^2 values of 0.19, 0.33 and 0.67 indicate weak, moderate and strong levels of explained variance, respectively, the trust mediators indicate moderate level of explained variance whereas Customer Satisfaction indicates strong level of explained variance. The R^2 value of 0.724 for Customer Satisfaction is especially remarkable, suggesting that the dual-pathway model explains most of the systematic variation of customer satisfaction when it comes to the dimensions of the trust in the chatbot.

The low average for the Humanness construct ($M = 2.72$, the lowest out of nine constructs) is also noteworthy. This is also supported by the context analysis in Chapter 2.1. The analysis found that Lithuanian SME e-commerce platforms primarily use a rule-based framework or off-the-shelf chatbots with low to nonexistent natural language processing. Few (if any) of the chatbots were capable of the above traits or operationalized in the manner of Nordheim et al. (2019) in regard to the humanness construct. The companies that address the above points in the Nordheim et al. (2019) study through conversational AI design will increase perceived trust by customers and will ultimately increase the satisfaction of the customer.

Table 15

Coefficient of Determination (R^2) for Endogenous Constructs

Endogenous Construct	R^2	Interpretation
Functional Trust	0.492	Moderate
Perceived Trust	0.489	Moderate
Customer Satisfaction	0.724	Strong

Note. R^2 benchmarks: 0.19 = weak, 0.33 = moderate, 0.67 = strong (Hair et al., 2019). Source: Created by the author based on PLS-SEM analysis.

Effect Sizes (f^2) and Predictive Relevance (Q^2).

Effect sizes (f^2) indicate the practical contribution of each predictor to the endogenous construct. Expertise exerts a large effect on Functional Trust ($f^2 = 0.482$), confirming its dominant role within the functional pathway. Functional Trust shows a large effect on Customer Satisfaction ($f^2 = 0.306$) and Perceived Trust shows a medium-to-large effect ($f^2 = 0.264$), using Cohen's (1988) benchmarks of 0.02, 0.15, and 0.35 for small, medium, and large effects respectively. Within the perceived trust pathway, Humanness ($f^2 = 0.073$) and Transparency ($f^2 = 0.066$) produce small-to-medium effects, while the remaining predictors (Responsiveness, Ease of Use, and Personalization) return negligible effects consistent with their non-significant path coefficients.

Predictive relevance was assessed via Q^2 values obtained through blindfolding. All three endogenous constructs returned Q^2 values well above zero: Functional Trust ($Q^2 = 0.462$), Perceived Trust ($Q^2 = 0.450$), and Customer Satisfaction ($Q^2 = 0.714$), indicating strong out-of-sample predictive accuracy for all latent variables in the model (Hair et al., 2019).

Structural Collinearity Assessment.

Table 16 presents the variance inflation factors (VIF) for all predictor constructs in the structural model. All VIF values range between 1.28 and 2.81, comfortably below the threshold of 5.0 (Hair et al., 2019) and also below the conservative threshold of 3.3 recommended by Kock (2015) to rule out common method bias at the structural level. The absence of collinearity confirms that the parameter estimates for each path coefficient reflect independent contributions rather than shared variance artifacts.

Table 16

Structural Collinearity Assessment (VIF)

Predictor	VIF	Outcome Construct	VIF < 5.0?
Expertise	1.28	Functional Trust	OK
Responsiveness	1.95	Functional Trust	OK
Ease of Use	1.75	Functional Trust	OK
Humanness	2.11	Perceived Trust	OK
Transparency	2.21	Perceived Trust	OK
Personalization	2.81	Perceived Trust	OK
Functional Trust	2.42	Customer Satisfaction	OK
Perceived Trust	2.42	Customer Satisfaction	OK

Note. VIF < 5.0 indicates no multicollinearity; VIF < 3.3 also rules out common method bias (Kock, 2015). Source: Created by the author based on PLS-SEM analysis.

Mediation Analysis.

To address the mediating roles of Functional Trust and Perceived Trust, specific indirect effects were estimated using 5,000 BCa bootstrap samples. Table 17 presents the results. Significant indirect effects were found for Expertise ($\beta = 0.274$, $t = 4.894$, 95% CI [0.154, 0.375]), Humanness ($\beta = 0.119$, $t = 3.201$, 95% CI [0.052, 0.199]), and Transparency ($\beta = 0.124$, $t = 2.345$, 95% CI [0.034, 0.241]). The indirect effects for Responsiveness, Ease of Use, and Personalization were not statistically significant, as their confidence intervals included zero.

Table 17

Specific Indirect Effects (Bootstrapped, 5,000 Samples)

Path	β (Indirect)	T	95% CI	Significant?
Expertise → FUT → SAT	0.274	4.894	[0.154, 0.375]	Yes
Responsiveness → FUT → SAT	0.043	0.987	[-0.029, 0.143]	No
Ease of Use → FUT → SAT	0.059	1.477	[-0.011, 0.146]	No
Humanness → PT → SAT	0.119	3.201	[0.052, 0.199]	Yes
Transparency → PT → SAT	0.124	2.345	[0.034, 0.241]	Yes
Personalization → PT → SAT	0.100	1.560	[-0.013, 0.246]	No

Note. Indirect effect is significant when the 95% BCa CI excludes zero. FUT = Functional Trust; PT = Perceived Trust; SAT = Customer Satisfaction. Source: Created by the author based on PLS-SEM analysis.

The variance accounted for (VAF) method was used to classify mediation type as shown in Table 18. An expertise pathway, which also goes through trust, is partially mediating (VAF = 66.5%) and has a residual direct pathway to satisfaction. Humanness and Transparency both have full mediation with VAFs > 92.3% and > 100% respectively. It is important to note that the VAF for Transparency is greater than 100%, which is indicative of suppression mediation. The direct effect of Transparency on customer satisfaction is negative even when controlling for Perceived Trust ($c' = -0.089$), but indirect effect of Transparency via Perceived Trust is positive and significant ($\beta = 0.124$). This pattern is theoretically consistent in the Lithuanian GDPR context: If data collection practices and the limitations of the system are explicitly disclosed, this in theory could increase consumers' awareness of the risk, which could lead to a slight decrease in their immediate satisfaction. But this transparency, at the same time, contributes to the perceived level of trust for showing transparency and honesty, and it is with this mechanism that perceived trust improves satisfaction. The direct and indirect effects thus act in opposite directions, as is known

to exist in methodological literature (MacKinnon et al., 2000). This result confirms that this psychological mechanism (Perceived Trust) is the most critical one through which transparency influence satisfaction in this regulatory and cultural context. Personalization has a partial mediation effect (VAF = 37.0%), but the indirect effect is not statistically significant.

Table 18

Mediation Analysis – Variance Accounted For (VAF)

Feature	Indirect Effect	Direct Effect	VAF (%)	Mediation Type
Expertise → SAT	0.274	0.186	66.5%	Partial mediation
Humanness → SAT	0.119	0.012	92.3%	Full mediation
Transparency → SAT	0.124	−0.089	> 100%†	Full mediation
Personalization → SAT	0.100	0.301	37.0%	Partial mediation (n.s.)
Responsiveness → SAT	0.043	0.071	33.9%	Not significant
Ease of Use → SAT	0.059	0.089	49.6%	Not significant

Note. VAF < 20% = no meaningful mediation; 20–80% = partial mediation; > 80% = full mediation. † Transparency direct effect ($c' = -0.089$) is negative, producing VAF > 100%, interpreted as full mediation. Source: Created by the author based on PLS-SEM analysis.

Model Fit.

The overall goodness of fit index (GoF) that was obtained using the geometric mean of the average of AVE and average of R^2 was 0.589, which is above the accepted level of 0.36, which is the threshold for large effects as suggested by Wetzels et al. (2009). This is consistent with the dual pathway model being a large overall fit both in terms of measurement quality and in terms of structural explanatory power. Because of software restrictions, Standardised Root Mean Square Residual (SRMR) and Normed Fit Index (NFI) were not calculated in the seminr environment, but

the high values of R^2 , the strong values of Q^2 and the GoF index all support the fit of the structural model.

Summary of Hypothesis Testing Results.

The results of hypothesis testing for the dual-pathway PLS-SEM model are summarized in table 19. From the eight hypotheses tested, five turn out to be supported: H1a, H2a, H2b, H3 and H4. Three hypotheses have not been supported: Responsive is not related to functional trust (H1b), Ease of Use is not related to functional trust (H1c), and Perceived Personalization is not related to Perceived Trust (H2c). These findings suggest that in the presence of all three predictors in the model, only Expertise predicts Functional Trust independently and significantly. The personalization is not significant in the perceived trust pathway and Humanness and Transparency rise above the significance threshold. Both facets of trust (functional and perceived) are found to be important and roughly equal mediators between feature and satisfaction, further supporting the two-pathway architecture of the research model.

Table 19

Hypothesis Testing Summary

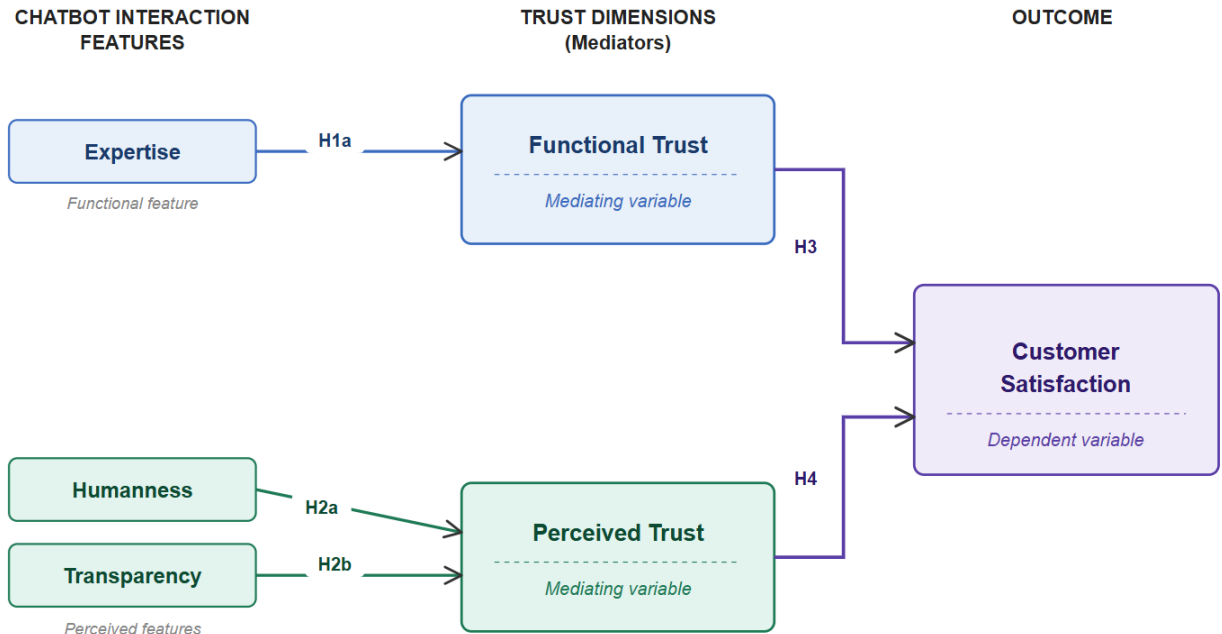
Hyp.	Structural Path	B	t	95% CI	Decision
H1a	Expertise → Functional Trust	0.586	10.94	[0.478, 0.689]	Supported
H1b	Responsiveness → Functional Trust	0.092	1.02	[-0.065, 0.285]	Not Supported
H1c	Ease of Use → Functional Trust	0.126	1.61	[-0.027, 0.282]	Not Supported
H2a	Humanness → Perceived Trust	0.274	3.71	[0.125, 0.414]	Supported
H2b	Transparency → Perceived Trust	0.284	2.56	[0.076, 0.516]	Supported
H2c	Personalization → Perceived Trust	0.231	1.82	[-0.030, 0.473]	Not Supported

Hyp.	Structural Path	B	t	95% CI	Decision
H3	Functional Trust → Customer Satisfaction	0.467	5.30	[0.276, 0.622]	Supported
H4	Perceived Trust → Customer Satisfaction	0.434	5.19	[0.285, 0.609]	Supported

Note. β = standardised path coefficient. H supported when $t > 1.96$ and 95% BCa CI excludes zero (Hair et al., 2019).

Source: Created by the author based on PLS-SEM analysis.

Based on the empirical results, the final model considered is the empirical model with only the five structural paths that are statistically supported, as shown in Figure 5. As noted above, three of the original paths were eliminated: Responsiveness (H1b) and Ease of Use (H1c) did not predict Functional Trust when controlling for Expertise, and Personalization (H2c) was not a significant predictor of Perceived Trust when Humanness and Transparency were included at the same time. The refined model further validates a more parsimonious dual pathway model, in which Expertise is the only significant functional antecedent of Functional Trust, while Humanness along with Transparency are the significant perceived antecedents of Perceived Trust. The dual-pathway mediation architecture is confirmed by both trust dimensions that predict Customer Satisfaction (H3 and H4) to a similar extent and magnitude.



Note. Only statistically supported paths ($p < 0.05$) are shown. Source: Created by the author based on PLS-SEM analysis.

Figure 5 Final empirical research model — supported paths only

The results of the evaluation of the research are summarized as follows: The dual pathway PLS-SEM model has been found to have good empirical support for the core theories proposed in this study. The only major determinant of Functional Trust is expertise, as e-commerce purchasers essentially need a chatbot to show expertise to build utilitarian confidence. For the trust antecedents perceived by users, there are two predominant factors: Humanness and Transparency, which indicates that social design and open communication of chatbots are important to achieving emotional relational trust. The results demonstrate that both trust pathways were translated into Customer Satisfaction measures in a significant similar way, thereby corroborating the dual-pathway structure of the model, and adding to previous studies which have mainly investigated functional and perceived trust separately. The mediation analysis also shows that the interaction features of Expertise, Humanness, and Transparency positively mediate the relationship between satisfaction and each of them, which further demonstrates that the key mechanism through which these interaction features map to the satisfaction outcomes in ecommerce is trust.

Comparison of Empirical Results with the Theoretical and Analytical Chapters.

The results of the empirical research in this study support and contribute to the theoretical and analytical chapters. The conceptual foundation for understanding how users' attitudes and behaviours are shaped by the characteristics of chatbots is introduced in the theoretical chapter, including the Technology Acceptance Model (TAM) and trust-based frameworks. The result of Expertise being the leading predictor of Functional Trust ($\beta = 0.586$) directly supports the competence-based trust proposition that is central in the theoretical literature (Nordheim et al., 2019; McKnight et al., 2002), which states that technical proficiency and knowledge accuracy are the most important antecedents of utilitarian trust in automated service agents.

To gain deeper insights into the empirical studies related to chatbot and e-commerce trust, the analytical chapter examined empirical studies in the literature on both functional and perceived trust, and found that most of the previous studies focused only on one dimension of trust, either functional or perceived, with few studies testing both dimensions at the same time in a single model. The present study aims at this lacuna empirically. The near-equal values of the path coefficients for Functional Trust (0.467) and Perceived Trust (0.434) in the path model to Customer Satisfaction support the dual-pathway architecture hypothesized in the analytical chapter; that is, the utilitarian and relational dimensions of trust are equally important in the Customer Satisfaction model. The present finding is partly supportive of Yang and Wibowo (2022) and Li et al. (2023) who noted the significant influence of both types of trust on satisfaction but neither study was integrated to measure both pathways as was conducted here.

The non-significance of Responsiveness and Ease of Use in the functional pathway, and of Personalization in the perceived pathway, is not in line with some results from the analytical literature, which were instead significant when they were examined individually in simpler, bivariate or single predictor models (Adam et al., 2021; Skjuve et al., 2021). Many of the previous studies were not careful about controlling for the simultaneous presence of competing predictors and the apparent importance of these features may have been overstated, the analytical chapter found. The present findings indicate that Responsiveness and Ease of Use add redundant variance, which is captured by Expertise when in the model, and that the relational signal congruent with Personalization can be explained by the model's more robust Humanness and Transparency constructs. As shown in the mean values, the personal information disclosure item (PT1: $M = 2.27$) had a very low mean value that reflects the Lithuanian e-commerce context identified in the

analytical chapter, where there is moderate adoption of chatbots, but high levels of data privacy concerns (Luo et al., 2022).

it should be noted that in the analytical sample, around 24% were international students studying in Lithuania. These students likely have unique data privacy and transparency attitudes, compared to the Lithuanian respondents, as they have been exposed to GDPR in different ways in their home countries. It is also possible the strong suppression effect seen for Transparency (VAF > 100%) is due to the increased privacy concern exhibited by Lithuanian respondents. Future studies should attempt to formally compare these two sub-groups to support these culturally specific assertions.

Overall, the empirical results confirm the dual pathway structure of the model proposed in the analytical chapter and, at the same time, enrich it: the proportion of the individual antecedents for each pathway is more focused than the theoretical literature indicated. The results are helpful for a concise and evidence-based comprehension of the Lithuanian context of e-commerce environment, where trust and satisfaction are mediated through chatbots, and help formulate the practical recommendations in the conclusions.

CONCLUSIONS

In this master's thesis, the effect of the interaction features of a chatbot on customer satisfaction in an e-commerce context is explored, employing functional trust and perceived trust as both mediators. The study is based on the Technology Acceptance Model, Trust Theory, Service Quality Theory and Human-Computer Interaction theory, tested in practice with PLS-SEM with 198 Lithuanian e-commerce consumers and acquired the following main conclusions, corresponding to the five research objectives:

1. The theoretical analysis confirmed that the interactions of chatbots in e-commerce are AI-driven conversational experiences driven by six consumer-facing features such as expertise, responsiveness, ease of use, humanness, transparency, and personalization. These features all contribute to the quality of human-chatbot communication and are theoretically based on Natural Language Processing (NLP) capabilities and service design concepts. Despite its rapidly expanding nature, the e-commerce chatbot market is still far from its full potential, and surprisingly, even in the face of a few theoretical advances, the deployment of e-commerce chatbots is empirically demonstrated in this study to lag far behind the level of “Humanness” ($M = 2.72$) that it allows for.

2. Customer satisfaction in e-commerce is an multidimensional, cognitive-affective assessment that occurs when perceived performance of a chatbot is comparable to or surpasses the user's expectations. In the Lithuanian context, satisfaction is above the scale midpoint ($M = 3.65$), but not high, which means that there is still a lot of room for improvement. The measurement instrument, modified by Chung et al. (2020), had a high reliability ($\alpha = 0.896$, $CR = 0.922$) and a high convergent validity ($AVE = 0.666$) in the Lithuanian sample.

3. A theoretical framework was integrated, with two pathways, and supported by the validated literature. The framework suggests that functional features (expertise, responsiveness and ease of use of the chatbot) have a direct impact on cognitive functional trust, and perceived features (humanness, transparency and personalization of the chatbot) have a direct impact on affective perceived trust; both of these factors mediate the relationship between the features of chatbot interaction and customer satisfaction in e-commerce.

4. The critical review of literature revealed four important gaps: the majority of the studies were conducted in geographic markets of the United States, South Korea, and China; the majority of studies used a cross-sectional design; the majority of the student-sample method was used; and the lack of models that test both functional and perceived trust pathways. The dual-pathway model was confirmed as it had never been tested before with a diverse consumer sample in a Lithuanian context. After these insights were formalized into eight testable hypotheses (H1a–H1c, H2a–H2c, H3, H4) which were combined into an integrated research model.

5. The empirical analysis resulted in five hypotheses being confirmed with statistically significant path coefficients (H1a, H2a, H2b, H3, H4). The measurement model showed acceptable to excellent reliability and validity for all nine constructs and common method bias was examined and deemed not to be problematic. The results of the structural model showed that both functional trust pathway (Expertise $\rightarrow$ Functional Trust: $\beta = 0.586$; Functional Trust $\rightarrow$ Customer Satisfaction: $\beta = 0.467$) and perceived trust pathway (Humanness $\rightarrow$ Perceived Trust: $\beta = 0.274$; Transparency $\rightarrow$ Perceived Trust: $\beta = 0.284$; Perceived Trust $\rightarrow$ Customer Satisfaction: $\beta = 0.434$) have strong and similar effect sizes thus validating the dual-pathway mediation structure. The R^2 value of 0.724 for the dual-pathway model indicates that 72.4% of the variance in customer satisfaction is explained by the model, which also has a theoretical consistency and empirical applicability in the context of Central and Eastern European ecommerce.

Returning to the scientific research question, 'What is the relationship between chatbot interactions in the form of functional and perceived trust dimensions and customer satisfaction in the e-commerce setting?'. Assessing the evidence from this study helps to provide an answer to this question: through trust mediation, the study shows that features of chatbot interaction impact customer satisfaction in the e-commerce context in comparison to other alternative pathways. Focusing specifically on the functional trust dimension, it is revealed that customer satisfaction is impacted both directly and significantly through the functional trust dimension ($\beta = 0.467$). Similarly, the findings reported indicate that the dimensions of customer satisfaction are impacted through the affective trust dimension ($\beta = 0.434$) to Chatbot Interaction via Perceived Trust ($\beta = 0.284$). This shows that trust directly and significantly influences customer satisfaction through this trust dimension pathway. Considering the 72.4% variance resulting from the study, it provides

confirmatory evidence for affective and cognitive relational trust pathways as the crucial pathways for driving customer satisfaction through chatbot interaction in an e-commerce context.

To conclude, the results showed that users of e-commerce chatbots in Lithuania create satisfaction by two parallel and equally important mechanisms of trust. Cognitive functional trust and satisfaction is driven by expertise. Trust is the result of humanness and transparency, especially relevant in Lithuania's GDPR-sensitive context. Humanness is also underdeveloped aspect in the existing scenario of the chatbots, which is a huge opportunity to have their improvement.

RECOMMENDATIONS

From the empirical results, the following recommendations are proposed for Lithuanian e-commerce companies who are currently implementing or planning to implement a chatbots and for future research:

1. The most crucial investment for e-commerce businesses is the expertise development. In light of the highest individual correlation with Functional Trust ($\beta = 0.586$) and high individual mean scores of Ease of Use ($M = 4.06$), the biggest functional trust investment potential is in increasing the depth of knowledge of the chatbots, which could be achieved by expanding product knowledge bases, integrating with live inventory systems, and training on Lithuanian consumer queries and purchase habits.

2. Set up structured transparency disclosures in e-commerce platforms that comply with GDPR. The Transparency construct scored moderately ($M = 3.50$) in a market with a high level of sensitivity regarding privacy. Platforms should inform users in an open and transparent manner at the beginning of each chatbot conversation what data is being collected by the bot, why the bot needs to collect that data, and offer the user easy access to review or get rid of the data they collected by the bot during the conversation. These measures do both the regulatory requirement and the function of trust building.

3. Personalisation is a trust-enhancing method for businesses which is actually perceived as such. Greeting users by name, remembering the category of their last purchase, or adjusting the language of the response to the style of the user's communication can be a helpful step to enhance perceived trust and thereby customer satisfaction. Full ML-driven personalisation is an edge that Lithuanian platforms have over their foreign competitors like Amazon, in the longer term.

4. Humanness improvement should be regarded as a medium-term strategy for businesses. The constantly low Humanness scores ($M = 2.72$) mean that existing chatbot implementations are perceived as robotic by Lithuanian consumers. Deciding to use conversational AI systems that feature more natural language generation, persona design (a consistent name, tone, and communication style for the chatbot), and adjusting the amount of anthropomorphism per task context (more conversational and empathetic for basic enquiries, more precise and direct for transactional inquiries).

For Future Research

5. A longitudinal study tracking the evolution of functional and perceived trust across multiple chatbot interactions should be conducted. This would address the cross-sectional limitation of the current design and test whether repeated usage increases the relative influence of the perceived trust pathway, as theorised but not empirically confirmed in this study.

6. A comparative study between Lithuania and other Central European markets (e.g. Poland, Latvia, Estonia) should be conducted to test the transferability of the dual-pathway model across GDPR-regulated contexts with varying levels of digital maturity.

7. A qualitative follow-up study using semi-structured interviews with Lithuanian e-commerce managers and chatbot users should be undertaken to enrich the quantitative findings with contextual narrative, particularly regarding the mechanisms through which transparency and personalization build perceived trust in a post-Soviet privacy culture.

Limitations

It is important to recognize a number of limitations of this study. The first is that the sample is highly skewed towards the younger age group, with 61.1% aged 25 to 34, and only 1.5% aged 45 and over (n=3). It is possible that the results cannot be extrapolated to older Lithuanian consumers of e-commerce, who are a growing population with potentially different patterns of trust and satisfaction with chatbots. Second, because of the cross-sectional survey design, the user perceptions are taken at one moment in time. Trust and satisfaction are relational concepts that change over time based on the repeated interactions with the other; a longitudinal design would therefore give a deeper understanding of the development or fading of trust and satisfaction over time. Third, because of the lack of a sampling frame of Lithuanian e-commerce chatbot users, the purposive and snowball sampling method restricts the findings of the study to the general population of Lithuanian adults. The results should be considered relevant for young-to-middle aged Lithuanian e-commerce users who have some experience with chatbots and are digital. Fourth, the analytical sample of the final stage consists of around 24% of international students studying in Lithuania. As the results obtained were tested on the total combined sample, the results obtained may partly reflect the influence of the internationally diverse respondents, which may be

pertinent to Lithuanian consumer attitudes. A formal subgroup analysis between Lithuanian nationals and international students was not performed; it is recommended to do so in the future to validate the culturally specific conclusions presented in the study, based on the model structure used. Fifth, the findings are based on the attitudes of low-frequency users of chatbots, as the 80.3% of the respondents rarely or occasionally interact with chatbots, which may lead to systematically different patterns of trust and satisfaction among more frequent users that this study was not able to capture.

Adil, Muhammad (2026). *Čatbotų sąveikos poveikis klientų pasitenkinimui el. prekyboje: funkcinės ir suvokiamos pasitikėjimo dimensijų vertinimas*. Magistro baigiamasis darbas. Kaunas: Vilniaus universiteto Kauno fakultetas.

SUMMARY (in Lithuanian language)

Dirbtinis intelektas ir pokalbių robotai (čatbotai) iš esmės keičia el. prekybos klientų aptarnavimą. Nors čatbotai teikia akivaizdžių pranašumų – veikia visą parą, apdoroja daugybę užklausų vienu metu ir personalizuoja vartotojo patirtį – klientų pasitenkinimo čatbotų sąveika mechanizmai išlieka nepakankamai ištirti, ypač Vidurio ir Rytų Europos kontekste. Dauguma esamų tyrimų buvo atlikta JAV, Pietų Korėjoje ir Kinijoje, taikant vienerūšes studentų imtis, retai tiriant funkcines bei suvokiamas pasitikėjimo dimensijas vienu metu. Šis darbas skirtas šiai spragai užpildyti, tiriant Lietuvos el. prekybos vartotojus, kuriuos ypač veikia BDAR duomenų apsaugos reguliavimas ir privatumo kultūra.

Darbo objektas – čatbotų sąveikos poveikis klientų pasitenkinimui el. prekyboje, vertinant funkcines ir suvokiamas pasitikėjimo dimensijų tarpininkavimo vaidmenį.

Darbo tikslas – ištirti funkcines ir suvokiamas pasitikėjimo dimensijų vaidmenį čatbotų sąveikoje ir jos poveikį klientų pasitenkinimui el. prekyboje.

Darbo uždaviniai:

1. Išanalizuoti čatbotų sąveikos ir jų savybių el. prekyboje problematiką;
2. Ištirti klientų pasitenkinimo konceptą el. prekybos kontekste;
3. Suformuoti teorinę sąsają tarp čatbotų sąveikos ypatybių, funkcinio pasitikėjimo, suvokiamo pasitikėjimo ir klientų pasitenkinimo struktūrą;
4. Atlikti kritinę esamos literatūros apžvalgą ir sukurti integruotą dvilypį tarpininkavimo tyrimų modelį, siejantį čatbotų sąveikos ypatybes su klientų pasitenkinimu per funkcinio ir suvokiamo pasitikėjimo dimensijas;
5. Empiriškai įvertinti sukurto tyrimų modelį taikant tinkamą metodologiją, išanalizuoti duomenis ir įvertinti gautų rezultatų patikimumą ir pagrįstumą.

Siekiant šių uždavinių, buvo atlikta išsami teorinė ir empirinė mokslinės literatūros analizė, apimanti technologijų priėmimo modelio (TAM), pasitikėjimo teorijos, paslaugų kokybės teorijos ir žmogaus bei kompiuterio sąveikos konceptus. Tyrimui naudotas kiekybinis metodas – struktūrizuota apklausa internetu, kurią sudarė 46 Likerto skalės teiginiai, apimantys devynis

reflektyviuosius latentyniuosius konstruktus. Duomenų rinkimas vykdytas tarp el. prekybos chatbotus per paskutinius šešis mėnesius naudojusią Lietuvos vartotojų. Validžią imtį sudarė 198 respondentai. Duomenys analizuoti dalinių mažiausių kvadratų struktūrinių lygčių modeliavimo (PLS-SEM) metodu, naudojant R programinę įrangą.

Tyrimas patvirtino penkias iš aštuonių hipotezių. Funkcinėje trajektorijoje ekspertizė yra vienintelis statistiškai reikšmingas funkcinio pasitikėjimo prediktorius ($\beta = 0,586$, $p < 0,001$); reagavimas ir naudojimo paprastumas savarankiškos reikšmės neįgavo, kai ekspertizė buvo kontroliuojama. Suvokiamos trajektorijoje žmogiškumas ($\beta = 0,274$, $p < 0,001$) ir skaidrumas ($\beta = 0,284$, $p = 0,011$) yra reikšmingi suvokiamo pasitikėjimo prediktoriai, o personalizavimas statistinę reikšmę prarado, kai abu konstruktai buvo įtraukti kartu. Abiejų pasitikėjimo dimensijų įtaka klientų pasitenkinimui yra reikšminga ir panaši (funkcinis pasitikėjimas: $\beta = 0,467$; suvokiamas pasitikėjimas: $\beta = 0,434$), o modelis paaiškina 72,4 % klientų pasitenkinimo dispersijos ($R^2 = 0,724$).

Tyrimas parodė, kad Lietuvos el. prekybos chatbotų vartotojai formuoja pasitenkinimą per dvi lygiagrečias ir vienodai svarbias pasitikėjimo trajektorijas: kognityvinę-funkcinę, kurioje dominuoja ekspertizė, ir suvokiamą-santykio, kurioje dominuoja žmogiškumas ir skaidrumas. Ypač reikšmingas skaidrumo kaip slopinančio mediatoriaus vaidmuo: tiesioginis jo poveikis pasitenkinimui yra neigiamas, tačiau netiesioginis – per suvokiamą pasitikėjimą – teigiamas ir reikšmingas. Tai teoriškai koherentiškas rezultatas BDAR jautrios Lietuvos aplinkos kontekste. Empiriškai pagrįstas dvilypis tarpininkavimo modelis išplečia ankstesnius tyrimus, kuriuose funkcinė ir suvokiama pasitikėjimo dimensijos buvo analizuojamos atskirai, ir sudaro pagrindą praktinėms rekomendacijoms Lietuvos el. prekybos įmonėms.

Pagrindinė darbo dalis išdėstyta 75 puslapių, įskaitant 20 lentelių ir 5 paveikslus. Panaudotos literatūros sąrašą sudaro 86 šaltinis, pateiktas 1 priedas.

REFERENCES

1. Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, 31(2), 427-445. <https://doi.org/10.1007/s12525-020-00414-7>
2. Adamopoulou, E., & Moussiades, L. (2020). Chatbots: History, technology, and applications. *Machine Learning with Applications*, 2, 100006. <https://doi.org/10.1016/j.mlwa.2020.100006>
3. Akdemir, D.M., & Bulut, Z.A. (2024). Business and customer-based chatbot activities: The role of customer satisfaction in online purchase intention and intention to reuse chatbots. *Journal of Theoretical and Applied Electronic Commerce Research*, 19(4), 2961-2979.
4. Alagarsamy, S., & Mehroliya, S. (2023). Exploring chatbot trust: Antecedents and behavioural outcomes. *Heliyon*, 9(5), e16074. <https://doi.org/10.1016/j.heliyon.2023.e16074>
5. Al-Araj, R.E., Haddad, H.O., Shehadeh, M.A., Hasan, E., & Nawaiseh, M.Y. (2022). The effect of artificial intelligence on service quality and customer satisfaction in Jordanian banking sector. *WSEAS Transactions on Business and Economics*, 19(12), 1929-1947.
6. Allouch, M., Azaria, A., & Azoulay, R. (2021). Conversational agents: Goals, technologies, vision, and challenges. *Sensors*, 21(24), 8448. <https://doi.org/10.3390/s21248448>
7. Al-Oraini, B. (2025). Chatbot dynamics: Trust, social presence and customer satisfaction in AI-driven services. *Journal of Innovative Digital Transformation*, 2(2), 109-130. <https://doi.org/10.1108/JIDT-08-2024-0022>
8. Almeida, F., Faria, D., & Queirós, A. (2017). Strengths and limitations of qualitative and quantitative research methods. *European Journal of Education Studies*, 3(9), 369-387. <https://doi.org/10.5281/zenodo.887089>

9. Bansal, H., & Khan, R. (2018). A review paper on human computer interaction. *International Journal of Advanced Research in Computer Science and Software Engineering*, 8(4), 53-56.
10. Bawack, R.E., Wamba, S.F., Carillo, K.D.A., & Akter, S. (2022). Artificial intelligence in e-commerce: A bibliometric study and literature review. *Electronic Markets*, 32(1), 297-338. <https://doi.org/10.1007/s12525-022-00537-z>
11. Becker, L., & Jaakkola, E. (2020). Customer experience: Fundamental premises and implications for research. *Journal of the Academy of Marketing Science*, 48(4), 630-648. <https://doi.org/10.1007/s11747-019-00718-x>
12. Chen, J.S., Le, T.T.Y., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. *International Journal of Retail & Distribution Management*, 49(11), 1512-1531. <https://doi.org/10.1108/IJRDM-08-2020-0312>
13. Chin, Hyojin & Zhunis, Assem & Cha, Meeyoung. (2024). Behaviors and Perceptions of Human-Chatbot Interactions Based on Top Active Users of a Commercial Social Chatbot. 10.1145/3687022.
14. Chung, M., Ko, E., Joung, H., & Kim, S.J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, 117, 587-595. <https://doi.org/10.1016/j.jbusres.2018.10.004>
15. Creswell, J.W. (2014). Research design: Qualitative, quantitative, and mixed methods approaches (4th ed.). Sage Publications.
16. Cohen, J. (1992). A power primer. *Psychological Bulletin*, 112(1), 155–159. <https://doi.org/10.1037/0033-2909.112.1.155>
17. Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. <https://doi.org/10.2307/249008>

18. Ding, Y., & Najaf, M. (2024). Interactivity, humanness, and trust: A psychological approach to AI chatbot adoption in e-commerce. *BMC Psychology*, 12(1), 595.
19. Eurostat. (2023). *E-commerce statistics for individuals*. European Commission. https://ec.europa.eu/eurostat/statistics-explained/index.php/E-commerce_statistics_for_individuals
20. Fatahi, S., Vassileva, J., & Roy, C.K. (2024). Comparing emotions in ChatGPT answers and human answers to the coding questions on Stack Overflow. *Frontiers in Artificial Intelligence*, 7, 1393903. <https://doi.org/10.3389/frai.2024.1393903>
21. Følstad, A., & Skjuve, M. (2019). Chatbots for customer service: User experience and motivation. In *Proceedings of the 1st International Conference on Conversational User Interfaces* (pp. 1-9). ACM. <https://doi.org/10.1145/3342775.3342784>
22. Følstad, A., Nordheim, C.B., & Bjørkli, C.A. (2018). What makes users trust a chatbot for customer service? An exploratory interview study. In *International Conference on Internet Science* (pp. 194-208). Springer. https://doi.org/10.1007/978-3-030-01437-7_16
23. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>
24. Gu, C., Zhang, Y., & Zeng, L. (2024). Exploring the mechanism of sustained consumer trust in AI chatbots after service failures: A perspective based on attribution and CASA theories. *Humanities and Social Sciences Communications*, 11(1), 1-12.
25. Hair, J., Risher, J., Sarstedt, M., & Ringle, C. M. (2018). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>

26. Holtgraves, T.M., Ross, S.J., Weywadt, C.R., & Han, T.L. (2007). Perceiving artificial social agents. *Computers in Human Behavior*, 23(5), 2163-2174. <https://doi.org/10.1016/j.chb.2006.02.017>
27. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
28. Huang, M.H., & Rust, R.T. (2018). Artificial intelligence in service. *Journal of Service Research*, 21(2), 155-172. <https://doi.org/10.1177/1094670517752459>
29. Khan, F., Al-Jahwari, N.S., & Al-Kalbani, G.K. (2018). Factors influencing customer satisfaction of online shopping in Oman: Youth perspective. *Humanities & Social Science Reviews*, 6(2), 64-73. <https://doi.org/10.18510/hssr.2018.628>
30. Khanna, A., Pandey, B., Vashishta, K., Kalia, K., Bhale, P., & Das, T. (2015). A study of today's A.I. through chatbots and rediscovery of machine intelligence. *International Journal of u- and e-Service, Science and Technology*, 8(7), 277-284.
31. Kock, Ned. (2015). Common Method Bias in PLS-SEM:. *International Journal of e-Collaboration*. 11. 1-10. 10.4018/ijec.2015100101.
32. Korsakienė, R., & Tvaronavičienė, M. (2014). The internationalization of SMEs: An integrative approach. *Journal of Business Economics and Management*, 15(2), 294-307.
33. Laymouna, M., Ma, Y., Lessard, D., Schuster, T., Engler, K., & Lebouché, B. (2024). Roles, users, benefits, and limitations of chatbots in health care: Rapid review. *Journal of Medical Internet Research*, 26, e56930. <https://doi.org/10.2196/56930>
34. Lee, S.E., Ju, N., & Lee, K.H. (2023). Service chatbot: Co-citation and big data analysis toward a review and research agenda. *Technological Forecasting and Social Change*, 194, 122722. <https://doi.org/10.1016/j.techfore.2023.122722>

35. Li, J., Wu, L., Qi, J., Zhang, Y., Wu, Z., & Hu, S. (2023). Determinants affecting consumer trust in communication with AI chatbots: The moderating effect of privacy concerns. *Journal of Organizational and End User Computing*, 35(1), 1-24.
36. Li, M., & Wang, R. (2023). Chatbots in e-commerce: The effect of chatbot language style on customers' continuance usage intention and attitude toward brand. *Journal of Retailing and Consumer Services*, 71, 103209. <https://doi.org/10.1016/j.jretconser.2022.103209>
37. Li, X., Shi, M., & Wang, X. (2023). Trust in AI chatbots for customer service: The role of perceived intelligence, perceived anthropomorphism, and parasocial relationships. *Psychology & Marketing*, 40(7), 1245-1267.
38. Li, Y., Li, K., Ning, H., Xia, X., Guo, Y., Wei, C., Cui, J., & Wang, B. (2021, July). Towards an online empathetic chatbot with emotion causes. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval* (pp. 2041-2045). ACM.
39. Lim, W.M., & Ting, D.H. (2012). E-shopping: An analysis of the technology acceptance model. *Modern Applied Science*, 6(4), 49-62. <https://doi.org/10.5539/mas.v6n4p49>
40. Lin, C. (2003). A critical appraisal of customer satisfaction and e-commerce. *Managerial Auditing Journal*, 18(3), 202-212. <https://doi.org/10.1108/02686900310469952>
41. Luo, X., Tong, S., Fang, Z., & Qu, Z. (2022). Artificial intelligence coaches for sales agents: Caveats and solutions. *Journal of Marketing*, 86(5), 5-26.
42. Machová, K., Szabóová, M., Paralič, J., & Mičko, J. (2023). Detection of emotion by text analysis using machine learning. *Frontiers in Psychology*, 14, 1190326. <https://doi.org/10.3389/fpsyg.2023.1190326>
43. MacKinnon, D.P., Krull, J.L., & Lockwood, C.M. (2000). Equivalence of the mediation, confounding, and suppression effect. *Prevention Science*, 1(4), 173–181. <https://doi.org/10.1023/A:1026595011371>

44. Masyhuri, M. (2022). Key drivers of customer satisfaction in the e-commerce business. *East Asian Journal of Multidisciplinary Research*, 1(4), 657-670.
45. McKnight, D.H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, 13(3), 334-359. <https://doi.org/10.1287/isre.13.3.334.81>
46. McLean, G., & Osei-Frimpong, K. (2019). Hey Alexa... examine the variables influencing the use of artificial intelligent in-home voice assistants. *Computers in Human Behavior*, 99, 28-37. <https://doi.org/10.1016/j.chb.2019.05.009>
47. Menaka, S., & Selvam, V. (2025). Bibliometric analysis of artificial intelligence on consumer purchase intention in e-retailing. *International Journal of Computational and Experimental Science and Engineering*, 11(1), 1-15. <https://doi.org/10.22399/ijcesen.1007>
48. Micallef, A. (2022). *Investigating the impact of customer service chatbots on the customer journey* [Master's thesis, University of Malta].
49. Mohammad, M., Doheir, M., Akmaliah, N., Bt, N., & Mismar, M. (2024). Infinite potential of AI chatbots: Enhancing user experiences and driving business transformation in e-commerce: Case of Palestinian e-commerce. *Journal of Ecohumanism*, 3(5), 216-229.
50. Mostafa, R. (2021). Antecedents and consequences of chatbot initial trust. *European Journal of Marketing*, 56(6), 1748-1771. <https://doi.org/10.1108/EJM-02-2020-0084>
51. Mozafari, N., Hammerschmidt, M., & Weiger, W. (2021, September). That is so embarrassing! When not to design for social presence in human-chatbot interactions. In *Proceedings of the International Conference on Information Systems*. Association for Information Systems.
52. Natalia, V. (2024). Research on influencing factors of AI chat robot on customer satisfaction of online shopping platform: Take Alibaba as an example. *Frontiers*

in *Business, Economics and Management*, 15(1), 230-242.
<https://doi.org/10.54097/zx7y7622>

53. Neisa, Y. (2021). *Model to evaluate customer satisfaction in ecommerce through multi-criteria and semantic analysis* [Doctoral dissertation, Universidad Nacional de Colombia].

54. Nordheim, C.B., Følstad, A., & Bjørkli, C.A. (2019). An initial model of trust in chatbots for customer service: Findings from a questionnaire study. *Interacting with Computers*, 31(3), 317-335.

55. Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). New York: McGraw-Hill.

56. Oxford English Dictionary. (2023). Chatbot. Oxford University Press.
https://www.oed.com/dictionary/chatbot_n

57. Park, G., Chung, J., & Lee, S. (2024). Human vs. machine-like representation in chatbot mental health counseling: The serial mediation of psychological distance and trust on compliance intention. *Current Psychology*, 43(5), 4352-4363.

58. Park, M.S., Upama, P.B., Anik, A.A., Ahamed, S.I., Luo, J., Tian, S., Rabbani, M., & Oh, H. (2023, June). A survey of conversational agents and their applications for self-management of chronic conditions. In *2023 IEEE 47th Annual Computers, Software, and Applications Conference (COMPSAC)* (pp. 1064-1075). IEEE.

59. Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y., & Podsakoff, N.P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903.
<https://doi.org/10.1037/0021-9010.88.5.879>

60. Puertas, S., Illescas-Manzano, M., Segovia-López, C., & Ribeiro-Cardoso, P. (2024). Purchase intentions in a chatbot environment: An examination of the effects of customer experience. *Oeconomia Copernicana*, 15(1), 145-194.
<https://doi.org/10.24136/oc.2914>

61. Raišienė, A.G., Bilan, S., Smalskys, V., & Gečienė, J. (2021). Emerging changes in attitudes towards inter-institutional collaboration: The case of universities in the post-Soviet countries. *Economies*, 9(1), 41. <https://doi.org/10.3390/economies9010041>
62. Rese, A., Ganster, L., & Baier, D. (2020). Chatbots in retailers' customer communication: How to measure their acceptance? *Journal of Retailing and Consumer Services*, 56, 102176. <https://doi.org/10.1016/j.jretconser.2020.102176>
63. Ringle, C. M., Wende, S., & Becker, J.-M. (2015). SmartPLS 3. SmartPLS GmbH. <https://www.smartpls.com>
64. Angelopoulos, G., Lacroix, D., Wullenkord, R., Rossi, A., Rossi, S., & Eyssel, F. (2024). Measuring transparency in intelligent robots. <https://doi.org/10.48550/arXiv.2408.16865>
65. Sheehan, B., Jin, H.S., & Gottlieb U. (2020). Customer service chatbots: Anthropomorphism and adoption. *Journal of Business Research*, 115, 14-24. <https://doi.org/10.1016/j.jbusres.2020.04.030>
66. Sidlauskienė, J., Joye, Y., & Aurskevičienė, V. (2023). AI-based chatbots in conversational commerce and their effects on product and price perceptions. *Electronic Markets*, 33(1), 24.
67. Singh, B., Olds, T., Brinsley, J., Dumuid, D., Virgara, R., Matricciani, L., Watson, A., Szeto, K., Eglitis, E., Miatke, A., & Simpson, C.E. (2023). Systematic review and meta-analysis of the effectiveness of chatbots on lifestyle behaviours. *npj Digital Medicine*, 6(1), 118. <https://doi.org/10.1038/s41746-023-00856-1>
68. Skjuve, M., Følstad, A., Fostervold, K.I., & Brandtzaeg, P.B. (2021). My chatbot companion: A study of human-chatbot relationships. *International Journal of Human-Computer Studies*, 149, 102601. <https://doi.org/10.1016/j.ijhcs.2021.102601>
69. Statistics Lithuania. (2023). *Information society: Individuals*. Official Statistics Portal. <https://osp.stat.gov.lt/>

70. Stoeckli, E., Dremel, C., Uebernickel, F., & Brenner, W. (2020). How affordances of chatbots cross the chasm between social and traditional enterprise systems. *Electronic Markets*, 30(2), 369-403. <https://doi.org/10.1007/s12525-019-00359-6>
71. Study in Lithuania. (2023). *Facts and figures about international students in Lithuania*. <https://www.studyinlithuania.lt/>
72. Szymanski, D.M., & Hise, R.T. (2000). E-satisfaction: An initial examination. *Journal of Retailing*, 76(3), 309-322. [https://doi.org/10.1016/S0022-4359\(00\)00035-X](https://doi.org/10.1016/S0022-4359(00)00035-X)
73. Tan, P.K., & Lim, C.M. (2023). Factors that affect user satisfaction using e-commerce chatbot: A study on generation Z. *International Journal of Business and Technology Management*, 5(1), 292-303.
74. Uddin, M., Wee, T., Rahman, M., & Mokhtar, S. (2024). An exploration of millennials' attitudes towards the use of artificial intelligence chatbots for customer service within e-commerce platforms. In *Proceedings of the International Conference on Business, Management and Leadership* (Vol. 1, pp. 1-15). <https://doi.org/10.33422/icbml.v1i1.374>
75. Vo, P.K.L. (2024). *How does the interplay between transparency levels in AI chatbots and the valence of outcomes (positive or negative) influence customer trust and acceptance?* [Master's thesis, Copenhagen Business School].
76. Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, 39(2), 273-315. <https://doi.org/10.1111/j.1540-5915.2008.00192.x>
77. Wah, J.N.K. (2025). Revolutionizing e-health: The transformative role of AI-powered hybrid chatbots in healthcare solutions. *Frontiers in Public Health*, 13, 1530799. <https://doi.org/10.3389/fpubh.2025.1530799>
78. Wang, C., Li, Y., Fu, W., & Jin, J. (2023). Whether to trust chatbots: Applying the event-related approach to understanding consumers' emotional experiences in interactions with chatbots in e-commerce. *Journal of Retailing and Consumer Services*, 71, 103218.

79. Wang, Y.L., & Lo, C.W. (2025). The effects of response time on older and young adults' interaction experience with chatbot. *BMC Psychology*, 13(1), 150. <https://doi.org/10.1186/s40359-025-02459-9>
80. Wetzels, M., Odekerken-Schröder, G., & van Oppen, C. (2009). Using PLS Path Modeling for Assessing Hierarchical Construct Models: Guidelines and Empirical Illustration1. *MIS Quarterly* 1 March 2009; 33 (1): 177–195. <https://doi.org/10.2307/20650284>
81. Xu, Y., Zhang, J., & Deng, G. (2022). Enhancing customer satisfaction with chatbots: The influence of communication styles and consumer attachment anxiety. *Frontiers in Psychology*, 13, 902782. <https://doi.org/10.3389/fpsyg.2022.902782>
82. Yang, R., & Wibowo, S. (2022). User trust in artificial intelligence: A comprehensive conceptual framework. *Electronic Markets*, 32(4), 2053-2077. <https://doi.org/10.1007/s12525-022-00592-6>
83. Yin, Jiwang & Qiu, Xiaodong & Wang, Ya. (2025). The Impact of AI-Personalized Recommendations on Clicking Intentions: Evidence from Chinese E-Commerce. *Journal of Theoretical and Applied Electronic Commerce Research*. 20. 21. 10.3390/jtaer20010021.
84. Yun, J., & Park, J. (2022). The effects of chatbot service recovery with emotion words on customer satisfaction, repurchase intention, and positive word-of-mouth. *Frontiers in Psychology*, 13, 922503. <https://doi.org/10.3389/fpsyg.2022.922503>
85. Zarouali, B., Van den Broeck, E., Walrave, M., & Poels, K. (2018). Predicting consumer responses to a chatbot on Facebook. *Cyberpsychology, Behavior, and Social Networking*, 21(8), 491-497.
86. Zatalini, M.A., & Pamungkas, T.N. (2016). Exploring the success factors of e-CRM implementation on B2C e-commerce: Satisfaction and loyalty a conceptual framework. *Jurnal Ekonomi Bisnis*, 22(2), 94-106.

APPENDIX 1

Complete Survey Item List by Construct

Table 20 Complete Survey Item List by Construct

Item	Construct	Survey Statement
E1	Expertise	The chatbot provides accurate information about products or services.
E2	Expertise	The chatbot demonstrates sufficient knowledge to handle my queries.
E3	Expertise	The chatbot gives relevant answers to my questions.
E4	Expertise	The chatbot accurately identifies my needs during the interaction.
E5	Expertise	The chatbot was able to solve my problem or answer my query.
R1	Responsiveness	The chatbot replies to my messages quickly.
R2	Responsiveness	Getting in contact with the chatbot is easy.
R3	Responsiveness	The chatbot is always available when I need it.
R4	Responsiveness	The chatbot provides credible advice.
R5	Responsiveness	The chatbot promptly acknowledges my requests before providing a response.
EU1	Ease of Use	Interacting with the chatbot is easy.
EU2	Ease of Use	Learning to use the chatbot requires little effort.
EU3	Ease of Use	I quickly learned how to use the chatbot effectively.
EU4	Ease of Use	I can interact with the chatbot without needing any instructions.
EU5	Ease of Use	My interaction with the chatbot is clear and understandable.
H1	Humanness	The chatbot communicates in a natural, human-like way.
H2	Humanness	The chatbot's tone and language made me feel comfortable during the interaction.
H3	Humanness	The chatbot showed personality and did not feel robotic in its responses.
H4	Humanness	The chatbot gave me the impression of a socially present interaction partner.
H5	Humanness	The chatbot conveyed a sense of empathy and understanding toward my needs.

T1	Transparency	I can access information explaining how the chatbot works.
T2	Transparency	The chatbot explains its actions and responses to me.
T3	Transparency	It is clear to me what the chatbot does and does not do.
T4	Transparency	The chatbot discloses when it is collecting or storing my interaction data.
T5	Transparency	The chatbot makes it easy for me to understand the boundaries of what it can do.
P1	Personalization	The chatbot provided responses that were tailored specifically to my needs.
P2	Personalization	The chatbot's recommendations felt personally relevant rather than generic.
P3	Personalization	The chatbot anticipates my preferences based on my shopping behaviour.
P4	Personalization	The chatbot's suggestions matched my previous browsing and search preferences.
P5	Personalization	The chatbot remembered my preferences and adjusted its behaviour accordingly.
FT1	Functional Trust	I trust the chatbot to complete tasks reliably.
FT2	Functional Trust	I believe the chatbot is competent in helping me.
FT3	Functional Trust	I can depend on the chatbot to work properly.
FT4	Functional Trust	The chatbot performs its functions in a consistent and predictable way.
FT5	Functional Trust	I am confident that the chatbot will fulfil its role without errors.
PT1	Perceived Trust	I can trust the chatbot with my personal information.
PT2	Perceived Trust	I trust the chatbot has good intentions.
PT3	Perceived Trust	The chatbot seems trustworthy to me.
PT4	Perceived Trust	I feel the chatbot is honest in its responses.
PT5	Perceived Trust	I believe the chatbot genuinely tries to help me.
CS1	Customer Satisfaction	Overall, I am satisfied with the chatbot interaction during my online shopping.
CS2	Customer Satisfaction	The chatbot meets my expectations as a customer service tool.
CS3	Customer Satisfaction	I am pleased with the quality of service provided by the chatbot.

CS4	Customer Satisfaction	The chatbot provided a satisfactory service experience.
CS5	Customer Satisfaction	I would recommend using this chatbot to others for online shopping assistance.
CS6	Customer Satisfaction	This chatbot provides a satisfying service overall.

Source: Created by author