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Analysis of Chatbot technology and Associated Problems of Human-Machine Interactions

Master's Thesis

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VESTLUSBOTI TEHNOLOOGIA JA PROBLEEMID INIMESE-MASINA SUHTLUSES

Lõputöö liik: magistritöö

Juhendaja
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Author’s declaration of originality

I hereby certify that I am the sole author of this thesis. All the used materials, references to the literature and the work of others have been referred to. This thesis has not been presented for examination anywhere else.

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Abstract

In scope of this thesis author investigated issues of the implementation of chatbot technologies into the work processes of the technical support service, the problems associated with it and leading technologies in this domain. The purpose of this thesis is to understand what factors influence the negative experience of human-bot communication, as well as to assess the minimum resources needed for the implementation of chatbot technology and the payback period of the chatbot implementation project to the support team in Kühne+Nagel.

The results of the analysis of academic research have shown the main problems associated with human-machine communication. Incorrect chatbot design, lack of "intelligence" and "humanity", incorrect choice of subject area, insufficient training of the chatbot in new communication scenarios are the main problems in human-machine interaction that can lead to a negative perception of chatbot technologies.

The analysis of popular chatbot development platforms and machine learning technologies allowed us to determine the main chatbot technologies and requirements for development platforms. Platform Boost.ai was selected for the implementation in the workflows of the technical support service. The analysis of the main factors and their quality attributes affecting the user experience of a person communicating with a chatbot is carried out. A questionnaire has been developed to assess the experience of communication between KN employees and the chatbot of the technical support service. A survey of the company's employees was conducted and its results were analyzed. The analysis of the survey results allowed us to answer questions about the factors contributing to bias and perceived negative perception of chatbots by users, as well as how we can increase confidence in high-tech communications.

Calculations of ROI parameters allowed us to determine the minimum resources required for the technology implementation to the support team and expected expected payback period.

This thesis is written in English and occupies 59 pages, including 6 chapters, 11 figures and 10 tables.

Annotatsioon

Käesoleva lõputöö raames uuris autor vestlusboti-tehnoloogiate juurutamise küsimusi tehnilise toe talituse tööprotsessidesse, sellega kaasnevatesse probleemidesse ja selle valdkonna juhtivaid tehnoloogiad. Selle lõputöö eesmärk on mõista, millised tegurid mõjutavad inimese ja masina suhtluse negatiivset kogemust, samuti hinnata vestlusbotide tehnoloogia rakendamiseks vajalikud minimaalsed ressursid ja vestlusboti juurutamise projekti tasuvusaeg tugimeeskonnale Kühne+Nagelis.

Akadeemiliste uuringute analüüsi tulemused on näidanud peamised sellega seotud probleemid inimese ja masina suhtlusega. Ebakorrektne chatboti disain, "intelligentsuse" puudumine ja "inimlikkus", vale ainevalik, vestlusroboti ebapiisav koolitus uues kommunikatsioonistsenaariumis - need on peamised probleemid inimese ja masina vahelises suhtluses, mis võivad viia vestlusrobotite tehnoloogiate negatiivse arusaamani.

Populaarsete vestlusrobotite arendusplatvormide ja masinõppetehnoloogiate analüüs võimaldas meil määrata peamised vestlusrobotite tehnoloogiad ja arendusnõuded platvormidele. Platvorm Boost.ai valiti tehnilise toe teenuse töövoogudes juurutamiseks. Analüüsiti peamisi tegureid ja nende kvaliteeditunnuseid, mis mõjutavad vestlusbotiga suhtleva inimese kasutuskogemust. Oli välja töötatud küsimustik hindamaks suhtluskogemust KN-i töötajate ja tehnilise toe teenuse chatbot vahel. Ettevõtte küsitlus töötajatele viidi läbi ja selle tulemusi analüüsiti. Küsitluse tulemuste analüüs võimaldas meil vastata küsimustele eelarvamusi soodustavate ja negatiivsete tegurite kohta kasutajate arusaama vestlusrobotitest, samuti seda, kuidas saame suurendada usaldust kõrgtehnoloogia vastu.

ROI parameetrite arvutamine võimaldas meil määrata minimaalsed vajalikud ressursid tehnoloogia juurutamiseks tugimeeskonnale ja eeldatava tasuvuse perioodi.

Lõputöö on kirjutatud inglise keeles ning sisaldab teksti 58 leheküljel, sealhulgas 6 peatükki, 11 joonist, 10 tabelit.

List of abbreviations and terms

A.L.I.C.E.	Artificial Linguistic Internet Computer Entity
AI	Artificial Intelligence
AIML	Artificial Intelligence Markup Language
ANOVA	Analysis of variance
API	Application Programming Interface
ASU	Automatic Semantic Understanding
BI	Business Intelligence
CBR	Cased-Based Reasoning
CF	Cash Flow
CMC	Computer-Mediated Communication
CNN	Convolutional Neural Network
COVID-19	Coronavirus disease
CRM	Customer Relationship Management
DCF	Discounted Cash Flow
FAQ	Frequently Asked Question
GPT	Generative Pre-Trained Transformer
GRU	Gated Recurrent Unit
HCI	Human–Computer Interaction
HCMS	Human Capital Management System
HR	Human Resources
IC	Invest Capital
IM	Instant Messaging
IoT	Internet of Things
IPC	Interpersonal Communication
KN	Kühne+Nagel
KPI	Key Performance Indicator
LSTM	Long Short-Term Memory
MIT	Massachusetts Institute of Technology
ML	Machine Learning
NLP	Natural Language Processing
NLU	Natural Language Understanding

NN	Neural Networks
NPS	Net Promoter Score
OPI	Operations Procedure Instruction
PA	Personal Assistant
PaaS	Platform as a Service
PLS	Partial Least Square
PP	Pay-Back Period
PPR	Performance and Potential Review
Q&A	Questions and Answers
ROI	Return on Investment
RPA	Robotic Process Automation
RQ	Research Question
RT	Request Tracker
SA	Software Architecture
SE&SP	Software Enhancement and Support Program
SIML	Synthetic Intelligence Markup Language
SIRI	Speech Interpretation and Recognition Interface
SQ	Survey Question
SQL	Structured Query Language
STS	Socio-Technical Systems
TCA	Text-Based Conversational Agent
TCO	Total Cost Of Ownership
UPS	United Parcel Service
UX	User Experience
VA	Virtual Assistant
XML	Extensible Markup Language

Table of Contents

List of Figures

List of Tables

1. Introduction

The end of the 20th and the beginning of the 21st century were characterized by a leap in the development of information technologies and a technical revolution that affected all spheres of society, creating and integrating a more informal environment into everyday processes. Today, thanks to this scientific and technological revolution, the challenge of using a fundamentally new type of technology has come to the fore. The study of the sphere of human-machine interaction has found its application in the most complex projects, including the development of space technologies and computer chips, robotics, people's working life or daily routine [1]. A chatbot is a computer program that simulates a real conversation with a person. The origins of modern chatbots can be traced to 1964 when Joseph Weizenbaum developed a chatbot called Eliza [2] at the Massachusetts Institute of Technology. This was followed in 1991 by the Lobner Prize, which encouraged AI researchers to create chatbots that could pass Turing's tests and help advance AI. These chatbots include A.L.I.C.E., JabberWacky, Rose, and Mitsuku [3]. In 2014, at the Turing Competition, a chatbot called Eugene Goostman, imitating a 13-year-old child managed to fool 33 % of the judges, thereby passing the test [4].

Spoken Dialogue Systems are systems that could support contextual conversations with users to handle conversational tasks such as booking tickets, monitoring other systems, and teaching students. These were the forerunners of today's chatbots and conversational human-machine interfaces. In 2011, Apple released an intelligent assistant called SIRI. SIRI was modelled as a personal user assistant and its release was one of the most significant events that reset the history of human-machine interfaces [5].

In 2011, IBM introduced Watson, a question-answering system that competed on a game show called Jeopardy and won it over previous winners, Rutter and Jennings [6]. The next big thing was the arrival of Microsoft's Cortana in 2013 as a standard feature on smartphones running the Windows operating system. Cortana is a personal assistant that managed tasks such as setting reminders, answering questions, etc. In November 2014, Amazon invited its prime members to try out a personal assistant called Alexa. Alexa was available on its Amazon product called Echo. Users could speak to Alexa using their voice, and ask it to perform tasks such as setting reminders, playing music, and more. In April 2016, the social networking site Facebook announced that it was opening its popular Messenger platform for chatbots. It was a radically different approach compared to the conversational interfaces SIRI, Alexa and Cortana. Unlike these personal assistants, Facebook's Messenger led to the creation of custom and branded chatbots. These chatbots are very similar to SIRI, Cortana, and Alexa, but can be customized to the needs of those who create them.

Chatbots now have the potential to change the way of working for multiple markets such as customer service, sales, marketing, technical support and more. Many messaging platforms such as Skype, Telegram and others have become available for integration into chatbots [7, 8, 9]. In May 2016, Google announced the Assistant, its version of a personal chatbot, to be available on multiple platforms such as the Google Allo and Google Home (a smart speaker similar to the Amazon Echo). All assistants such as SIRI, Cortana, Alexa and Google Assistant have also opened up as conduits for third-party conversational capabilities. Thus, it is now possible to personalize Alexa and Google Assistant software by adding conversational capabilities from a library of third-party solutions. Just as brands can create their own chatbots for various messaging services (Skype and Facebook Messenger), they can also develop Alexa skills or Google Assistant actions. In 2018, Apple's Homepod smart speaker was released, powered by the SIRI voice platform. Parallel to these developments, there has also been a significant growth in terms of the tools available for building and hosting chatbots.

The past two years have seen an exponential growth in the number of tools for designing, modelling, composing, deploying, managing and monetizing chats [10, 11, 12]. Examples of such tools are platforms such as MobileMonkey[1] – a popular platform that allows you to create chatbots on Facebook Messenger, Botsify allows you to create AI chats for your website or Facebook messenger. Botsify is integrated with several services including WordPress, Shopify, Slack, Alexa, Google Sheets, RSS Feed, JSON API, ZenDesk, The Flow XO chatbot platform that gives you the ability to create "smart" chatbots for Facebook or your personal website. This has resulted in an ecosystem that designs and builds conversational interfaces for businesses, charities, governments and other organizations around the world.

This thesis discusses the business processes of the technical support service. Technical support customers often need answers to the same questions. To simplify the process of obtaining the knowledge necessary for a particular person, one can create a chatbot that contains lists of frequently asked questions with well-prepared and detailed answers to them. In addition to helping the end-user, this will also reduce the inefficient workload of consultants who would otherwise have to repeatedly give the same answers to different

[1] `https://mobilemonkey.com/`

people at different times. Thus, building a system that would automatically give answers to frequently asked questions of technical support customers is an actual task.

This thesis focuses on promoting an increase in the efficiency of work by reducing the burden on technical support managers through the development of an intelligent chatbot designed to help the technical support staff. During the analysis process, this thesis addresses the following research questions:

RQ1: *What are the most prominent chatbot technologies used, and the problems encountered in the literature related to them in human-machine interactions?*
Hypothesis: Negative usage experience and a lack of human connection form a bias towards technology-advanced communication.

RQ2: *What are the factors contributing to the bias and perceived negative user experience with chatbots, and how we can increase trust and confidence using them?*
Hypothesis: Negative user experience and lack of human connection form a bias towards technology-advanced communication.

RQ3: *What are the minimal resource requirements for utilizing chatbot technology and the expected payback period?*
Hypothesis: The resources invested in Chatbot utilization will pay off within the first six-month period.

An analysis of the literature on the problem of using chatbots showed the existence of two different approaches – the use of a knowledge base based on frequently encountered questions and answers to them, as well as the processing of questions in natural language. The main problem in creating a chatbot and organizing its interaction with a person is the processing of a person's natural language with artificial intelligence tools. This thesis considers the problem of creating and configuring an intelligent chatbot for technical support customers.

An analysis of the problem of using a chatbot in various areas of human activity has shown that there are difficulties in creating an intelligent chatbot. To create a chatbot based on machine learning technologies and neural networks, a lot of preparatory work is required in order to create a corpus of questions and answers, to prepare conversation templates, train a neural network and etc. Moreover, when creating a chatbot without any negative user experiences, it is necessary to clearly define the design of the chatbot personality. For a positive perception of a chatbot by a person, it is necessary to endow the robot with the features of a person's linguistic personality, their own style of conversation. In this thesis, the main stages of creating a chatbot personality design are considered: determining the goals and features of the dialogue, building the general logic of the communication process, creating a dialogue script.

The major goal of this thesis is to investigate questions related to chatbot technology in the technical support services, using the Boost AI[2] platform. In particular, we analyze the most prominent chatbot technologies used and investigate the problems of human-machine interaction. We also discuss the resources needed to create an intellectual chatbot. This study allows us to optimize the use of resources invested in designing intellectual chatbot. Finally, we introduce the intellectual chatbot design for the clients of technical support services based on the Boost AI platform.

The rest of the thesis is structured as follows. Chapter 2 addresses related works and provides a literature overview on the challenges of creating and using intelligent chatbots. The studies related to the problem of human-machine interaction with the help of chatbots are considered. Chapter 3 focuses on the main concepts and technologies for creating chatbots. Chapter 4 analyzes the data of the intellectual chatbot for the technical support service: tools for creating a chatbot, examples of using the chatbot, flow, and statistics on active users are described. The main business processes in the technical support service after the implementation of the chatbot are considered. The following Chapter 5 presents an experiment and analysis of the results. The conclusion in Chapter 6 6 is summarizing this thesis.

[2] `https://www.boost.ai`

2. Related works

Communication technologies based on instant messengers and chatbots have gained particular relevance. Recent studies have shown that telephones are more often used for messaging than for other purposes [13, 14]. In addition, according to BI Intelligence [15], the total audience of users of the four leading instant messengers WhatsApp, WeChat, Messenger, Viber exceeded the audience of the four largest social networks Facebook, Instagram, Twitter, Linkedin. Many of the works of scientists are devoted to the problems of approaches for the creation and use of chatbots in various fields of human-machine interaction: healthcare, marketing, training, tourism, social services and others [15, 16]. However, the literature review of the available publications on the use of intelligent chatbots presented in this thesis showed a lack of research relating to the creation and use of intelligent chatbots within the technical support services area. Thus, in this thesis, research will be conducted to bridge this gap.

Appel et al. [17] discusses methods and tools that will help the developer community in the early stages of chatbot development to overcome the most popular and difficult topics that practitioners face when developing chatbots. Hendriks et al. [18] presents experimental studies on the use of humanoid robots when communicating with users. The paper notes that users still prefer to interact with human interlocutors. As noted in research [18], one of the main reasons why customers prefer to communicate with a live employee instead of a chatbot is satisfaction with the service. Knowing that a service provider can allocate an employee instead of a chatbot for customer service leads to higher customer satisfaction, as this is facilitated by the individual approach of an experienced employee to the client. On the other hand, the client's communication with the chatbot leads to a lower level of satisfaction. Thus, more research is needed to find effective methods for combining chatbots and humans to provide the best customer experience.

The problems of human-machine interaction have been considered in many studies. According to Ley et al. [19], as well as the research of Araujo [20], end-user perception and service satisfaction are influenced by the disclosure of its virtual essence by the chatbot. In this article [20] Araujo compares the experience of using chatbots and IM in the tourism and hospitality sectors. Also, experiments have been conducted in the scientific publication by authors Rodrigues et al. [21] to study the influence of humanoid traits such as the style of the language, the name and structure of chatbot, and the effects of adding two types of human signals, such as visual signals (e.g. a human avatar) and relational cues (e.g. empathy) [22] for the perception of a chatbot as a social presence. The results of these studies [21] [22] showed that adding humanoid features to a chatbot has a significant impact on its positive perception by a human interlocutor. In addition, Wallis and Norling [23] argue that social intelligence is an integral component of any conversational agent. Conversational interfaces with a sense of social identity circumvent several common problems. Such agents can promote ease of use, encourage participation, and set limits naturally. Väänänen et al. [24] researched the use of chatbots (CivicBots) to support youth (16–27 years old) in participating in society, and the work of Ciechanowski and others [25] is devoted to experimental studies of human-robot interaction. The authors of the work [25] conducted experimental studies using a set of questionnaires to assess a person's readiness for interaction and cooperation of a person with a chatbot. The results of Ciechanowski and others showed that users experience a more positive influence when communicating with simple dialogue chatbots than when communicating with more complex participants experienced less supernatural effects and less negative influence when collaborating with a simpler text chatbot than with a more complex chatbot with an animated avatar. The outcome of this study can be used in the development of more advanced chatbots and will contribute to the development of the field of human–computer interaction Følstad et al [26] discuss the problems of the influence of chatbots on the individual, group and social level. The paper discusses the directions and problems of research related to the design and development of intelligent chatbots and also identifies six main areas of research: users and consequences, user experience and design, frameworks and platforms, collaborative chatbots, the democratization of chatbots, ethics and confidentiality. As a conclusion of a study by Følstad et al. [26] they provide an overview of the state of affairs in each of the six subject areas of chatbot research. The authors proposed the main research problems and areas of prospective research in each of the proposed areas.

The use of chatbots in various areas of human activity, especially in online travel agencies, is addressed by Li et al. [27], who identified five aspects of chatbot quality of service and explored their impact on user confirmation. This study proposes five qualitative characteristics (understandability, reliability, responsiveness, assurance, and interactivity) for chatbot services which affects the continuity of use through confirmation and satisfaction. Among the five characteristics, understandability, reliability, confidence, and interactivity are strongly associated with confirmation and, in addition, are positively associated with chatbot usage duration through satisfaction. Therefore, when developing chatbots, it is necessary to test those four quality parameters that were found to be important in this study [27].

Miner et al [28] address the challenges of designing and implementing chatbots to quickly share up-to-date information about COVID-19, encourage desired health behaviours, and reduce the psychological damage caused by fear and isolation. Research by Miner et al [28] has shown that intelligent chatbots can help prevent misinformation and help identify symptoms of COVID-19. The active adoption of chatbots allows for the formation of behaviours that limit the spread of infection and provides an opportunity to reduce the mental health burden associated with responding to a pandemic. Leboeuf et al. [29] discuss the challenges of implementing chatbots to support the software development process with distributed development teams. The results of the study showed that the use of chatbots can reduce the time spent on agreeing on software development requirements by an average of 30%. For example, Følstad et al. [30] explore the possible social benefits of chatbots and conversational user interfaces in the realm of commercial service providers. The results of the study allowed determine the main motivational factors for using chatbots, the main one of which is "productivity". The use of chatbots helps customers quickly get useful information and help. The results obtained will be useful to developers when designing chatbots that reflect different user motivations. Hasal et al. [31] investigate the security of data transmitted and processed by intelligent chatbots. When communicating with the chatbot, users can transmit data that contains personal information (social security numbers, credit cards, phones, etc.). This creates an additional security risk in human-computer interaction. Hasal et al explore the problems of storing and using data received from a user when communicating with a chatbot, and the authors also offer some standard solutions for protecting human data in human-bot communication.

The challenges of training neural networks for the Meena chatbot are discussed in Adiwardana et al. [32] and Roller et al. [33], where an open domain humanoid chatbot is fully trained on extracted and filtered data from public conversations on social media. An intelligent chatbot based on a neural network is proposed in the work of Adiwardana et al. The neural network is trained on a data set to minimize confusion with the next token when communicating between a person and a chatbot. Also, Roller et al. [33] proposes a human assessment metric called the mean SE&SP that captures the key elements of a human-like multi-turn conversation. A large-scale model is proposed that is trained on real data to train and select a strategy for generating responses in human-machine communication. These studies demonstrated that during the training of chatbot's neural networks, it is necessary to take into account other components (availability of topics for conversation, the ability of a chatbot to demonstrate its knowledge, empathy and individuality), which are also important for a high-performance results.

A study by Alepis and Patsakis [34] shows that the threat to the privacy of personal data transmitted and processed by voice-controlled intelligent personal assistants (Amazon

Echo, Google Home) is not just potential, but quite real and more dangerous than originally thought. This threat of data loss is exacerbated by the internal mechanisms of the underlying operating systems of smart mobile devices, the growing capabilities of voice-controlled smart assistants, and the proximity of these devices to other IoT devices. Alepis and Patsakis discuss and demonstrate some types of attacks (performing unauthorized commands using voice, launching a voice assistant to call an attacker, who then issues his commands through a headset, hiding voice commands, using an frequency modulation antenna to transmit voice signals, etc.) on such devices and analyze their impact on data security in real-world scenarios.

Interest in the design and development of chatbots has led to the emergence of a large number of different platforms and technologies (MobileMonkey, Chatfuel[1], Botsify[2], FlowXO[3] and more). For example, the studies by Ahmad et al. [35] and Augello [36] provides an overview of chatbots design techniques (AIML, Pattern Matching, Language Tricks, Chatscript, Parsing, SQL and relational database, Markov Chain) used to develop chatbots. The problems of creating a decision advisor chatbot are discussed in the study by Power et al. [37]. This publication provides an overview of the prospects of the new technologies for the developing conversational software to help and advise people in personal and organizational decision-making situations. The results of the study will help in the design, development and deployment of decision advisor chatbots for use by managers, customers and clients. The literature review made in Chapter 2 of this thesis shows various platforms and tools that can be used to create chatbots. When implementing a chatbot, it is necessary to solve the problem of choosing a development tool based on the goals of creating a chatbot and its payback. Each platform is unique and gives completely different results. The cost of developing a chatbot on a particular platform depends on the content of the chatbot with information, and the number of actions performed by the chatbot. In section 5.3, a study will be conducted on the payback of a chatbot for a technical support service implemented on the Boost AI platform.

Many review articles provide historical overviews of the evolution and development of chatbot technology, so the study by Adamopoulou and Moussiades [38] presents the classification of chatbots according to various criteria, such as the field of knowledge they belong to, the need they serve, and others, and Caldarini et al. [39] presented an overview of recent advances in the field of chatbots using artificial intelligence and natural language processing, the study highlights the main problems and limitations of the current work and makes recommendations for future research. The authors of the review publications [38,

[1] `https://chatfuel.com/`
[2] `https://botsify.com/`
[3] `https://flowxo.com/`

39] identify several subject areas in which chatbots are used: e-learning, health protection, e-commerce, search engines, and the social sphere. The main technologies used in the development of chatbots are AIML, deep learning, machine learning, and information retrieval methods. Using machine learning and deep learning requires a large amount of data to train machine learning algorithms. Information Retrieval may be the best solution for most chatbots. As can be seen from these reviews [38, 39], very little attention is paid to chatbots of technical support services and technologies for their creation. In Chapter 3 of this thesis, technologies and platforms for creating an intelligent support service chatbot will be considered.

Recently, there has been a trend in the use of artificial intelligence technologies when creating chatbots. The issues of creating humanoid chatbots and using machine learning methods are also discussed in scientific publications. Therefore in the study Adamopoulou and Moussiades [40], two main technologies for the implementation of chatbots are considered and analyzed, namely the pattern matching approach and machine learning, Suta et al. [41] present research on trends in the development of humanoid chatbots and an overview of chatbots using an intelligence map. In addition, Shapa et al. [42] show the possibilities of using Rasa Stack to create a library chatbot using open source conversational artificial intelligence, Arsovski and others [43] presented a study of the similarities and differences in the implementation methods of chatbots, and analyze the most commonly used open-source languages used in the development of chatbots (AIML and ChatScript), describes the possibility of creating a chatbot for a mobile application. As research shows [40, 41, 42, 43] there are many different tools for developing interactive and intelligent chatbots. The choice of a chatbot development tool is determined by the complexity of the chatbot and the scope of its use.

The literature review [14, 15, 17, 18, 19, 21, 23] showed that one of the main problems in human-bot interaction is the problem of "humanity" and "intelligence" of the chatbot. The "humanity" of a chatbot is understood as its ability to understand the context of a conversation with a person and the ability to communicate on free topics. The "intelligence" of a chatbot is determined by its ability to learn during a conversation, imitating interaction with the user by creating an intelligent dialogue interface. This thesis proposes one of the approaches to solving the problem of "intelligence" of a chatbot for a technical support service. The proposed approach is based on using the boost.ai platform to train a chatbot and increase its "humanity" by improving its knowledge base based on the experience of communicating with real support service customers. Section 5.1 of the thesis proposes a technical methodology for evaluating a chatbot from the point of view of the end-user based.

Also, the literature review made it possible to determine the number of factors that must be taken into account when creating the design of an intelligent chatbot. Thus, in the study [27], four main quality parameters (reliability, efficiency, guarantee and interactivity) are identified that affect the impression of communicating with a chatbot and allow increasing trust in it. Section 5.2 analyzes these characteristics for a helpdesk chatbot. As shown in the literature review, there are many different platforms and approaches to developing chatbots. There is also the problem of choosing a platform and return on investment in the development and implementation of chatbots for various fields of activity: e-medicine, tourism, banking, e-learning, and social services. The review showed a lack of publications related to the problem of choosing a platform and implementing chatbots for the field of maintenance services. This thesis considers an example of using a platform boost.ai for a technical support chatbot. Section 5.3 also discusses the ROI of resources invested in a help desk chatbot.

When compiling the literary review, the following search databases of scientific publications were used: Google Scholar, Web of Science, Scopus, ScienceDirect. For example, in the Web of Science, upon request, the database provides all articles that are cited as research in the found article. At the same time, all related papers that contain a link to the article can be opened. When searching for articles, Scopus allows selecting up to 10 sources by key indicators: the number of citations, the number of articles published per year, the percentage of articles not cited and the percentage of review articles, etc. Google Scholar made it possible both to find articles by keywords and to view similar articles and articles in which the found article is cited. On average, a search query produced up to 10 publications that coincided with the subject of the query. The citation search yielded about 5 to 10 similar articles. An overview of the literature and its relationship to the research questions of this work is presented in Table 1. The field *Method applied* describes the applied methods that are considered in scientific research, the research context describes the scientific questions of the studies.

Table 1. *Summary of literature review regarding research context*

RQ#	Reference	Method applied	Research context
RQ1	[16]	Topic Modeling and NLU	SA
RQ1	[17]	ANOVA Test	HCI
RQ1	[18]	Cluster Analysis	Smart PA
RQ1	[19]	CMC and IPC Theories	Human-Like Agents
RQ1	[20]	Topic Modeling	TCA
RQ1	[21]	One-Way ANOVA	TCA
RQ1	[22]	Optimized Social Models	Anthropomorphic VA
RQ1	[23]	Microlinguistics	Chatbot Design Techniques
RQ1	[24]	ANOVA	HCI
RQ1	[25]	Topic Modeling	HCI
RQ2	[26]	Literature Review	Chatbot UX
RQ2	[27]	PLS Methods	Human-Like Agents
RQ2	[28]	Topic Modeling	Human-Like Agents
RQ2	[29]	STS for Collaborative Work	HCI
RQ2	[30]	Public Values Framework	HCI
RQ2	[31]	NLP and ML Techniques	Chatbot UX
RQ2	[32]	Neural Network	HCI
RQ2	[33]	Neural Network	HCI
RQ2	[34]	Topic Modeling	Voice Controlled PA
RQ3	[35]	Review of Design Techniques	Chatbot Design Techniques
RQ3	[36]	Review of Design Techniques	Chatbot Design Techniques
RQ3	[37]	Literature Review	Decision Adviser Bots
RQ3	[38]	Review of Design Techniques	Chatbot Design Techniques
RQ3	[39]	AI and NLP	Chatbot Design Techniques
RQ3	[40]	NLP	Chatbot Design Techniques
RQ3	[41]	NLP	Chatbot Design Techniques
RQ3	[42]	AI and NLP	Chatbot Design Techniques
RQ3	[43]	AI and NLP	Chatbot Design Techniques

Abbreviations:

AI: Artificial Intelligence
ANOVA: Analysis of variance
CMC: Computer-Mediated Communication
HCI: Human–Computer Interaction
IPC: Interpersonal Communication
ML: Machine Learning
NLP: Natural Language Processing
NLU: Natural Language Understanding
PA: Personal Assistant
PLS: Partial Least Square
RQ: Research Question
SA: Software Architecture
STS: Socio-Technical Systems
TCA: Text-Based Conversational Agent
UX: User Experience
VA: Virtual Assistant

3. Chatbots in human-machine interaction

3.1 Chatbots basic concepts and definitions

The first information about chatbots can be considered an experiment – namely the Turing test [44], published in 1950, which boils down to the fact that artificial intelligence can be recognized as a program capable of conducting a conversation like a human. In 1964, MIT professor Joseph Weizenbaum wrote the ELIZA program [45]. This program imitated the language of a stereotypical psychotherapist, constantly answering the remarks of the human interlocutor with counter questions. Although communication was an illusion based on script and a primitive one, Weizenbaum was amazed at how much people admired the conversation.

By 1990, the tree-based rules underlying ELIZA and other similar programs had become so elaborate and complex that the Turing test as a philosophical concept had become a real test. One year later the annual AI Loebner Prize was established. Then came the very first concept of "chatbot". It is associated with Julia [46] – an electronic assistant developed by Michael Moldings in 1994. Julia was much better at simulating communication than its predecessors, but it still used keywords to choose the right lines. A year later, the chatbot A.L.I.C.E. [46] appeared, which could conduct a dialogue with a person by formulating relevant phrases by analyzing heuristic patterns. Communicating with A.L.I.C.E. already resembled a fully-fledged dialogue. The program did not pass the Turing test, but it was recognized three times (in 2000, 2001 and 2004) as the best chatbot in the AI Loebner competition. Mitsuku chatbot [47], developed by Steve Warswick, managed to break this record only in 2018. In 2006, IBM began developing the Watson supercomputer [48], which had comprehensive knowledge and could answer questions aloud. Four years later, such solutions became available to the general public. The voice assistant service appeared relatively recently but has already earned a huge audience. Voice assistants are actively developing. Apple introduced the voice assistant SIRI, followed by Google Now, Alexa from Amazon, Microsoft Cortana and Yandex Alice [49].

A chatbot is an interlocutor program that simulates human communication (Figure 1) and has a user-friendly interface for interaction with systems that provide answers based on the analysis results of vast amount of information [38, 39]. Chatbots help automate

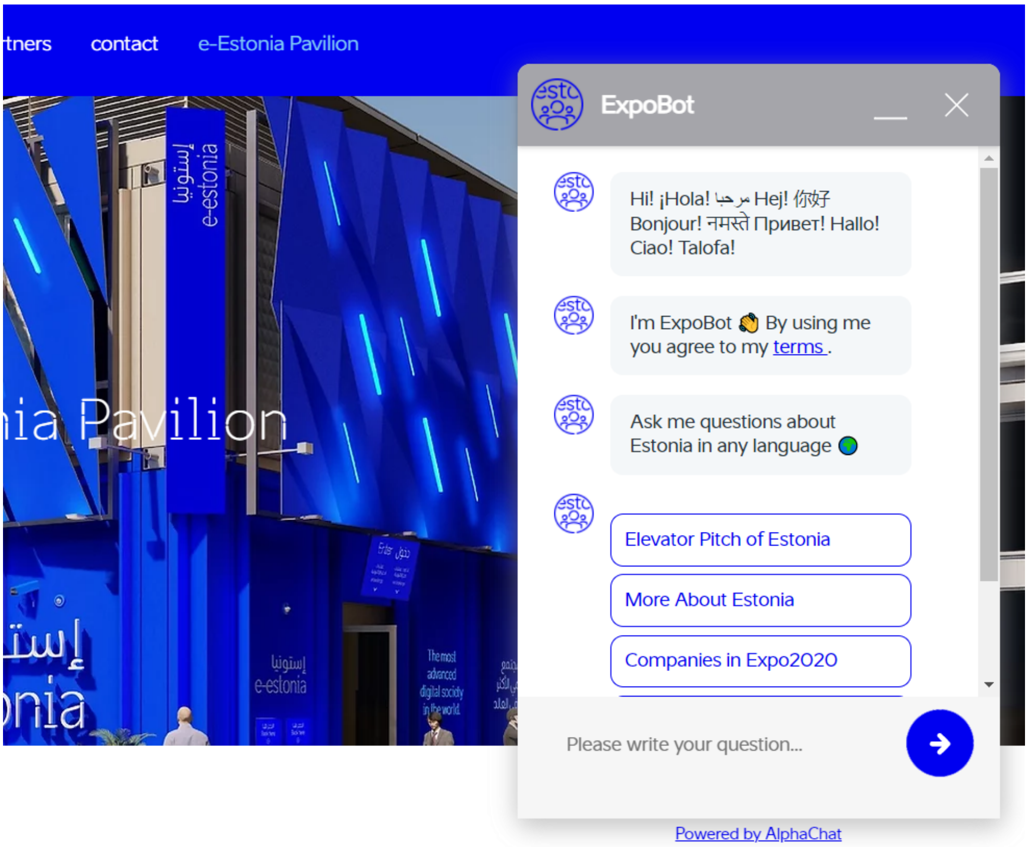

Figure 1. *Multilingual ExpoBot powered by AlphaChat*

tasks by working according to a given algorithm. They conduct a dialogue with the user and fulfilling requests by answering questions and sometimes entertaining users their responses. Today, chatbots are becoming the de-facto standard interface for interactions between humans and software services. This is due to the widespread use of messaging platforms (such as Facebook Messenger for social network users and Slack for developers) due to advances in natural language tools supported by many chatbots. Another driving force is the widespread use of big data and machine learning algorithms. Large software companies recognize the convenience of chatbots for communication channels and user associations. Facebook, for example, wants to gradually replace all programs with chatbots on the Messenger messaging platform. At the same time, Microsoft says that the operating system of the future is the intelligent dialogue platform [50]. The growing popularity of robot programs can be judged by developing services such as Alexa, SIRI and IBM Watson. There are also many chatbots for messaging platforms used by software developers to communicate with colleagues (Slack, Microsoft Teams and HipChat) [51, 52, 53].

Simultaneously, chatbots are becoming ubiquitous – we interact with them in the car, at home, at work and beyond. For example, the Nissan Chatbot provides information about Nissan vehicles, searches for authorized dealers, books a test drive, offers 24/7 customer support, etc. The same assistant from Kia is available on WhatsApp messenger, which promptly provides information regarding the status of service work for the car owner.

Primitive chatbots can be created from scratch and deployed on your resources, but third-party platforms are used when you need to simplify development and distribution. The number of tools for developing chatbots is increasing, but there is a difference between the platforms for creating chatbots and the distribution platforms they run. Companies such as Microsoft, Facebook, Telegram and others provide comprehensive tools for the development and distribution of chatbots programs (such as FlowXO[1], Chatfuel[2], Botsify[3], SAP Conversational AI[4] and others). Some companies offer specialized resources for specific creation and distribution tasks.

Chatbot development platforms provide various software tools, frameworks, programming interfaces and additional features such as NLP, image search and analysis. They can be targeted to a specific distribution platform or designed to create chatbots that can be deployed on many platforms, including the Microsoft Bot Framework,[5] Botkit[6] and Pandorabots[7]. In addition to that documentation, code templates and even a no-code solution (i.e Chatfuel) can be offered to the customers. These popular development platforms are used by developer communities, whose members can communicate in relevant online groups, exchange experiences and links to thematic publications, receive advice and answers to questions and participate in discussions. Some of these communities, such as Slack's Botmaker[8] and Chatbot Magazine[9], have been the focus of discussions on a wide range of robot-related topics.

There are two types of chatbots classification that stand out: business classification of chatbot applications (Figure 2) and classification of chatbot applications by technical parameters (Figure 3) [52].

The business classification of chatbot applications includes:

1. Conversational chatbots. Created for humanlike conversation but have different goals (e.g., Slush – answers FAQs in real-time, Vainu – enriches customer conversations without filling up the form, Dominos – delivers a smooth customer experience via

[1] https://flowxo.com/
[2] https://chatfuel.com/
[3] https://botsify.com/
[4] https://www.sap.com/products/conversational-ai.html
[5] https://dev.botframework.com/
[6] https://botkit.ai/
[7] https://home.pandorabots.com/
[8] https://botmaker.com/en/
[9] https://chatbotsmagazine.com/

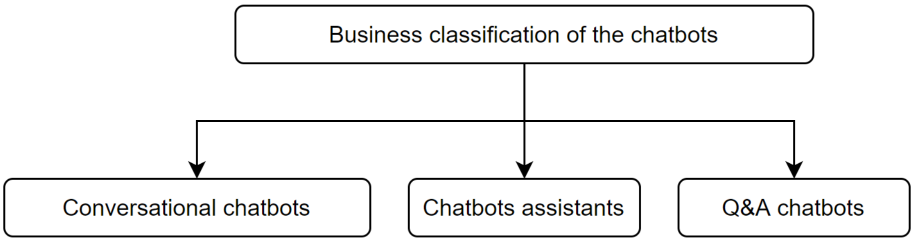

Figure 2. *Business classification diagram of chatbots*

Facebook messenger);

2. Chatbots assistants. They have a specific predetermined purpose and can substitute human support for certain operation fulfillment. The necessary information can be extracted from the user responses and used for the web forms, such as obtaining a bank statement or applying for a mortgage online (Woebot – this downloadable chatbot is a robotic therapist for those who need mental health support);
3. Q&A. Chatbots are designed to give simple answers based on 1 question – 1 answer. They can serve as a replacement for FAQ sections of various sites.

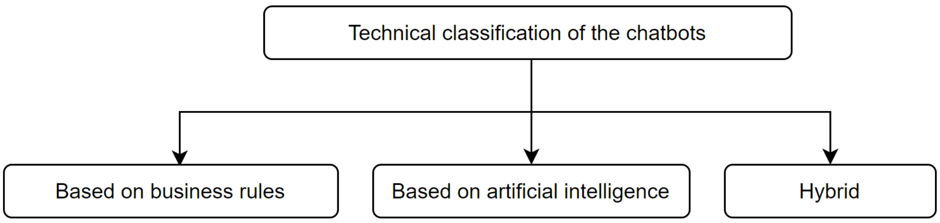

Figure 3. *Technical classification of chatbot applications*

The classification of chatbot applications by technical parameters:

1. Based on business rules. It has a tree-like conversation structure. The conversation with the user follows a certain path, which the developer has already predetermined. As the main participant of the chat, the user makes decisions in such a conversation but can never deviate from the predetermined path. Typically, these types of chatbots eschew open-ended questions and instead contain many buttons as an alternative;
2. Based on artificial intelligence, these chatbots are built entirely on artificial intelligence (NLP, NLU, NN and etc.). Unlike business rule-based chatbots, they do not have a predetermined conversation path. Instead, the conversation path is implicitly determined based on the training data used to train the machine learning model. The chatbot decides what question to ask and what to answer based on the past dialogues

used in training. This brings us to the main disadvantage of AI chatbots – they require large datasets for seamless conversations;
3. Hybrid chatbots are a combination of the first two types of chatbots. Chatbots of this type conduct a conversation with the user along a predetermined path but use AI to recognize user intentions and extract valuable data from user messages (name, date, period, etc.). This type of chatbot is the most widely used in commercial applications.

At one time, the appearance of chatbots was a breakthrough in customer service. Chatbots have replaced support professionals in many tasks at different stages of the customer journey. For example, Oracle, one of the world's largest vendors of business solutions, found that every eight out of ten services have already implemented artificial intelligence in technical support or are planning to do so. Since, in this thesis, the technical support service is defined as a subject area, we need to consider the classification of chatbots for this subject domain (Figure 4) [52].

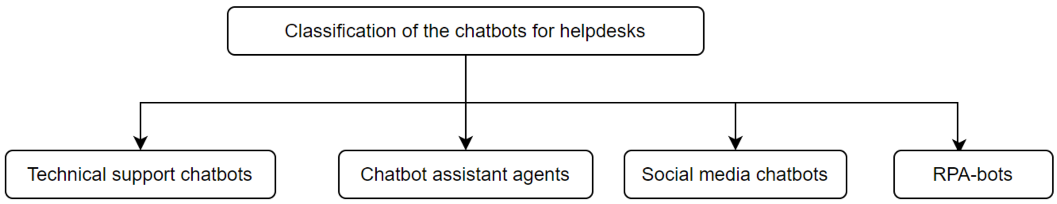

Figure 4. *The chatbots classification diagram for service desk*

The helpdesk chatbots classification consists of:

1. Technical support chatbots. The main task of these chatbots is to release support teams from answering repetitive questions from customers. These chatbots provide 24/7 real-time information support. AI-driven chatbot programs build a dialogue constructively by analyzing the context of the conversation according to various criteria. For example, intelligent chatbots can understand the interlocutors mood using vocabulary and punctuation. They also transfer the user to a live support specialist when the dialogue goes beyond the prescribed scenario. Another vital advantage of support chatbots is fast learning. They build a strategy for communicating with customers based on incoming questions, comparing them with ready-made service scenarios. And this is guaranteed progress, which is not always possible in the case of support specialists. Support chatbots are embedded both on web pages and mobile applications;
2. Chatbot assistant agents do not interact with customers but with support agents. AI

performs routine tasks that were previously assigned to technical support employees. These chatbots make the job of a support agent easier by automating many processes in the following way:

- Tracking incoming calls. Chatbot assistants scan email and social networks for messages requiring a support agents response and signal this;
- Distribution of incoming calls by groups. For example, finance department support agents will only see payment questions;
- Building scripts. In the chatbot editor, you can script dialogues with different types of customers, adding recommendations, instructions and other tools for engagement and retention;
- Reducing the information load on agents. AI determines from responses like "Thank you" or "Understood" that the client's problem is solved and closes tickets. Therefore support agents can focus on the dialogues that require their participation.

3. Chatbots for social networks help to attract new customers [54]. The potential of AI in terms of lead generation is huge. Social networks are filled with information about the customer's consumer habits. Support specialists do not need to pull this data from the client, it is already available in his/her social networks and helps to build high-converting dialogues. Chatbots find potential customers in social networks and provide technical support specialists with information about them. Chatbots for social networks based on artificial intelligence have learned to create the illusion of live communication. Instead of short monosyllabic answers, they engage the user in a dialogue, define their problem and expectations and transfer them to a technical support specialist at the right time. Moreover, chatbots have learned to sell directly in social media messengers. They help with the choice of goods and even with the payment of the order. This world is not ready to complete replace the consultants, but it is moving towards that.
4. Robotic process automation bots allow you to automate entire processes. The functions of these chatbots are similar to the previous types of chatbots, but are characterized by a deeper and longer immersion into business processes. The implementation of RPA allows you to automate entire stages of working with a client rather than specific actions. For example, processing and systematization of incoming email requests.

As described in the detailed classification presented above, using chatbots in the technical support service allows employees to get rid of repetitive customer questions, increases productivity and attracts new customers.

3.2 Using chatbots in the context of digital business transformation

Digital transformation is a natural, evolutionary and market process. Many breakthrough innovations have significant prospects and can radically change society's economic and social aspects. Digital transformation involves the introduction of modern technologies into an enterprise's business processes [20, 26]. This approach implies not only the installation of contemporary hardware or software but also fundamental changes in management approaches, corporate culture and external communications. As a result, the productivity of each employee and the level of customer satisfaction increases and the company acquires a reputation as a progressive and modern organization.

Digitalization technologies allow you to organize the most personalized interaction that most customers prefer. By user experience, we mean not only the interaction with the company of the external user but also internal user. Furthermore, digital transformation of processes optimizes the work of the company's employees, which increases the productivity of each team member.

This thesis considers the problem of organizing human-machine interaction in the technical support service. When a company scales its activities, the customer support service faces many routine and similar tasks. At first, they are performed by ordinary employees, but their resources become insufficient over time. In addition, the lack of time for staff to process customer requests affects the quality of the responses provided. As a result, employees make mistakes and provide incorrect or outdated information when answering frequently asked questions.

One of the solutions to this problem is to increase the number of employees who work on weekdays and weekends and holidays. However, this increase leads to a significant increase in costs. In addition, the human factor also has a negative impact, which is why customers have to wait a long time for a response when the operator cannot quickly find the correct information. All this can significantly damage the company's reputation with a negative impact upon sales.

Thanks to digital transformation, customers have become more informed and, consequently, more demanding, so providing them with poor service is a factor that can hinder the prosperity of a company or business. Another solution that we will consider in this thesis's scope is chatbot technology. The integration of a chatbot into the business processes of the technical support service will free employees from the same type of customer questions, the answer to which can be given by the chatbot rather than the real person. The main advantage of the technical support service chatbot is the availability of a wide range of features, ease of configuration and high efficiency. Among the most common indicators that will improve after integrating the chatbot into the company's technical support service are response speed, loyalty to the company, conversion to purchase, workload reduction on the technical support service and growth in customer retention.

3.3 Overview of programs and platforms for creating chatbots

There are two approaches how to create a chatbot. The first approach is to create a bot coding using a specific framework and the second approach by using a no-code solution on a development platform. The first approach requires specific coding skills and also knowledge related to frameworks, NLP technologies and analytics services for future optimizations. The most common chatbot frameworks include:

- BotKit is an open-source toolkit designed for Node.js. Suitable as the first platform for learning and experimenting with chatbots. Botkit has a Botkit Studio service that contains standard sets of applications, basic libraries and plugins for expanding the functionality of a chatbot and allows create chatbots for Facebook Messenger, Slack and Cisco Spark;
- Claudia Bot Builder is a chat builder that can be used with AWS Lambda. It includes a library for Claudia.js that helps build chatbots for Facebook Messenger, Telegram, Skype, Slack slash, Twilio, Kik and GroupMe;
- Bottr.me is the simplest Node.js framework for creating and using personal chatbots. This service allows testing of the created chatbot.

In the scope of this thesis we consider the second approach that requires us to compare the most popular platforms for the chatbot development. In order to provide an answer to RQ1 (What are the most prominent chatbot technologies used and the problems encountered in the literature related to them in human-machine interactions?) we list these platforms in Table 2 based on the surveys from Sourceforge[10][11] and Boost.ai[12]. Four attributes that characterize the basic functionality of the platforms are used in the Table 2. The *Multiplatforms* attribute describes the possibility of supporting multiple messaging platforms (e.g., Facebook, Slack, Messenger, Whatsapp). *Wide integration* attribute shows the presence of integration with third-party services (e.g., SalesForce, Pay-Pal, Twilio, Twili, Python, Node.js, Ruby). The *Analytics* attribute, is the presence of analytical tools for analyzing

[10] www.sourceforge.net/software/compare/Boost.ai-vs-Botsify-vs-MobileMonkey-vs-Conver ai/

[11] www.sourceforge.net/software/compare/boost.ai-vs-Wit. ai-vs-SnatchBot/

[12] https://www.boost.ai/compare-conversational-ai-solutions# compare-solutions

the results of chatbot implementation and finally *UX* field, the presence of a user-friendly graphical interface for creating chatbots. It should be noted that only in two platforms from our list analytical functionality is available. Converse.ai – supports intelligent analysis of dialogues using feedback during the survey. Boost.ai – contains built-in tools for detailed analysis of the chatbot.

Table 2. *Characteristics of Chatbot Development platforms*

Name	Multiplatforms	Wide Integrations	Analytics	UX
SnatchBot	X			X
Conversed.ai	X	X	X	
Smooch	X			
Mobilemonkey				X
Wit.ai				X
Boost.ai	X	X	X	X

An analysis of the behavior of a chatbot when communicating with a user is a necessary component of their use. Chatbot monitoring implies constant optimization of their behavior and dialogue scenarios based on the analysis of user interaction with the chatbot. Only two platforms, from those considered in Table2: Conversed.ai and Boost.ai have built-in analytical tools. For other platforms in Table2, it is necessary to use third-party analytical platforms, which are discussed in Table3. Services for analyzing the effectiveness of chatbots include Botmetric[13], Chatbase[14], Botanalytics[15], Dashbot[16] and Botlytics[17] are presented in Table3.

Having considered the chatbot development tools presented in Table 2 and analytical tools from Table 3, we can conclude that the platform Boost.ai has the best functionality (UX, Multiplatforms, Wide Integration) and analytical capabilities. Thus, this platform has been chosen for further research in this thesis.

3.4 Software for query analysis in natural language

Despite many existing chatbots, they can all be divided into two broad categories depending on the technology used for intellectual dialogue: NLP and and programs based on Case-Based Reasoning technology. Chatbots on natural language word processing technologies begin parsing user remarks, resulting in splitting sentences into familiar non-terminal and terminal characters. Chatbots with NLP technology do not have a database with clearly

[13] www.botmetric.com
[14] www.chatbase.com
[15] www.botanalytics.co
[16] www.dashbot.io
[17] www.botlytics.api-docs.io

Table 3. *Characteristics of services for analyzing user interaction with a chatbot*

Name	Short description	Characteristics
Botmetric	Flexible open source analytical system	Track chatbot performance - number of users, chatbot messages, chatbot messages, image uploads. Obtain conclusions with recommendations for changing the dialogue
Chatbase	Cloud service for analysis and optimization	Analysis of key performance indicators of the chatbot. Search for errors in the work of the chatbot based on machine learning technology
Botanalytics	User lifecycle tracking	Segmentation of dialogues, identification of bottlenecks, measuring the degree of user involvement
Dashbot	Analysis of the content of conversations and analysis of user moods	Track chatbot performance – number of users, user retention, etc.
Botlytics	Cloud platform for chatbot analysis and communication	Track messages sent by chatbots, their number, as well as the dialogues in which it participates

defined response patterns. Instead, the reaction to user input is synthesized each time based on the rules of grammar used, the structure of previously entered user text and keywords found in it. Some of these robots do not have the original grammar but use an inductive method of grammar output, which allows you to learn during a dialogue with the user and "tune" to his manners.

The most well-known Cased-Based Reasoning (CBR) program is the ALICE program, founded in the late 1990s by R. Wallace. A specially developed AIML programming language was used to create A.L.I.C.E. AIML is a modified version of the XML language. Many other chatbots use the same code but are slightly changed. For example, the popular Mitsuku chatbot is based on Alice's AIML files [47].

The purpose of developing the AIML language was to provide the functions necessary for the extraction and processing of knowledge corresponding to a given template structure and the formation of output signals according to the scheme "response stimulus". The AIML language, its specifications and interpreters for translating program text into standard object-oriented programming languages are currently distributed free of charge. In addition, the relative simplicity of the technologies used (ALICE is based on the principle of minimalism – *"A large amount of data, small program code."*) and the availability of information have led to massive popularity and widespread chatbots of this family. Using the principle of open-source allowed programmers to implement their applications and contribute to the development and improvement of the AIML language.

AIML-based chatbots use "default" response templates. If the chatbot does not find a suitable answer, then it uses general answers or changes the topic of conversation. The success of such maneuvers depends only on the ingenuity of the developers and the stubbornness of the user. For example, suppose the answers are standard, based on the psychological aspects of dialogue and are not repeated too often. In that case, the user will no likely notice a change in the topic of conversation and, even more so, does not recognize it as a "weak spot" of the system. At the same time, the chatbot saves all user replicas in response to which "default" replicas have been used, so chatbot developers gain access to chat logs and can easily expand and improve the program's knowledge base. The AIML programming language also allows you to embed commands written in other languages, such as Javascript or C ++, which significantly increases the program's scope and will enable you to embed it in a variety of applications.

Currently, there is a tendency to NLP based chatbot technologies for practical applications, in telephone service centers, for automatic responses to email requests, to access databases and provide the requested information to remote users, for the provision of banking services by telephone, etc. However, the use of these programs in e-commerce systems is still minimal and at this stage, these programs are used only as prototypes, which are not widespread.

PandoraBots and Synthetic Intelligence Network[18] are companies that provide API for the creation of chatbots and related services:

- Pandorabots provides access to its API based on a fairly simple XML-like Markup Language (AIML), which implements all the technologies necessary to create simple commercial chatbots;
- Synthetic Intelligence Network offers SIML, conceptually similar to AIML and created based on it, as well as its development environment – Syn Chatbot Studio[19] under .NET

It was noted in Section 2.2 that the main negative experience in human-bot communication is the lack of "intelligence" and "humanity". However, in [25, 26, 27, 32] was stated that related this negative experience risks can be reduced and user confidence increased by use of machine learning, deep learning and NLP methods in the chatbot development. The review conducted in Section 3.4 allowed us to identify the most popular technologies cur-

[18] http://simlbot.com/
[19] https://developer.syn.co.in/tutorial/bot-studio/index.html

rently used in developing intelligent chatbots. Successful examples of creating intelligent chatbots using the technologies mentioned above are also given in Section 3.1. In order to choose an intelligent chatbot development platform for technical support we will do a comparison of prominent development platforms.

Table 4 proposes an analysis of existing platforms for creating chatbots from the point of view of their capabilities to create intelligent chatbots and process requests in natural language.

Table 4. *Characteristics of chatbots development platforms with AI and NLP*

Name	**NLP**	**AI Engine**	**Text Recognition**	**Language**
SnatchBot	X	X	X	6
Conversed.ai			X	1
Smooch	X	X	X	1
ChattyPeople			X	1
Wit.ai	X		X	11
Boost.ai	X	X	X	31

The overview of chatbots development tool platforms presented in Sections 3.3 and 3.4 showed that the platform Boost.ai has the most outstanding technical capabilities for creating a chatbot. Platform tools allow creating (UX, Multiplatform, Wide Integration), teaching (NLP, AI) and improving (Analytics) chatbots in order to handle customer requests in a natural language. These tools help to create intelligent and interactive chatbots for websites and messages platforms. In addition, they can also reduce waiting times by automatically answering repetitive questions. A graphical editor for creating chatbot scripts is available on the following platforms: Snatchbot[20], Mobilemonkey, Wit.ai[21] but only the Boost.ai has a conversation script flow editor that can train chatbots without additional technical knowledge. In addition, this platform supports the processing of requests in 32 languages including those of the Baltic region(Latvian, Estonian and Lithuania). Thus, the author has chosen an chatbot development instrumental platform that supports technologies for creating an intelligent chatbot. Using this platform allows the creation of "intelligent" and "human" chatbots that reduce the negative experience of human-bot communication. Furthermore, the use of artificial intelligence tools makes it possible to train a chatbot using the experience of communicating with people. Thus, improving the chatbot will increase trust levels and attract new users to this type of technical support service.

[20] https://snatchbot.me/
[21] https://wit.ai/

3.5 ChatBot Development Technologies

The literature survey [51, 52] allowed us to identify various domains and real-world application scenarios. Also, based on recent publications [51, 52, 53], it is possible to identify the leading technologies that are used in the design of chatbots. The review in Section 3.2 and 3.3 showed that artificial intelligence technologies are used to process natural human language, especially conversational style. Creating a database containing sets of possible user questions and corresponding answers to them is necessary to make an intelligent chatbot. NLP, NLU, NN and other technologies allow trained chatbots to replenish vocabulary and learn the context of a conversation, the language features and communication style. The challenge of modeling intelligent chatbots using artificial intelligence technologies requires additional research. An overview of the subject domains and technologies used for chatbots is presented in Table 5.

Table 5. *Overview of chatbot domains and technologies*

Domain	**Technologies used**	**Chatbot examples**
Education and Research	Information Retrieval or AIML	Freudbot[10], Ethnobot[11], Cleverbot[12], CSIEC[13]
HealthCare	Information Retrieval	Helthily[14], Ada[15], Woebot[16], Clara[17]
E-commerce	Information Retrieval with Deep Learning algorithms	Peloton[18], Sephora[19], Dominos AnyWare[20], MHFeedback[21]
Law and HR services	Machine Learning and Deep Learning	AllyO Assist[22], HumanLy[23], Olivia[24]
Finance	Information Retrieval	Kasisto[25], Tars[26], Haptik[27]

It is worth noting that chatbots are increasingly being used in various domains. However, the literary survey [35, 38, 40] demonstrated a lack of literary publications for customer

[22] https://psych.athabascau.ca/html/Freudbot/Freudbot.html
[23] https://www.designinformatics.org/research_output/the-ethnobot/
[24] https://www.cleverbot.com/
[25] http://www.csiec.com/
[26] https://www.livehealthily.com/app
[27] https://ada.com/
[28] https://woebothealth.com
[29] https://www.cdc.gov/coronavirus/2019-ncov/symptoms-testing/coronavirus-self-checker.html#content
[30] https://www.onepeloton.com/
[31] https://www.sephora.com/
[32] https://anyware.dominos.com/
[33] https://apk.support/app/com.malaysiaairlines.mhfeedback
[34] https://www.allyo.com
[35] https://hi.humanly.io
[36] https://www.paradox.ai
[37] https://kasisto.com
[38] https://hellotars.com
[39] https://www.haptik.ai/

service and technical support areas. Modeling chatbots for a specific subject domain (technical support service) is an exciting task. To train such a chatbot, deep learning technologies and NLP are necessary. The integration of such a chatbot into the technical support service as an assistant will create new opportunities and open up new areas of research. This is confirmed by the increasing number of publications in recent years. Despite a large number of review articles about technologies and implementations of chatbots in various subject domains, recent reviews are lacking the latest advances in language models that can be applied to chatbots. Therefore, a deeper analysis of the use of these models while designing chatbots for the selected domain would be useful. Section 5 of this thesis will give an example of using this technology for support team chatbot. Chatbot should be an addition to the existing support team. Therefore, organizations should adhere to a balanced approach when implementing chatbots in customer support practice. This will reduce the load on the support teams and the positive influence of service quality.

The review of development platforms and technologies for chatbots performed in Sections 3.2 and 3.3 gave us the opportunity to identify technologies that allow us to train intelligent chatbots. The overview of the platforms made it possible to choose a development platform Boost.ai , which contains all the necessary chatbot development, training and analysis tools. This section summarizes the results of the literature review and an overview of chatbot development platforms and technologies, answers RQ1, identifies the main problems of human-bot communication, provides an overview of the subject areas of using chatbots in specific subject domains.

As a review of subject domains in Table5 shows the lack of information for customer support, we propose to continue the study of the factors that affect the experience of human-machine communication. As well as the assessment of the necessary resources for the use of chatbot technology will be considered in the following sections of the thesis.

In concluding this chapter and providing an answer to RQ1, the author, highlighted that in Section 2.2, the most prominent technologies for creating intelligent chatbots are technologies based on artificial intelligence methods. Natural Language Processing and Machine Learning methods are used when building dialogue scripts for AI chatbots. These technologies are based on the analysis of the dialogue during human-bot communication to improve the communication skills of the chatbot. In addition, NLP technology is used to process the context of the dialogue. Using this technology allows you to determine the essence of sentences, understand the context of the dialogue and highlight keywords that will then be used to improve the communication skills of chatbots. Neural networks of various architectures (LSTM, GRU, CNN, etc.) are most often used as machine learning methods.

4. AI-based chatbots for customer service

4.1 Trust in AI-based chatbots and trust engineering

The application of virtual communication systems based on artificial intelligence has been studied for many years [40, 41, 45, 46, 47]. Today, the problem of virtual communication is relevant because of quick access to information, the possibility of simultaneous work in the system of many users, information exchange, interaction to solve any issues, support training, communication with customers and business partners, conducting analytical research, collecting necessary information, professional development and other advantages [18, 19, 20, 21, 23]. The main issues in creating communication systems are developing a communication model, a communication participant model, the development of means, primarily semantic, pragmatic and descriptions of the environment (language, user and communication system models). Therefore, to solve these issues, it is necessary to determine the principles of work, the features of imitation of human speech behavior in communication, the development of a communication model and the writing of a chatbot. Among the programs of the interlocutors, there are programs created based on artificial intelligence [32, 33, 52]. Knowledge of psychology and principles of constructing phrases of human speech is necessary when creating chatbots. The correct definition of language restrictions and the subject domain will allow using existing artificial intelligence methods to create human-machine chatbots. One factor that negatively affects the process of human-bot communication in a natural language is the need to develop a semantic description of the structures of texts and sentences. Another factor is the limitations of the subject domain associated with the lack of means to represent a dynamically changing world. These factors influence the chatbot's perception of statements and the chatbot's learning ability.

The principle of processing user requests by a chatbot consists of the following steps/milestones, which are described in the literature [1, 3, 8]: the chatbot receives incoming messages, analyzes them, sends the result of execution and/or executes a command. Therefore, communication with chatbots is carried out by entering messages and outputting the answer (opinion) of the interlocutor. There are two types of conversation possible: a typical talk and a discussion of an important issue. Unlike human conversations, the program does not have flexible intelligence, so most virtual interlocutors are programmed to conduct a simple conversation. Such programs belong to the class of programs with a natural language interface [12, 15, 16]. The processing of natural human language, especially conversational style, is a problem concerning artificial intelligence. The issue of creating interlocutor programs based on artificial intelligence that can simulate human intellectual activity remains open today. Unfortunately, modern virtual interlocutors only partially solve the issue of imitating a human conversation. The basis of their functioning is the knowledge base. In the simplest case, it contains sets of possible user questions and corresponding answers to them. The most common methods of choosing solutions, in this case, are the following: reaction to keywords, matching the user's phrase with the one in the knowledge base, the program can also take into account the word order. Conversationalist programs cannot use terms saturated with pronouns. In such cases, programs analyze the user's previous phrases and choose the most acceptable answer. The selection of synonyms can also be problematic.

To understand the main factors of rejection in human-bot communication, we will analyze the results of Chatbot Rank 2021 study [55] that was conducted by UX research and consulting agency Markswebb. The Chatbot Rank 2021 study notes that customers who have not previously had experience with interactive chatbots are hostile to them, as they prefer to communicate with live interlocutors (operators) and believe that the operator has a great qualification in solving their problems. It is also claimed that after getting a positive experience of solving their problem, customers change their attitude toward chatbots. The success rate of solving problems when communicating with a text dialog chatbot was 69%, as shown by the results of the study [55]. From these 69% successfully solved tasks, the chatbot solved 66% of these tasks without involving a human operator. The average customer satisfaction index, according to the results of the Chatbot Rank 2021 study, was slightly more than 70%. It should also be noted that many problems in human-bot communication still need to be solved. Unfortunately, there are still a lot of poor-quality solutions and the average customer dissatisfaction index on the market exceeds 10%. Naturally, this generates dislike for chatbots. Here are some of the main problems that arise in human-machine communication:

- The chatbot does not understand the context of messages. When communicating in messengers, people most often write messages in a specific manner: they do not separate sentences with punctuation marks, split the question into several messages, refer to previous phrases, etc. This causes problems in human-bot communication since the chatbot cannot always understand the question's meaning. The user cannot communicate in his/her comfortable way but has to re-phrase the question the way the bot will get it. This leads to a negative experience in human-bot communication. This problem arises due to difficulties in understanding the context of written speech by a chatbot. To solve this problem, you can use the previously prescribed scenario of quick answers, which the chatbot will offer to return the conversation to the desired topic. The best result is a combination of three methods of developing digital assistants — simple algorithmic chatbots (rule-based assistants), chatbots with NLP and assistants on complex neural network architectures (humanoid assistants). This way, you can achieve maximum flexibility in understanding customer requests.

- The chatbot misunderstands the user's task. When communicating with a client, the chatbot incorrectly detects the client's request. This kind of error can lead to either calling an operator or launching the wrong functions, which will create additional problems for the user. To better understand the client's task, you can use several approaches: rule-based methods, semantic similarity, intent recognition and others. All of them are based on the fact that the digital assistant has a set of scenarios and tries to choose the most suitable option and launch it. Of course, the choice of a specific model depends on the available data, limitations on server capacity, system performance as a whole and other parameters.
- The chatbot does not let you reach to the operator. The task of the chatbot is to reduce the workload the support operator as much as possible and minimize the client's requests for tasks that he can solve on his own. But sometimes, the chatbot cannot decrypt the request, or the user fundamentally does not want to communicate with the digital assistant and immediately asks to translate to a person. If the chatbot cannot fulfill a specific client request and does not switch it to a person in any way, the reaction will be negative. Thus, it is necessary to prescribe chatbot communication scenarios so that in any of them, the chatbot should immediately execute a request for access to a human operator. Therefore, in the Chatbot Rank 2021 study, it was noted that some users experienced psychological discomfort when communicating with chatbots.
- Chatbot closes the conversation ahead of time. One of the metrics of the effectiveness of chatbots is the number of completed dialogues when the digital assistant coped with the client's request. However, chatbots misinterpret a long silence or a closed application and end the conversation. Premature closure of the conversation leads to a low user assessment of support and unwillingness to use this communication channel in the future. Improving the algorithm for closing the dialog session is necessary to solve this problem.
- Chatbot jokes inappropriately. Chatbot development teams are trying to teach them a direct manner of communication so that the digital assistant looks more like a person in a dialogue. But very often, chatbot jokes lead to entirely different results and cause a negative user experience. Until neural networks have reached real opportunities to conduct a dialogue taking into account the user's characteristics, it is better to avoid using them. On the other hand, if there is a desire to make human-machine

communication more accessible, then you can integrate humor into standard answers, which at the same time will help create an informal atmosphere and not spoil the client's experience.

Thus, it can be concluded that increasing the ability of neural networks to learn will lead to a decrease in misunderstanding and negative experience of communication between people and chatbots. The number of client-oriented chatbots will increase, and the number of problem areas will also expand. For a chatbot to benefit business and customers, it must be able to fully replace operator and respond to requests as efficiently and thoroughly as a real human. Otherwise, customer loyalty will fall and the business will not see the value from the implementation. We will consider, in Section 4.2, the case of implementing a chatbot to the technical support service to check the effectiveness of using a chatbot to automate repetitive tasks.

4.2 Improving Customer Service Business Process with AI Chatbot

In this section, we will consider a case related to implementing a chatbot to automate the technical support service. The chatbot must answer customer questions, freeing the support team staff from routine activities.

In this thesis we will use an example of technical support service in Kühne+Nagel (KN). KN is a large logistics and IT company that employing over 50,000 people globally. For the successful running of the business KN has in total more than 5000 internal and external applications that requires support and the Human Capital Management System (HCMS) is one of them. All KN employees have the profiles in HCMS and once a year they have to complete their Performance and Potential Review. KN employees ask the same recurring questions to the technical support service every year.

Consulting users in real-time creates a significant burden on the technical support staff. One of the solutions could be an increase in number of technical support employees, but if we consider the costs of maintaining the office, staff costs, etc., this leads to significant financial investments. Therefore, it is necessary to go another way and find a more financial efficient solution. Such a solution is the introduction of an AI chatbot into the business processes of the technical support service.

The company's technical support service uses a classic three-level scheme at the moment:

- 1st Level (L1) — Basic help desk resolution and front-line support teams;
- 2nd Level (L2) — In-depth technical support;

- 3rd Level (L3) — Expert product and service support.

The process for tickets (user request to technical support) resolution is following:

- 1st Level. The requester fills the online form with the key points (request type, category, subject and description) of the request. As soon as requester hits the send button the ticket will be created in ticketing system called Request Tracker[1] (RT) and will appear on the dashboard of the relevant support team. The ticketing form (Tic form) is presented in Figure 5 and the request processing flowchart without chatbot implementation in Figure 6. Based on service level agreement, type and category of the ticket the severity and priority will be populated automatically. The 1st Level support team will proceed with the ticket resolution using Operations Procedure Instructions (OPI) or escalate it to the 2nd Level team, along with the increase of the priority of the ticket. If the answer cannot be found and resolution requires deeper analysis then it has to be forwarded to the next level.

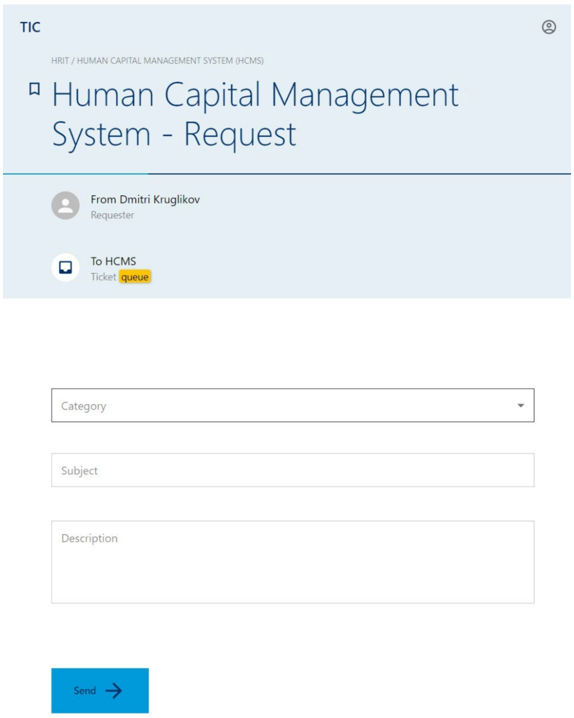

Figure 5. *The ticketing form for HCMS system*

- 2nd Level. As soon as ticket appeared on the dashboard team starts with the investigation. Documentation, manuals and the OPI's are the keys for the successful resolution of the issue. If more information is needed for the resolution then support team is able to communicate with the requester. However, if 2nd Level support is

[1] `https://bestpractical.com/request-tracker`

not able to resolve this issue then this request will be escalated to the 3rd Level of support. Escalation is performed by the pre-task creation in RT. The priority and severity of the initial ticket is increased.

- 3rd Level. Most of the pre-tasks that are created to the 3rd Level support team are related to the system bugs and inconsistencies in functionality. The resolution of this kind of case will require involvement of the product owner, vendor developers

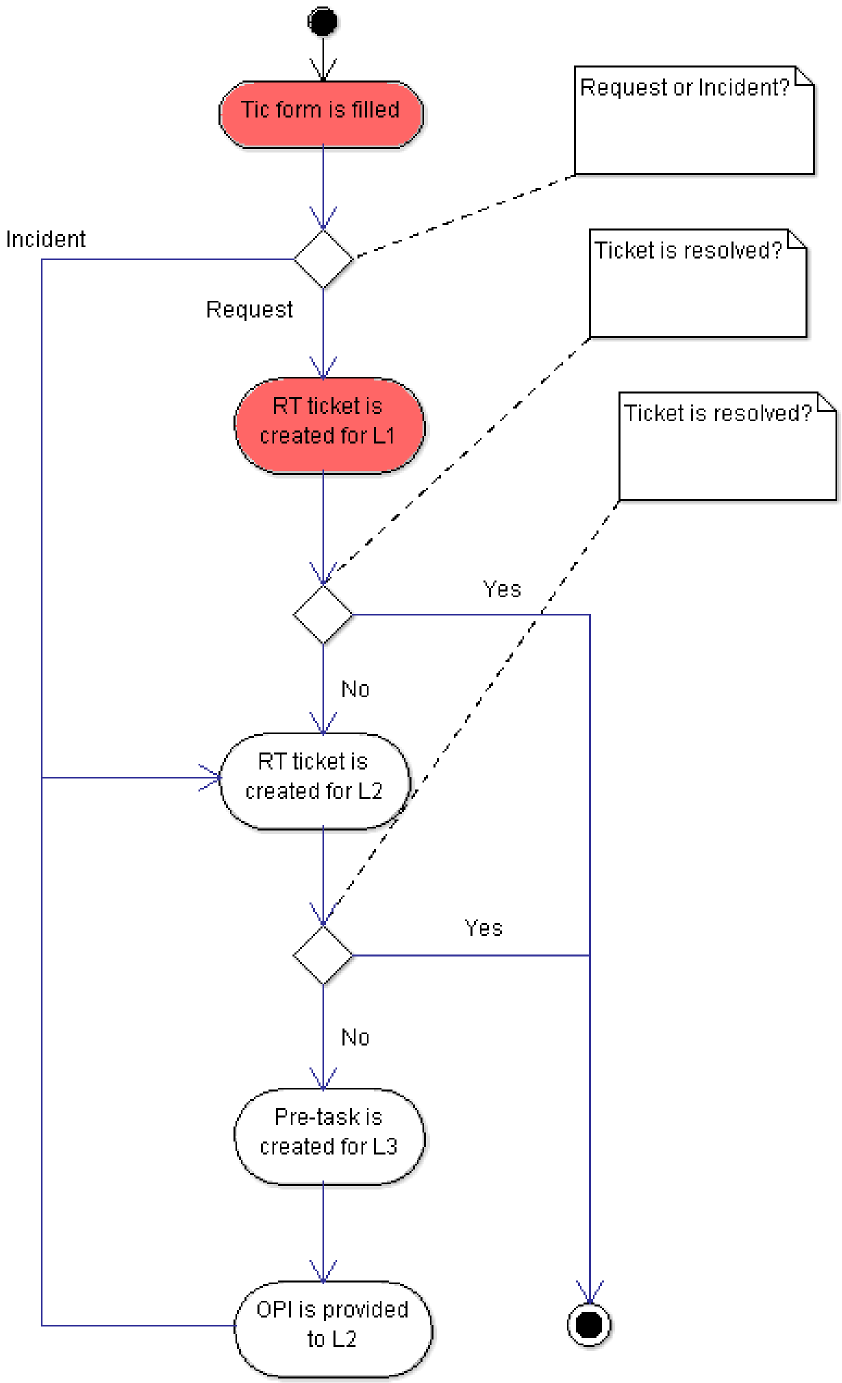

Figure 6. *The request processing flowchart without chatbot implementation*

and financial controllers. If resolution is not related to the explanation of certain functionality of the system to the 2nd Level support team then the resolution will take some time.

Let's consider the existing business process for implementing a chatbot in the technical support service. After analyzing the technical support service Figure 6, it was decided to implement an AI chatbot using platform Boost.ai. The workflow area that is affected

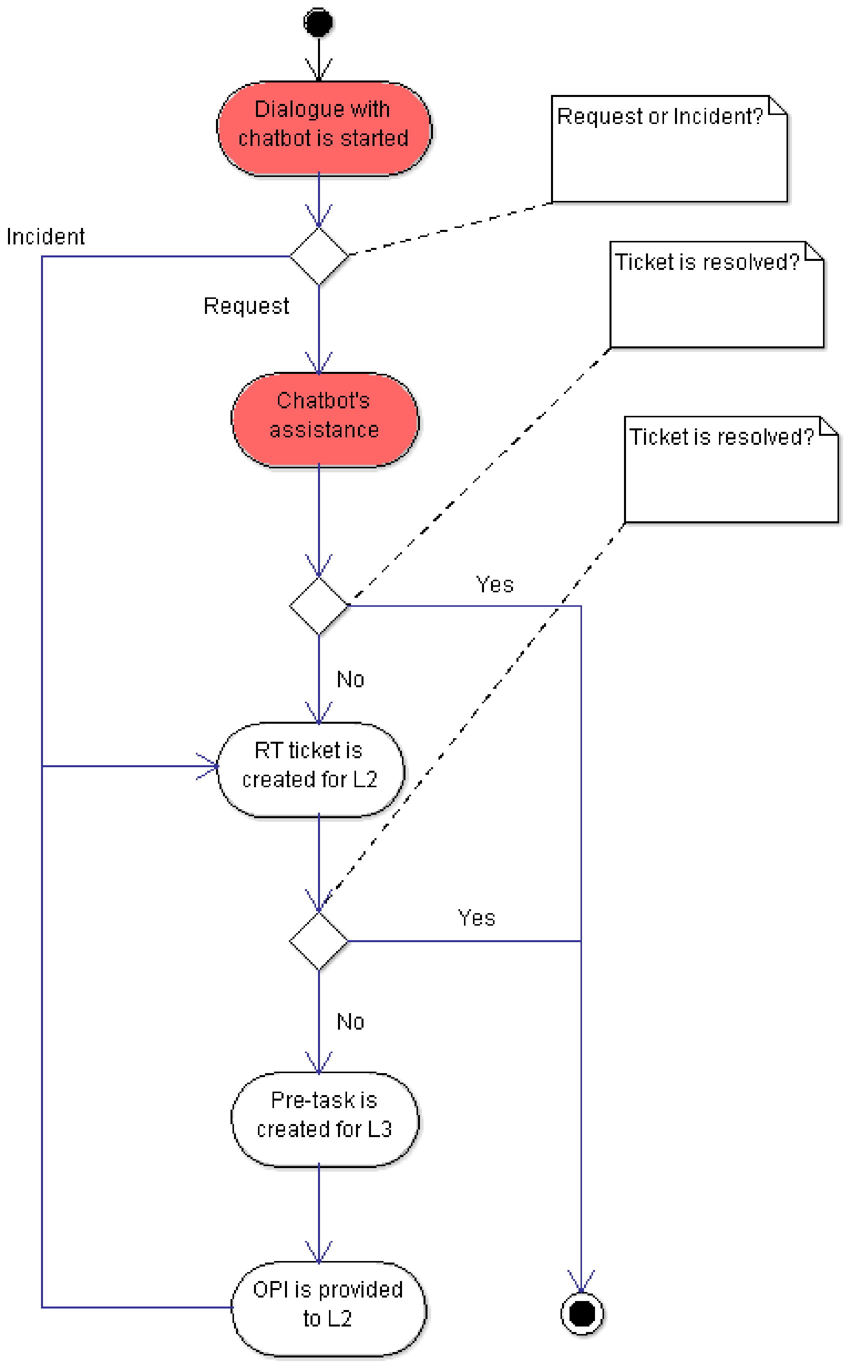

Figure 7. *The request processing flowchart with chatbot implementation*

by the chatbot implementation is highlighted in light-red color. The implementation of a chatbot into the support service workflows will release the 1st Level operators and the team leader. Changes in the flow chart of the technical support service process diagrams after the implementation of the chatbot are shown in Figure 7 and highlighted with light-red color. *Dialogue with chatbot is started* indicates the identification of the type and subject of inquiry. Under *Chatbot's assistance* chatbot is proving the support to the requestor. Suppose the chatbot cannot resolve the inquiry and the requestor is willing to proceed with the human backing. In that case, the conversation history will be pasted into the body of the RT ticket that will be created for the 2nd Level.

It is expected that the implementation of a chatbot will improve the business process of the technical support service by improving the following indicators:

- Increase in efficiency of the workforce;
- Increase in average ticket resolution time;
- Automation of communication;
- Standartisation of the issue.

Chatbots can be an effective tool for improving customer interaction, reducing the burden on company employees and improving the end-user service quality.

4.3 Case study of chatbot implementation for support team

In today's digital world, focused on servicing a large number of unique connections, automation in the form of AI-based chatbots is becoming increasingly common when working with clients. Business interaction with customers is becoming more and more highly automated and occurs through the latest technologies, such as chatbots, for faster, more accurate and convenient work. Chatbots with artificial intelligence make it easy to implement automated contextual responses to specific customer requests, which saves their time and reduces the organization's costs for customer support.

The best way to use chatbots in customer support is to balance automated and human interaction. This means that chatbots will solve common issues through automated conversations, while customer support staff will provide individual assistance on requests that requires a personalized approach. In general, using an intelligent chatbot in the technical support service will help save time and bring tangible benefits in the form of increased efficiency, productivity and cost reduction. However, the integration and implementation of the chatbot should be carried out, taking into account possible negative consequences and factors that may affect human-bot communication. The lack of understanding of these problems and ways to solve them can deteriorate the company's image, leading to a loss of customer loyalty and a decrease in the number of customers. Based on the literature review [20, 26, 31, 34, 38], the below requirements for service desk chatbot were formed:

- Multichannel. This is the ability of a chatbot to cover different channels of communication with customers: website, social networks, email and instant messengers. Multi-channel chatbots communicate consistently and are cheaper for businesses than separate solutions for each channel;
- The presence of a script designer. Allows agents to build dialogue chains from ready-made blocks without knowing the program code. This simplifies and speeds up the work with clients;
- Learnability. With every new interaction chatbot improves in request understanding which requires data for the training and repetition of the questions;
- Integration with other services. Chatbot can be integrated with CRM system, task scheduler, cloud system and etc.;
- Built-in analytics and reporting. These features help evaluate the chatbot's effectiveness and build a client portrait. Metrics are the essential tools for the improvement management and providing answers to the questions such as what are the most repetitive problems, what are the requestors expectations and how do they evaluate the service.
- Digital security. Data leakage can lead to financial and reputational losses for a company. Self-written chatbots created on constructors are significantly inferior in security to ready-made solutions;
- Flexible, intuitive setup.

The AI chatbot was implemented in Kühne+Nagel at the end of 2020. Chatbot modeling and deployment is carried out on the platform Boost.ai. Most of Tallinn and some employees from other European offices had an opportunity to get familiar with *Abi* (name of the service desk chatbot used in Kühne+Nagel). Therefore author decided to survey employees who used the chatbot for request resolution. This study allowed us to identify the main factors affecting the user experience of a person communicating with a technical support chatbot. To verify the hypothesis that negative user experience and lack of communication with people form a prejudice in favor of high-tech communication.

Mallet et al. [56], in their study showed that users expect chatbots to have a more neutral and objective attitude towards themselves. At the same time, it was expected that there would be fewer conflict situations when solving a user's problem since chatbots are programmed for specific behavior. It was shown by Lee and Choi [56] that a user's understanding of the nature of a chatbot can reduce negative user experience and increase user confidence in technology-advanced communication. The literature review [26, 27, 29, 30, 32, 57, 56] allowed us to identify factors that affect the experience of human-bot communication. The list of factors and their quality attributes in Table 6 will allow us to identify the factors and their quality attributes that will be investigated when interviewing users of the technical support chatbot.

Table 6. *Human-bot communication factors and quality attributes*

Factors	**Quality Attribute (from literature review)**
HUMAN-BOT COMMUNICATION EFFECTIVENESS	
Functionality	Accurate speech synthesis; Interprets commands accurately; Use appropriate degrees of formality, linguistic register; Linguistic accuracy of outputs; Execute requested tasks; Facilitate transactions and follows up with status reports; General ease of use; Engage in on-the-fly problem solving; Contains breadth of knowledge, is flexible in interpreting it.
Humanity	Passes the Turing test Does not have to pass the Turing Test; Transparent to inspection, discloses its chatbot identity; Include errors to increase realism; Convincing, satisfying; Natural interaction; Able to respond to specific questions; Able to maintain themed discussion.
HUMAN-BOT COMMUNICATION SATISFACTION	
Affect	Provide greetings, convey personality; Give conversational cues; Provide emotional information through tone, inflection and expressivity; Exude warmth and authenticity; Make tasks more fun and interesting; Entertain and/or enable participant to enjoy the interaction; Read and respond to moods of human participant.
Ethics & Behavior	Respect, inclusion, and preservation of dignity (linked to choice of training set); Ethics and cultural knowledge of users; Protect and respect privacy; Nondeception; Sensitivity to safety and social concerns; Trustworthiness (linked to perceived quality); Awareness of trends and social context.
Accessibility	Responds to social cues or lack thereof; Can detect meaning or intent; Meets neurodiverse needs such as extra response time and text interface.
HUMAN-BOT COMMUNICATION EFFICIENCY	
Performance	Graceful degradation; Robustness to manipulation; Robustness to unexpected input; Avoid inappropriate utterances and be able to perform damage control; Effective function allocation. Provides appropriate channels for human-machine interaction.

To assess the perception of the quality attributes (Table 6) influencing the perception of human-bot communication, in case of the chatbot implementation for customer service at KN, the author developed a questionnaire[2]. The survey was conducted among KN employees who had used a chatbot at least once already. The questionnaire was sent to 300

[2] https://forms.gle/t7J6JTAUNJSodsZ27

employees on 18th of April and 54 (18%) responses was received in total at the end of the survey on 30th of April. All the questions from this questionnaire are listed in Appendix 6.

The survey results showed that 33% of respondents are satisfied with the quality of service, 65% are satisfied partially and 12% are not satisfied at all. Poor question understanding, bad location of the chatbot icon and formed bias towards technology-advanced communication were the most common disappointment reasons. These users prefer the human operator support over the chatbot. However, the initial version of the chatbot included list of questions mostly oriented to Performance and Potential Review domain (PPR) and could not include all the possible question. Therefore the expansion of questions database and additional chatbot training will improve the rate of satisfaction.

The questionnaire contained questions that make it possible to assess the quality of the chatbot's work and are also designed to evaluate the employee's communication experience with the chatbot. Table 7 shows the quality attributes, survey parameters and evaluation scale for data collection. The questionnaire was compiled by the author personally on the basis of a literary review [26, 27, 29, 30, 32, 57, 56]. For the performance evaluation the question "*Which of the following topics have you needed Abi's assistance with (SQ02) and How many times you had chat with Abi (SQ03)?*" was used in questionnaire. For the humanity evaluation the question *"How would you rate the quality of Abi's support (SQ04)?" and "Please indicate to which degree you believe the answers provided by our support chatbot Abi were correct and reliable for solving your support request (SQ06).*" were used in questionnaire. For the affect evaluation the question "*How would you rate the "intelligence" of our service chatbot (SQ07)?*" was used in questionnaire. For the affect evaluation the question "*How "human" did you perceive your communication with the Abi chatbot (SQ08)?"* was used in questionnaire.

Table 7. *Chatbot evaluation factors, attribute and scaling*

Factors	**Attibute**	**Scale**	**SQ#**
Performance	Provides appropriate channels for human-machine interaction	% of successes	SQ02, SQ03
Humanity	Able to respond to specific questions; Able to maintain themed discussion	five-point Likert scale	SQ04, SQ06
Affect	Provides greetings; pleasant personality	five-point Likert scale	SQ07
Accessibility	Can detect meaning and intent	five-point Likert scale	SQ08

Let's analyze the results of a survey of company employees to evaluate the service chatbot as a channel for human-bot communication. Figure 8 shows the results of the analysis of the frequency of using the chatbot to solve the problem by employees.

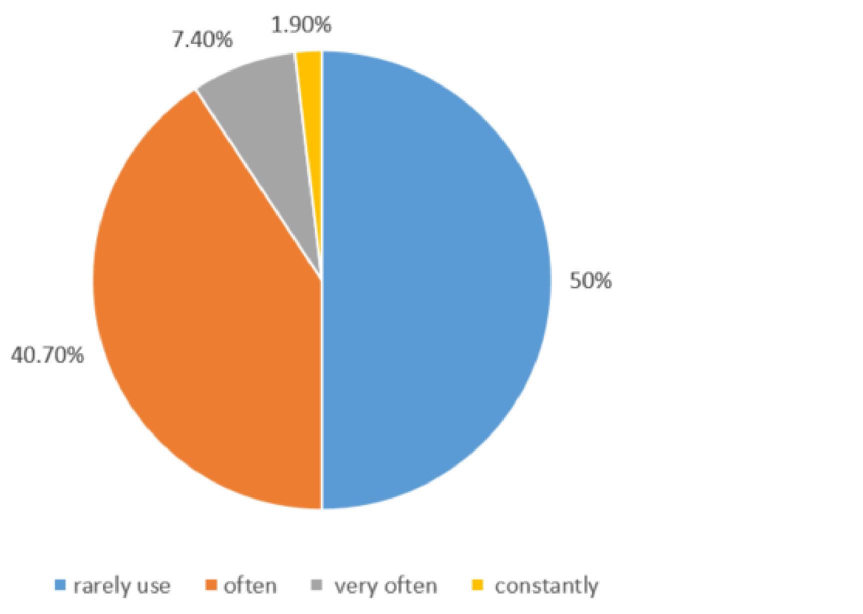

Figure 8. *Evaluation of chatbot performance*

More than 40% of respondents often use the chatbot communication channel to solve their problems, as can be seen in Figure 8. The majority of respondents – 50% rarely use the chatbot communication channel (the survey involved users who solved their problems at least once using a chatbot), which confirms the assumption that users distrust technological communication when solving their questions. This can be explained by the short period of use of the chatbot in the technical support service (starting from the end of 2020) and insufficient amount of training data. However, the list of topics that can be covered by chatbot is constantly expanding, such as HR, Onboarding, IT and others.

Figure 9 shows estimates of quality attributes for the "humanity" factor. 48.1% of respondents noted a fair chatbot ability to respond to specific questions. The 57.4% of respondents rates *Abi's* ability to conduct a dialogue on specific topics as "good" and 24.1 as "fair". The negative feedback was received from approximately 10% of the respondents. It is necessary to analyze more thoroughly the problems faced by these users during the communication with the chatbot and make changes to the chatbot's dialect scripts or expand the database for lacking questions and answers.

The accessibility factor was evaluated as the chatbot's ability to recognize the meaning and intent of the dialog. In our questionnaire, this attribute is evaluated as the "intelligence" of the chatbot. Figure 10 shows the results of the evaluation of the "intelligence" parameter by the respondents of our survey. The "intelligence" of the *Abi* was rated quite highly – 5.6% as excellent, 13% as good, 63% as fair. Withal 18.6% of respondents rated the intelligence of the chatbot as relatively low. Based on the suggestions provided by the respondents

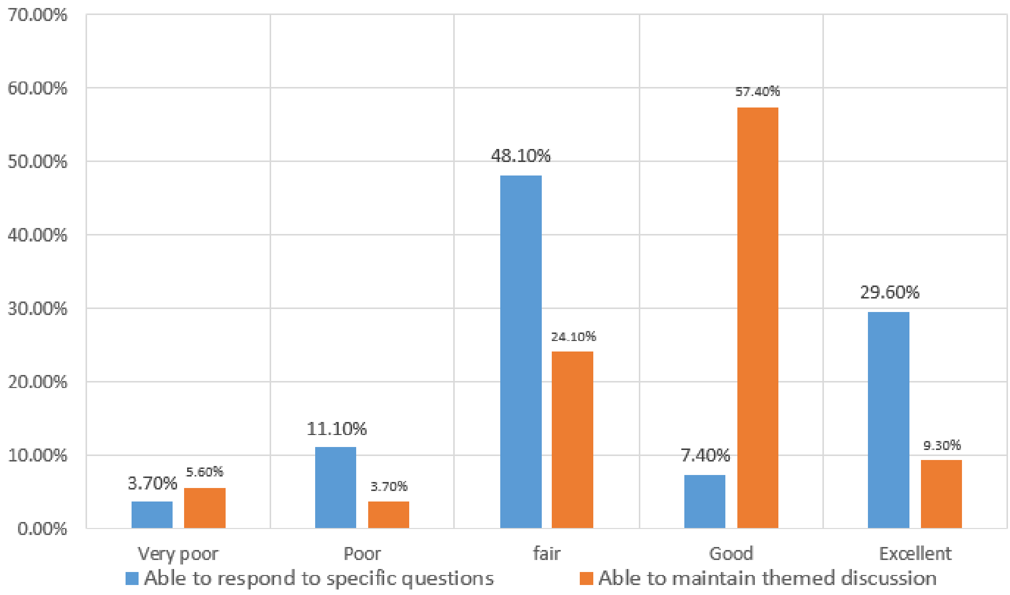

Figure 9. *"Humanity" chatbot estimation*

the following shortcomings were indicated: insufficient ability to recognize the context of a conversation, inability to understand the meaning of questions, irrelevant answers to questions, switching to the operator is not always available. Also, in the future, it is planned to continue research on improving the chatbot's intelligence through its additional training on an expanded database of questions and answers. Despite the average ratings on the intelligence of the chatbot, most of the respondents noted the *Abi* as a good assistant (51.9%) and a necessary tool (13%).

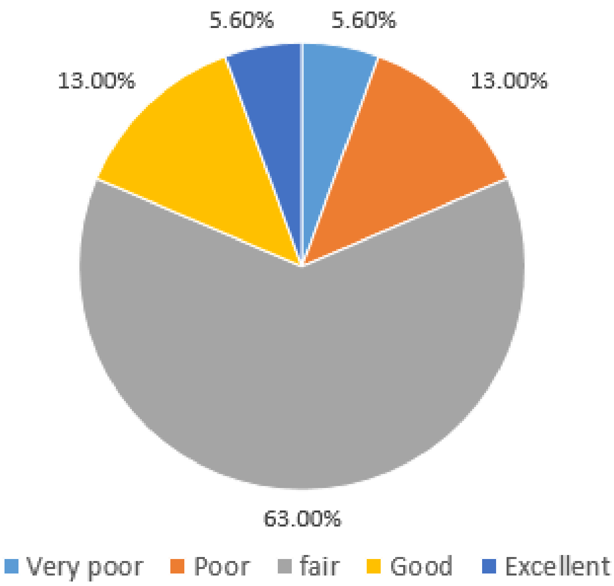

Figure 10. *"Intelligence" evaluation*

Figure 11 shows respondent's assessments of the chatbot's ability to conduct a "human" dialogue. 61.1% of respondents rated the *Abi's* ability to maintain a "human" dialogue as fair. About 13% of respondents noted the lack of humanity and rated it unsatisfactory. The principal wishes in the development of this chatbot factor were: the addition of an animated avatar and the introduction of jokes in the dialogue scripts. In the future, it is planned to include these functions too. In addition, most of the respondents will recommend that their colleagues and acquaintances contact the *Abi* to solve issues (probably – 38.9% and very likely – 40.7%). At the same time, 9.3% rated the chatbot experience as excellent compared to the operator and 57.4% as good. Notably, 51.9% are likely to turn to the chatbot again to solve their next problem and only less than 12% will prefer communication with the operator. We confirmed the hypothesis that the negative experience of communicating with chatbots and the lack of the possibility of solving the problem by a human operator can lead to formation of bias towards human-machine communication. A positive experience of solving problems with which a person turned to a chatbot can improve a person's attitude to a chatbot. A positive experience in communicating with a chatbot improves the user experience of communication. Users who were able to solve their problems with the help of a chatbot will re-contact him and will recommend the chatbot to their colleagues. The conclusions of our work completely coincide with the results of the Chatbot Rating 2021 study .

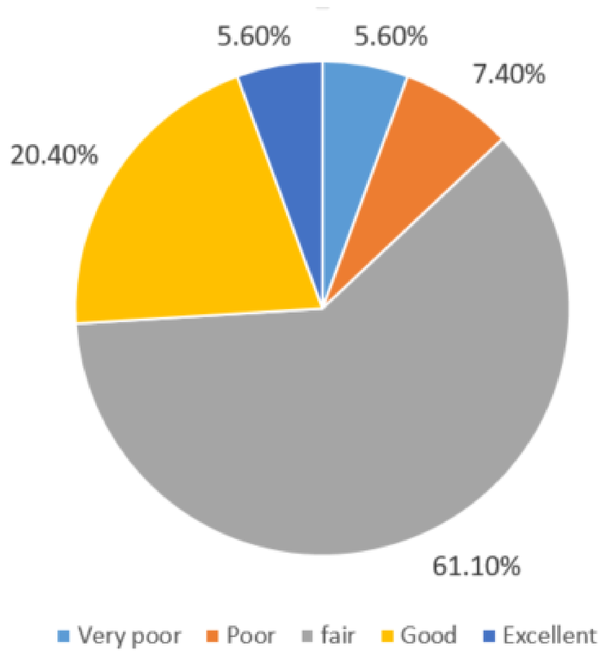

Figure 11. *The ability to conduct a "human" dialogue with the user*

Thus, the review conducted in Section 4.1 and the experimental studies in Section 4.3 give us the opportunity to formulate an answer to RQ2 (What are the factors contributing to bias and perceived negative user experiences when communicating with chatbots, and how can we increase trust in chatbots?). Based on the literature review, the main factors and attributes of quality that affect the user experience of human-bot communication were identified. These factors include: Functionality, Humanity, Affect, Ethics & Behavior, Accessibility, Performance. Secondly, the selected factors (humanity, affect, accessibility, performance) and their quality attributes can be used for human-bot interaction assessment. The questionnaire was developed and a survey of KN employees was conducted to evaluate the selected factors. Analysis of the survey results showed that the main factors influencing the negative user experience are low "humanity" and "intelligence" level of chatbot. Also, the negative perception of communication with chatbots arises due to the inability to translate the solution of the user's problem to a human operator. Thus, our study confirms the hypothesis that negative usage experience and lack of human connection form a bias towards technology-advanced communication.

To reduce the negative impact of these factors and increase confidence in human-machine communication, it is necessary to constantly monitor the user experience of communicating with a chatbot, improve dialogue scenarios and expand the database of questions and answers. It is also advisable to add anthropomorphic chatbot styles: animated avatars, jokes, a special style of communication and much more. All these measures can lead to additional financial costs that may not pay off.

5. Economic gain from chatbot technology

5.1 Approaches to chatbot evaluation

Intelligent chatbots are the new direction in human-machine interaction and therefore, international standards for assessing the quality of AI chatbots have not yet been created. However, several studies in the scientific literature offer various metrics for evaluating AI chatbots. Peras [58] reviews existing evaluation metrics and analyze them. Peras offers an AI chatbot evaluation system that considers five perspectives: user experience perspective, information retrieval perspective, linguistic perspective, technology perspective and business perspective. There are also 14 categories for evaluating AI chatbots: usability, performance, affect, satisfaction, accuracy, accessibility, efficiency, quality, quantity, relation, manner, grammatical accuracy, humanity and business value. It is worth noting that these categories require additional analysis and research.

Kuligowska [59], in her study, offers several metrics that can evaluate the performance, usability and overall quality of the implementation of a conversational agent. These metrics analyzed and assessed the most popular Polish language commercial chatbots in various subject domains. When analyzing Polish language commercial chatbots, multiple parameters were taken into account and evaluated on a five-point scale: visual appearance, form of implementation on the website, speech synthesis unit, built-in knowledge base (with general and specialized information), knowledge representation, conversational abilities and contextual sensitivity, personality traits, personalization options, emergency response measures in unforeseen situations and ability to evaluate the chatbot and the website by the user. Such an assessment makes it possible to perform a multidimensional assessment of the deployment of a commercial AI chatbot.

In Section 4.3 we have already evaluated our AI chatbot according to such parameters as usability, performance, affect, satisfaction, accuracy, efficiency, quality, humanity and business value. All assessments were carried out using a five-point scale based on survey of chatbot users at KN. Since AI chatbots imitate the work of the real employees then their performance should also be evaluated. Therefore, to evaluate the effectiveness of the *Abi* chatbot in scope of this thesis, author suggests using the KPI metric. A review of studies showed that KPIs were used to evaluate IT projects. For example, Ganguly and Rai [60] used KPI metrics for supply chain information system implementation, Sulistiani et al. [61] proposed quality models based on KPI metrics for Evaluation of Academic Information System implementation, Mahmodabadi et al. [62] studied the use of key performance indicators for a hospital pharmacy digital dashboard. However, the research analysis showed that KPI metrics have not yet been used to evaluate AI chatbot implementation projects. On the other hand, since chatbots are software, standard software evaluation methods can be applied. Thus, the methods of assessing the quality of chatbot applications can be divided into two categories:

- Evaluation methods for measuring business indicators;
- Evaluation methods for measuring technical indicators.

Since we need to determine the minimum resources and the payback period for the implementation of the chatbot of the technical support service, we will focus on the first category of assessment – business efficiency assessment. A set of metrics for evaluating business indicators is the most important from a business point of view. It helps to calculate how long the costs of developing a bot will pay off and whether it meets expectations. The following are the evaluation metrics that are proposed to be used in this thesis:

- Reduction of the workload (man-hours) of technical support staff. Since most of the technical support requests are standard, chatbots can easily handle them as a human. Our chatbot *Abi* serves users in the chat and redirects to "live" operators only when required. The implementation of the *Abi* chatbot into the technical support service helps reduce the number of operators at the first level and reduce the load on the technical support team at the second level. The assessment of the economic efficiency of introducing a chatbot to the technical support service can be calculated as Operator Rate $\times$ Ticket Processing Time $\times$ Average Number Of Tickets Per Operator;
- Number of users. Allows us to track the total number of users for a specified period and compare it with the previous period. The total number consists of new users and returning ones. The number of the latter is a valuable metric. It shows how many users are reusing our chatbot compared to the previous period. If this indicator is growing, our users were satisfied with the bot's response earlier and willingly chose this channel for communication;
- Net Promoter Score (NPS) is the consumer loyalty index (an assessment of user loyalty towards the company). A chatbot is a convenient tool for conducting a survey and calculating the NPS indicator. Usually, such a survey is conducted through email newsletters, calls, pop-ups, etc. It is more convenient and faster to conduct such an assessment with a chatbot. At the end of the dialog, the user can be asked to rate

the conversation. Based on the answer, we can identify the reason for the negative assessment by analyzing the history of this dialogue. Based on the ratings received from users, this metric can be calculated using the Equation 5.1:

$$NPS = \frac{(\text{ sum of rating from } 9 \text{ to } 10) - (\text{ sum of rating from } 0 \text{ to } 6)}{\text{num of all respondents } \cdot 100} \tag{5.1}$$

Calculation of the Return on Investment (ROI) indicator will make it possible to estimate the minimum required resources and the expected payback period for the implementation of the *Abi* chatbot into the business processes of the technical support service. The implementation process itself is a long-term IT strategy, during the implementation of which the payback of this project is analyzed. The primary indicator, in this case, is the ROI. Several publications describe the use of ROI to evaluate minimal resource requirements and the expected payback period for the chatbot technology utilization. Kousa [63], investigates the factors influencing the success of the use of chatbot technologies, suggests using ROI as the main assessment factors. Kumar [64] uses ROI to evaluate the Chatbot development project for the business team using a Google Dialog flow. Singh et al. [65] consider ROI as a tool for measuring the success of chatbot implementation for large enterprises.

Currently, there is an worldwide tendency in increasing financing of IT budgets, which supports the rapid growth of companies. Based on the general cost reduction policy, IT budgets are among the first to be reduced and it is crucial to assess the feasibility of each implementation. It is assumed that the resources invested in using the chatbot will pay off within the first six months. To confirm this hypothesis, in Section 5.3, we will conduct ROI assessments for the project of implementing the AI chatbot in the technical support service.

5.2 Analysis of the chatbot implementation costs and ROI

Let's consider an example of calculating ROI when implementing a technical support chatbot at KN. The calculation is based on expenses related to chatbot implementation and maintenance, relocation of the 1st level support team of 6 supporters and one team leader to other position or termination of employment. Capital expenditures are represented as the sum of the external cost and the cost of internal resources. The external cost is expressed in the cost of the license to use the platform Boost.ai for the *Abi* chatbot implementation. Since the chatbots of the technical support service were developed using the platform Boost.ai , then the PaaS (Platform as a Service) model was chosen for this project. PaaS model includes infrastructure (servers, storage and network equipment), as well as middleware, development tools, business intelligence (BI), database management system services, and more. In our case the expenses related to infrastructure rental, as well as chatbot development and configuration were paid in the first year of the project. As a result, capitalization expenses in the first year amounted to 20,000 €. Further, a fixed fee is charged for the use of the platform and access to the chatbot placed on it, according to the selected subscription plan. In our case, Quick automation plan was chosen that cost 10,000 €/year (in 2021). The Quick automation plan includes[1]:

- 1 virtual agent;
- 2 languages (English + 1);
- Unlimited channels;
- Unlimited intents;
- Self-learning capabilities;
- Online AI Trainer courses;
- Access to the AI Trainer community and knowledge base;
- Dedicated support, advice and guidance from Boost.ai;
- Technical support;
- GDPR-compliant privacy features;
- Enterprise security features;
- Voice integration (Google Assistant, Amazon Alexa, etc.);
- AWS cloud hosting.

The list of non-capitalized costs includes *B2 Annual Licensing and Support* – this is the cost of the annual Quick Automation tariff plan for the boost.ai platform. Cost *B1 Software Implementation*, in turn, includes *B1.1 Internal Services* 35 393 €/year – salary of the company's IT specialist, *B1.2 Product Implementation* 8 000 €. The implementation of a software product includes work on setting up the company's messengers and setting up the software itself for specific operating conditions and is paid as a lump sum bonus for DevOps engineers. *B1.3 Employee training* 5000 € first year only. This thesis discusses the economic efficiency indicators from the implementation of a chatbot for the two years 2020 and 2021. The savings in cash flow (CF) amounted to 164,353 € per year. Cash flow was 95,960 € for 2020 and 118,960 € for 2021. The Total Cash flow amounted to 214,920 € for two years. Discounted cash flow amounted to 90,528 € in 2020 and 105,874 € in 2021. The total discounted cash flow for two years amounted to 196,402 €. Table 8 shows the total cost of ownership (TCO) calculations for the technical support chatbot.

The first advantage of chatbot implementation is the optimization of the response time of the first-level technical support staff to standard questions. After the implementation

[1] `https://www.boost.ai/plans`

Table 8. *Cost assesment of chatbot implementation, €*

Cost assesment	2020	2021	Total
CAPITALIZED COSTS			
A1 Software licensing	20,000	0	20,000
NON-CAPITALIZED COSTS			
B1 Software implementation			
B1.1 Internal services	35,393	35,393	70,786
B1.2 Product implementation	8,000	0	8,000
B1.3 Employee training	5,000	0	5,000
B2 Annual licensing and support	0	10,000	10,000
Investment sum total	**68,393**	**45,393**	**113,786**

of the chatbot, it became possible to reduce the number of employees at the first level by replacing them with a chatbot. For wage fund calculation used in Table 9 we have used the average annual total cost for employer for an L1 Application Support Specialist as 21,460 €[2] and L1 Team Leader as 35,593 €[3].

Table 9. *Savings cash flow, €*

Position	No. of employees	Salary/year	Wage fund
Operator L1	6	21,460	128,760
Team leader L1	1	35,593	35,593
Total			**164,353**

On daily basis support teams answer repetitive question and perform repetitive tasks. This part can be easily optimized by the introduction of the chatbot. The working time can used more wisely and the performace of the whole department/team can be improved.

The Return On Investment (ROI) is dispalyed in the Equation 5.2 and determined by the ratio of the profit received and the costs saved during the implementation to the costs of the chatbot. The higher the profit from the project and the lower the project expenses, then greater the ROI indicator will be.

$$ROI = \frac{(\text{Savings Cash Flow} - \text{Cost of Investment})}{\text{Cost of Investment}} \tag{5.2}$$

Currently, several approaches to assessing investments in IT projects are widespread and actively used. One of the popular methods for evaluating investments in IT projects is the Discounted Cash Flow (DCF) method. The discounted cash flow method consists

[2] https://www.salaryexpert.com/salary/job/applications-support-specialist/estonia/tallinn

[3] https://www.salaryexpert.com/salary/job/operations-team-leader/estonia/tallinn

in determining the current value of the net CF as given by Equation 5.3, where DCF – Discount Cash Flow and CF_i – Cash Flow, r – discount rate and n – number of years.

$$DCF = \sum_{i=1}^{n} \frac{CF_i}{(1+r)^i} \tag{5.3}$$

The discount rate is recommended at the level of 6% for projects implementing IT technologies in the company's work processes, according to the results of the study [66]. When calculating the profit and costs for the year, the ROI will be inversely proportional (1/r, r= 6% - discount rate) to the number of years (n=2) after which the project will reach the break-even point.

Table 10 shows the ROI calculation for two years of implementation and use of the technical support chatbot. The payback period is calculated by the Equation 5.4, where PP (Pay-Back Period) -– payback period, expressed in years; IC (Invest Capital) -– the amount of initial investment (Table 8); CF (Cash Flow) is the expected average annual cash flow (Table 10).

$$PP = \frac{\text{IC}}{\text{CF}} = \frac{113{,}786}{214{,}920} = 0.53 \text{ year} = 6.4 \text{ months} \tag{5.4}$$

The chatbot implementation project at KN will pay off in 6.4 months (0.53 years) after the start of its implementation. The minimum financial investments for the use of chatbot technology have been calculated and the expected payback period for the introduction of chatbot technology to the technical support service has been determined in order to answer to RQ3 (What are the minimum resource requirements for using chatbot technology and the expected payback period?). To implement a chatbot in the technical support service,

Table 10. *Data for ROI calculation, €*

Fiscal year	**2020**	**2021**	**Total**
Capitalized investment	20,000	0	20,000
Non-cap. implementation	48,393	35,393	83,786
Non-cap. ongoing operation	0	10,000	10,000
Cost of investment (CI)	68,393	45,393	113,786
Savings Cash Flow	164,353	164,353	328,706
Cash Flow (CF)	95,960	118,960	214,920
Discounted cash flow	90,528	105,874	196,402
ROI	**140%**	**262%**	

we will need the following resources:

- a license to use the platform boost.ai;
- one IT specialist to develop and support a chatbot;
- implementation and maintenance costs;
- staff training costs.

The costs of paying an IT specialist and an annual license are required annually in the future. The introduction of a chatbot will save on the remuneration of employees of the first level of technical support of the company. To confirm the hypothesis of a return on investment in the project of implementing a chatbot of the technical support service, ROI calculations were carried out and the payback period was determined. According to the calculations given in section 5.3 of the dissertation, the payback period is 6.4 months. After 6.4 months of implementing the chatbot, the return on investment will be 105%, which means that the project will begin to make a profit. Thus, sections 5.2 and 5.3 answer the third research question RQ3.

6. Summary

The unique capabilities of the Internet: speed, efficiency, accessibility of communication between users allows use the network as a means of communication. New interactive forms of communication: chats, forums, teleconferences, e-mail and others are emerging. Artificial intelligence programs are replacing real interlocutors: chatbots, voice consultants and assistants and others. A chatbot does not have a flexible mental intelligence and is not able to maintain a dialogue on a free topic, unlike a person-to-person communication. Modern virtual interlocutors only partially solve the problem of imitating a human conversation and have limited abilities in finding answers to the interlocutor's questions. A lot of research on human-bot communication has appeared recently. These studies show the relevance of the topic related to the analysis of chatbot technologies and the problems associated with human-bot communication.

Chatbot technologies and problems related to human-machine interaction are studied in this thesis. An attempt to estimate the minimum resources needed to implement chatbot technology into the business processes of the technical support service and the expected payback period were also evaluated in this thesis. The review of the problem of using chatbot technologies allowed us to formulate three research questions (RQ1 – RQ3) and hypotheses of this thesis.

The author conducted a literary review of research on the problem of human-machine interaction. The review revealed the main problems associated with the human-machine interaction. The literature review showed that the incorrect design of the chatbot, the lack of "intelligence" and "humanity", the wrong choice of subject area, the lack of training of the chatbot in new communication scenarios are the main problems in human-machine interaction. The lack of attention on the part of chatbot developers to these problems can lead to a negative experience of using chatbot technologies. The author of this thesis conducted an overview of modern chatbot development platforms and chatbot technologies. Machine learning technologies, natural language processing, and neural networks are most often used to train intelligent chatbots. A review and analysis of chatbot development platforms revealed the main requirements for such platforms. The chatbot development platform should support: a visual chatbot designer, machine learning technologies, analytical tools, chatbot integration into popular messenger platforms, integration with other business tools. Analysis of popular chatbot development platforms made it possible to choose a platform Boost.ai. This platform meets all the requirements for development platforms and provides: a visual chatbot designer, machine learning technologies, analytical tools, chatbot integration into popular messenger platforms, integration with other business tools. Platform Boost.ai was used to implement a chatbot into the technical support service of KN. These studies made it possible to answer RQ1, allowing to identify problems and technologies that are used for the implementation of chatbots and confirmed the hypothesis put forward in this thesis that problems with the use of chatbot technologies lead to a negative attitude towards high-tech communications.

The literature review conducted by the author allowed to identify the main factors and quality attributes that affect the user experience of a person communicating with a chatbot. The following factors: humanity, influence, accessibility, performance and their qualitative characteristics were used in this thesis to evaluate a person's communication experience with a KN technical support chatbot. This thesis examines the technical case of implementing a chatbot into the work processes of the KN technical support service. A questionnaire has been implemented to survey the company's employees in order to assess the selected factors and the experience of communicating with the chatbot of the technical support service. A survey was conducted and its results were analyzed. The survey result and it's analysis allow us to formulate an answer to RQ2 about the factors contributing to the bias and perceived negative user experience with chatbots, and how we can increase trust and confidence using them. Our study confirms the hypothesis that negative user experience and lack of communication with a human operator hinders the implementation of high-tech communication solutions.

Calculations of the ROI indicator to assess the minimum necessary financial and technical resources for implementing a chatbot in the technical support service are performed in this thesis. The minimum necessary resources and minimum financial investments are determined. The expected payback period for the introduction of chatbot technology to the technical support service has been determined.These studies answered RQ3 and determined the minimum resource requirements for the use of chatbot technology and the expected payback period for the project on the implementation of chatbot technology in the technical support service of KN. Research has also confirmed the hypothesis that the resources invested in using the chatbot will pay off within the first six months.

In this thesis we demonstrated the possibility of introducing chatbots into a new subject area – technical support. The results of the study supported the hypothesis that the negative experience of communicating with a chatbot and the inability to solve the problem with the help of a human operator can reduce the effectiveness of the introduction of chatbot technologies. Promising technologies and platforms for the development of chatbots are analyzed in this thesis. The analysis showed that the most popular platforms for developing chatbots are platforms that have graphical chatbot designers, analytical tools and use machine learning technologies and neural networks. The implementation of chatbot technologies requires certain financial resources and can bring profit and pay off within 1 year after implementation.

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Appendices

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Appendix 2 – Questionnaire Questions

SQ#	Question
01	The name of your position is ...
02	Which of the following topics have you needed Abi's assistance with?
03	How many times you had chat with Abi?
04	How would you rate the quality of Abi's support?
05	Did you feel comfortable communicating with our support robot Abi?"
06	Please indicate to which degree you believe the answers provided by our support chatbot Abi were correct and reliable for solving your support request.
07	How would you rate the "intelligence" of our service chatbot?
08	How "human" did you perceive your communication with the Abi chatbot?
09	Have you felt anxiety when communicating with Abi?
10	What is the probability that you will recommend Abi to others?
11	Which of the following words would you use to describe our chatbot?
12	How well did the chatbot help solve your last issue?
13	How would you rate the experience of communicating with a chatbot compared to communicating with an operator?
14	What is the probability that you will solve the next problem with the help of a chatbot, and not an operator?
15	What would you recommend to improve out chatbot communication (e.g. humor, animation, human avatars)?
16	Do you expect something more from Abi?