Contributions to
Chatbots and Digital Analytics in Industry

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Abstract

This cumulative dissertation includes ten scientific papers contributing to the knowledge of digital analytics, technology acceptance measurement, and chatbots. The papers aim to simplify and support the development, implementation, and management of technologies by developing frameworks that describe the most important steps, e.g., listing important related questions, naming the stakeholders to be involved, and presenting the appropriate tools to be considered. Taxonomies are developed and presented that show the range of design options that currently exist, while the identified archetypes present design combinations that can be observed and adapted. Identifying the most common reasons for the failure and development of critical success factors also contributes to the objective of facilitating the development and management process. As end-users decide the acceptance, and usage and, consequently, the success of a technology, the approaches demonstrate how user acceptance of technologies can be measured and how users can be involved in the development process at an early stage.

Keywords: Digital Analytics, Chatbots, Technology Acceptance, User-oriented Design, Customer Service, Business-to-Business, Human–Computer Interaction

Zusammenfassung

Diese kumulative Dissertation umfasst zehn wissenschaftliche Artikel, die zur Forschung digitaler Analytik, Messung von Technologieakzeptanz und Chatbots beitragen. Ziel der Artikel ist es, die Entwicklung, Implementierung und Verwaltung von Technologien zu vereinfachen und zu unterstützen. Modelle werden entwickelt, welche die wichtigsten Schritte beschreiben und unter anderem relevante damit zusammenhängende Fragen auflisten, die zu beteiligenden Interessengruppen benennen und geeignete Tools vorstellen, welche berücksichtigt werden sollten. Es werden Chatbot Taxonomien entwickelt und vorgestellt, welche die Bandbreite der derzeit bestehenden Gestaltungsmöglichkeiten aufzeigen, während identifizierte Archetypen zu beobachtende Kombinationen aufzeigen. Die Identifizierung der häufigsten Gründe für Misserfolge und die Entwicklung kritischer Erfolgsfaktoren tragen ebenfalls zu dem Ziel bei, den Entwicklungs- und Managementprozess zu erleichtern. Da die Endnutzer über die Akzeptanz und Nutzung und damit über den Erfolg einer Technologie entscheiden, werden Ansätze genutzt, wie die Nutzerakzeptanz von Technologien gemessen werden kann und wie Nutzer frühzeitig in den Entwicklungsprozess eingebunden werden können.

Schlagworte: Digital Analytics, Chatbots, Technologieakzeptanz, Nutzerorientiertes Design, Kundenservice, Business-to-Business, Mensch-Computer Interaktion

Management Summary

In the age of digital transformation, several companies are seeking for new digital communication techniques that can enable them to reach customers in a more efficient manner by providing 24/7 support and minimizing call center costs by automating manual processes. More and more B2B companies are deploying chatbots, known as one of the fastest-growing communication services (Kushwaha et al. 2021). Chatbots are software programs that automatically interact with humans within a simulated conversation to fulfill tasks or provide information (Bittner et al. 2019). For enterprises, one of the major challenges is to develop, deploy, and manage these tools in a way that provides value to the end-user as well as the organization. For this reason, the chatbots must meet the requirements and tasks of the users so that they can trust these chatbots to fulfil their needs.

On the other hand, users leave a digital footprint when browsing the internet, and digital analytics tools enable to capture this data to analyze the behavior of website visitors (Booth & Jansen 2009; Palomino et al. 2021). Used wisely, these tools can be essential to assess consumer needs. However, employees are inundated with ever-increasing amounts of data, sourced from a variety of tools (Du et al. 2021; Morgan & Lurie 2021). Thus, approaches outlining how target-group-specific information about the company's stakeholders can be provided on various channels are required to ensure that interpretations can be derived and appropriate actions are undertaken.

Contributing to the knowledge of digital analytics, technology acceptance measurement, chatbots, and user involvement, this cumulative dissertation is based on ten scientific papers. The papers aim to simplify the development, deployment, and management of technologies. This is done in the form of chatbots and web analytics reports, by building and applying frameworks, presenting possibilities for involving end-users, developing taxonomies, identifying archetypes, and measuring technology acceptance. To address the research needs, qualitative research, taxonomy development, and quantitative research approaches were applied, which are described in Chapter 2.

Chapter 3, "Digital Analytics and Technology Acceptance" focuses on presenting approaches to analyzing (potential) customer behavior on different digital channels and measuring technology acceptance. Frameworks are developed and applied in two papers to analyze the users' behavior on corporate websites and to predict the

personality traits of Twitter users. These frameworks can be used by practice as a basis to monitor and improve communication activities.

Web analytics tools for analyzing website visitors' behavior have become common in digital analytics (Harb et al. 2020). However, this data not only is relevant for the marketing department, which usually manages these tools, but also provides valuable information for the various business units in companies, such as the press department, product management and human resources. To this end, Janssen et al. (2019) developed a reusable and transferable web analytics model for individual web traffic report development based on a literature review and expert interviews. By applying participatory design (PD) methods, the model enables the development of target-group-specific reports in an industrial context by involving future users from different business units within the development process. Figure 1 (p. IV) presents the final model for web traffic report development in which stakeholders participate within the whole development process.

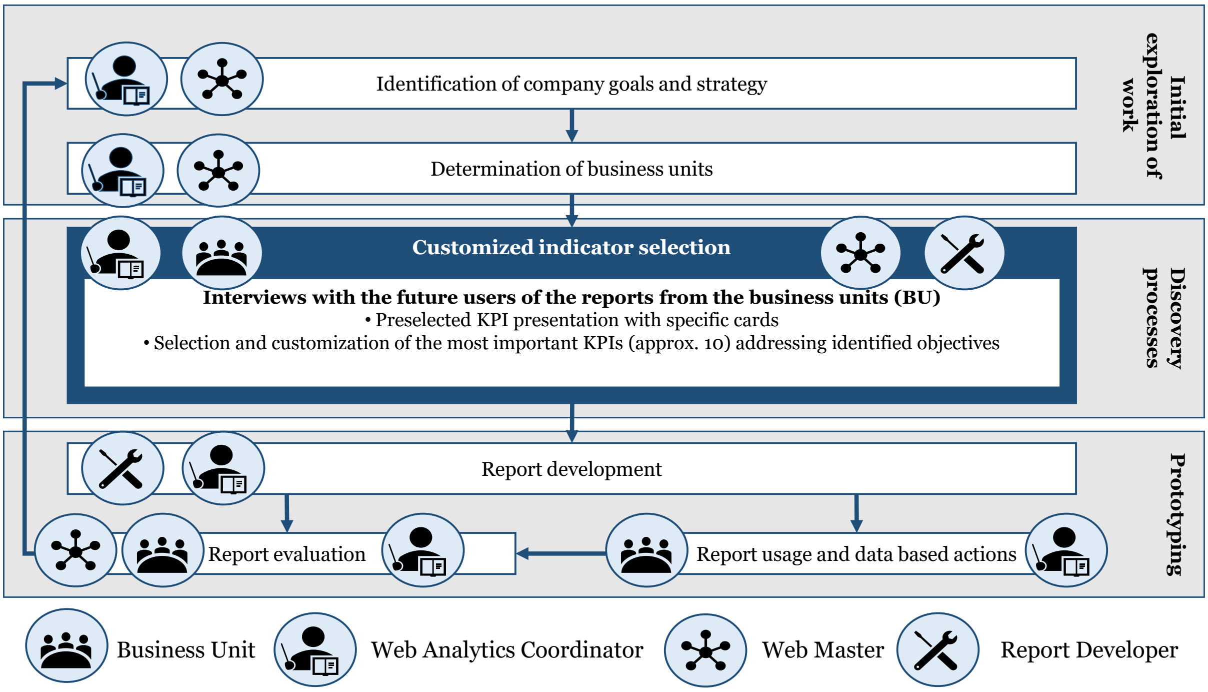

Figure 1: Participatory Design Model for Web Analytics Report Development (Janssen et al. 2019 p. 7)

The first step concentrates on detecting the overall goals and strategy of a company and identifying the relevant business units. This step is followed by the customized indicator selection process in which employees of the business units describe the main purposes of the business unit before identifying and customizing appropriate indicators. The process is supported by using a PD gamification card method, helping to easily select and prioritize the relevant indicators. In the subsequent steps, the report with relevant indicators is developed, evaluated, and released so that the business units can use the reports to draw conclusions. As part of an applicability check, the model was applied in an industrial automation company leading to a greater adoption and higher interest demonstrated by the involved users when the reports were individually tailored to their needs. We conclude that a comprehensive and early involvement of future users by applying PD methods is an effective way that can be adopted in other fields. This model further provides suitable indicators without losing focus on the actual goals of the business units and the organization.

By publishing posts about their own experiences, feelings, and opinions, Twitter users disclose a wealth of personal information about themselves (Carducci et al. 2018). The ever-growing dataset of Twitter posts enables a variety of automated analyses such as the prediction of personality traits, that is, information that can be used for marketing, healthcare, or recruitment purposes. In this regard, Klebansky et al. (2021) provide a framework to predict OCEAN (Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) personality traits based on the tweets of Twitter users. This approach allows the analysis of target audiences without directly involving and interviewing users, which can minimize bias in the results, compared to the traditional questionnaire-based approaches. The framework was tested through an applicability check, demonstrating how the model can be applied to gain in-depth insights into the personality profiles of Twitter's active users which can be used, e.g., for product recommendations (Buettner 2017).

The acceptance of a technology by a target group is crucial for its success. In addition to analyzing usage and behavior statistics by monitoring actual users, gaining insights into intentions, concerns, and reasons for use is feasible by surveying potential and current users on acceptance, which is done in two papers. First, Rodríguez Cardona et al. (2020) investigated the technology acceptance of robo-advisor systems in the German finance sector. Robo-advisor chatbots are intelligent interfaces that automatically provide professional financial advice to private users based on a previously conducted dialogue (Adam et al. 2019; Hildebrand & Bergner 2021). To investigate acceptance in form of the behavioral intention to use robo-advisor chatbots, the unified theory of acceptance and the use of technology 2 (UTAUT2) model of Venkatesh et al. (2012) were applied in an online survey with 250 respondents. The results indicate that the expected performance and the degree of automation are the most decisive factors for the intention to use robo-advisor chatbots in Germany, even though socio-economic factors also have a certain impact. Further, Rodríguez Cardona et al. (2021) conducted an online survey-based study to investigate the impact of the trust and technology acceptance aspects on the intention to use insurance chatbots. To investigate the intention to use insurance chatbots by testing hypotheses, the technology acceptance model (TAM) (Davis 1989) was extended to include trust and privacy concerns and was applied in an online survey involving 215 participants. The findings reveal that while trust has a significant positive influence on the intention to communicate with an insurance chatbot, perceived usefulness has a stronger positive influence on the intention to use it. Thus, the functional features of an insurance chatbot that provide a practical added value to the customer experience are most decisive in the intention to use the chatbot. Consequently, this implies that functional features should be carefully selected and developed by involving future users in strengthening their perceived usefulness. Furthermore, the functionalities should be promoted by the companies. Due to the circumstance that both finance and insurance firms promote services that may need further explanation in a conservative industry, the results could also be useful for B2B companies whose industries are considered similarly conservative while selling complex products and services.

Chatbots have been developed in recent years for application in a wide variety of areas such as education, health, and customer service. They can automatically fulfill specific tasks on websites, social media channels, and apps by using natural language processing (Zierau et al. 2020; Diederich et al. 2019b). However, little is known from a practical and scientific perspective about what design features characterize chatbots in the global market of domain-specific chatbots. Therefore, Chapter 4, "Chatbot Taxonomies, Archetypes, and Design Implications" contributes to the chatbot field in human–computer interaction and information systems (IS). Three taxonomies are developed to understand conceptually grounded and empirically validated chatbot design elements and their availability across chatbots from different application domains.

In the paper of Janssen et al. (2020), the literature on chatbots, as well as 103 chatbots from six application domains, is classified using an iterative approach to develop a design elements taxonomy of domain-specific chatbots. The final taxonomy, which can be seen in Table 1 (p. VII), contains 17 dimensions and 49 characteristics ordered into the three perspectives: intelligence, interaction, and context. The columns contain the percentage distribution values of the 103 domain-specific real-world chatbots across the various characteristics and large differences can be seen in terms of frequency. This classification indicates that in 2019, most of the analyzed chatbots were far from offering all technical capabilities from an intelligence and interaction perspective. Five archetypes (i.e., goal-oriented daily chatbots, non-goal-oriented daily chatbots, utility facilitating chatbots, utility expert chatbots, and relationship-oriented chatbots) were identified. These archetypes will help support practitioners in identifying appropriate characteristics, depending on the task and application area.

Table 1: Final Taxonomy of Design Elements for Chatbots (Adapted from Janssen et al. 2020, p. 217)

Layer 1: Perspective	Layer 2: Dimensions D_i	Layer 3: Characteristics $C_{i,j}$ (% distribution)		
Intelligence	D_1 Intelligence framework	$C_{1,1}$ Rule-based system (73%)	$C_{1,2}$ Utility-based system (17%)	$C_{1,3}$ Model-based system (6%)
		$C_{1,4}$ Goal-based system (2%)	$C_{1,5}$ Self-learning system (2%)	
	D_2 Intelligence quotient	$C_{2,1}$ Only rule-based knowledge (41%)	$C_{2,2}$ Text understanding (42%)	$C_{2,3}$ Text understanding and further abilities (17%)
	D_3 Personality processing	$C_{3,1}$ Principal self (96%)	$C_{3,2}$ Adaptive self (4%)	
	D_4 Socio-emotional behavior	$C_{4,1}$ Not present (88%)	$C_{4,2}$ Present (4%)	
	D_5 Service integration	$C_{5,1}$ None (22%)	$C_{5,2}$ Single integration (59%)	$C_{5,3}$ Multiple integration (18%)
Interaction	D_6 Multimodality	$C_{6,1}$ Unidirectional (91%)	$C_{6,2}$ Bidirectional (9%)	
	D_7 Interaction classification	$C_{7,1}$ Graphical (23%)	$C_{7,2}$ Interactive (77%)	
	D_8 Interface personification	$C_{8,1}$ Disembodied (71%)	$C_{8,2}$ Embodied (29%)	
	D_9 User assistance design	$C_{9,1}$ Reactive assistance (79%)	$C_{9,2}$ Proactive assistance (21%)	
	D_{10} Number of participants	$C_{10,1}$ Individual human participant (96%)	$C_{10,2}$ Two or more human participants (4%)	
	D_{11} Additional human support	$C_{11,1}$ No (80%)	$C_{11,2}$ Yes (20%)	
	D_{12} Front-end user interface channel	$C_{12,1}$ App (7%)	$C_{12,2}$ Collaboration and communication tools (7%)	$C_{12,3}$ Social media (34%)
		$C_{12,4}$ Website (39%)	$C_{12,5}$ Multiple (14%)	
Context	D_{13} Chatbot role	$C_{13,1}$ Facilitator (39%)	$C_{13,2}$ Peer (3%)	$C_{13,3}$ Expert (58%)
	D_{14} Relation duration	$C_{14,1}$ Short-term relation (84%)	$C_{14,2}$ Long-term relation (16%)	
	D_{15} Application domain	$C_{15,1}$ E-customer service (21%)	$C_{15,2}$ Daily life (47%)	$C_{15,3}$ E-commerce (9%)
		$C_{15,4}$ E-learning (4%)	$C_{15,5}$ Finance (13%)	$C_{15,6}$ Work and career (7%)
	D_{16} Collaboration goal	$C_{16,1}$ Non goal-oriented (23%)	$C_{16,2}$ Goal-oriented (77%)	
	D_{17} Motivation for chatbot use	$C_{17,1}$ Productivity (19%)	$C_{17,2}$ Entertainment (29%)	
		$C_{17,3}$ Social/relational (7%)	$C_{17,4}$ Utility (45%)	

Depending on the use case, chatbots are contacted by a user once (e.g., dialogue to complain about a product) or multiple, recurring times over a long period (e.g., tutoring dialogues throughout the school year). This frequency and duration of use necessitate different requirements for the design of the chatbot. Nißen et al. (2022) concentrated on identifying design elements that characterize and distinguish short-, medium-, and long-term chatbots across diverse application domains. Within seven iterations, in which 120 real-world chatbots and scientific literature were investigated, a design taxonomy for chatbots with different temporal profiles was developed. The final taxonomy contains in total 61 characteristics within 22 dimensions, which are clustered into the perspectives temporal profile, appearance, intelligence, interaction, and context. By applying a time-dependent chatbot archetype formula, three archetypes were identified: ad-hoc supporters, temporary advisors, and persistent companions. By analyzing the chatbot–user relationship across several time horizons, significant differences can be observed across the archetypes. Ad-hoc supporter chatbots primarily fulfill tasks in a short-time horizon without inserting gamification elements, while persistent companion chatbots, which communicate with a user over a long period, are more socially oriented and show socio-emotional behavior within a personalized dialogue.

Especially in customer service, chatbots are employed to guarantee 24/7 assistance, automate frequently repeated manual processes, and minimize call center costs. In the B2B sector, companies increasingly use chatbots for customer communication purposes too. In the scientific literature, the B2B chatbot area has hardly been researched yet, though there is demand for it, because, in the B2B sector, the products and services that are marketed are often complex and require explanation. Face-to-face contact is considered essential, and various people of a buying center are often involved in the long purchasing processes. To classify the prevailing B2B customer service chatbots, Janssen et al. (2021a) developed a design elements taxonomy for B2B customer service chatbots. Relevant scientific literature and 40 B2B customer service chatbots were classified resulting in a final taxonomy with 17 dimensions and 45 characteristics. Based on a cluster analysis, whose results are presented in Table 2 (p. IX), three archetypes (i.e., lead generation chatbots, aftersales facilitator chatbots, and advertising FAQ chatbots) were identified. According to the results, B2B customer service chatbots are predominantly used for FAQ and lead generation purposes, as well as in aftersales. Table 2 illustrates which characteristics are present in these archetypes, visualized by a color intensity code. In comparison to the other two taxonomies, which included chatbots from diverse application areas, it becomes apparent that additional human support in the B2B area is extremely important and that there is still a lot of undiscovered potential in terms of intelligence.

Table 2: Final B2B Customer Services Chatbot Taxonomy with Identified Archetypes (Janssen et al. 2021a, p. 184)

	Label	Lead generation chatbot	Aftersales facilitator chatbot	Advertising FAQ chatbot
	Archetype	1	2	3
	n	8	10	22
Industry classification	Financial services industry	0%	10%	5%
	Manufacturing industry	0%	50%	18%
	Marketing industry	0%	10%	14%
	Software industry	100%	30%	64%
Business integration	No	75%	40%	77%
	Yes	25%	60%	23%
Access to business data	No	88%	70%	100%
	Yes	13%	30%	0%
Dialogue structure	Predefined	88%	20%	45%
	Open	0%	40%	9%
	Both	13%	40%	45%
Data policy	Not provided	38%	60%	77%
	Provided	63%	40%	23%
Handoff to human agent	Not possible	0%	20%	14%
	Possible	100%	80%	86%
Small talk	Not possible	100%	60%	82%
	Possible	0%	40%	18%
Human-like avatar	No	100%	70%	95%
	Yes	0%	30%	5%
Content related service	Content advertisement	75%	0%	100%
	Content consumption	25%	100%	0%
Account authentication	Not required	50%	60%	68%
	Optional	0%	20%	14%
	Required	50%	20%	18%
Question personalization	None	50%	0%	5%
	FAQ	0%	20%	82%
	Personalized account questions	38%	70%	9%
	Highly personalized questions	13%	10%	5%
Customer service orientation	Knowledge-oriented	0%	0%	95%
	Task-oriented	100%	100%	5%
Company information	No	100%	60%	64%
	Yes	0%	40%	36%
Service/product information	No	38%	10%	9%
	Yes	63%	90%	91%
Pricing	No	100%	60%	82%
	Yes	0%	40%	18%
Action request	Book/show a demo	25%	0%	5%
	Callback request	25%	40%	32%
	Both	50%	20%	36%
	None	0%	40%	27%
Service request	Support question/ticket	13%	40%	36%
	Billing details	0%	0%	5%
	User management	0%	10%	0%
	Multiple	0%	40%	0%
	None	88%	10%	59%

The three developed taxonomies and the identified archetypes help researchers and practitioners in selecting design options when developing chatbots and provide support in determining which characteristics are typical for a particular use case. Even though the identified design elements offer an overview of the design possibilities of chatbots, this does not mean that chatbots will actually be used and accepted. However, more aspects need to be considered while developing, deploying, and managing chatbots successfully, which is illustrated in two more papers.

Several chatbots fail in practice because they fail to understand the user's intent, do not respond, or become undetectable. This is annoying not only for the end-user but also for the company providing the chatbot whose reputation may suffer and which has invested a lot of time and money in the development. Even from a global perspective, the failure of chatbots is problematic because the reputation of chatbots, in general, might get affected. To avoid chatbot failure in the future, Janssen et al. (2021c) focused on investigating the main reasons for the failure of chatbots by analyzing real-world chatbots, performing a literature review, and conducting 20 expert interviews. To explore the extent to which chatbot failure is an issue in practice, 103 chatbots from the dataset of Janssen et al. (2020) were revisited, revealing that 53% could not be found after 15 months. Through the expert interviews, six main reasons for chatbot failure were identified: insufficient resources in the form of the human, organizational, or technical capacity to continually manage the chatbot, the lack of a business case, ignorance of user expectations, poor conversation design, poor content, and the provision of false, incomplete, or outdated information. To avoid future failure of chatbots, twelve critical success factors (CSFs) were developed based on the findings evaluated in a focus group discussion (FGD). The design implications of the CSFs and the knowledge of failure risks may help researchers and practitioners continually improve chatbots.

When developing a chatbot, it seems obvious to focus on the technical functionalities or the dialogue tree construction. However, as outlined based on the previous paper, several chatbots fail because of organizational issues in the team or because the wrong use case was chosen. Janssen et al. (2022) concentrated on developing a user-oriented eight-step model for developing a chatbot, which is presented in Figure 2 (p. XI). By interviewing 15 experts, 102 questions were identified which were clustered into the four elements people, activity, context, technology (PACT) (Benyon et al. 2005) and ordered into eight steps. The model was evaluated through interviews, a FGD, and a case study application. The chatbot implementation model starts with of focusing on business-context-related questions to find out, before identifying an appropriate use case, whether a chatbot is the appropriate communication tool. The eight-step model, as well as the list of 102 questions to be asked in the chatbot implementation process, help and guide practitioners and researchers in structurally developing and managing chatbots under the consideration of the most important questions. It also includes the step of asking whether chatbot technology is appropriate for the use case to be realized.

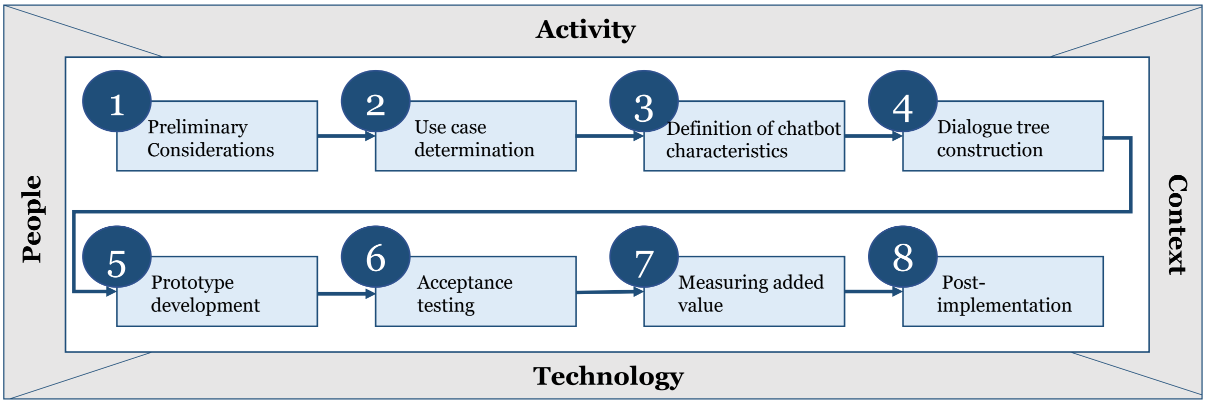

Figure 2: Chatbot Implementation Model (Janssen et al. 2022)

In summary, this cumulative dissertation contributes to the field of digital analytics and chatbots. The guidance provided simplifies the development, deployment, and management of technologies by developing and applying frameworks and reference models, presenting methods for involving end-users, building taxonomies, deriving archetypes, and measuring technology acceptance. To move from a micro perspective to a more general view, communication channels should essentially fit into the overall corporate strategy and fulfill an added value for both the provider and the end-user. Many companies aim to be pioneers in the use of new technologies to demonstrate their innovative prowess to the public. However, apparently the mere use of a technology does not add value but can lead to reputational losses if users become frustrated. Eventually, the benefit and acceptance of the end-user determine whether the use of a technology, such as a chatbot or a digital analytics tool, is successful, as it is the users who decide whether they will use a chatbot again and whether the dialogue will lead to success or even to reputational damage. Therefore, the research papers included in this dissertation provide user-centered design, instead of company-centered design. The papers also indicate the existence of a variety of behavioral analytics options that do not directly involve users. The multitude of analysis options can lead to a flood of data. It is, therefore, essential to question what users really need to be able to target and to efficiently control their decisions.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AI	Artificial Intelligence
AMCIS	Americas Conference on Information Systems
API	Application Programming Interface
AVE	Average Variance Extracted
B2B	Business-to-Business
B2C	Business-to-Customer
BI	Business Intelligence
BISE	Business & Information Systems Engineering
BItU	Behavioral Intention to Use
BU	Business Unit
C	Characteristic
CA	Conversational Agent
CHB	Computers in Human Behavior
CRM	Customer Relationship Management
CSF	Critical Success Factors
D	Dimension
DSR	Design Science Research
e.g.	Exempli gratia
Exp	Expert
EXP	Experience
FAQ	Frequently Asked Questions
FGD	Focus Group Discussion
H	Hypothesis
HCI	Human Computer Interaction
HICSS	Hawaii International Conference on System Sciences
HTMT	Heterotrait Monotrait Ratio of Calculations
i.a.	Inter alia
i.e.	Id est
ICIS	International Conference on Information Systems
IF	Impact Factor
IJHCS	International Journal on Human–Computer Studies

INT_USE	Intention to Use
IoT	Internet of Things
IS	Information Systems
IT	Information Technology
KPI	Key Performance Indicator
LNCS	Lecture Notes in Computer Science
ML	Machine Learning
NLP	Natural Language Processing
N.U.	Name Unknown
OCEAN	Openness to Experience, Conscientiousness, Extraversion, Agreeableness, Neuroticism
P	Paper
PACT	People, Activity, Context, Technology
PD	Participatory Design
PEOU	Perceived Ease of Use
PLS-SEM	Partial Least Squares Structural Equation Modeling
PRIV	Privacy Concerns
PS	Purpose Statement
PU	Perceived Usefulness
Q&A	Questions and Answers
RD	Research Direction
RQ	Research Question
SSBI	Self-Service Business Intelligence
TAM	Technology Acceptance Model
TR	Trust
UTAUT2	Unified Theory of Acceptance and Use of Technology 2
VHB	Verband der Hochschullehrer für Betriebswirtschaft
WKWI	Wissenschaftliche Kommission Wirtschaftsinformatik

Overview of Publications and Task Allocation

The cumulative dissertation includes ten papers. All papers were authored in collaborative teams with a total of thirteen involved co-authors. The division of tasks for each publication, as well as a brief description of the content of each paper, is provided below. An overview of all papers is presented in Table 3 (p. XXIII).

The paper "Using Web Analytics Data: A Participatory Design Model for Individual Web Traffic Development" (Janssen et al. 2019; Appendix A1) develops an iterative web analytics model with the aim of involving future users in the building of individual web analytics reports. While Jens Passlick and I developed the idea of a process that allows the structural individual web analytics report development, I was responsible for the paper organization and for providing a theoretical literature review. Jens Passlick had the idea of using participatory design (PD) methods and, together with Prof. Dr. Michael H. Breitner, we developed the PD model for web traffic development. I organized the applicability check by conducting nine interviews, inserting PD methods before creating individual dashboards. Together, Jens Passlick, Michael H. Breitner, and I wrote the Discussion section. I presented our results at the Americas Conference on Information Systems (AMCIS) in Cancún, Mexico.

The paper "Virtual Assistance in any Context – A Taxonomy of Design Elements for Domain-Specific Chatbots" (Janssen et al. 2020; Appendix A2) focuses on developing a design elements taxonomy for domain-specific chatbots by analyzing scientific literature as well as 103 chatbots from 23 application domains. The final taxonomy contains 17 dimensions with a total of 45 characteristics within the perspectives of intelligence, interaction and context. The paper is written by four authors. I was primarily responsible for organizing the research project within the whole submission process. Along with Jens Passlick and Davinia Rodríguez Cardona, I analyzed scientific literature as well as classified chatbots. Moreover, with Davinia Rodríguez Cardona, I defined the identified dimensions and characteristics within a codebook. I was also responsible for conducting two out of three focus group discussions (FGDs) as well as describing the evaluation procedure and results in the paper. Jens Passlick conducted the hierarchical and partitioning cluster analysis. Collaboratively, we analyzed the taxonomy results and archetypes and discussed the contributions and limitations, which I wrote down in the Discussion section. The paper was published in the special issue "User Assistance for Intelligent Systems" in the Journal Business & Information Systems Engineering (BISE), Volume 62, Issue 3. The special issue focuses on research about assistance systems that help humans fulfill specific IT-based tasks through human–computer interaction (Morana et al. 2020a). The paper was accepted after a double-blind peer-review process with three reviewers and three revisions. In Information Systems, BISE is one of the leading European journals and publishes papers in the English language dealing with research problems across design, analysis, and management of socio-technical systems[1]. In 2019, the journal had a five-year impact factor of 7.361.

The paper "Nutzerakzeptanz von Robo-Advisor Systemen für das digitale Investitionsmanagement in Deutschland" (Rodríguez Cardona et al. 2020; Appendix A3) deals with the acceptance of robo-advisors in the German insurance sector. Davinia Rodríguez Cardona was responsible for the coordination and conceived the idea of the paper. She also wrote the Theoretical Background, Methods and Result sections. I was responsible for writing the Abstract, Introduction and Conclusions sections. Julian Uphaus and Julian Fischer conducted the survey-based study with 250 participants and calculated the Partial Least Square-Structural Equation Modeling (PLS-SEM). The paper was published in the IWI Discussion Paper Series.

The paper "More than FAQ! Chatbot Taxonomy for Business-to-Business Customer Services" (Janssen et al., 2021a; Appendix A4) presents a taxonomy of B2B customer service chatbots. I had the idea of adapting the taxonomy development approach to the B2B context and was responsible for the structure of the paper and the sections titled Theoretical Background as well as the Discussion, Limitations and Implications for Research and Practice. Davinia Rodríguez Cardona wrote the Methodology and Research Procedure sections. Together, we conducted a comprehensive literature review and classified 40 B2B chatbots. I was responsible for calculating the Ward algorithm and K-means algorithm, while we together interpreted the archetypal results. I presented the final taxonomy and the three resulting archetypes at the 4th International Workshop on Chatbot Research on the 24th of November. The paper was accepted after a double-blind review process and was presented at the CONVERSATIONS, 4th International Workshop on Chatbot Research which was held online from November 23 to November 24, 2020, due to COVID-19 pandemic. The paper was published in the conference proceedings book "Chatbot Research and Design," which is a part of the Lecture Notes in Computer Sciences (LNCS) book series

[1] https://www.springer.com/journal/12599

ranked C in VHB Jourqual. The workshop included presentations on conceptual, empirical, and design research on chatbot and conversational user interface across several application domains (Følstad et al. 2021). This paper won the "CONVERSATIONS Best Paper Award" based on the review score and paper presentation.

The paper "A Matter of Trust? Examination of Chatbot Usage in Insurance Business" (Rodríguez Cardona et al., 2021; Appendix A5) reveals through an online survey-based study the impact of trust and technology acceptance on the intention to use insurance chatbots. Davinia Rodríguez Cardona developed the idea of the study and coordinated the research paper process while Julian Milde developed the survey questionnaire and collected the data. I wrote the Foundations section with an insurance chatbot classification and derived the hypotheses. Nadine Guhr was responsible for calculating and describing the procedure of structural equation modeling. Davinia Rodríguez Cardona wrote the Introduction, Results, and Conclusions sections and created the tables and figures. Together, we analyzed and interpreted the results which I wrote down in the Discussion section. Davinia Rodríguez Cardona presented the paper at the virtual 54^{th} Hawaii International Conference on System Sciences (HICSS) 2021.

The paper "The Role of User Involvement: Relationship between Participatory Design and Design Science Research" (Janssen et al. 2021b; Appendix A6) is a conceptual paper and contrasts design science research (DSR) and user-oriented PD through a comprehensive literature review. It shows that PD is used in three different layers: as a research design, as a method within DSR and as a method within a developed artefact using DSR. Based on Janssen et al.'s paper (2019), in which a combination of DSR and PD was applied, I proposed comparing DSR and PD. Davinia Rodríguez Cardona wrote the abstract and introduction. I conducted the literature review based on which DSR and PD were compared. I further wrote the discussion and conclusion section. The paper was published in the IWI Discussion Paper Series.

The paper "See You Soon Again, Chatbot? A Design Taxonomy to Characterize User-Chatbot Relationships with Different Time Horizons" (Nißen et al. 2021; Appendix A7) investigates how the temporal profile of short-, medium-, and long term chatbots influences their design considerations. The paper has been written by Marcia Katharina Nißen, Driton Selimi, Antje Janssen, Davinia Rodríguez Cardona, Michael H. Breitner, Tobias Kowatsch, and Florian von Wangenheim. Marcia Nißen, ETH Zurich, initialized the research project by having the idea of studying differences based on chatbot's temporal goals. With Driton Selimi, from the University of St. Gallen, they conducted the first six iterations and developed an initial taxonomy with associated definitions. Based on a phone conversation, Marcia Nißen and I came up with the idea of further applying the data set of our paper "Virtual Assistance in Any Context" (Janssen et al. 2020; Appendix A2) to the temporal profile context taxonomy and starting a cross-institutional study. Therefore, Davinia Rodríguez Cardona and I revisited all 103 chatbots and classified them to confirm the developed temporal profile taxonomy and provided suggestions for changes to the definitions in the codebook. I was responsible for writing Iteration 7 and the evaluation procedure and further wrote a chat protocol guide that helps future researchers to easily interpret chatbot dialogues according to our dimensions. Together, we analyzed and interpreted the results, which Marcia Nißen wrote down in the Discussion section. Michael H. Breitner, Tobias Kowatsch, and Florian von Wangenheim made important contributions to the paper by supervising the whole process as well as reviewing and editing. The paper has been accepted at the Journal of Computers in Human Behavior after one double-blind peer review round. The journal has an impact factor of 6.829 and, according to the Scimago Journal & Country Rank, is one of the leading journals in HCI[2].

The paper "We Know your Personality! An Automated Personality Mining Approach on Twitter Data" (Klebansky et al. 2021; Appendix A8) deals with the development of a procedure model to automatically analyze the OCEAN personality traits of Twitter users. Through an applicability check analyzing 60,729 Brexit tweets, twelve hypotheses were examined. The idea of the paper as well as the methods to be used originated from Michael Klebansky. Together, we developed the procedure model and the hypotheses, while Michael Klebansky collected the data, calculated the personality traits, and analyzed the results. I structured the paper and wrote the Discussion of the Results and the Contributions. The paper was published in the IWI Discussion Paper Series.

The paper "Why do Chatbots fail? A Critical Success Factors Analysis" (Janssen et al. 2021c; Appendix A9) focuses on investigating the main reasons why chatbots fail by analyzing real-world chatbots and performing a literature review, as well as conducting 20 expert interviews. To prevent chatbots from failing in the future, CSFs were identified based on the findings and evaluated. I conceived the idea and identified the

[2] https://www.scimagojr.com/journalrank.php?category=1709

research need to systematically examine the reasons for chatbot failure. Furthermore, I was responsible for organizing the research project process. Lukas Grützner conducted the literature review and 20 expert interviews and described them, in addition to writing the Introduction, and Results sections, while I organized, performed, and described the FGD for evaluation, chatbot analysis and Conclusion. All of us contributed to Discussion, Limitations, and Further Research Directions. My task inhabited to write the Discussion section. The paper was accepted for the International Conference on Information Systems (ICIS) 2021 and was published in the conference proceedings. Together, Lukas Grützner and I presented the paper at the ICIS in Austin, Texas. The paper was nominated for the “Kauffman Best Student Paper Award” at the ICIS.

The paper “How to Make Chatbots Productive – A User-Oriented Implementation Framework” (Janssen et al. 2022; Appendix A10) presents an eight-step user-oriented implementation framework including 102 identified questions to be asked when developing a chatbot. The paper was written by Davinia Rodríguez Cardona, Jens Passlick, Michael H. Breitner, and me. I devised the idea of developing a chatbot implementation framework, while Jens Passlick suggested involving the PACT framework. I coordinated and partly conducted the interviews and FGD and Davinia Rodríguez Cardona coded and described the results. Together, we developed the framework, clustered the questions into eight steps, and contributed to the Discussion section. The paper was published in the International Journal on Human-Computer Studies, Volume 168, a double-blind peer-reviewed journal in the HCI area with an impact factor of 3.632[3].

[3] https://www.journals.elsevier.com/international-journal-of-human-computer-studies

Table 3: Overview of Publications (Own Representation)

Paper	Year	Title	Authors	Conference / Journal	WKWI[4]	VHB[5]	IF[6]	Chapter	Appendix
P1	2019	Using Web Analytics Data: A Participatory Design Model for Individual Web Traffic Development	**A. Janssen,** J. Passlick, M. H. Breitner	Proceedings of the 25th Americas Conference on Information Systems (AMCIS), Cancún, Mexico.	C	D		3.2	A1
P2	2020	Virtual Assistance in any Context: A Taxonomy of Design Elements for Domain-Specific Chatbots	**A. Janssen,** J. Passlick, D. Rodríguez Cardona, M. H. Breitner	Business & Information Systems Engineering (BISE), vol. 62, issue 3, pp. 211–225.	A	B	7.343	4.2	A2
P3	2020	Nutzerakzeptanz von Robo-Advisor Systemen für das digitale Investitionsmanagement in Deutschland	D. Rodríguez Cardona, **A. Janssen,** J. Uphaus, J. Fischer, M. H. Breitner	IWI Discussion Paper Series, Institut für Wirtschaftsinformatik, Leibniz Universität Hannover, paper 96.				3.5	A3
P4	2021	More than FAQ! Chatbot Taxonomy for Business-to-Business Customer Services	**A. Janssen,** D. Rodríguez Cardona, M. H. Breitner	Følstad A. et al. (eds) Chatbot Research and Design. CONVERSATIONS 2020. Lecture Notes in Computer Science, vol 12604. Springer, Cham, pp. 175–189. (Winner of "CONVERSATIONS Best Paper Award")	B	C		4.3	A4
P5	2021	A Matter of Trust? Examination of Chatbot Usage in Insurance Business	D. Rodríguez Cardona, **A. Janssen,** N. Guhr, M. H. Breitner, J. Milde	Proceedings of the 54th Hawaii International Conference on System Sciences (HICSS), Maui, USA	B	C		3.4	A5
P6	2021	The Role of User Involvement: Relationship between Participatory Design and Design Science Research	**A. Janssen,** D. Rodríguez Cardona, M. H. Breitner	IWI Discussion Paper Series, Institut für Wirtschaftsinformatik, Leibniz Universität Hannover, paper 97.				2.5	A6
P7	2022	See You Soon Again, Chatbot? A Design Taxonomy to Characterize User-Chatbot Relationships with Different Time Horizons	M. Nißen, D. Selimi, **A. Janssen**, D. Rodríguez Cardona, M. H. Breitner, F. von Wangenheim, T. Kowatsch	Computers in Human Behavior (CHB), vol. 127, 107043 pp. 1–15.			6.829	4.4	A7
P8	2021	We Know your Personality! An Automated Personality Mining Approach on Twitter Data	M. Klebansky, **A. Janssen,** M. H. Breitner	IWI Discussion Paper Series, Institut für Wirtschaftsinformatik, Leibniz Universität Hannover, paper 98.				3.3	A8
P9	2021	Why do Chatbots fail? A Critical Success Factors Analysis	**A. Janssen,** L. Grützner, M. H. Breitner	Proceedings of the 42nd International Conference on Information Systems (ICIS), Austin, USA. (Nominated for the "Kauffman Best Student Paper Award")	A	A		4.5	A9
P10	2022	How to Make Chatbots Productive – A User-Oriented Implementation Framework	**A. Janssen,** D. Rodríguez Cardona, J. Passlick, M. H. Breitner	International Journal on Human-Computer Studies (IJHCS), 168, 102921, pp. 1–22.			3.632	4.6	A10

[4] WI-Orientierungslisten, Wissenschaftliche Kommission für Wirtschaftsinformatik 2008, https://doi.org/10.1365/s11576-008-0040-2
[5] JOURQUAL3 Verband der Hochschullehrer für Betriebswirtschaft (VHB 2015), https://vhbonline.org/fileadmin/user_upload/JQ3_WI.pdf
[6] Impact Factor Scopus https://www.scijournal.org/impact-factor-of-BUS-INFORM-SYST-ENG.shtml

1. Introduction

1.1. Research Motivation

"[In 2041], *a virtual customer service representative and a salesperson can be optimized to maximum customer satisfaction or revenue, respectively, while conducting a conversation based on all that is known about a given customer."*

(Kai-Fu Lee and Chen Qiufan 2021, p. 164)

While business-to-customer (B2C) markets in which companies promote their products and services to individual private consumers have been strongly online-driven for a long time, business-to-business markets (B2B), distributing their products and services to other organizations, have also increasingly transitioned toward digital and AI-based marketing and sales activities, as well as from human to machine interaction in recent years (Kaghyan et al. 2018; Lin et al. 2022; Paschen et al. 2020; Wang & Wang 2020). The COVID-19 pandemic and the increase of remote work have contributed to even more sales activities moving online using a wide variety of platforms (Cortez & Johnston 2020; Kang et al. 2020; Kliens 2020). This is challenging, as B2B selling processes are often characterized by face-to-face interactions, selling complex products and services through long decision-making processes (Cortez & Johnston 2020). Due to this complexity, the processes often involve various professionals with different backgrounds, commonly called buying centers, which, in turn, influence the use of communication channels and communication itself (Paschen et al. 2020; Rėklaitis & Pilelienė 2019). The behavior of B2B customers in the buying process has changed as well, meaning that customers more independently inform themselves online about products and services instead of relying primarily on the statements of offline sales staff, as was previously the case (Adamson & Tomas 2020). It is, therefore, important to support this self-learning process of customers by providing 24/7 answers to questions as they arise, which is done by delivering technical information on, e.g., corporate websites, webinars, and social media channels (Cortez & Johnston 2020) or by employing chatbots (Janssen et al. 2021a; Kushwaha et al. 2021; Lin et al. 2022).

In turn, this digital information-seeking and buying behavior enables deep analytics through the high volume of data, which makes it even more possible to provide precise in-depth analytics (Adamson & Tomas 2020; Paschen et al. 2020), which were previously partly perceived as "*unnecessary costs*" (Cortez & Johnston 2020). The capabilities and discoveries that have emerged from analyzing customer behaviors on, e.g., social media, stretch far beyond what was otherwise painstakingly achieved through traditional tools, such as surveys (Du et al. 2021). Nowadays, by contrast, marketeers are being flooded with expanding data from an ever-increasing number of channels and sources, which is analyzed by various digital tools (Du et al. 2021; Morgan & Lurie 2021). A flood of data can distract employees from their daily business and may lead to them not knowing what to focus on (Du et al. 2021). Thriving in the face of competitive pressures in B2B industries, it is about leveraging existing data even more effectively, analyzing it, and providing customers with the information and services they need within a cost-effective marketing plan (Du et al. 2021; Kaghyan et al. 2018; Paschen et al. 2020). Approaches are needed that describe how to deliver target-group-specific information about the behavior of company stakeholders (e.g., (potential) customers) on different channels, which can be used to develop interpretations and derive actions.

Companies seek new communication technologies that allow them to reach (potential) customers even better, automate manual processes, ensure 24/7 support and minimize call center costs (Kushwaha et al. 2021). Thus, an increasing number of B2B companies are choosing to deploy chatbots, which are one of the fastest-growing communication services and enable human-like customer communication (Kushwaha et al. 2021; Janssen et al. 2021c; Lin et al. 2022). However, the research on B2B chatbots is still sparse (Brachten et al. 2021; Janssen et al. 2021c; Kushwaha et al. 2021). Chatbots, also known by the term conversational agents (CA) (Zierau et al. 2020), are primarily internet-based software programs interacting with humans in a simulated conversation for exchanging information and services (Bittner et al. 2019; Brandtzæg & Følstad 2018; Diederich et al. 2019b). Using natural language processing (NLP), these services can understand user input by parsing isolated words, sentences, and phrasal constructions to converse about a specific issue (Diederich et al. 2019b; Følstad et al. 2019; Nguyen & Sidorova 2018). Compared to other communication technologies, chatbots have the distinct advantage of having anthropomorphic characteristics, such as an avatar or showing emotions that matter in the perception of services (Adam et al. 2021b; Crolic et al. 2022; Elshan et al. 2022; Riquel et al. 2021). Even though chatbots are not a new technology and the first chatbot ELIZA was built in the 1960s (Weizenbaum 1966), they have become more widespread in the last five years due to the latest technological advances in artificial intelligence (AI) (Adam et al. 2021b; Diederich et al. 2022; Elshan et al. 2022). However, the challenge is to develop, deploy, and manage these tools such that they fulfill the requirements and tasks of end-users, leading them to use and accept the chatbots.

This cumulative dissertation aims to contribute to research and practice in the field of digital analytics and chatbots by addressing four overarching research questions, which are described in the next sub-chapter. In addition to the focus on papers from the B2B sectors, other application domains are also covered to draw conclusions and point out implications that could also be useful and implementable for B2B companies.

1.2. Research Questions and Structure of this Thesis

The cumulative dissertation addresses the thematic areas of how to analyze stakeholder activities and behavior as well as how to develop, deploy and manage chatbots. The allocation of the ten papers in the chapters can be seen in Figure 3 (p. 5). Four overarching research questions (RQs) within two thematical segments are to be addressed. The first RQ contributes to the digital analytics field:

> **RQ1:** How to analyze (a) the user behavior on websites and (b) the personality traits of Twitter users?

In two papers, approaches in form of frameworks are presented to analyze the user behavior on corporate websites as well as the personality traits of Twitter users. These frameworks serve as a basis to monitor communication activities and improve them. Janssen et al. (2019) and Klebansky et al. (2021) provide approaches to analyze the target audience behavior without the direct involvement and questioning of users, which can minimize bias in the results. However, when it concerns the general acceptance of technologies, it is not purposeful analyzing only the usage and behavioral statistics of actual users. By surveying potential and current users about technology acceptance, insights can be gained into the intent, concerns, and reasons for use, leading to the second RQ:

> **RQ2:** How to measure the technology acceptance of chatbots?

To answer RQ2, two papers analyze the technology acceptance of robo-advisor and insurance chatbots. Similar to B2B companies, insurers and financial companies also promote and sell complex products and services that require an explanation as well as trust, which is why the use of digital tools requires more detailed consideration. To answer the RQ2, the unified theory of acceptance and the use of technology 2 (UTAUT2) and the technology acceptance model (TAM) approaches with extensions of trust and privacy concerns are applied. Chatbots not only are applied in the insurance and finance sector but have also been developed in recent years for numerous applications with which various goals are to be fulfilled. This diversity and wide range of design elements must be systematically classified to present the broad spectrum of different chatbots and to serve as a basis for defining characteristics in the development process which is addressed in RQ3:

> **RQ3:** What are conceptually grounded and empirically validated design elements for chatbots across application domains?

To systematically understand, describe and analyze phenomena, taxonomy development is a widely used approach (Kundisch et al. 2021). From an external user perspective, three taxonomies are developed to answer this research question from different perspectives. Janssen et al. (2020) concentrated on identifying domain-encompassing chatbot design elements from six different application areas. Nißen et al. (2021) built on the results by re-examining the chatbots still available from the Janssen et al. (2020) dataset and extending them with further chatbot analyses focusing on the different time horizons in usage. The third taxonomy development paper (Janssen et al. 2021a) focuses on exclusively classifying chatbots from the B2B customer service area. Comparing the results of the three taxonomy papers, B2B customer service chatbots seem to occasionally have major differences from other application areas, resulting in various untapped potentials. Even though the identified design elements provide an overview of the broad possibilities of how chatbots can be designed, this does not imply that chatbots will be used and accepted. Therefore, the fourth RQ examines as follows:

> **RQ4:** What must be considered when conceptualizing, developing, and managing chatbots?

While the taxonomies form a basis on which design options are possible, two papers focus on what aspects need to be considered when conceptualizing, developing, and managing chatbots. Whereas Janssen et al. (2021c) identified six reasons for chatbot failure before presenting twelve chatbot CSFs, Janssen et al. (2022) focused on developing a user-oriented eight-step model for developing a chatbot containing 102 questions. The design implications of both papers may help researchers and practitioners to continually improve chatbots.

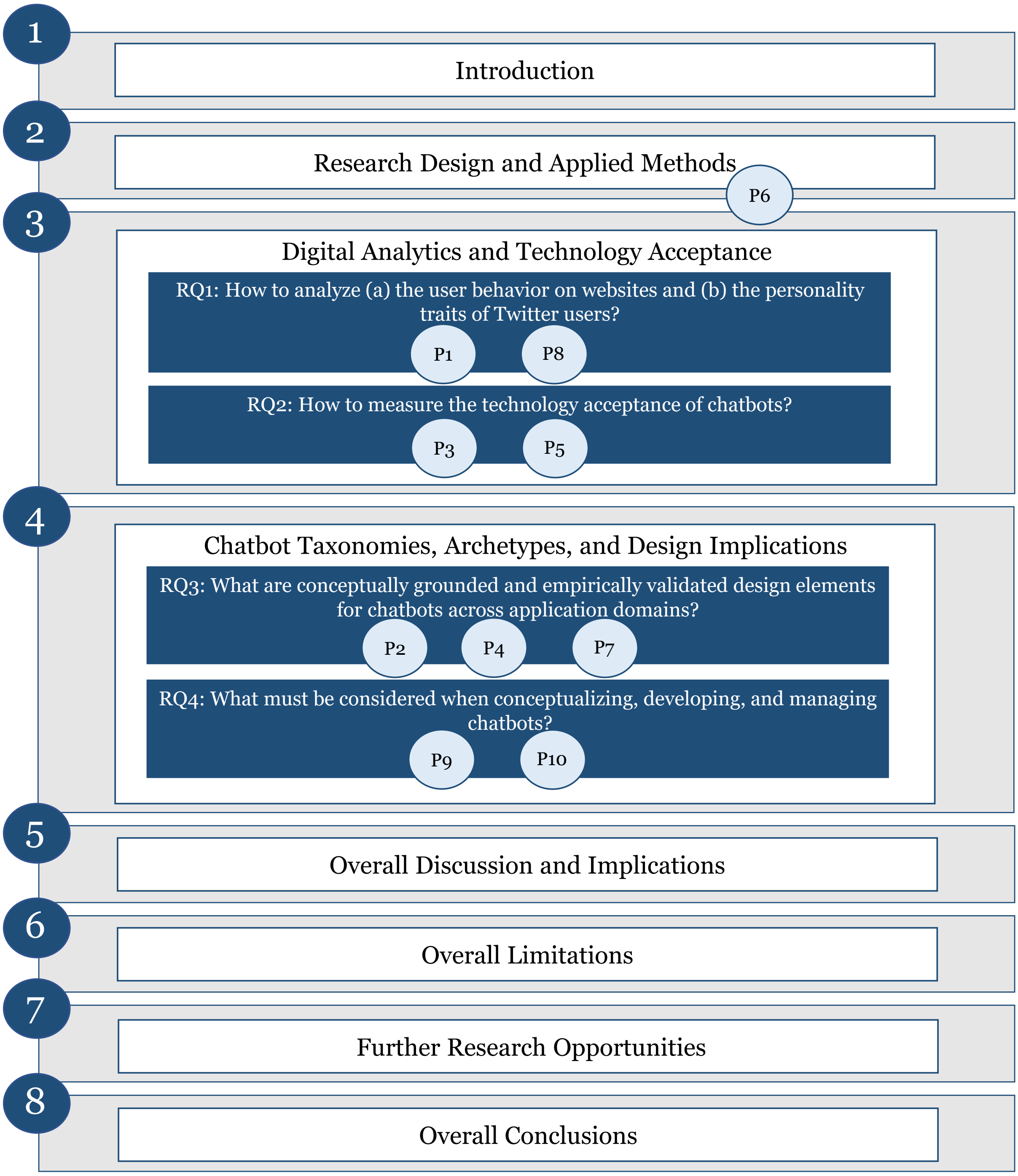

Figure 3: Structure of the Dissertation (Own Representation)

The cumulative dissertation is structured as follows. After giving an overview of the task allocation between the co-authors in all ten research papers mentioned in this thesis and describing the motivation and four overarching research questions to be addressed in Chapter 1, Chapter 2 presents the research designs and methods used in the papers. Chapter 3 deals with digital analytics approaches on websites and Twitter and chatbot context while addressing RQ1 and RQ2. Chapter 4 concentrates on presenting taxonomies, archetypes, and design implications for chatbots and focuses on answering RQ3 and RQ4. Chapters 3 and 4 both start with an introduction to the chapter before summarizing the procedure and results of every paper in separate sub-chapters. In the final sub-chapters of the two chapters, the conclusion focuses on the contributions to and implications for B2B industries. Chapter 5 presents an overall discussion in which papers are newly discussed in an abstract manner. The limitations are outlined in Chapter 6, and general directions for further research are described in Chapter 7. The cumulative dissertation ends with an overall conclusion in Chapter 8.

2. Research Design and Applied Methods

2.1. Introduction and Overview of Inserted Methodologies

"Research design is a blueprint for the collection, measurement, and analysis of data."
(Jan Recker 2021, p. 39)

As information systems (IS) research is a broad and diverse research discipline, the methods and methodologies used are diverse and depend on the research goal, the environment, and the theory (Recker 2013). In this cumulative dissertation, the ten papers can be categorized into three research approaches: design science research (DSR), quantitative research, and taxonomy development. The appropriate research designs and methodologies were selected based on the research questions and objectives to be answered, which is a crucial process as it greatly impacts the research outcome (Recker 2013). In all papers, a literature review was conducted, in which scientific papers provided the conceptual basis, before other scientific methods (e.g., interview conduction, object classification, and survey conduction) were applied. Table 4 (p. 7) overviews the underlying methodologies applied in each paper, which are described in more detail in the following sub-chapters (2.2.–2.4.).

Table 4: Overview of Research Methodologies used in the Papers (Own Representation)

P	Year	Title	DSR	Taxonomy	Quantitative
P1	2019	Using Web Analytics Data: A Participatory Design Model for Individual Web Traffic Development	•		
P2	2020	Virtual Assistance in any Context: A Taxonomy of Design Elements for Domain-Specific Chatbots		•	
P3	2020	Nutzerakzeptanz von Robo-Advisor Systemen für das digitale Investitions-management in Deutschland			•
P4	2021	More than FAQ! Chatbot Taxonomy for Business-to-Business Customer Services		•	
P5	2021	A Matter of Trust? Examination of Chatbot Usage in Insurance Business			•
P6	2021	The Role of User Involvement: Relationship between Participatory Design and Design Science Research	(•)		
P7	2022	See You Soon Again, Chatbot? A Design Taxonomy to Characterize User-Chatbot Relationships with Different Time Horizons		•	
P8	2021	Personality Traits in Political Discussions on Twitter: An Automated Personality Mining Approach			•
P9	2021	Why do Chatbots fail? A Critical Success Factors Analysis	•		
P10	2022	How to Make Chatbots Productive – A User-Oriented Implementation Framework	•		

Paper P6 (Janssen et al. 2021b) differentiates itself from all other papers, as in it, a literature review and analysis has been conducted to compare two research approaches

(DSR and participatory design (PD)), in contrast to the other papers, in which research approaches have been used to answer a practice-oriented research question. This paper is therefore presented in Chapter 2.5.

2.2. Design Science Research

DSR is described as a problem-solving paradigm for deriving design knowledge and theoretical evidence, which is accomplished by creating theory-based artefacts or executing empirical design principles (Baskerville et al. 2018; Hevner 2007; Janssen et al. 2021c; Rai 2017; vom Brocke et al. 2020a). In the fields of IS, DSR is seen as a central research paradigm (Hevner et al. 2019) and is widely applied in the context of computational DSR to develop human-centered HCI artefacts (Rai et al. 2017). In IS and HCI, the three DSR modes are differentiated: exterior, interior and gestalt mode (Adam et al. 2021a; Sonnenberg & vom Brocke 2012). The interior mode involves technical studies to design and develop HCI-centered IT systems (Adam et al. 2021a). The exterior mode involves studies focused on the observational analysis of user behavior and HCI (Adam et al. 2021a). The gestalt mode combines technical development methods and observational methods to balance IT systems and user behavior (Adam et al. 2021a). Table 5 (p. 8) presents an overview of how DSR is applied in the papers of the dissertation.

Table 5: Overview of Design Science Research Studies (Own Representation)

	P1 (Janssen et al. 2019)	P9 (Janssen et al. 2021c)	P10 (Janssen et al. 2022)
Research mode	Interior mode	Gestalt mode	Interior mode
Method in relevance cycle	Expert interviews, participatory design CARD method	Expert interviews, classification of 103 chatbots	Expert interviews
Method in rigor cycle	Literature review	Literature review	Literature review
Design cycle artefact	Web analytics implementation model	List of failure reasons and CSFs	Chatbot implementation model
Evaluation method	FGD	FGD	FGD, interviews, applicability check

Figure 4 (p. 9) exemplarily applies the research design procedure of P10 (Janssen et al. 2022) to the research design cycles of Hevner (2007) with minor extensions of vom Brocke et al. (2020a). The relevance cycle links artefact design to the research environment involving organizations, people, and technical systems whereas the rigor cycle includes method, domain, and theory knowledge from research (Hevner 2007; vom Brocke et al. 2020a). Synthesizing the findings from the relevance and rigor cycles constitutes the basis of the design cycle in which the artefact in form of a model, framework, construct, or technical prototype is developed and deployed (Hevner et al. 2019; vom Brocke et al. 2020a).

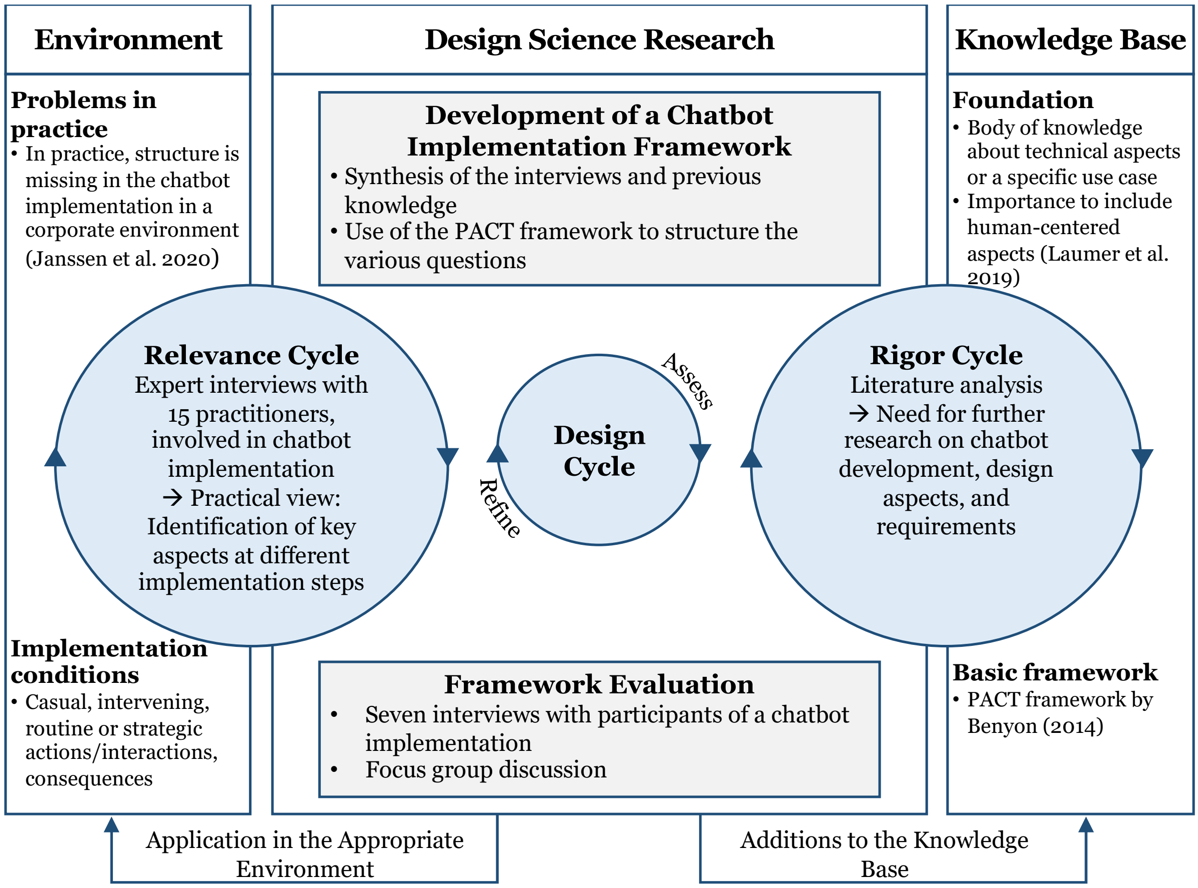

Figure 4: Applied Research Design Based on Hevner (2007) and vom Brocke et al. (2020a) (Own Representation Based on Janssen et al. 2022)

In addition to the design of the artefact, a central component of the design cycle is the evaluation (see Chapter 2.2.4) of the artefact to prove practical applicability as well as to obtain suggestions for improvement as early as possible, which are then implemented (vom Brocke et al. 2020b). The evaluation methods applied in the three DSR papers can be seen in Table 5 (p. 8). Critical for success is the contribution of a DSR study in the form of the artefact to be developed by providing a novel real-world solution as well as scientific knowledge (Baskerville et al. 2018). The methods used in the DSR projects to develop artefacts are described in more detail in the following sub-chapters.

2.2.1. Literature Review

A literature review is seen as the foundation for any IS research (Webster & Watson 2002). Before starting with artefact development, three types of scientific knowledge need to be gathered by a literature analysis: domain knowledge, theory knowledge, and research method knowledge (Recker 2013; Recker 2021). This is necessary, as it lays down a knowledge foundation by identifying research gaps and needs, in the context of previously used methods, procedures, and framing theories (Recker 2013; Webster & Watson 2002). The chapter below concentrates on the literature analysis in three DSR papers (see Table 5, p. 8). This literature search and analysis approach was followed in all the ten papers included in this doctoral thesis.

To gather knowledge from scientific papers (rigor cycle) (Hevner 2007; vom Brocke 2020a), a structured literature search and analysis was conducted in the DSR papers (see Table 6, p. 10) by following the guidelines of Webster and Watson (2002), vom Brocke et al. (2015), and Watson and Webster (2020).

Table 6: Overview of Conducted Literature Analyses in Design Science Research Studies (Own Representation)

	P1 (Janssen et al. 2019)*	P9 (Janssen et al. 2021c)	P10 (Janssen et al. 2022)*
Search string / Used keywords	"Traffic Analytics"; "Website Performance"; "Web Analytics"; KPIs; Framework; Industrial	("chatbot" OR "chat bot" OR "conversational agent") AND ("unsuccess" OR "fail" OR "failure" OR "success" OR "success factor" OR "critical success factor")	(chatbot* OR "conversational agent*" OR chatterbot* OR "dialog system*" OR talkbot*) AND (implementation OR development OR design OR prototype OR framework)
(Number of) Databases	(4) AISeL, Google Scholar, IEEE Xplore, TSISQ	(5) ACM, AISeL, Google Scholar ScienceDirect, SpringerLink	(9) ACM, AISeL, EBSCO, IEEE Xplore, ScienceDirect, Web of Science, Wiley Online Library, TIB
Hits relevant by title	309	308	385
Forward search	●	●	●
Backward search	●	●	●
Similarity search		●	
Number of relevant papers	96	154	51

*Contains implicit knowledge from the researcher which is not written in the paper in detail.

Every study started with an explorative literature search identifying popular keywords. Out of this, a search string was formulated with the previously defined list of search parameters to structurally and efficiently finding relevant scientific papers (vom Brocke et al. 2015). As each scientific database has its own focus of topics and/or only a limited number of journals and conferences, between four and nine databases (see Table 6, p. 10) were used in all literature reviews to acquire the broadest possible perspective on the current state of research (vom Brocke et al. 2015). In all papers, the literature search was complemented by a reference-based backward and forward search (vom Brocke et al. 2015; Webster & Watson 2002), further supplemented partly by a Google Scholar similarity search. The identified literature was then classified in a concept matrix, forming the basis of the research project (Webster & Watson 2002).

2.2.2. Interview Conduction and Analysis

Expert interviews were performed in three papers to gather practical knowledge and experience. Before conducting interviews, an interview guide had to be developed, which contains central questions and sub-questions that could be used if necessary (Bogner & Menz 2009; Janssen et al. 2022; Myers & Newman 2007). All interviews were semi-structured so that deviations and spontaneous reformulations by both the interviewer and interviewee were possible to avoid disrupting the flow of conversation (Bogner & Menz 2009). In most cases, the interview guide was sent to the participants in advance enabling a preparation possibility (Janssen et al. 2021c; Janssen et al. 2022).

Experts were selected through a random sampling process (e.g., on conference pages and company blogs) with request messages via email and the career-oriented social network LinkedIn (Janssen et al. 2021c; Janssen et al. 2022) and from an internationally operating automation company (Janssen et al. 2019). In total, 51 experts (16 in Janssen et al. (2019); 20 in Janssen et al. (2021c); 15 in Janssen et al. (2022)) were included from six different countries (i.e., Germany, Israel, Luxembourg, Switzerland, the Netherlands, and the United States of America) located on three continents. While few interviews took place on-site, due to the large geographic distances and the COVID-19 pandemic, most interviews were conducted via telephone or Microsoft Teams (Janssen et al. 2019; Janssen et al. 2021c; Janssen et al. 2022). All interviews were recorded, transcribed, and coded with the MAXQDA software following the open coding guidelines of Myers (2020) (in Janssen et al. 2022) and Wiesche et al. (2017) (in Janssen et al. 2021c).

2.2.3. Participatory Design

To involve future end-users in the whole design process as full participants and, consequently, to increase the acceptance and quality of work the social-technical PD approach can be applied (Carrol 1997; Muller 2003; Sanders et al. 2010), which is done in two papers of this thesis. In the three stages “initial exploration,” “discovery process,” and “prototyping” (Spinuzzi 2005), end-users and developers bring together professional experiences from the work environment and technical, organizational, and conceptual knowledge (Spinuzzi 2005; Muller and Kuhn 1993; Sanders et al.

2010). Whereas P1 (Janssen et al. 2019) develops a PD model for web analytics dashboard development based on Spinuzzi (2005), P6 (Janssen et al. 2021b) compares PD with DSR at research design, method, and artefact levels.

2.2.4. Evaluation via Focus Group Discussion

DSR projects can be abstracted into two central activities, i.e., building and evaluation (Hevner et al. 2004; Sonnenberg & vom Brocke 2012; vom Brocke et al. 2020b). Evaluation is necessary to determine whether the developed artefact is understandable, comprehensive, and useful (Gregor & Hevner 2013). The context and purpose of a DSR project determine which methods and criteria are the most appropriate for the DSR evaluation (Kuechler & Vaishnavi 2008; Sonnenberg & vom Brocke 2012). When evaluating a DSR artefact, we followed the evaluation framework of Pries-Heje et al. (2008) by considering the questions "what" (object of evaluation, i.e., design artefact), "who" (subject of evaluation, e.g., individuals from practice or research), and "how" (method of evaluation, e.g., FGD). All three DSR papers conducted a FGD in which in total 20 experts (10 in Janssen et al. (2019); 5 in Janssen et al. (2021c); 5 in Janssen et al. (2022)) from three countries (i.e., Germany, Switzerland, and Luxembourg) participated. After presenting the research procedure and artefact in the FGDs, the results were discussed by inserting a predefined question structure. The outcomes of the FGDs were used to revise the artefacts and describe possibilities of applicability in practice.

2.3. Quantitative Analysis

Quantitative methods include techniques that use quantitative data to address research questions (Recker 2013). Quantitative-empirical studies are predominantly numerical and aim to explain an issue by creating a cross-sectional picture based on a sample, which is then used to draw conclusions about the population (Wilde & Hess 2007). Before quantitative studies are conducted, research hypotheses are typically formulated based on the theories and previously conducted surveys in the domain. Results are usually analyzed by employing statistical techniques (Recker 2013). Three papers in this dissertation concentrated on applying quantitative techniques. An overview of these three quantitative studies can be observed in Table 7 (p. 13).

Table 7: Overview of Quantitative Studies (Own Representation)

	P3 (Rodríguez Cardona et al. 2020)	P5 (Rodríguez Cardona et al. 2021)	P8 (Klebansky et al. 2021)
Number of hypotheses	10	8	12
Data collection method	Online survey	Online survey	Automated personality mining with tweets
Number of observed objects	250 respondents	215 respondents	60,729 tweets
Adopted measurement model	UTAUT2	TAM & privacy concerns & trust	OCEAN personality traits
Data analysis method	PLS-SEM	PLS-SEM	IBM Watson Personality Insights

2.3.1. Survey Method

Surveys are preferred when research revolves around the questions *"what is happening and how and why is it happening?"* (Recker 2013, p. 76) when the context does not allow or enable to control independent and dependent variables (Recker 2013). The survey technique succeeds when a large number of randomly chosen individuals, who represent represent the basic population as much as possible, are consulted to describe the phenomena being researched (Recker 2013). First, it is necessary to choose and adapt well-known theoretical models and to identify measurement items (Recker 2013). In P5 (Rodríguez Cardona et al. 2021), the TAM of Davis (1989) was chosen, which is a widely used model that allows the measurement of several acceptance factors (e.g., Kasilingam 2020). To strengthen the predictive and explanatory capability (Guhr et al. 2020), we further included trust (Gebert-Persson et al. 2019; Kasilingam 2020; Pavlou 2003) and privacy concerns (Baba et al. 2019; Pavlou 2003; Rese et al. 2020). P3 (Rodríguez Cardona et al. 2020) applied the UTAUT2 of Venkatesh et al. (2003; 2012),which is an advancement of TAM, including further measurement items such as hedonic motivation, price value, and effort expectancy, to explain behavioral intention to use a technology from different perspectives (Venkatesh et al. 2012). Both surveys (P3 and P5) were conducted online and had more than 200 respondents (see Table 7, p. 13). The multivariate technique partial least squares structural equation modeling (PLS-SEM) was chosen to analyze the collected data, enabling simultaneous investigation of multiple measurements and reliability and validity issues (Haenlein & Kaplan 2004; Hair et al. 2016; Recker 2013).

2.3.2. Personality Mining

Personality mining allows the assessment of the feelings and opinions of humans systematically and automatically by applying natural language processing (NLP) to textual data (Carducci et al. 2018). Through this, it is possible to draw demonstrably accurate conclusions about the personality traits of individuals based on their behavior on, e.g., social media (Arnoux et al. 2017; Azucar et al. 2018). P8 (Klebansky et al. 2021) uses the personality mining approach to predict the personality traits of Twitter users. In this paper, we followed the three-step process of the social media analytics framework of Stieglitz and Dang-Xuang (2013), starting with defining the purpose and scope before collecting and preprocessing data. From this data, personality traits were predicted which are the basis for hypotheses tests (Klebansky et al. 2021). To automatically predict the intrinsic personality traits, several scientific studies (e.g., Gera & Kaur 2018; Siemon et al. 2018) employed pre-engineered personality mining systems such as IBM Watson Personality Insights, which was also applied in Klebansky et al. (2021). IBM announced in 2020 that the IBM Watson Personality Insights service will be discontinued by December 1, 2021, without a replacement (IBM Personality Insights 2021). By using an application programming interface (API), IBM Watson calculated intrinsic OCEAN (openness to experience, conscientiousness, extraversion, agreeableness, neuroticism) personality traits on textual data from, e.g., Twitter, by using linguistic methods, open vocabulary, and deep learning approaches (Hu et al. 2016). The tool produced a score between 0 (low) and 1 (high) for each trait and user (Hu et al. 2016; IBM Personality Insights 2021).

2.4. Taxonomy Development

The taxonomy development procedure of Nickerson et al. (2013) was applied in three papers (P2, P4, and P7), which is described below on a conceptual level. Taxonomies are widely used design science artefacts in the IS and HCI domain as they provide the opportunity to empirically and systematically develop design principles based on existing artefacts from which conclusions can be drawn for future developments (Kundisch et al. 2021; Williams et al. 2008; Szopinski et al. 2019; Szopinski et al. 2020). According to Nickerson et al. (2013), a taxonomy (T) comprises a number of dimensions (D_i), each with its own subset (k_i) of characteristics ($C_{i,j}$). Every dimension has at least two characteristics, while every object must be assigned to exactly one characteristic in each dimension. The following formula (1) of Nickerson et al. (2013) comprises the mentioned conditions:

$$T = \{D_i, i = 1, \ldots, n \mid D_i = \{C_{ij}, j = 1, \ldots, k_i; k_i \geq 2\}\} \quad (1)$$

2.4.1. Taxonomy Development Procedure

The taxonomy development procedure of Nickerson et al. (2013) contains seven steps, starting with the definition of the purpose and the meta-characteristic, specifying the focus of the taxonomy (Kundisch et al. 2021). The meta-characteristics of the three papers can be viewed in Table 8 (p. 15). As taxonomy development is an iterative process, the ending conditions must be defined to avoid finding no development end. We adopted the set of subjective and objective ending conditions according to Nickerson et al. (2013) to decide when the development was completed. Thirdly, the framework offers the option to complement conceptual knowledge from research and empirical observations via either a conceptual-to-empirical or an empirical-to-conceptual pathway (Nickerson et al. 2013) to be applied alternatingly until all ending conditions are fulfilled.

Table 8: Overview of Taxonomy Studies (Own Representation)

	P2 (Janssen et al. 2020)	P4 (Janssen et al. 2021a)	P7 (Nißen et al. 2022)
Meta-characteristic	"All distinctive technical, situational and knowledge design elements that frame the structure of domain-specific chatbots"	"All design elements that characterize the structural and functional composition of B2B customer service chatbots"	"All design elements having a visible or experiential influence on the interaction between user and chatbot"
Number of conceptual-to-empirical iterations	1	1	2
Number of empirical-to-conceptual iterations	4	3	5
Number of classified objects	103	40	120
Number of dimensions	17	17	22
Number of characteristics	49	45	61
Number of archetypes	5	3	3
Inter-rater reliability	0.63 (Fleiss 1971)	0.64 (Fleiss 1971)	0.9 (Kassarjian 1977)
Evaluation method	3 FGDs	/	Illustrative scenario

All three papers started with a conceptual-to-empirical step by conducting a literature review, using a predefined search string to conceptualize an initial taxonomy with possibly relevant dimensions and characteristics (Janssen et al. 2020; Janssen et al. 2021; Nißen et al. 2022). After iteration 1, all three studies followed empirical-to-conceptual iterations (see Table 8, p. 15) in the iterative process, in which a set of objects was classified in each iteration, and its dimensions and characteristics were added, deleted, and renamed based on these objects. An exception is iteration 4 in Nißen et al. (2022) in which a second conceptual-to-empirical iteration was performed. The taxonomy developments were completed after four (Janssen et al. 2021), five

(Janssen et al. 2020), and seven (Nißen et al. 2021) iterations when all ending conditions were met. Due to the high number of dimensions (between 17 and 22 dimensions, see Table 8, p. 15), additional perspectives were added to serve as thematic structuring.

2.4.2. Taxonomy Evaluation

To affirm that the taxonomy is understandable in terms of meaning and is adaptable to other application domains, a further evaluation iteration was performed by people uninvolved in the development of the taxonomy (Nißen et al. 2022; Szopinski et al. 2019). This was done by a minority of published taxonomy developments in IS (Kundisch et al. 2021; Szopinski et al. 2020), which is why Szopinski et al. (2019) developed a taxonomy evaluation framework with methods for guiding a systematic evaluation of taxonomies in IS. This framework is based on the design science evaluation strategies of Pries-Heje et al. (2008), previously described in the DSR evaluation chapter (Chapter 2.2.4). The framework (Szopinski et al. 2019) contains three categories: evaluation subject ("who?"), evaluation object ("what?") and evaluation method ("how?"), which makes a systematic and comprehensible evaluation possible. In P2 and P7, the authors decided to involve people who have a background as a practitioner, academic, or both, having a domain and method knowledge of chatbots. The taxonomies were reviewed in three FGDs (Janssen et al. 2020) or in an illustrative scenario (Nißen et al. 2022). The evaluation criteria usefulness, applicability, understandability, extendibility, and comprehensiveness of Szopinski et al. (2019; 2020) were adopted (Janssen et al. 2020; Nißen et al. 2022).

2.4.3. Archetype Identification

To detect the archetypes represented in our collected datasets, we applied Ward's algorithm (Ward 1963) in P2 and P4, which calculates the distances between all elements in a dataset (Gimpel et al. 2018b). It can be used without first determining the number of clusters (Gimpel et al. 2018b).

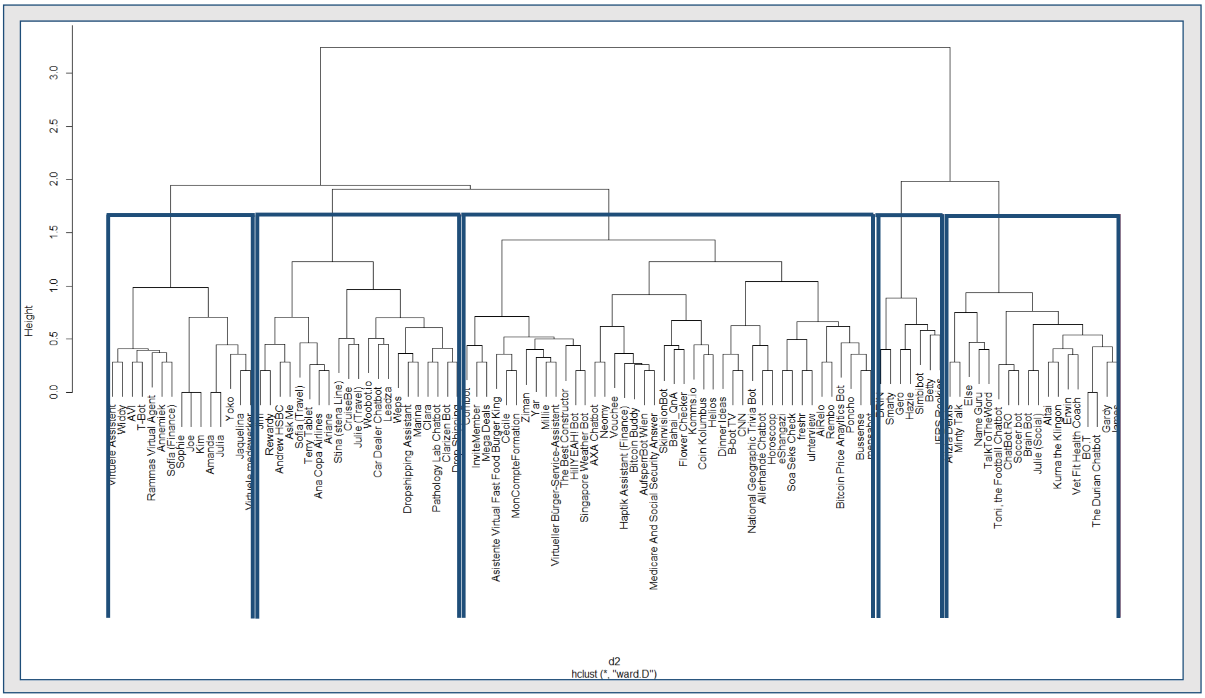

Figure 5: Exemplarily Result of the Ward Clustering Visualized by a Dendrogram (Janssen et al. 2020, p. 220)

As the scientific literature recommends combining hierarchical algorithms, such as that of Ward (1963), and non-hierarchical partitioning algorithms, such as K-means and K-medoids (Balijepally et al. 2011; Täuscher & Laudin 2018), we first analyzed the dendrogram obtained with the Ward algorithm by graphically determining the number of archetypes based on the distances between the groupings in the dendrogram (Täuscher & Laudien 2018). An exemplary dendrogram of Janssen et al. (2020) can be seen in Figure 5 (p. 17). The matching coefficient of Sokal and Michener (1958) was applied to measure the distances between clusters. After observing various splits in the dendrogram, we investigated the possibility of different numbers of clusters using the partitioning K-means algorithm before settling on a final archetype number based on content plausibility (Janssen et al. 2020).

2.5. Relationship between Participatory Design and Design Science Research

This chapter presents the results of paper P6 "The Role of User Involvement: Relationship between Participatory Design and Design Science Research" (Janssen et al. 2021b). At the beginning of each research project, the most appropriate research design and methods must be carefully considered, as they may affect the research outcome (Sanders et al. 2010). The ways how future users are involved in research approaches differ. Especially in the design process of socio-technical systems, user participation is considered one of the main success factors and choosing which methodology to use dictates the extent of user participation (Maceli & Atwood 2013). Therefore, the paper aims to investigate the role of end-user involvement by analyzing the different layers of the relationship between PD and DSR and identifying differences and similarities based on scientific literature.

For this purpose, a literature search and analysis were conducted. Applying the search string "("design science" OR "design science research" OR DSR) AND ("participatory design" OR PD)" in five scientific databases (i.e., Scopus, Google Scholar, ScienceDirect, IEEE, and AiSel) yielded 196 initial hits. After screening the title and abstract, 46 papers were included in a literature review according to Webster and Watson (2002).

The literature review revealed three different layers of interrelationships between PD and DSR. While PD as a method in DSR (fourteen articles) and PD as a methodology (nine articles) was frequently used, PD as a method in the final artefact was identified only in two articles (i.e., Hansen & Pries-Heje 2017; Janssen et al. 2019). When applying PD as a research design based on the concept of Rauterberg (1991) or Spinuzzi (2005), end-users are seen, besides designers, as essential team members throughout the whole design process, which was observed in several HCI articles. Most of the identified articles used PD research methods in a DSR process. For identifying the phases in which PD was inserted as a method in DSR, the identified articles were classified according to the six DSR steps of Peffers et al. (2007) (see Table 9, p. 19). This revealed that future users are involved with PD methods in DSR processes primarily in the design and development steps (six out of eight articles) and in the evaluation of the artefacts (six out of eight articles). In the problem identification step, only two articles used PD methods. As PD was discovered only in single DSR artefacts, this research topic is worth investigating in the future by, e.g., developing design principles for using PD in an artefact.

Table 9: Application of PD Methods According to the DSR Process Model of Peffers et al. (2007) (Janssen et al. 2021b)

Articles	1 Identify Problem & Motivate	2 Define Objectives of a Solution	3 Design & Development	4 Demonstration	5 Evaluation	6 Communication
Asaro (2000)			•		•	•
Berger (2014)		•				•
Bilandzic & Venable (2011)				•		
Bratteteig et al. (2012)	•		•	•	•	•
Clemmensen et al. (2016)			•		•	
Damodaran (1996)			•	•	•	
Ehn (1993)		•	•	•	•	
Hartswood et al. (2002)	•	•	•		•	
Number of articles	2	3	6	4	6	3

DSR as well as PD approaches are used to develop socio-technical systems for future users. Whereas DSR is conceptualized as a construction or design-oriented methodology (Hevner 2007), PD concentrates on involving future users to participate as full team members (Kohtala et al. 2020). Even though the literature review revealed a variety of combinations, all of them emphasize the importance of considering the future user in the design process. The collaboration of several stakeholders (e.g., designers, end-users, and innovators) fosters active community participation and acceptance for the self-created artefact but may create a divide for other end-users who were not involved.

3. Digital Analytics and Technology Acceptance

3.1. Introduction

"Through a new form of data usage, the entire sales process [in the B2B sector] is shifting towards the analysis and evaluation of needs structures."

(Werner Katzengruber and Andreas Pförtner 2017, p. 28)

In the digital marketing age, marketeers are inundated with ever-growing amounts of data from a wide variety of digital analytics tools (Du et al. 2021). Digital analytics is defined by Gupta et al. (2020) as *"[…] technology-enabled analyses of data and processes using new-age technologies (such as AI, machine learning (ML), internet of things (IoT), blockchain, drones, etc.) and other online and offline data sources to design and deliver continuous, one-on-one personalized engagement in real-time."* When used properly, these data and tools can be essential ingredients to learn more about customers and competitors (Du et al. 2021). The marketing science institute named "*measurement approaches and methodologies to drive marketing insights,"* including the selection of appropriate key performance indices (KPIs), as a major research priority (Du et al. 2021; Kahn 2020). Approaches are, therefore, needed to enable companies to access this data in a structured manner and to make it efficiently available to the stakeholders in the company so that actions can be taken. However, when providing digital services such as chatbots to customers, it is also important to determine what positively and negatively influences users' intention to use a technology, which is where quantitative surveys prove useful. To contribute to this research field, the chapter presents four research papers that aim to answer two overarching RQs (RQ1 and RQ2).

To answer RQ1, the paper "Using Web Analytics Data: A Participatory Design Model for Individual Web Traffic Development" (Janssen et al. 2019; cf. Appendix A1) will be presented. The paper focuses on presenting an approach how to develop individual web traffic reports for different stakeholders in an industrial company by involving these future users without previous technical knowledge in the design process. The developed model is applied and evaluated in an industrial company. The paper "We Know your Personality! An Automated Personality Mining Approach on Twitter Data" (Klebansky et al. 2021; cf. Appendix A8) concentrates on presenting a personality mining framework and describes the steps to be taken when automatically identifying the personality traits of Twitter users based on their tweets. To answer RQ2, which deals with measuring the technology acceptance in industries with complex products and services, two papers will be presented in this chapter. The paper "Nutzerakzeptanz von Robo-Advisor Systemen für das digitale Investitionsmanage-ment in Deutschland" [Eng.: "User Acceptance of Robo-Advisor Systems for Digital Investment Management in Germany"] (Rodríguez Cardona et al. 2020) investigates the technology acceptance of robo-advisor chatbots in the finance sector by using UTAUT2. The paper "A Matter of Trust? Examination of Chatbot Usage in Insurance Business" (Rodríguez Cardona et al. 2021) presents an online survey investigating technology acceptance and the influence of trust and privacy concerns aspects on the intention to use insurance chatbots. The implications from the results of this paper additionally provide some clues to the response to RQ4, which is addressed in Chapter 4. The original RQs and purpose statements (PS), which are assigned to the two overarching RQs presented in this chapter can be found in Figure 6 (p. 21).

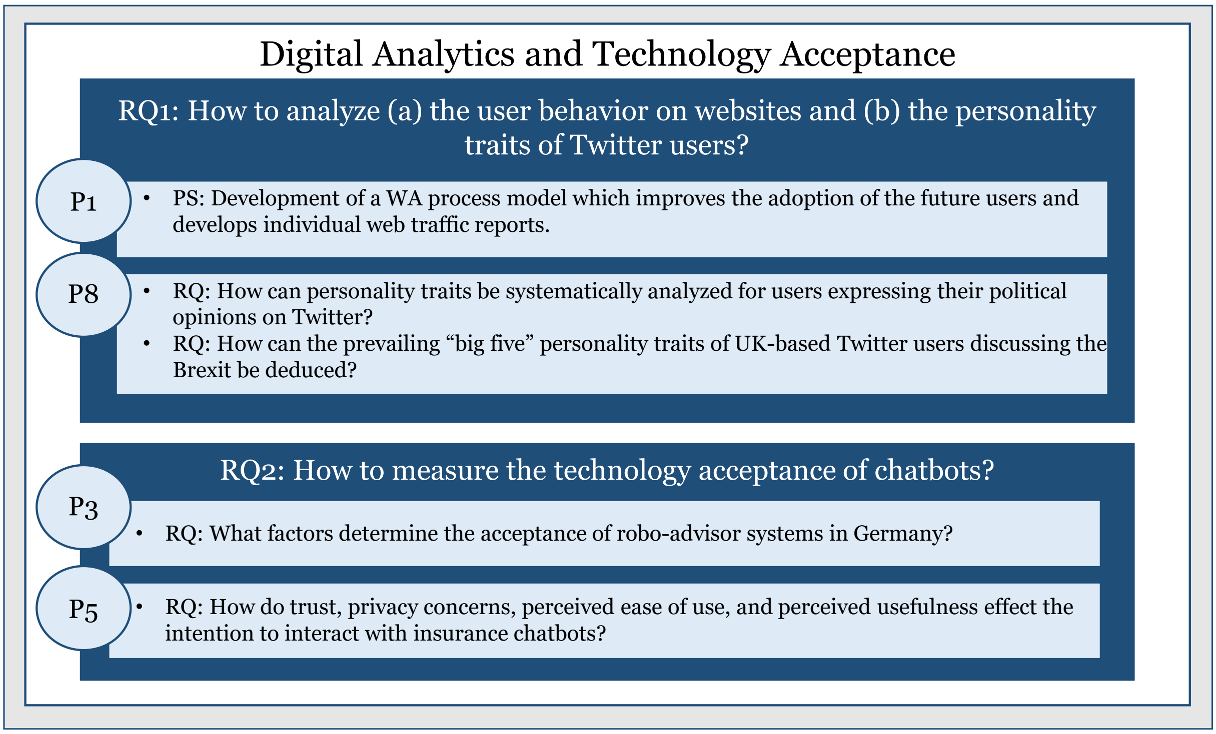

Figure 6: Research Questions of the Respective Papers in the Digital Analytics and Technology Acceptance Field (Own Representation)

3.2. Participatory Design Model for Individual Web Traffic Analysis

This chapter concentrates on the paper P1 “Using Web Analytics Data: A Participatory Design Model for Individual Web Traffic Development” (Janssen et al. 2029; cf. Appendix A1). Written by three authors, Antje Janssen, Jens Passlick, and Michael H. Breitner, the paper focuses on developing a PD framework helping companies to provide customized digital analytics dashboards by involving future users within the creation process.

Websites have long been an essential part of online presence, providing information to and engaging with the target audience (Bekavac & Praničević 2015; Harb et al. 2020). Companies are aware of the relevance of the data obtained during a website visit using web analytics tools, which makes it possible to collect and analyze this data for decision-making and for developing business strategies (Harb et al. 2020). These tools are widely used to monitor the behavior of website users, who may be, e.g., potential or actual customers, attendees, or journalists, who may be facing different issues when visiting a website (Booth & Jansen 2009; Palomino et al. 2021). By transforming user activity tracking on websites into quantitative analyzable data, these tools allow, by using some of the plenty of tracking options, to easily gain insights into, e.g., how users accessed the website and with which device, which pages they visited, and how long they stayed until they left the website (Palomino et al. 2021; Singal et al. 2014). However, this website data not only is relevant for the marketing department, which usually manages these tools to monitor marketing campaigns, but also provides valuable information for various business units in companies, such as the press department, product management, and human resources, all of which have different information needs but usually have little time and expertise for extensive analyses (Hausmann et al. 2012).

The authors address the research need by focusing on the development of an indicator selection process that allows the involvement of future users from different business units using PD methods. The objective is to develop individual reports containing only the KPIs relevant to the business units. By following the DSR guidelines of Hevner (2007) (see Table 5, p. 8), the authors conducted a literature review first and then semi-structured expert interviews before developing the web analytics model for individual web traffic development.

The final web analytics model for individual web traffic report development can be seen in Figure 7 (p. 23) and has six steps that are clustered in the three overarching PD steps of Spinuzzi (2005) (see Chapter 2.2.3). The model further shows which stakeholders (i.e., business unit, web analytics coordinator, web master, and report developer) should be involved in every step.

Step 1 "identification of company goals and strategy," focuses on detecting the overall goals and strategy of an organization whose goals the website should align with (Bekavac & Praničević 2015; Booth & Jansen 2009). This may be done by interviewing an employee who sees the big picture and interrelates between the company strategy and the corporate website. This is followed by step 2, "determination of business units," which involves identifying core business units that may be interested in gathering website data, for which the website navigation may provide the first indication (Booth & Jansen 2009). Step 3, "customized indicator selection," can be seen as the main step in which employees from different business units with little or nonexistent web analytics knowledge get involved. Through interviews, the aims and opportunities of using web analytics data are first explained before focusing on understanding the main purposes of the business unit.

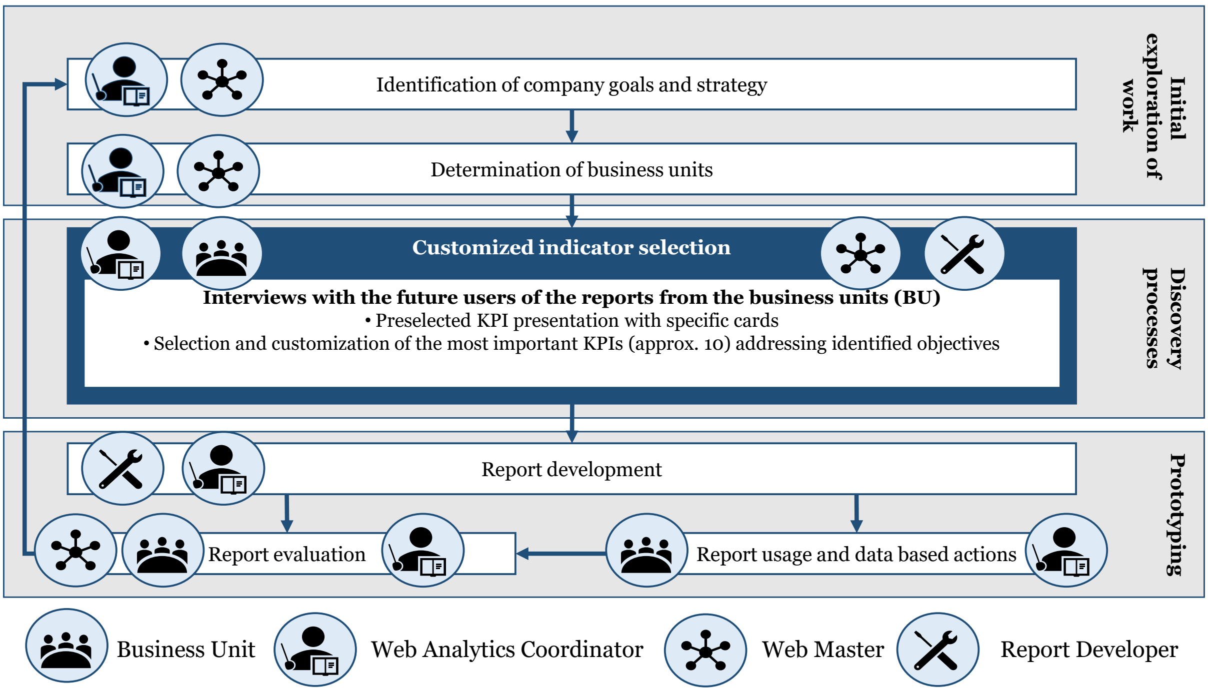

Figure 7: Developed Web Analytics Model Based on Spinuzzi (2005) (Janssen et al. 2019, p. 7)

These main purposes are the starting point for presenting and selecting appropriate KPIs from a list. The PD CARD method has gamification elements and can be seen as an appropriate method to promote storytelling in an interview situation by sorting, prioritizing, and categorizing physical cards (Tudor et al. 1993). For this purpose, the authors designed small playing cards, each containing an indicator on the front and the definition of this indicator on the back. A total of 10 cards have to be selected and sorted by relevance and the greatest benefit by the participant in the interview (Kibira et al. 2017). Furthermore, these KPIs must be individualized based on the goals to be achieved and must be linked to a specific measure to provide added value (Kibira et al. 2017; Waisberg & Kaushik 2009). The customized reports are developed in step 4, “report development.” Critical to this step is delivering accurate filter settings and subpage information, which turns a general indicator into a customized and valuable indicator. In step 5, “report usage and data based actions,” the reports are made available to the business units, ensuring that the users actively use them to draw conclusions. As the need for KPIs changes over time due to new challenges and changing business foci, it is important to conduct a regular assessment of usefulness, as addressed in step 6, “report evaluation.” However, changes in strategy occur over time not only at the business unit level but also at a corporate level, which is why this iterative process should regularly start again with step 1, as indicated by the arrow.

To demonstrate the model’s applicability, the authors applied the model to an internationally operating automation and engineering specialist who sells their products and services to B2B customers via trade fairs, onsite visits, and telephone calls. The corporate website, which is analyzed with the web analytics tool Google Analytics, is primarily used for informational purposes, addressing different stakeholders in sub-sites. The model was used to develop web analytics reports for various business units with the inclusion of future users. After two interviews identifying the overall business strategy and the connection to the corporate website (step 1), as well as core business units (step 2), nine interviews with 14 interviewees were conducted, in which KPI cards were used to select and customize appropriate KPIs (step 3). “Page views” was selected by all participants followed by “traffic source,” “click and contact,” and “depth of visit.” These reports were developed (step 4) and deployed to the business units (step 5). Compared to the old web analytics tool and to other non-involved users who received only the final results, a significantly higher acceptance and interest could be identified among the involved business unit members, which was also reflected by their high interest in training participation and further developments.

In this paper (P1), a six-step iterative web analytics model to individually develop reports for several business units by involving them in the design process using PD methods was developed. To test applicability, the web analytics process model was applied in an industrial manufacturing company, to this end, 14 employees were interviewed, which led to nine individual reports being developed. With the PD model, we contribute to the web analytics field by presenting an approach to provide the accessible relevant data of a web analytics tool to multiple stakeholders who receive only the information they require.

3.3. Personality Mining Framework

This chapter concentrates on the paper P8 "We Know your Personality! An Automated Personality Mining Approach on Twitter Data" (Klebansky et al. 2021 and cf. Appendix A8). To answer the RQ of how to systematically predict the personality traits of Twitter users, this paper focuses on developing a framework to automatically assess the OCEAN personality traits in tweets. To evaluate the framework, 12 hypotheses in the Brexit political context are investigated, on which a minor focus is placed due to the research focus of this doctoral thesis.

By texting about their own experiences, emotions, and opinions, social media users reveal a lot about themselves (Carducci et al. 2018). This huge and ever-growing dataset offers diverse opportunities for automated analysis such as personality mining prediction. A person's personality is considered a stable internal factor that is deeply embedded in the unconscious and influenced by deeply rooted psychological dispositions (Cottam et al. 2010; Gallego & Oberski 2012), which is called the trait paradigm (Cervone & Caprara 2000). In the past, several studies (e.g., Arnoux et al. 2017; Azucar et al. 2018; Buettner 2017) focused on using automated personality trait analysis of tweets to accurately predict and prove personality traits. This automated personality analysis based on tweets has a major advantage over questionnaire-based self-reports that have been traditionally used in that it is less expensive and more efficient, as it uses much larger samples (Carducci et al. 2018; Park et al. 2015) and minimizes measurement error by eliminating the self-report bias (Ebstrup et al. 2011). Various domains, e.g., in recruiting (e.g., Hu et al. 2016) or in healthcare (e.g., Rüegger et al. 2016), have already successfully applied personality mining to automatically determine personality traits based on publicly available tweets. Buettner (2017) further used this data to automatically recommend products based on the predicted personality profile of a user. However, a detailed framework on how to predict the personality traits of user groups on Twitter is not available. Therefore, in this paper, a framework is developed how to systematically predict users' personality traits of two different predefined groups on Twitter.

To develop the personality mining framework, a structured literate search and analysis was conducted in seven scientific databases using a search string ("Personality Traits" AND "Social Media" AND "Mining"), which revealed 26 appropriate papers based on which the framework was developed. Figure 8 (p. 26) shows the final framework, which is divided into four steps.

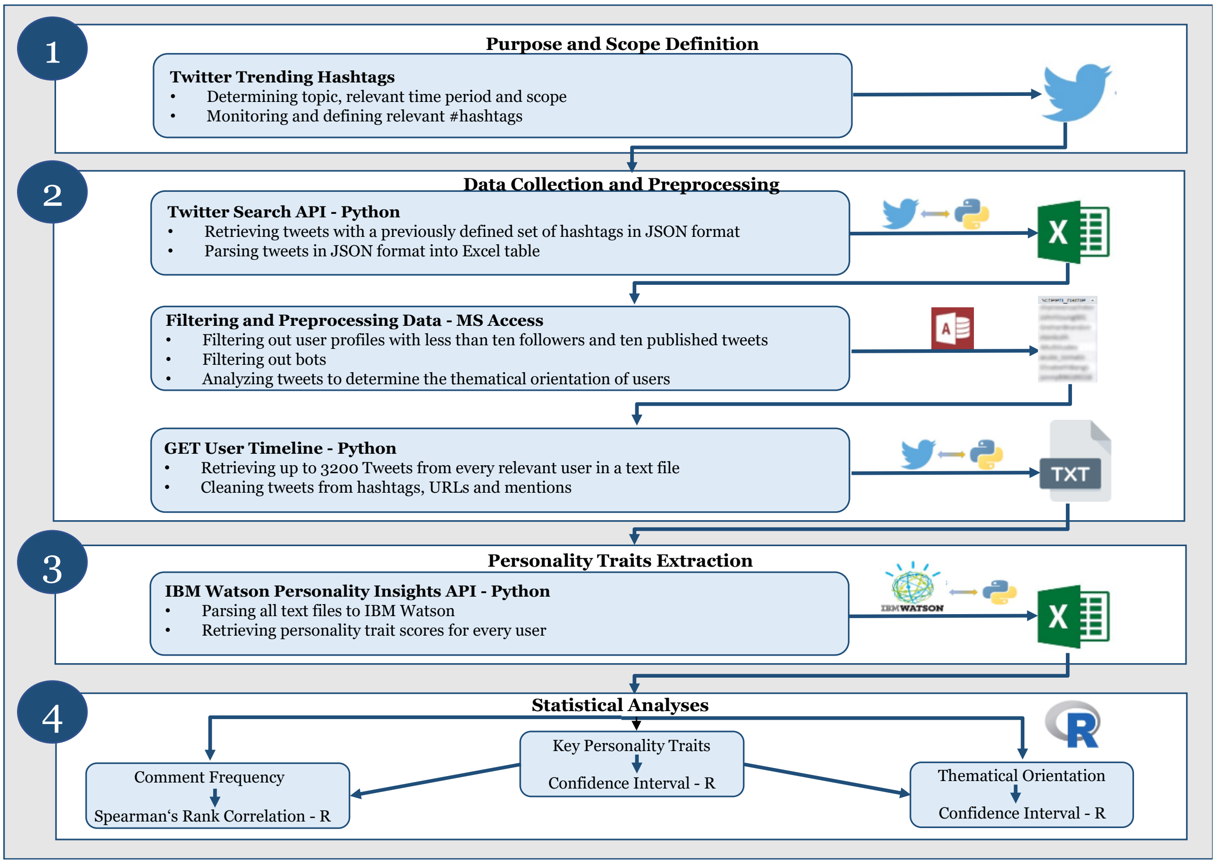

Figure 8: Personality Mining Framework
(Based on Klebansky et al. 2021, p. 9)

In the first step, the purpose and scope of the data analysis are defined, and the analyzed hashtags are selected. Step 2 comprises data collection and preprocessing. Thus, Twitter data is extracted via an API, for which the Twitter search API and the Twitter streaming API can be used (Gimpel et al. 2018a; Recuero et al. 2019). This is followed by filtering, cleaning, and preprocessing the tweets to exclude accounts with too few tweets from the automated personality mining (Tommasel et al. 2015). Twitterbots that automatically publish tweets need to be identified by, e.g., searching for patterns in form of, e.g., short time intervals between tweets (Gilani et al. 2019; Wright & Anise 2018; Yaqub et al. 2020). In the next step (step 3), to calculate the personality trait expressions, all items in the tweets that do not contribute any value to the analysis should be discarded (e.g., URLs, mentions, hashtags, and non-alphanumeric characters) (Oh & Kumar 2017; Pak & Paroubek 2010). For automated personality trait prediction in step 3, the pre-engineered IBM Watson Personality Insights API was used, which had predominantly been applied by other researchers earlier (e.g., ElSherief et al. 2018; Siemon et al. 2018; Tommasel et al. 2015). For automatically calculating the intrinsic personality traits of a user, the IBM Watson algorithm needs at least 600 words. IBM Watson outputs a normalized value between 0 and 1 for each personality trait, which represents the percentile ranking of the author's trait level compared to the sample population. Scores above 0.75 are considered as a high level of the trait. Step 4 includes the statistical analyses to test the previously determined theoretical assumptions. Three different approaches are presented in the paper to determine key personality traits to investigate the comment frequency in relation to personality traits and the relationship between a thematic topic and personality traits.

By applying the developed framework in the context of UK Brexit discussions, we analyzed 60,729 tweets published by 800 UK-based users who were the most active contributors to political discussions on Twitter around the withdrawal date of Brexit. Thus, the applicability of the model was tested. The analyses reveal that the sampled Twitter users who published about Brexit demonstrated higher levels of neuroticism than individuals who revealed their opinions in offline political discussions (Hibbing et al. 2011), which could be attributed to anonymity on Twitter. The Brexit Twitter user analysis demonstrates how the framework can be applied for obtaining profound insights into the personality profiles of active users on Twitter and to test previously formulated hypotheses. Of the Fortune 500 companies, 89% had active Twitter accounts in 2020, making it the second most-used social media platform after LinkedIn (Barnes et al. 2020). Contrary to the general assumption that buying decisions are based more on objective metrics due to the organizational buying context, while in B2C, more emphasis is placed on emotional aspects, Swani et al. (2014) revealed in their study that B2B companies also share more emotional appeal than functional appeal in their corporate tweets. Therefore, this personality mining approach can help determine the extent to which the personality trait characteristics of users who follow B2B or B2C accounts on Twitter differ.

3.4. Chatbot Trust and Acceptance in Insurance Industry

The following chapter refers to the publication P5 “A Matter of Trust? Examination of Chatbot Usage in Insurance Business” (Rodríguez Cardona et al. 2021; Appendix A5), which was authored by Davinia Rodríguez Cardona, Antje Janssen, Nadine Guhr, Michael H. Breitner, and Julian Milde.

Although chatbots are used in numerous application areas, various factors differently influence, depending on the application area, whether a chatbot is accepted and used by a user. In the insurance sector, which is characterized by complex services and strong legacy regulations (Gebert-Persson et al. 2019; Rodríguez Cardona et al. 2019), chatbots are increasingly being used (Koetter et al. 2019). In 2020, six out of 40 German-speaking insurance companies offered chatbots in customer communication to market services, conclude an insurance contract, or settle claims via a human–chatbot dialogue (Rodríguez Cardona et al. 2021). The question that arises consequently is which factors influence insurance customers in their use of an insurance chatbot, which is why this study examines a total of eight hypotheses (see Table 10, p. 28). To analyze the effect of technology acceptance factors as well as trust and privacy concerns on the intention to use insurance chatbots, the TAM of Davis (1989) (see Chapter 2.3.1) is adopted by expanding it with trust and privacy concerns.

Table 10: Hypotheses Overview of Chatbot Acceptance in Insurance Business (Rodríguez Cardona et al. 2021, p.559–560)

H_n	Hypotheses
H_1	Perceived ease of use is positively related to the intention to use insurance chatbots.
H_2	Perceived usefulness is positively related to the intention to use insurance chatbots.
H_3	Perceived ease of use is positively related to the perceived usefulness of insurance chatbots.
H_4	Trust is positively related to the intention to use insurance chatbots.
H_5	Trust is positively related to the perceived usefulness of insurance chatbots.
H_6	Perceived ease of use is positively related to trust in insurance chatbots.
H_7	Privacy concerns are negatively related to trust in insurance chatbots.
H_8	Privacy concerns are negatively related to the intention to use insurance chatbots.

To answer the hypotheses posed (see Table 10, p. 28) and to use the previously chosen conceptualized constructs, we published a standardized cross-sectional online survey on the Circle3 portal. The questionnaire in German language contained an introduction text, which was followed by the questions for gathering information on chatbot experience and demographic characteristics and closed-ended questions using Likert scales and differential word pairs. The closed-ended questions addressed 22 measurement points around the following categories: intention to use, perceived usefulness, perceived ease of use, trust, and privacy concerns. A total of 215 participants (51.1% male and 48.9% female) completed the online survey of which 9% already had experiences in interacting with insurance chatbots.

SmartPLS was used for PLS-SEM (Chin 1998; Hair et al. 2016) to thoroughly test our proposed theoretical assumptions against the collected empirical datasets and to explore the relationships behind the intention to use chatbots in the insurance context. Outer-loading and cross-loading calculations were performed to assess the item and composite reliability (Chin 1998; Cho 2016), the average variance extracted (AVE) (Fornell & Larcker 1981) and the heterotrait-monotrait ratio of calculations (HTMT) (Henseler et al. 2015) were calculated to assess the convergent and discriminant validity, resulting in appropriate results (see Rodríguez Cardona et al. 2021 for more details).

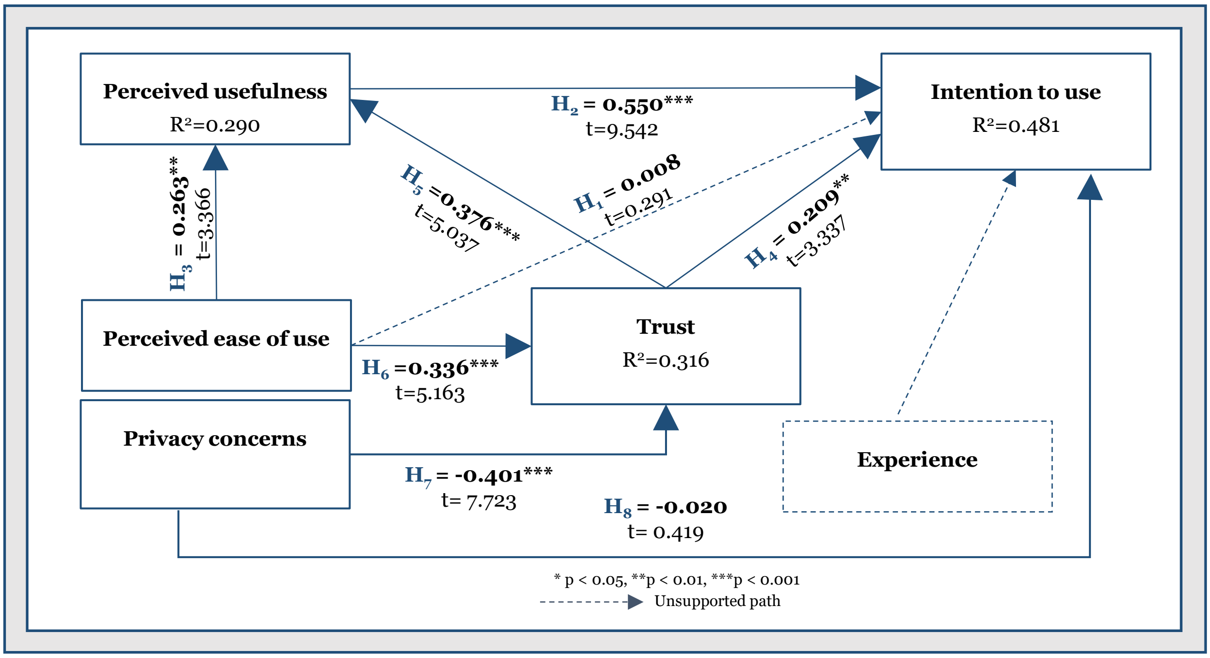

Figure 9: Partial Least Squares Results for the Structural Model of Chatbot Acceptance in Insurance (Rodríguez Cardona et al. 2021, p. 562)

Figure 9 (p. 29) shows the PLS-SEM path coefficients and their significances (p-values) as well as the t-values, which were calculated by the bootstrap procedure through

3,000 replications (Henseler et al. 2015) to depict the assumed theoretical relationships between these constructs (Hair et al. 2016).

R^2 shows that 29.0% of the variance in the perceived usefulness can be explained by trust and perceived ease of use, while the intention to use can be 48.1% explained by trust, perceived ease of use, perceived usefulness, privacy concerns, and trust. Trust can be 31.6% explained by the constructs privacy concerns and perceived ease of use (see Figure 9, p. 29).

Six out of the eight hypotheses could be supported through the online survey (see Table 11, p. 30). The results reveal that privacy concerns significantly and negatively affect trust, but do not significantly affect intention to use. The largest significant positive influence on the intention to use a chatbot has perceived usefulness, while trust and ease of use also show a significant positive influence. The covariate experience does not significantly influence the intention to use insurance chatbots. The effect size (f^2) between trust and the intention to use insurance chatbots, and the effect size between the perceived ease of use and perceived usefulness indicate a minor impact.

Table 11: Partial Least Squares Results and Measurement Model Statistics (Rodríguez Cardona et al. 2021, p. 562)

H_n	Relationship	β	T-value	P-value	f^2	Results
H_1	PEOU → INT_USE	0.008	0.291	0.771	0.000	Not supported
H_2	PU → INT_USE	0.550	9.542	0.000	0.409	Supported
H_3	PEOU → PU	0.263	3.366	0.001	0.082	Supported
H_4	TR → INT_USE	0.209	3.337	0.001	0.052	Supported
H_5	TR → PU	0.376	5.037	0.000	0.167	Supported
H_6	PEOU → TR	0.336	5.163	0.000	0.161	Supported
H_7	PRIV → TR	-0.401	7.723	0.000	0.229	Supported
H_8	PRIV → INT_USE	-0.020	0.419	0.675	0.001	Not supported

Note: PEOU = Perceived Ease of Use; EXP = Experience; INT_USE = Intention to Use; PU = Perceived Usefulness; TR = Trust; PRIV = Privacy Concerns

Note: H = Hypothesis; β = path coefficient; Cohen's f^2-statistics = [R^2incl. - R^2 excl.] / [1-R^2incl.] (1988); $f^2 \geq 0.02$, 0.15 and 0.35 correspond to small, medium, and large effects.

By performing an online survey with 215 participants and conducting PLS-SEM analysis, we aimed to examine the influence of usefulness, perceived ease of use, privacy concerns, and trust on the intention to use insurance chatbots. The findings reveal that while trust significantly and positively influences intention to use, perceived usefulness has a larger positive influence on intention to communicate with an insurance chatbot.

3.5. Robo-Advisor Chatbot Acceptance in Finance Industry

This chapter presents the procedure and results of the paper P3 “Nutzerakzeptanz von Robo-Advisor Systemen für das digitale Investitionsmanagement in Deutschland” (Rodríguez Cardona et al. 2020). The paper was written by Davinia Rodríguez Cardona, Antje Janssen, Julian Uphaus, Julian Fischer, and Michael H. Breitner.

Robo-advisor chatbots are intelligent web-based interfaces that aim to provide automated professional financial advice to private users without human assistance and at a low cost (Adam et al. 2019; Bruckes et al. 2019; Hildebrand & Bergner 2021; Morana et al. 2020b). Robo-advisor chatbots provide users with individualized and algorithm-based investment suggestions after the user answers specific questions in a dialogue about, e.g., risk tolerance, personal financial situation, and the amount to be invested (Adam et al. 2019; Bruckes et al. 2019). Robo-advisors are receiving greater attention, and compared to conventional banks, these intelligent advisor systems are considered to possess the potential to revolutionize the financial industry (Bruckes et al. 2019; Werth et al. 2019).

While financial companies see the potential to save consulting costs and reach new target groups through the automated process, there are various challenges, which may impact trust and user acceptance. These include data protection and government regulations (Bruckes et al. 2019; Guo et al. 2019) and the users’ assumption and prejudice that human advisors can understand the customer much better compared to an automated system (Hildebrand & Bergner 2021). Therefore, with a user-centered online survey, this paper aims to identify the factors that determine the end-user acceptance of robo-advisor chatbots in Germany and to provide insights into the nature of the relationships between these systems. To investigate the acceptance in form of the behavioral intention to use robo-advisor chatbots, the extended UTAUT2 model of Venkatesh et al. (2003; 2012) was applied (see Chapter 2.3.1 for further details), in which the role of “performance expectancy,” “effort expectancy,” “social influence,” “risk perception,” “price value,” “degree of automation,” “cost structure,” and “facilitating conditions” was considered. Additionally, four potential individual differences, “education,” “income,” “savings,” and “risk tolerance” were considered along with the two constructs of “age” and “investment experience” in the UTAUT2 model (Venkatesh et al. 2012). Table 12 (p. 32) presents an overview of eight hypotheses formulated based on the acceptance factors of robo-advisor chatbots identified and analyzed through a structured literature review.

To investigate the behavioral intention to use robo-advisor chatbots in Germany, a German-language online survey was conducted, in which 250 people (50.7% male, 40.2% female, and 9.0% not specified) with a median age of 27 and an average age of 34 participated over three weeks, of which 199 survey responses could be used. The participants' median income is 1,700€ and average income 1,984€. The average wealth is 73,850€. PLS-SEM was used to analyze the causal relationships among variables (see Chapter 2.3.1 for further information).

Table 12: Hypotheses Overview Robo-Advisor Chatbot Acceptance (Rodríguez Cardona et al. 2020, p. 5–7)

H_n	Hypotheses
H_1	Performance expectancy related to the efficient portfolio optimization will have significant positive influence on the BItU robo-advisors.
H_2	Effort expectancy will have a significant influence on the BItU robo-advisors.
H_3	Positive recommendations lead to an increase of the BItU robo-advisors.
H_4	Excessive concern for the protection of personal financial data will reduce the BItU robo-advisors.
H_{5a}	The presence of FC in robo-advisors increase the BItU robo-advisors.
H_{5b}	An enhanced degree of automation increases the BItU robo-advisors.
H_{6a}	A robo-advisor system must be much cheaper than a personal advisor to increase the BItU robo-advisors.
H_{6b}	A transparent flat rate pricing model contributes to an increased BItU robo-advisors.

Note: BItU = Behavioral Intention to Use

Figure 10 (p. 33) presents the survey results, indicating that four (H_1, H_3, H_{5b}, and H_{6b}) of the eight hypotheses were confirmed in the online study. Most survey participants doubted whether robo-advisor chatbots could recommend appropriate investments to investors based on individual assessments of investment needs, and whether they would minimize the time invested in this process. The conducted analysis revealed that the latent variable of performance expectancy (H_1) positively and significantly influences the behavioral intention to use (BItU) robo-advisor chatbots with a significance level of $p < 0.05$. This finding implies that the behavioral intention to use increases when the expected return from the robo-advisor exceeds that from a traditional human bank advisor. According to the respondents, a much higher return on investment is expected with robo-advisor usage compared to the return on investment of traditional banks, which is why a small additional return in the form of 0%–0.05% would not persuade most participants to switch financial advisors. Positive recommendations from personal surroundings (e.g., family and friends) were also found to increase the behavioral intention to use (H_3). To estimate the level of awareness, respondents were presented with eight logos of well-established robo-advisor chatbots during the survey. The results showed that more than 60% of the respondents did not know any of the eight logos provided, indicating a low level of awareness and experience among the respondents.

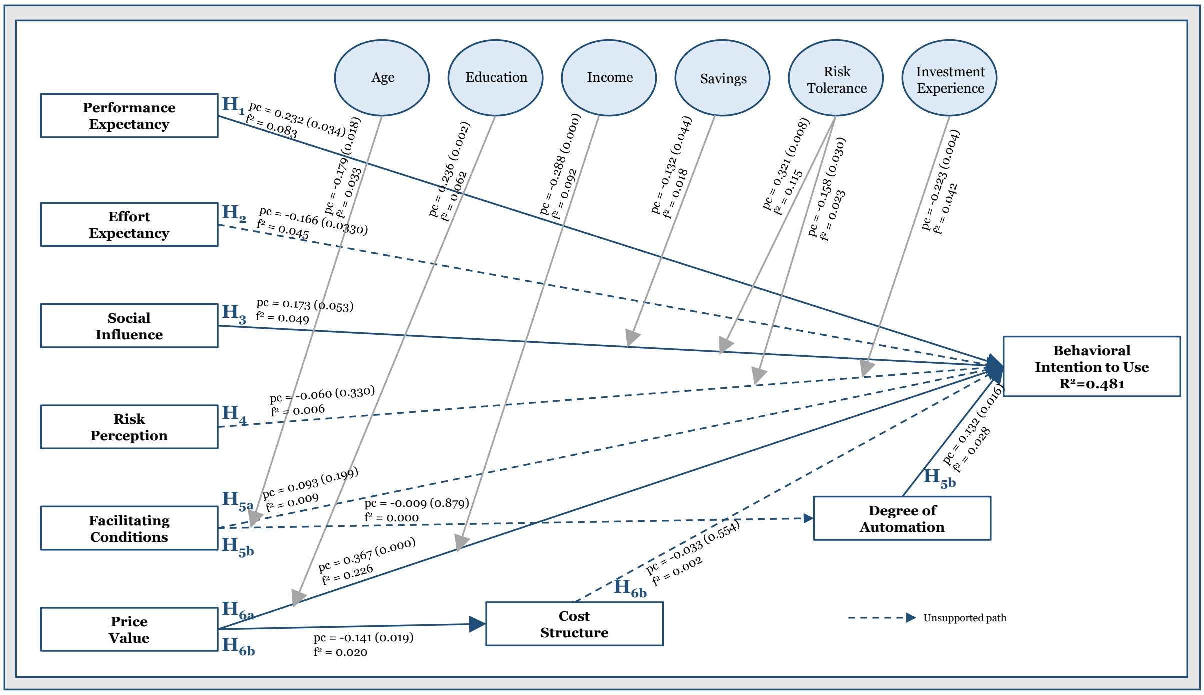

Figure 10: Partial Least Squares Results for the Structural Model (Rodríguez Cardona et al. 2020, p. 13, translated)

Overall, the results of the structural model indicate that the expected performance and the degree of automation are the decisive factors for the intention to use robo-advisor chatbots in Germany, even though socio-economic factors (i.e., education, income, and age) constitute important mediating variables.

3.6. Conclusion

This chapter summarizes the findings of four papers in the digital analytics and technology acceptance field clustered into two RQs, focusing on the contributions to and implications for B2B industries.

RQ1 aimed to offer approaches how to analyze user behavior on websites and Twitter, which was addressed in two papers. Frameworks were presented and applied to monitor the behavior of website visitors on corporate websites and to analyze the OCEAN personality traits of Twitter users. These frameworks can be applied in the B2B sector to monitor and improve marketing and communication activities. The paper on individual web traffic reports developed an approach to design individual web analytics reports for different stakeholders and their purposes, which was applied in an industrial manufacturing company in the B2B area. The developed iterative five-step model contains PD methods to actively involve future users from several business units with limited knowledge in the design and indicator selection process. Klebansky et al. (2021) presented an approach to analyzing target audiences' behavior on Twitter by predicting their personality traits without directly involving and interviewing users. The presented framework may be used in the future to classify the personality traits of individuals who follow B2B and B2C corporate Twitter accounts according to the OCEAN model. While impulsive and emotional buying decisions are also being made in the B2C area, the B2B selling process is said to rely more on rational arguments (Rėklaitis & Pilelienė 2019). Therefore, investigating how companies should communicate on Twitter may be interesting.

Two online surveys to investigate technology acceptance were further presented in this chapter to address RQ2. The studies revealed the importance of focusing on the users and their added value, which, in customer service, is characterized by the simplicity of handling and features that enable the user to achieve a goal (Rodríguez Cardona et al. 2020; Rodríguez Cardona et al. 2021). Although both studies on the usage intentions of insurance chatbots (Rodríguez Cardona et al. 2021) and robo-advisor chatbots (Rodríguez Cardona et al. 2020) target the B2C end-consumer context, these sectors show some parallels to the B2B industry in terms of conservatism and complexity (Janssen et al. 2021a; Rodríguez Cardona et al. 2021), leading to the suggestion that these findings may well be worthwhile for the B2B context as well, which requires further investigation.

4. Chatbot Taxonomies, Archetypes, and Design Implications

4.1. Introduction

"Chatbots are now playing an increasingly important role in improving customer services in B2B marketing."

(Xiaolin Lin, Bin Shao, and Xuequn Wang 2022, p. 45)

B2B marketing communication has changed from push communication, in which the benefits of products and services are described through the clearest and most consistent messages possible in different communication channels, to constant interactions with customers (Kaghyan et al. 2018). By presenting the answers to the questions when they arise, chatbots may be a communication technology suitable for this shift (Kushwaha et al. 2021). Besides B2B customer service purposes, chatbots have become hugely prevalent in recent years in private as well as corporate application scenarios, such as education, health, and customer service (Adamopoulou & Moussiades 2020; Følstad et al. 2019; Janssen et al. 2020; Nißen et al. 2021) for automatically interacting with users to perform tasks or provide information (Adamopoulou & Moussiades 2020; Brandtzæg & Følstad 2018; Diederich et al. 2022). More and more companies face the challenge of introducing and maintaining a chatbot that suits their needs as well as the needs of their customers. This chapter is dedicated to five papers thematically clustered into two RQs.

In this chapter, we first step back and look at how real-world chatbots are currently characterized, helping to establish an integrative knowledge foundation. To answer RQ3, taxonomies help systematically classify objects with a conceptual and empirical lens to enable object differentiation based on identified characteristics and hypothesize about relationships in the thematic domain (Szopinski et al. 2020). When observing chatbots, one notices many different application areas, goals, and visual features. To recognize structured patterns, the taxonomy development and archetype identification approaches are used in three papers. This helps identify structured elements and objectively classify characteristics and their manifestations. The first paper, "Virtual Assistance in any Context" (Janssen et al. 2020), is dedicated to the design-element classification of domain-specific chatbots from various application domains. The paper "See You Soon Again, Chatbot? A Design Taxonomy to Characterize User-Chatbot Relationships with Different Time Horizons" (Nißen et al. 2021) concentrates on time-dependent chatbot characteristics across several application domains. The third paper "More than FAQ! Chatbot Taxonomy for Business-to-Business Customer Services" (Janssen et al. 2021a and Appendix A4) is devoted to the B2B customer service area and analyzes the predominant design elements across the chatbots in this sector. While these three papers examine existing publicly available real-world chatbots and scientific literature, the question of what needs to be considered to develop and manage a successful chatbot arises, leading to the fourth overarching RQ in this chapter. To address RQ4, two papers will be presented. The next paper "Why do Chatbots fail? A Critical Success Factors Analysis" (Janssen et al. 2021c and Appendix A9) starts with the end of the chatbot lifecycle by first concentrating on identifying reasons for chatbot failure in practice. Further, the CFSs in chatbot literature and practice are extracted, which will help future developers and managers keep the most critical factors in mind to avoid the failure of future chatbots due to repetitive patterns. The paper "How to Make Chatbots Productive – A User-Oriented Implementation Framework" (Janssen et al. 2022) develops a user-centered eight-step chatbot implementation model, which includes a list of questions to be asked when developing, deploying, and managing a chatbot. Figure 11 (p. 36) provides an overview of the RQs.

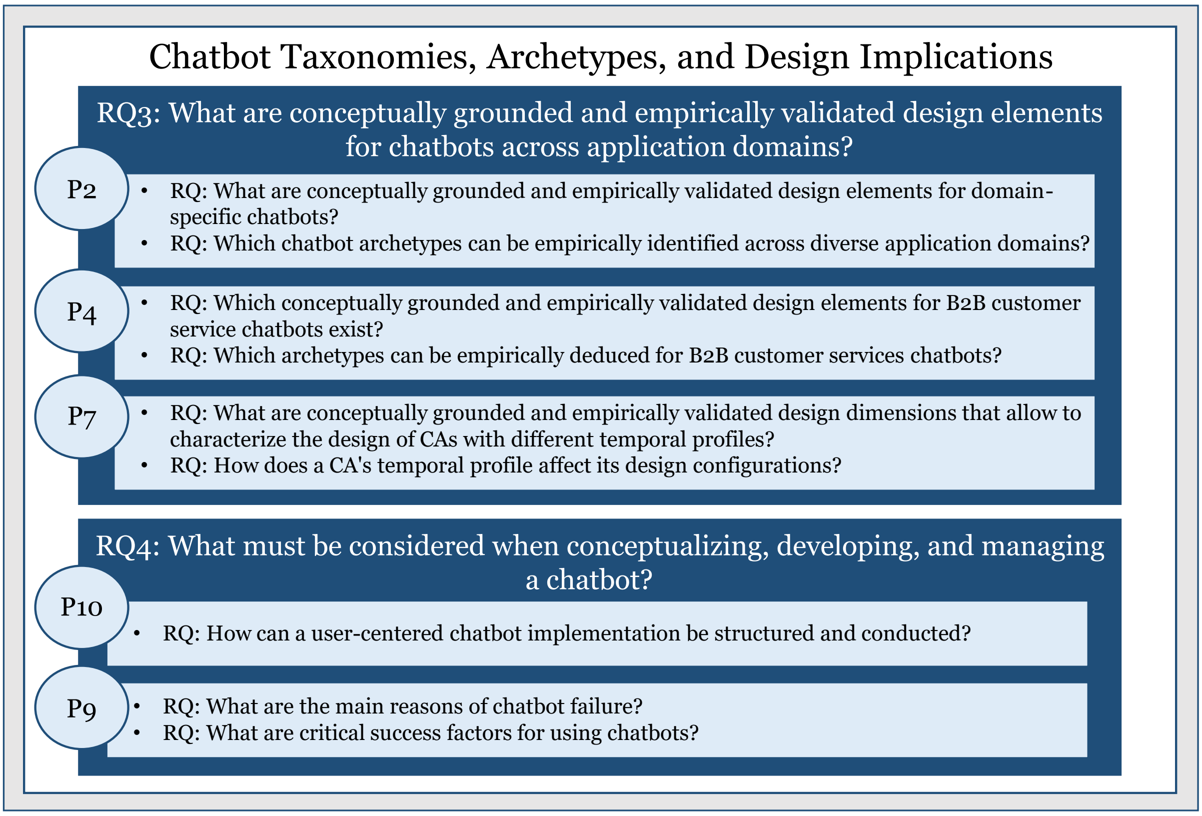

Figure 11: Research Questions of the Respective Papers in the Chatbots Field (Own Representation)

4.2. Taxonomy of Design Elements for Domain-Specific Chatbots

This chapter presents the paper P2 "Virtual Assistance in Any Context – A Taxonomy of Design Elements for Domain Specific Chatbots" (Janssen et al. 2020 and cf. Appendix A2). This paper was written by Antje Janssen, Jens Passlick, Davinia Rodríguez Cardona and Michael H. Breitner.

Domain-specific chatbots are nowadays used in a variety of domains, such as education, health, customer service, and online shopping, but a systematic knowledge of their distinguishing characteristics is lacking. While some researchers (e.g., Di Prospero et al. 2017) have identified cross-domain design elements, previous studies have focused predominantly on single application domains (Bittner et al. 2019; Diederich et al. 2019b; Følstad et al. 2019) or particular design aspects (Di Prospero et al. 2017; Gnewuch et al. 2017). However, a classification, differentiation, and categorization especially for domain-specific chatbots that considers the application domain-spanning scientific and practical knowledge about chatbot design elements are missing. Therefore, a development of a design element taxonomy on options for designing domain-specific chatbots, as well as archetype identification, are needed to bridge the gap between research and practice by giving practitioners a guidance on design options for designing chatbots.

To develop a design element taxonomy by analyzing scientific literature as well as chatbots from several application domains, we followed the seven-step taxonomy development approach of Nickerson et al. (2013), described in Chapter 2.4. The meta-characteristic is to extract all design elements that describe domain-specific chatbots. In this context, "design elements" refer to *"the distinctive technical, situational and knowledge features that frame the structure of chatbots and act as delimiting factors of the extent to which domain-specific chatbots can maintain a human-like interactive communication process with awareness for and understanding of the discussed topic*" (Janssen et al. 2020, p. 213). The subjective and objective ending conditions of Nickerson et al. (2013) were applied to define the end of the iterative development, which were met within iteration 5.

The taxonomy development started with a conceptual-to-empirical iteration in which an initial taxonomy was conceptualized based on a structured literature review on four scientific databases using the search string ("chatbot*" OR "conversational agent*" OR "dialog system*" OR "computer user communication*" OR "conversational robot*") as well as forward and backward search. Out of 1076 hits, 24 scientific papers presented relevant design elements or classification frameworks. In the first iteration, *intelligence*, *interaction,* and *context* were identified as the three central perspectives, structuring all dimensions and characteristics. Intelligence and interaction have been previously used in IS research to summarize the design features of chatbots (Knote et al. 2019; Maedche et al. 2016; Morana et al. 2020a; Stoeckli et al. 2019). The term context is used to describe the chatbot's contextual environment and application domain (i.e., general and domain-specific (Diederich et al. 2019b; Gnewuch et al. 2017), which in turn impacts chatbot design (Knote et al. 2018).

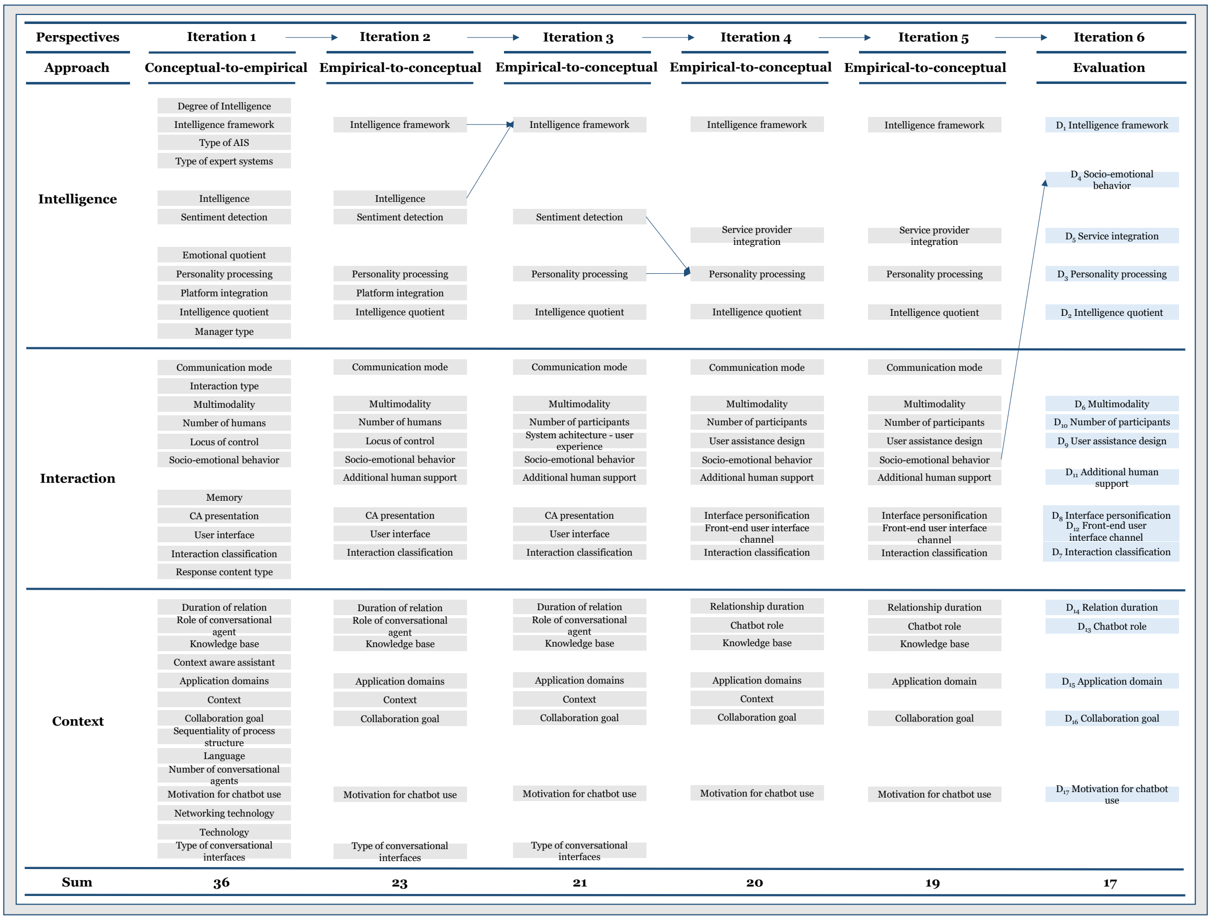

Figure 12: Dimension Development Across Iterations (Janssen et al. 2020, p. A-1)

The empirical-to-conceptual approach was followed for the next four iterations and started with an initial set of 12 chatbots from botlist.co. To obtain an all-encompassing view of the current state of the available chatbots, we analyzed five chatbot databases (botlist.co, chatbots.org, chatbottle.co, 50bots.com, and botfinder.io) in iteration 3 before choosing chatbots.org, from which we then analyzed 10% of the chatbots from all 27 application domain categories. In total, 103 chatbots (iteration 2: n = 12, iteration 3: n = 66 iteration 4: n = 13, iteration 5: n = 12) were considered. The empirical classification of the chatbots was primarily based on targeted interaction by conducting a conversation with the chatbot and secondarily partly on available videos, papers, and blogs. In every iteration, dimensions and characteristics were added, merged, deleted, renamed, and sorted to another perspective (see Figure 12, p. 38).

To test understandability, applicability, extensibility, and completeness (Szopinski et al. 2019), we evaluated the final taxonomy in three FGDs which lasted between 40 and 105 minutes. In total, twelve individuals from academia and practice participated who have taxonomy development method and/or chatbot domain knowledge and who were not involved in taxonomy development (for details, see Chapter 2.4). All participants confirmed the usefulness and adaptability for both, research, and practice. After six iterations, all subjective and objective ending conditions were fulfilled, and the taxonomy development process ended, as no dimension or characteristic was added, deleted, split, or merged. We conducted an inter-coder reliability test by randomly coding a set of chatbots by all coders involved in the process. The calculated Fleiss' (1971) kappa coefficient is 0.63, meaning a "substantial" agreement (Landis & Koch 1977).

The final taxonomy with design elements for domain-specific chatbots can be seen in Table 13 (p. 40) and consists of 17 dimensions and 49 characteristics with the three perspectives: intelligence, interaction, and context. The intelligence perspective includes five dimensions describing the level of intelligence in the form of being able to conduct meaningful and human-like conversations by understanding the topic (Chaves & Gerosa 2019; Jain et al. 2018). The interaction perspective comprises seven dimensions describing the degree to which a chatbot can establish a mediated setting (Kiousis 2002) while conducting the dialogue as naturally as possible to mimic a face-to-face conversation (Diederich et al. 2019b). The context perspective includes five dimensions describing all explicitly and implicitly visible situational data that describe the situation and environment the chatbot is employed (Abowd et al. 1999; Diederich et al. 2019b; Gnewuch et al. 2017; Kim et al. 2018).

Table 13: Final Taxonomy of Design Elements for Chatbots (Adapted from Janssen et al. 2020, p. 217)

Layer 1: Perspective	Layer 2: Dimensions D_i	Layer 3: Characteristics $C_{i,j}$ (% distribution)		
Intelligence	D_1 Intelligence framework	$C_{1,1}$ Rule-based system (73%)	$C_{1,2}$ Utility-based system (17%)	$C_{1,3}$ Model-based system (6%)
		$C_{1,4}$ Goal-based system (2%)	$C_{1,5}$ Self-learning system (2%)	
	D_2 Intelligence quotient	$C_{2,1}$ Only rule-based knowledge (41%)	$C_{2,2}$ Text understanding (42%)	$C_{2,3}$ Text understanding and further abilities (17%)
	D_3 Personality processing	$C_{3,1}$ Principal self (96%)	$C_{3,2}$ Adaptive self (4%)	
	D_4 Socio-emotional behavior	$C_{4,1}$ Not present (88%)	$C_{4,2}$ Present (4%)	
	D_5 Service integration	$C_{5,1}$ None (22%)	$C_{5,2}$ Single integration (59%)	$C_{5,3}$ Multiple integration (18%)
Interaction	D_6 Multimodality	$C_{6,1}$ Unidirectional (91%)	$C_{6,2}$ Bidirectional (9%)	
	D_7 Interaction classification	$C_{7,1}$ Graphical (23%)	$C_{7,2}$ Interactive (77%)	
	D_8 Interface personification	$C_{8,1}$ Disembodied (71%)	$C_{8,2}$ Embodied (29%)	
	D_9 User assistance design	$C_{9,1}$ Reactive assistance (79%)	$C_{9,2}$ Proactive assistance (21%)	
	D_{10} Number of participants	$C_{10,1}$ Individual human participant (96%)	$C_{10,2}$ Two or more human participants (4%)	
	D_{11} Additional human support	$C_{11,1}$ No (80%)	$C_{11,2}$ Yes (20%)	
	D_{12} Front-end user interface channel	$C_{12,1}$ App (7%)	$C_{12,2}$ Collaboration and communication tools (7%)	$C_{12,3}$ Social media (34%)
		$C_{12,4}$ Website (39%)	$C_{12,5}$ Multiple (14%)	
Context	D_{13} Chatbot role	$C_{13,1}$ Facilitator (39%)	$C_{13,2}$ Peer (3%)	$C_{13,3}$ Expert (58%)
	D_{14} Relation duration	$C_{14,1}$ Short-term relation (84%)	$C_{14,2}$ Long-term relation (16%)	
	D_{15} Application domain	$C_{15,1}$ E-customer service (21%)	$C_{15,2}$ Daily life (47%)	$C_{15,3}$ E-commerce (9%)
		$C_{15,4}$ E-learning (4%)	$C_{15,5}$ Finance (13%)	$C_{15,6}$ Work and career (7%)
	D_{16} Collaboration goal	$C_{16,1}$ Non goal-oriented (23%)	$C_{16,2}$ Goal-oriented (77%)	
	D_{17} Motivation for chatbot use	$C_{17,1}$ Productivity (19%)	$C_{17,2}$ Entertainment (29%)	
		$C_{17,3}$ Social/relational (7%)	$C_{17,4}$ Utility (45%)	

Note: Due to rounding inaccuracies, the sum of a column in a dimension is not always exactly 100%

With regard to the 103 chatbots considered, 73% demonstrated rule-based behavior and 96% did not adapt to the user within the conversation (see Table 13, p. 40). Of the chatbots, 12% showed emotions and 29% had an avatar. Of the sample, 84% were developed for short-term interaction relationships and 77% were designed to conduct a specific goal. Of the chatbots, 21% proactively asked questions to the user, and 20% offered the possibility of connecting to a human employee.

We further applied the Ward (1963) algorithm to hierarchically identify the number of clusters in our dataset (see Figure 5, p. 17) and investigated the option of having two or five clusters. By applying the partitioning K-means algorithm (Täuscher & Laudin 2018) for two and five clusters, we decided to have five archetypes due to contextual plausibility.

Table 14: Results of the Cluster Analysis for Chatbot Archetype Identification (Janssen et al. 2020, p. 221)

		Label	Goal-oriented daily chatbot	Non-goal-oriented daily chatbot	Utility facilitator chatbot	Utility expert chatbot	Relationship-oriented chatbot
		n	24	19	22	29	9
		Archetype	A	B	C	D	E
Intelligence	Intelligence framework	Rule-based systems	88%	79%	77%	76%	
		Utility-based systems	13%	16%	18%	17%	33%
		Model-based systems		5%	5%		44%
		Goal-based systems				7%	
		Self-learning systems					22%
	Intelligence quotient	Only rule-based knowledge	46%	11%	95%	24%	11%
		Text understanding	38%	47%		72%	44%
		Text understanding and further abilities	17%	42%	5%	3%	44%
	Personality processing	Principal self	100%	100%	100%	100%	56%
		Adaptive self					44%
	Socio-emotional behavior	None/low	96%	84%	100%	100%	11%
		High	4%	16%			89%
	Service integration	None		68%	32%	7%	11%
		Single	92%	5%	45%	79%	56%
		Multiple	8%	26%	23%	14%	33%
Interaction	Multimodality	Unidirectional	100%	89%	86%	97%	67%
		Bidirectional		11%	14%	3%	33%
	Interaction classification	Graphical	8%	5%	64%	14%	33%
		Interactive	92%	95%	36%	86%	67%
	Interface personification	Disembodied	79%	68%	86%	72%	11%
		Embodied	21%	32%	14%	28%	89%
	User assistance design	Reactive assistance	75%	95%	91%	86%	
		Proactive assistance	25%	5%	9%	14%	100%
	Number of participants	Individual human partner	96%	100%	95%	93%	100%
		Two or more human participants	4%		5%	7%	
	Additional human support	No	100%	100%	45%	86%	44%
		Yes			55%	14%	56%
	Front-end user interface	App	8%	11%		3%	22%
		Social media	63%	32%	23%	21%	33%
		Collaboration and communication	8%		5%	14%	
		Website	13%	26%	55%	59%	33%
		Multiple	8%	32%	18%	3%	11%
Context	Chatbot role	Facilitator	54%	5%	77%	21%	33%
		Peer		16%			
		Expert	46%	79%	23%	79%	67%
	Relation duration	Short-term relation	75%	89%	86%	100%	44%
		Long-term relation	25%	11%	14%		56%
	Application domain	E-customer service	4%		27%	48%	11%
		Daily life	83%	95%	36%		22%
		E-commerce	4%		27%	7%	
		E-learning		5%			33%
		Finance	4%		5%	38%	
		Work and career	4%		5%	7%	33%
	Collaboration goal	Non-goal-oriented	4%	89%	5%		56%
		Goal-oriented	96%	11%	95%	100%	44%
	Motivation for chatbot use	Productivity	17%	11%	32%	7%	56%
		Entertainment	38%	84%	14%		22%
		Social/relational	25%	5%			
		Utility	21%		55%	93%	22%

Note: Due to rounding inaccuracies, the sum of a column in a dimension is not always exactly 100%.

The characteristic distribution according to the five archetypes (goal-oriented daily chatbot archetype (A), non-goal-oriented daily chatbot (B), utility facilitator chatbot (C), utility expert chatbot (D) and relationship-oriented chatbot (E)) can be seen in Table 14 (p. 41). These five identified chatbot archetypes orient chatbot developers to the characteristics widely used in specific application areas and specific primary objectives. Archetype A primarily consists of daily life chatbots (83%), which integrate services within the dialogue for achieving a specific goal (96%). Archetype B also includes daily life chatbots (96%), which mostly appear as experts (79%) but without aiming to reach a specific goal within the conversation (89%). Archetype C mainly comprises facilitator chatbots that assist in pursuing productivity (32%) or utility purposes (55%) by using rule-based knowledge (95%). Archetype D contains chatbots with utility purposes (93%) that communicate in an interactive (86%) way. Archetype E differentiates itself from the other archetypes completely by containing the most model-based (44%) and self-learning (22%) chatbots, as well as by demonstrating high socio-emotional behaviors (89%), while asking proactive questions (100%) within the conversations.

In this paper, we were able to develop a design elements taxonomy for domain-specific chatbots. By following the taxonomy development procedure of Nickerson et al. (2013) and conducting one conceptual and four empirical iterations and three FGDs for evaluating the taxonomy, we finalized a taxonomy with 17 dimensions and 49 characteristics, which are classified according to three perspectives: interaction, intelligence, and context. After analyzing 103 chatbots from 23 different application domains and including scientific literature, it was possible to provide a comprehensive overview of the current state of the design elements used and to identify a total of five archetypes based on a hierarchical and a partitioning cluster analysis. The analysis of the 103 domain-specific real-world chatbots in 2019 reveals that most of the classified chatbots were far from possessing all technical capabilities from an intelligence and interaction point of view.

4.3. Taxonomy for Business-to-Business Customer Services Chatbots

This chapter is based on the research paper P4 “More than FAQ! Chatbot Taxonomy for Business-to-Business Customer Services” (Janssen et al. 2021a and Appendix A4).

The paper was written by Antje Janssen, Davinia Rodríguez Cardona, and Michael H. Breitner.

Driven by customer expectations for a simple and fast service that must be as personalized and customized as possible (Sangroya et al. 2017), more and more B2B companies are discovering chatbots as a digital self-service solution for automating processes and providing 24/7 help (Corea et al. 2020). These firms deploy chatbots on their websites and social media channels to get in touch with their customers or to provide product information. Customer relationships in the B2B sector differ from those in the private sector in that very complex products and services are often sold over long decision-making processes that require a high level of expert advice (Corea et al. 2020; Cui et al. 2017; Sangroya et al. 2017), which may impact chatbots' design decisions. Even if single scientific papers address B2B chatbots (e.g., Damnjanovic 2019; Gnewuch et al. 2019; Rossmann et al. 2020), a comprehensive overview of which chatbots exist in B2B customer service, how these are characterized, and which archetypal patterns can be discovered is absent. Thus, a taxonomy that provides an overview of design possibilities is needed, which can, consequently, help practice and research identify design implications and opportunities for exploitation and provide a basis for B2B chatbot research.

For developing a design elements taxonomy for B2B customer service chatbots, we applied the taxonomy development framework of Nickerson et al. (2013) in four iterations. To maintain focus in taxonomy development, we defined and applied the following meta-characteristic: *"design elements for B2B customer service chatbots, i.e., the socio-technical features defining the structural and functional composition of B2B customer service chatbots"* (Janssen et al. 2021a, p. 178).

We started the taxonomy development process with a conceptual-to-empirical approach to include existing scientific knowledge about chatbots and customer support. We applied the search string ("chatbot" OR "conversational agent") AND ("customer service" OR "customer support") in five scientific databases resulting in 565 papers. After reading the abstract and performing a forward, backward, and similarity search, 14 papers were found to contain useful insights and information about the functionalities and features of customer service chatbots (see Table 15, p. 44). Out of these papers, 18 dimensions and 53 mutually exclusive characteristics were extracted for the first iteration.

In the subsequent three iterations, the empirical-to-conceptual approach was applied. A total of 40 B2B customer service chatbots (iteration 2 = 5; iteration 3 = 12; iteration 4 = 23) were classified, and presented on chatbot conference pages, websites of B2B companies, customer reference lists of chatbot developers, and chatbot blogs. In iterations 2 and 3, dimensions and characteristics were added, deleted, and renamed if they were named in scientific papers but not represented in the empirical data set under consideration. In iteration 4, even the large data set did not lead to the need to add more dimensions and characteristics so that all ending conditions were fulfilled at the end of the fourth iteration, and the taxonomy development was completed.

Table 15: Taxonomy Dimensions Conceptualized from the Literature (Janssen et al. 2021a, p. 180)

Dimension	Sangroya et al. 2017	Corea et al. 2020	Cui et al. 2017	Rossmann et al. 2020	Følstad & Skjuve 2019	Hwang et al. 2019	Feine et al. 2020a	Følstad et al. 2019	Herrera et al. 2019	Johannsen et al. 2018	Kvale et al. 2020	Li et al. 2017	Michaud 2018	Sousa et al. 2019
D_1 Business integration			●											●
D_2 Access to business data							●							
D_3 Dialogue structure	●	●				●		●			●			
D_4 Conversation beyond Q&A interaction			●							●				●
D_5 Data policy	●													
D_6 Handoff to a human agent	●				●				●		●	●		
D_7 Small talk		●								●			●	●
D_8 Features presentation							●							
D_9 Conversational memory							●	●	●					
D_{10} Human-like avatar					●									
D_{11} Content related service						●								
D_{12} Account-related services						●								
D_{13} Account authentication						●								
D_{14} Requests													●	
D_{15} Question personalization				●				●					●	
D_{16} Customer service orientation												●		
D_{17} User assistance design										●				●
D_{18} Context management						●								

To assess the inter-coder reliability of our classifications and thus ensure that the codings of independent coders correspond, we selected eight chatbots from the study as a random sample and had them coded by everyone involved in the coding process. From this, we calculated the kappa coefficient of Fleiss (1971), which was 0.64, indicating the significant strength of inter-coder agreement (Landis & Koch 1977).

Table 16 (p. 45) illustrates the final chatbot taxonomy for B2B customer services, which consists of 17 dimensions and 45 characteristics.

Table 16: Final Chatbot Taxonomy for B2B Customer Services (Janssen et al. 2021a, p. 182)

Dimensions D_i	**Characteristics $C_{i,j}$ (% distribution)**		
D_1 Industry classification	$C_{1,1}$ Financial services industry (5%)		$C_{1,2}$ Manufacturing industry (22%)
	$C_{1,3}$ Marketing industry (10%)		$C_{1,4}$ Software industry (63%)
D_2 Business integration	$C_{2,1}$ No (68%)		$C_{2,2}$ Yes (32%)
D_3 Access to business data	$C_{3,1}$ No (90%)		$C_{3,2}$ Yes (10%)
D_4 Dialogue structure	$C_{4,1}$ Predefined (48%)	$C_{4,2}$ Open (15%)	$C_{4,3}$ Both (37%)
D_5 Data policy	$C_{5,1}$ Not provided (65%)		$C_{5,2}$ Provided (35%)
D_6 Handoff to a human agent	$C_{6,1}$ Not possible (12%)		$C_{6,2}$ Possible (88%)
D_7 Small talk	$C_{7,1}$ Not possible (80%)		$C_{7,2}$ Possible (20%)
D_8 Human-like avatar	$C_{8,1}$ No (90%)		$C_{8,2}$ Yes (10%)
D_9 Content related service	$C_{9,1}$ Content advertisement (70%)		$C_{9,2}$ Content consumption (30%)
D_{10} Account authentication	$C_{10,1}$ Not required (63%)	$C_{10,2}$ Optional (12%)	$C_{10,3}$ Required (25%)
D_{11} Question personalization	$C_{11,1}$ None (12%)		$C_{11,2}$ FAQ (50%)
	$C_{11,3}$ Personalized account questions (30%)		$C_{11,4}$ Highly personalized questions (8%)
D_{12} Customer service orientation	$C_{12,1}$ Knowledge-oriented (53%)		$C_{12,2}$ Task-oriented (47%)
D_{13} Company information	$C_{13,1}$ No (70%)		$C_{13,2}$ Yes (30%)
D_{14} Service/product information	$C_{14,1}$ No (15%)		$C_{14,2}$ Yes (85%)
D_{15} Pricing	$C_{15,1}$ No (80%)		$C_{15,2}$ Yes (20%)
D_{16} Action request	$C_{16,1}$ Book/show a demo (8%)		$C_{16,2}$ Callback request (32%)
	$C_{16,3}$ Both (35%)		$C_{16,4}$ None (25%)
D_{17} Service request	$C_{17,1}$ Support question /ticket (32%)	$C_{17,2}$ Billing details (3%)	$C_{17,3}$ User management (3%)
	$C_{17,17}$ Multiple (10%)		$C_{17,5}$ None (52%)

Note: Due to rounding inaccuracies, the sum of a column in a dimension is not always exactly 100%.

To detect the clusters represented in our collected dataset of 40 chatbots, we applied the hierarchical Ward algorithm (Ward 1963) and graphically determined the number of archetypes based on the distances between groupings within the dendrogram and combined it with the non-hierarchical partitioning algorithm, such as K-means (Balijepally et al. 2011). The first splitting was observable at a height of 2.1, followed by splitting at about 1.75 and 1.5. Therefore, we investigated the possibility of three or four clusters using the partitioning K-means algorithm before deciding on three archetypes based on content plausibility.

Three archetypes were identified which we called lead generation chatbot, aftersales facilitator chatbot, and advertising FAQ chatbot (see Table 17, p. 46). These three archetypes guide chatbot developers in identifying relevant attributes based on the B2B customer services purpose.

Table 17: Results of the K-means Cluster Analysis (Janssen et al. 2021a, p.184)

	Label	Lead generation chatbot	Aftersales facilitator chatbot	Advertising FAQ chatbot
	Archetype	1	2	3
	n	8	10	22
Industry classification	Financial services industry	0%	10%	5%
	Manufacturing industry	0%	50%	18%
	Marketing industry	0%	10%	14%
	Software industry	100%	30%	64%
Business integration	No	75%	40%	77%
	Yes	25%	60%	23%
Access to business data	No	88%	70%	100%
	Yes	13%	30%	0%
Dialogue structure	Predefined	88%	20%	45%
	Open	0%	40%	9%
	Both	13%	40%	45%
Data Policy	Not provided	38%	60%	77%
	Provided	63%	40%	23%
Handoff to human agent	Not possible	0%	20%	14%
	Possible	100%	80%	86%
Small talk	Not possible	100%	60%	82%
	Possible	0%	40%	18%
Human-like avatar	No	100%	70%	95%
	Yes	0%	30%	5%
Content related service	Content advertisement	75%	0%	100%
	Content consumption	25%	100%	0%
Account authentication	Not required	50%	60%	68%
	Optional	0%	20%	14%
	Required	50%	20%	18%
Question personalization	None	50%	0%	5%
	FAQ	0%	20%	82%
	Personalized account questions	38%	70%	9%
	Highly personalized questions	13%	10%	5%
Customer service orientation	Knowledge-oriented	0%	0%	95%
	Task-oriented	100%	100%	5%
Company information	No	100%	60%	64%
	Yes	0%	40%	36%
Service/product information	No	38%	10%	9%
	Yes	63%	90%	91%
Pricing	No	100%	60%	82%
	Yes	0%	40%	18%
Action request	Book/show a demo	25%	0%	5%
	Callback request	25%	40%	32%
	Both	50%	20%	36%
	None	0%	40%	27%
Service request	Support question/ticket	13%	40%	36%
	Billing details	0%	0%	5%
	User management	0%	10%	0%
	Multiple	0%	40%	0%
	None	88%	10%	59%

Note: Due to rounding inaccuracies, the sum of a column in a dimension is not always exactly 100%.

0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%

The *lead generation chatbot archetype* (n = 8) includes chatbots from software companies that aim to generate new leads and contacts with potential customers by encouraging them to sign up for a demo version. After requesting contact information such as name, email address, job title, and company size in this process, these companies target to directly contact the users through a human employee. These chatbots are characterized as task-oriented in that they ask users for contact information within simply predefined dialogue structures without any detours or small talk. While some chatbots are just designed to grab customer data through newsletter signups (e.g., Botsify[7]), others ask specific questions about company size and industry to route contact information to the right person (e.g., CX bot[8], and Keet Health[9]). The *aftersales facilitator chatbot archetype* (n = 10) also includes task-oriented chatbots, but these chatbots offer more personalized and complex dialogs by asking users questions regarding their requirements to perform specific tasks. The Danfoss Drives Trouble Shooting chatbot[10], e.g., provides concrete assistance when a motor has a breakdown, while the Carla chatbot[11] asks the number of employees working on customer relationship management (CRM) systems and then suggests the appropriate products and services from the portfolio. The *advertising FAQ chatbot archetype* (n = 22) includes knowledge-oriented chatbots to promote the company's products and services. For this, the chatbots answer to standardized questions in the dialogue and partially link to blog papers with instructions or embed videos in the dialogue window. For example, ChatBot[12] promotes features of products with a video preview and a short sentence and then links to more in-depth papers or directly to the pricing page. LubeChat[13] (formerly called Shelly), a chatbot that answers questions about oil and lubricants, preempts questions such as "what is the right oil for my machine?" and then provides information for suitable oils based on the model of the vehicle specified by the user.

In this paper, a B2B customer services chatbot taxonomy with 17 dimensions and 45 characteristics was developed by analyzing scientific literature about customer service chatbots as well as classifying 40 B2B customer service chatbots. From this dataset, three archetypes were identified by applying Ward's algorithm and the K-means algorithm. It appears that chatbots for B2B customer services predominantly provide in-depth information about their services and products but so far mostly without

[7] https://botsify.com/
[8] https://www.gupshup.io/developer/home
[9] https://www.keethealth.com/
[10] https://mydrivechatbot.danfoss.com/
[11] https://www.copper.com/
[12] https://www.chatbot.com/
[13] https://www.shell.de/business-customers/lubricants-for-business/shell- lubechat.html

access to internal company or customer data. Additionally, most B2B customer service chatbots provide the possibility of connecting with a human employee. However, the three identified archetypes indicate major variations in the customer service orientation and service offerings that chatbots provide.

4.4. Taxonomy of User-Chatbot Relationships with Different Time Horizons

The following chapter is based on the paper P7 "See You Soon Again, Chatbot? A Design Taxonomy to Characterize User-Chatbot Relationships with Different Time Horizons" (Nißen et al. 2021). The paper was written by Marcia Katharina Nißen, Driton Selimi, Antje Janssen, Davinia Rodríguez Cardona, Michael H. Breitner, Tobias Kowatsch, and Florian von Wangenheim. Elements of the paper, including identified dimensions and characteristics and parts of the chatbot dataset, are based on the previously described paper "Virtual Assistance in any Context" (see Chapter 4.2).

As outlined in Chapter 4.2, people use chatbots for several purposes but also for different periods. While some chatbots, e.g., in e-commerce, tend to be used on a one-time basis to quickly acquire some product information (Chung et al. 2020; Janssen et al. 2021a), other chatbots accompany users, e.g., in the education or health domain over longer periods, e.g., to provide individual learning support to students over the entire school year (Okonkwo & Ade-Ibijola 2021) or to assist patients with chronic diseases (Kowatsch et al. 2018). The question that consequently arises is whether and how the design of chatbots differs depending on whether the chatbot is likely to be inserted to achieve short-, medium-, or long-term goals (Baraka et al. 2020). This research aims to fill this gap by identifying design elements that allow distinguishing between different durations of chatbot use through a taxonomy development approach and by demonstrating in archetypes how these temporal profiles of chatbots affect their design.

To identify design elements that characterize and distinguish short-, medium-, and long-term chatbots, we followed the taxonomy development procedure of Nickerson et al. (2013) (see Chapter 2.4). As our purpose was to develop design guideline classifications of chatbots that assist users with their short-, medium-, and long-term issues, we defined our meta-characteristic as all observable or experientable design elements within a human–chatbot interaction. The subjective and objective ending conditions of Nickerson et al. (2013) were used to determine the end of the taxonomy process, which was accomplished after seven iterations. Two conceptual-to-empirical iterations were performed, in which chatbot classifications and frameworks from scientific papers identified within a literature review were analyzed. Five empirical-to-conceptual iterations were undertaken, in which a total of 120 chatbots from four application domains were classified. In the first six iterations, dimensions and characteristics were added, deleted, assigned to other perspectives, and renamed. To confirm the applicability, completeness, and understandability of the taxonomy, a completely new chatbot dataset was employed in iteration 7, which included chatbots from application domains not yet considered in the previous iterations. For this evaluation that was oriented on the framework of Szopinski et al. (2019), the 41 chatbots still available from the original 103 chatbots from Janssen et al. (2020 and Appendix A2) were classified by two people not previously involved in the development process. This has resulted in minor changes in the definitions, which have been sharpened. Overall, however, the taxonomy was considered complete, comprehensible and coherent.

The final taxonomy comprises 22 conceptually and empirically based design elements and 61 design characteristics categorized into five perspectives (see Table 18, p. 50).

The temporal profile comprises dimensions dealing with the time horizon of the user-chatbot relationship (D_1), the duration of interactions (D_3) and the frequency of the interactions (D_2) (Baraka et al. 2020). The appearance perspective summarizes all design dimensions that define the visual identity of a chatbot in the form of, e.g., the primary communication style (D_6) (Verhagen et al. 2014) or the presence of an avatar (D_7). The intelligence perspective contains dimensions that describe inner working functionalities such as the ability to adapt the personality based on the user (D_{10}) and the ability to react socio-emotionally on emotions within user requests (D_{11}), or the ability to adapt the personality based on user's characteristics. The interaction perspective contains all design elements that describe the interaction among chatbots and their users including the communication channel (D_{13}) and the additional support offered by a human agent if desired (D_{18}) (Kowatsch et al. 2017). The context perspective comprises all design elements that describe the initial motivation of the user in the interaction with a chatbot.

Table 18: Design Taxonomy for Chatbots with Different Temporal Profiles (Adapted from Nißen et al. 2021, p. 5)

Layer 1: Perspective	Layer 2: Dimensions D_i	Layer 3: Characteristics $C_{i,j}$		
Temporal Profile	D_1 Time horizon	$C_{1,1}$ Short-term (55%)	$C_{1,2}$ Medium-term (20.8%)	
		$C_{1,3}$ Long-term (23.3%)	$C_{1,4}$ Life-long (0.8%)	
	D_2 Frequency of interactions	$C_{2,1}$ One-time only (39.2%)	$C_{2,2}$ Multiple times (60.8%)	
	D_3 Duration of interaction	$C_{3,1}$ Short (42.5%)	$C_{3,2}$ Medium (40.8%)	$C_{3,1}$ Long (16.7%)
	D_4 Consecutiveness of interactions	$C_{4,1}$ Unrelated (63.3%)	$C_{4,2}$ Related (36.7%)	
Appearance	D_5 Role	$C_{5,1}$ Expert (21.7%)	$C_{5,2}$ Facilitator (61.7%)	$C_{5,3}$ Peer (16.7%)
	D_6 Primary communication style	$C_{6,1}$ Task-oriented (70.8%)	$C_{6,2}$ Socially-/chat-oriented (29.2%)	
	D_7 Avatar representation	$C_{7,1}$ Disembodied (56.7%)	$C_{7,2}$ Embodied (43.3%)	
Intelligence	D_8 Intelligence framework	$C_{8,1}$ Rule-based (49.2%)	$C_{8,2}$ Hybrid (48.3%)	$C_{8,3}$ Artificially intelligent (2.5%)
	D_9 Intelligence quotient	$C_{9,1}$ Rule-based knowledge only (36.7%)	$C_{9,2}$ Text understanding (60.0%)	$C_{9,3}$ Text understanding+ (3.3%)
	D_{10} Personality adaptability	$C_{10,1}$ Principal self (94.2%)	$C_{10,2}$ Adaptive self (5.8%)	
	D_{11} Socio-emotional behavior	$C_{11,1}$ Not present (43.3%)	$C_{11,2}$ Present (55.8%)	
	D_{12} Service integration	$C_{12,1}$ None (31.7%)	$C_{12,2}$ External data (36.7%)	
		$C_{12,3}$ Media resources (20.8%)	$C_{12,4}$ Multiple (10.8%)	
Interaction	D_{13} Front-end user interface	$C_{13,1}$ App (19.2%)	$C_{13,2}$ Social media (28.3%)	$C_{13,3}$ Collaboration tools (9.2%)
		$C_{13,4}$ Website (37.5%)	$C_{13,5}$ Various (5.8%)	
	D_{14} Communication modality	$C_{14,1}$ Text only (85.0%)	$C_{14,2}$ Text+voice (15.0%)	
	D_{15} Interaction modality	$C_{15,1}$ Graphical (29.2%)	$C_{15,2}$ Interactive (70.0%)	
	D_{16} User assistance design	$C_{16,1}$ Reactive (39.2%)	$C_{16,2}$ Proactive (30.0%)	$C_{16,3}$ Reciprocal (30.8%)
	D_{17} Personalization	$C_{17,1}$ Static (55.0%)	$C_{17,2}$ Adaptive (45.0%)	
	D_{18} Add. human support	$C_{18,1}$ None (75.0%)	$C_{18,2}$ Yes (25.0%)	
	D_{19} Gamification	$C_{19,1}$ Not gamified (79.2%)	$C_{19,2}$ Gamified (20.8%)	
Context	D_{20} Application domain	$C_{20,1}$ Business (37.5%)	$C_{20,2}$ Education (20.0%)	
		$C_{20,3}$ Healthcare (30.0%)	$C_{20,4}$ Daily life (12.5%)	
	D_{21} Motivation/purpose	$C_{21,1}$ Productivity (7.5%)	$C_{21,2}$ Entertainment (5.0%)	$C_{21,3}$ Utility (39.2%)
		$C_{21,4}$ Informational (20.8%)	$C_{21,5}$ Coaching (26.7%)	
	D_{22} Collaboration goal	$C_{22,1}$ Non goal-oriented (15.0%)	$C_{22,2}$ Goal-oriented (85.0%)	

Note: Due to rounding inaccuracies, the sum of a column in a dimension is not always exactly 100%

To identify time-dependent chatbot archetypes, we used the results of the frequency analysis for statistical analyses. For this purpose, index (I_d) was calculated with the formula (2) for each of the 17 arrangeable design dimensions, based on which chatbots with different temporal profiles can be compared as well as archetypes derived.

$$Index\ I_d = \frac{1}{n} * \sum_{i=1}^{n} C_i * \left(1 + \left(\frac{4}{n-1}\right) * (i-1)\right) \tag{2}$$

Index (I_d) represents the mean value of the factorized frequencies of all the design characteristics of a design dimension, which can have a value between 1 and 5.

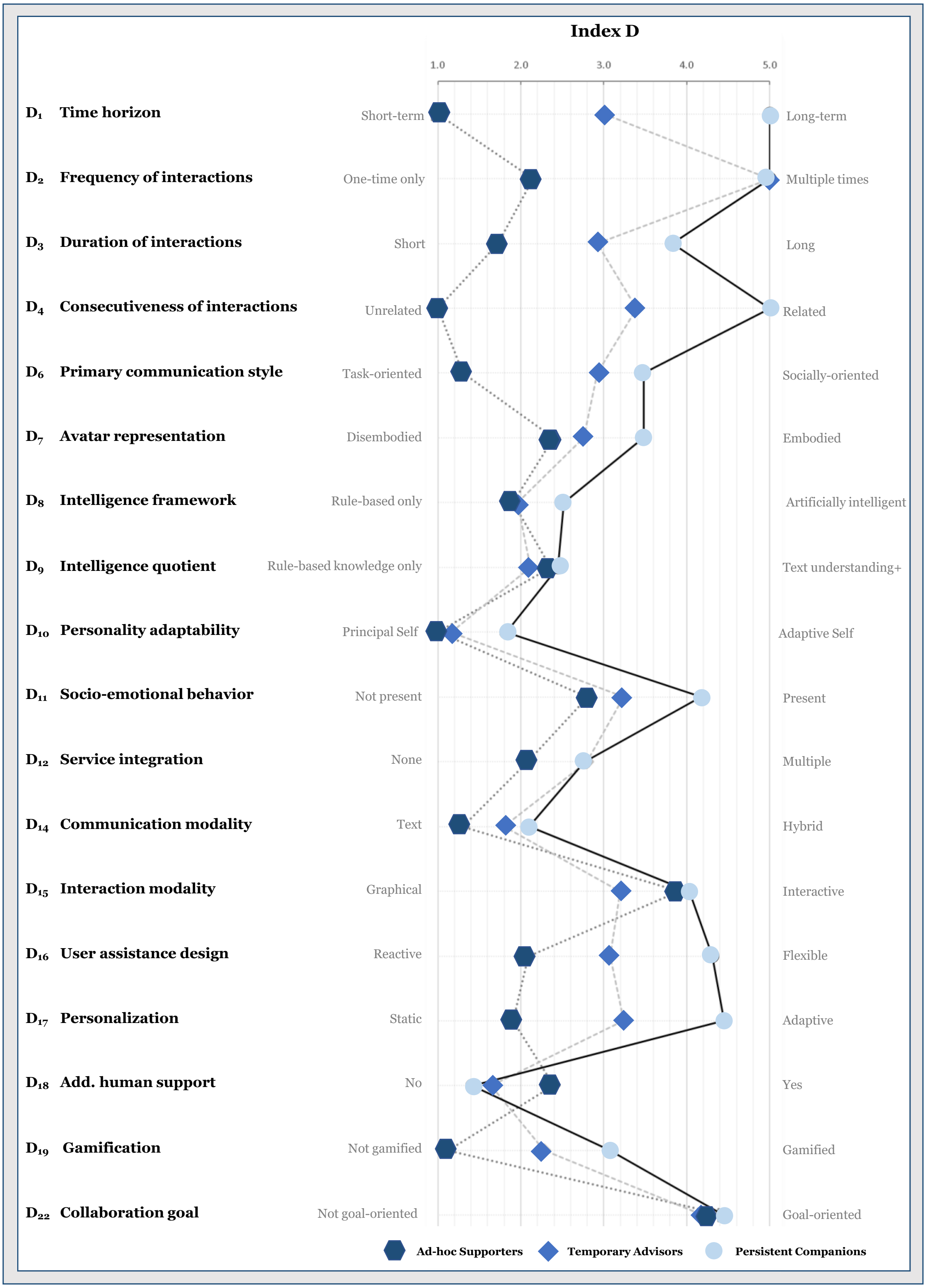

Figure 13: Comparison of the Chatbot Archetypes (Nißen et al. 2021, p. 7)

The number of design characteristics is represented by (n) for every design dimension (d), whereas (C_i) shows how frequently the (i)-th design characteristic is inserted. The results of the calculated indices for every temporal profile and dimension can be noted in Figure 13 (p. 51).

The archetype *Ad-hoc Supporters* consists of short-time chatbots that are primarily inserted for single, short, and isolated conversations to efficiently fulfill specific tasks. These bots are primarily inserted on firms' websites to complement other already available communication channels of organizations and often offer to get in touch with a human employee. Chatbots of the archetype *Persistent Companions* are typically built for long-term relationships, which is why they have advanced technological design elements that enable processes to build relationships between the user and the chatbots. Socially oriented, these chatbots are often stand-alone services that can adapt to the counterpart over some time and can be both reactive and proactive in the conversation. Chatbots of the archetype *Temporary Advisors* are designed to conduct mid-term relationships. In medium-length conversations, these chatbots can typically integrate further services within the dialogue to fulfill tasks.

With the comprehensive design taxonomy containing 22 dimensions and 61 characteristics, we provide a holistic perspective on the temporal profile of chatbots which may guide chatbot development optimization issues. By focusing on design elements in the chatbot–user relationship across several time horizons and investigating the dependency of design decisions on the temporal profile of a chatbot, we contribute to providing practitioners and researchers with an overview of which design elements fit their intended time horizon and which ones are negligible. The three identified time-dependent archetypes can guide to scholars by providing a vivid and comprehensible classification scheme using time horizon as a defining element.

4.5. Analysis of the Reasons for Failure and Critical Success Factors of Chatbots

The following chapter presents the paper P9 "Why do Chatbots fail? A Critical Success Factors Analysis" (Janssen et al. 2021c and Appendix A9). The paper has been written by Antje Janssen, Lukas Grützner, and Michael H. Breitner. Elements of the paper, i.e., a list of 103 chatbots, that is revisited and analyzed again are based on the paper Janssen et al. (2020 and Appendix A2).

The results of Nißen et al. (2022) (see Chapter 4.4), in which the 103 chatbots were revisited after 15 months, suggest a high chatbot failure rate in practice. The end-user is frustrated and disappointed when the chatbot is suddenly undetectable, unresponsive, or does not understand the dialogue (Benner et al. 2021; Brandtzæg & Følstad 2018; Filipczyk et al. 2016; Følstad et al. 2018; Seeger & Heinzl 2021), which is why chatbot failure is one of the central challenges in chatbot deployment (Følstad et al. 2018; van der Goot et al. 2021). The failure of chatbots is also a source of annoyance to the chatbot developers, as developers invest a lot of time and money into the development as well as for the chatbot market in general, as a single negative experience may impact the reputation of global chatbot technology (van der Goot et al. 2021). However, very few qualitative research studies have investigated the exact reasons why chatbots fail from a business perspective. The goal of this research is therefore to first investigate how common chatbot failure is in practice by analyzing design element patterns that may explain the failure and to identify technical, behavioral, and institutional reasons for failure through expert interviews. Additionally, CSFs that need to be considered to increase the likelihood of a chatbot's success are identified and described.

We followed a DSR approach (as described in Chapter 2.2) to investigate qualitative chatbot failure reasons in practice as well as extracting CSFs for chatbots. For identifying the research problem, we analyzed 103 chatbots from 35 different countries and four application domains previously identified in Janssen et al. (2020). Thus, we examined how many chatbots are no longer available or able to communicate with the user. Of the examined chatbots, 53% no longer existed after 15 months, and initial clues for causes why the chatbots failed could suggest the lack of additional human support, the user assistance design, and the front-end interface channel. The results provide initial indications, but no conclusions can be drawn about the causality between the characteristics and the failure of chatbots from an external point of view.

Therefore, the research goal was to examine chatbot failure reasons from the scientific as well as chatbot provider perspectives. To gain a deeper understanding of the current state of the art (rigor cycle) regarding CSFs and the reasons for failure in chatbots, we first conducted a literature review, identifying 154 relevant papers (see Table 6, p. 10 for further literature review details). The papers were categorized into 32 topics. After further clustering, ten potential CSFs for chatbots were identified (see Table 19, p. 55). Regarding the relevance cycle, we first contacted all the 53 companies and developers of the identified failed chatbots without success. That is why we further contacted 60 experts identified on chatbot conference lists and LinkedIn, resulting in 20 semi-structured expert interviews from five different countries. The interviewees were asked to talk about their own experiences with chatbot failure, based on which the reasons were identified as well as CSFs extracted and prioritized. The interviews were transcribed and coded with MAXQDA. For the coding, the 32 categories, as well as the corresponding CSFs from the literature review, were taken as a basis. By applying the open coding approach (Wiesche et al. 2017), we were able to iteratively expand and modify the original list of coding tags according to our findings, leading to 40 categories clustered into 12 CSFs (see Table 19, p. 55). These CSFs were then evaluated through a FGD. The virtual FGD involved five participants from chatbot research and practice. As a result, the reasons for chatbot failure and the list of CSFs were approved as comprehensible and conclusive.

In total, six generic reasons for chatbot failure were identified, which will be summarized below. The reason *"not enough resources"* was identified by six experts and points to circumstances, such as in which the previously responsible employee has left the company, financial resources are no longer available, or contracts with the chatbot service providers have expired. *"No business case"* was also mentioned by six experts indicating a missing use case or a missing business plan behind the use case. Instead, the company focused on introducing a chatbot to be a technological pioneer.

"Wrong use case" was encountered by five respondents, implying that a use case was realized using chatbot technology not suitable for the technology at all. "*Law regulations, data security, and liability concerns"* were highlighted witnessed by five participants, e.g., in such cases, data protection regulations could not be fulfilled. *"Ignorance of user expectation and bad conversation design,"* was mentioned by four experts and indicates an excessive focus on technological development and business process management instead of focusing on end-user expectations and requirements. The *"poor content"* reason for chatbot failure was encountered by three experts. In these situations, the chatbots failed because the requested chatbot responses were incomplete, incorrect, or outdated.

Table 19: Critical Success Factors for Chatbots (Janssen et al. 2021c, p. 8)

CSF	Associated Category from Coding	P*	Example Authors	Exp*
Technology availability	Technology & tool availability	70	Galitsky 2019; Schumaker et al. 2007	5
User centric use cases	Adequate use case	26	Rodríguez Cardona et al. 2019; Zamora 2017	16
	User requirements	17	Følstad & Brandtzæg 2020; Meyer von Wolff et al. 2020	13
	Acceptance to change operation methods	-	-	1
	General chatbot technology acceptance	17	Weber & Ludwig 2020; Mesbah & Pumplun 2020	6
Chatbot promotion	Communicating the intention to introduce/use a chatbot	1	Aoki 2020	8
Chatbot design	Data security	26	Lai et al.2018; Følstad et al. 2018	7
	Technical design elements	68	Janssen et al. 2020; Yuan et al. 2019	15
	Conversational design elements	73	Kvale et al. 2019; Gnewuch et al. 2020	13
	Design elements' simple editing and extensibility	1	Koetter et al. 2019	4
	Databases & backend systems accessibility	27	Kruse et al. 2019; Johannsen et al. 2020	8
	Word sensitivity	8	Yu et al. 2016; Canhoto & Clear 2020	2
	Level of intent & content understanding	37	Følstad & Brandtzæg 2020; AbuShawar & Atwell 2016	7
	Technical robustness & chatbot efficiency	2	Nguyen & Sidorova 2017; Weber & Ludwig 2020	3
Chatbot progress	Testing & training	17	Johannsen et al. 2018; Vijayaraghavan & Cooper 2020	8
	Continuous monitoring, updating and improvement	27	Jonke & Volkwein 2018; Brandtzæg & Følstad 2018	13
	Chatbot self-development	15	Zemčík 2020; Hancock et al. 2019	-
Top manage-ment support	Changing company structure and workflows	-	-	2
	Manage top management expectations in short & long term	-	-	12
	Top management support	7	Benbya et al. 2020; Pumplun et al. 2019	4
Project resources	Transparent cost management	-	-	2
	External resources	-	-	5
	Human resources	10	Galitsky 2019; Kruse et al. 2019	8
	Technical resources	16	Desouza et al. 2020; Winkler & Roos 2019	10
Under-stand the concept chatbot	Highly dynamic long-term process (instead of a classic project)	-	-	7
	Multidisciplinary process (not a pure IT and engineering based and driven)	-	-	2
	Start small, go big (quick wins)	-	-	3
Chatbot developing team	Team composition	-	-	6
	Team building	-	-	2
	Clear definition of used success and performance metrics to evaluate chatbot	-	-	2
	Content management core team	-	-	2
Usefulness	User expectation	67	Følstad & Brandtzæg 2020; Weber & Ludwig 2020	5
	User understanding of chatbot capabilities	17	Følstad et al. 2018; Aoki 2020	4
	Perceived usefulness (based, e.g., on TAM)	47	Wuenderlich & Paluch 2017; Følstad & Skjuve 2019	13
Usability	Unexperienced user guidance	3	Weber & Ludwig 2020; Piccolo et al. 2018	5
	Seamless chatbot integration in customer journeys	1	Kuligowska 2015	2
	Ease of use (based, e.g., on TAM)	36	Rodríguez Cardona et al. 2021; Rese et al. 2020	4
Trust	Trust in chatbot and operating company	8	Følstad et al. 2018; Sanny et al. 2020	2
	Trust in chatbot technology	49	Fiore et al. 2019; Nordheim et al. 2019	2
	Privacy concerns	30	Rodríguez Cardona et al. 2021; Kim et al. 2020	5

Note: P* = Number of papers; Exp* = Number of experts

To avoid chatbot failure, 12 CSFs with 40 categories were outlined. Of them, 10 were identified through the literature review of 154 papers, which were then confirmed by the 20 experts, who in turn named two additional CSFs. The final list of CSFs is presented in Table 19 (p. 55). By closely examining the frequency of the categories in the scientific literature and the expert interviews, it is found that there is noticeable agreement for chatbots' success in several categories, such as chatbot design and our centric use case. However, the practice puts a much stronger emphasis on the promotion of a chatbot. Further, the categories *"concept chatbot understanding"* and *"the composition of the chatbot team"* as well as *"management support"* were exclusively mentioned in the expert interviews, which show possibilities for research.

With this study, we contribute to the under-investigated topic of chatbot failure by discovering a high discontinuation rate of 53% after 15 months in the real-world and application domain superior chatbot analysis, indicating huge research need. We present six reasons for chatbot failure in practice based on 25 expert experiences described in interviews, which may help practitioners and researchers be aware of chatbot failure risks in the future. With the 12 CSFs and 40 categories identified based on 154 papers and expert opinions, we further contribute by providing an all-encompassing view of the factors one needs to consider for the successful deployment and management of chatbots and for illustrating the current state of chatbot research and practice.

4.6. Framework for User-Oriented Chatbot Implementation

This chapter presents the paper P10 "How to Make Chatbots Productive – A User-Oriented Implementation Framework" (Janssen et al. 2022, appendix A11). The paper has been written by Antje Janssen, Davinia Rodríguez Cardona, Jens Passlick, and Michael H. Breitner.

As described in the previous sub-chapters, plenty of design options are conceivable when designing chatbots for different application domains (Janssen et al. 2020; Janssen et al. 2021a; Nißen et al. 2021). In recent years, numerous chatbot startups, consulting companies, and chatbot development platforms have entered the market, advertising with slogans such as "FAQ Chatbot In a Day"[14]. Conversely, the previous Chapter 4.5 has shown that most chatbots fail in practice because the selected business

[14] https://nightingalehq.ai/inaday/chatbots-in-a-day/

case for a chatbot is unsuitable or because user expectations were ignored and therefore did not serve to satisfy the user (Janssen et al. 2021c). Rather than designing a chatbot and constructing dialogue trees based on the technical capabilities of a chatbot development platform, a comprehensive implementation method is needed to guide researchers and practitioners in the development, deployment, and management of chatbots, which considers not only technical factors but also (potential) users, their activities, and the particular context (Adam et al. 2021a; Benyon 2014; Zierau et al. 2020).

To address this research need, we used user-oriented DSR to develop an artefact in the form of guiding questions consolidated into a chatbot implementation model. After considering the scientific literature on chatbot implementation, 15 expert interviews were conducted in two iterations to identify user-oriented questions and eight stages of chatbot implementation. The initial model was evaluated in the second interview iteration and in a FGD. To check its practical applicability, a car dealership chatbot was developed based on the guideline. The final eight steps of the chatbot implementation can be observed in Figure 14 (p. 57).

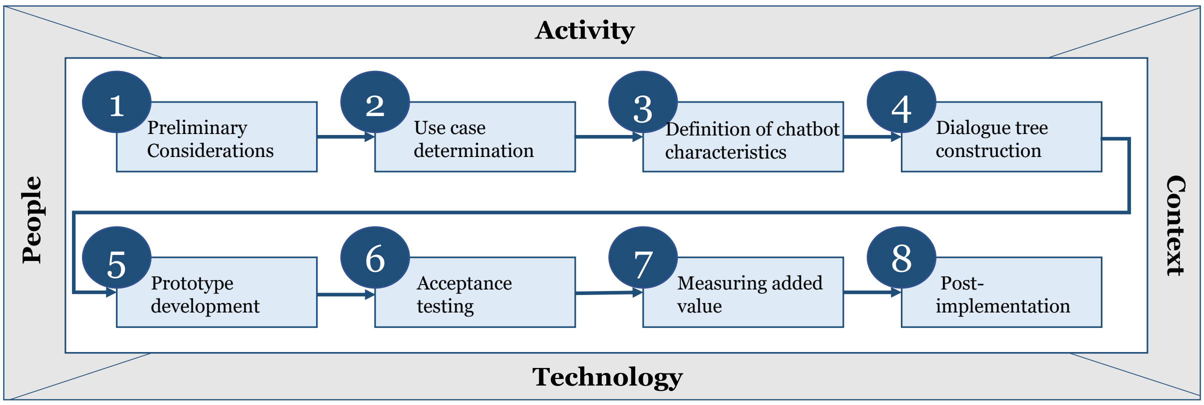

Figure 14: Chatbot Implementation Steps (Janssen et al. 2022)

The final model contains 102 guiding questions. According to Benyon et al.'s (2005, p. 29) statement *"People use technologies to undertake activities in contexts,"* the four elements people, activities, context, and technology were used to classify the questions within the eight levels to ensure that user-orientation exists in the model. As *people* differ by a wide variety of factors, such as their personalities and cognitive abilities, they have different needs in terms of the use of technologies (Benyon et al. 2005; Benyon 2014), which is why HCI systems must be developed for target groups that are as heterogeneous as possible. In the chatbot context, we identified 24 questions targeting this aspect within the eight steps, such as identifying the target audience (IIP1), determining their extrinsic motivation to use the chatbot (IIP4), and classifying the preferred vocabulary (IVP1). For the *activity* element, the goal is to find out what activities and purposes (Benyon et al. 2005) the chatbot is used for from the end-user point of view, for which a total of 26 questions were identified. Here, e.g., the question that arises is what the user expects as the result (IIA2) and whether the intent is goal-oriented or the dialogue is initiated without a specific goal (IIIA4). The activities of a person always depend on the *context*, such as the physical environment or situation the user is currently in, so this element should also be considered when designing a technology (Benyon et al. 2005). A total of 24 contextual questions were identified, which consider the context in which the chatbot is to be used. It describes, e.g., the application environment (IIC2), in which a person is currently in, such as if it is a noisy environment or the circumstance that the user does not have much time. This provides the basis for offering the appropriate solution depending on the situation and environment. The *technology* element includes technological functionality issues around hardware and software components (Johansson et al. 2015) to enable people to use the interactive systems (Benyon et al. 2005), for which a total of 28 questions were identified. The questions aim to identify, e.g., what technologies are already in use in this context (IIT2) and which other systems, such as databases, need to be connected (III3).

As shown in Figure 14 (p. 57), the chatbot implementation can be divided into eight steps summarized below. In practice, depending on the individual chatbot use case, steps can also be skipped, and it may be necessary to return to previous steps. The guideline starts with step 1 *"preliminary considerations"* concentrating on the business process and business context-related questions to identify whether chatbots are suitable. In step 2 *"use case determination,"* the use case is identified, and the focus is placed on what the requirements and natural environments are typically like in that use case from the end-user point of view. Step 3 *"definition of chatbot characteristics"* focuses on determining the needed chatbot characteristics to assure that the end-users can accomplish their intended output. The guiding questions for steps 1, 2, and 3 are presented in Table 20 (p. 59).

Table 20: Guiding Questions for PACT Chatbot Implementation in Steps 1-3 (Own Representation based on Janssen et al. 2022)

People (P)	Activity (A)	Context (C)	Technology (T)
(I) Preliminary considerations			
(IP1) What are the business processes in which the (internal or external) users' desire (need) to receive more (better) support to improve the customer/user value perception? **(IP2)** What type of communication technologies do the users use on a regular basis?	**(IA1)** What are the most repetitive/ monotonous activities from a user viewpoint? **(IA2)** What are the characteristics of the previously identified activities? **(IA3)** What type of activities should be handled by a human employee to achieve the best outcome for the user?	**(IC1)** In which area or business context do users present more (special) difficulties/problems? (e.g., customer service context) **(IC2)** In which task fields can a chatbot add value to the company? **(IC3)** In which cases can a chatbot relieve employees? **(IC4)** Do employees need to be trained in handling chatbots?	**(IT1)** Taking into account the value proposition of the organization, is a chatbot the appropriate technology to improve the customer/user value perception (e.g., by overcoming previously identified difficulties/problems)? **(IT2)** Which technology concerns should be considered (i.e., regulations and ethical and security issues)?
(II) Use case determination			
(IIP1) Who are the end-users? (i.e., target group) **(IIP2)** How is the target group segmented? **(IIP3)** What type of communication technologies do the target group use on a regular basis? **(IIP4)** What would be the end-users' main extrinsic motivation for using a chatbot? **(IIP5)** Which target group segments perceive added value in the potential use of a chatbot? **(IIP6)** What availability does the target group look for? (i.e., 24/7 service chatbot)	**(IIA1)** What are the collaborative requirements of the activity to be digitalized? **(IIA2)** What is the users' desired outcome? **(IIA3)** Do the users need (desire) to receive additional human support to accomplish their activity? (Handover) **(IIA4)** Does the activity require historical user information to be accomplished?	**(IIC1)** On which communication platforms is the target group active? **(IIC2)** What is the application domain? **(IIC3)** Is the chatbot intended for an internal or external context use? **(IIC4)** Is customer data necessary to optimally support the user? (i.e., login, 2-factor authentication) **(IIC5)** Which device does the target group use? (i.e., Smartphone or tablet?) **(IIC6)** Should the method of communication (i.e., e-mail, web interface) also attract potential customers? **(IIC7)** Where are possible or existing touch points with customers?	**(IIT1)** How is the data situation? (i.e., quality of the process/technical documentation) **(IIT2)** Through which communication channels have users been reached so far? **(IIT3)** What type of platform integration is needed? **(IIT4)** How does a typical chatbot interface look like in the application domain? **(IIT5)** Which server fulfils the requirements? (Cloud or on-premises?) **(IIT6)** In-house development or Outsourcing? **(IIT7)** Which provider fulfils the technical requirements?
(III) Definition of chatbot characteristics			
(IIIP1) How many users can be reached through the chatbot? **(IIIP2)** Self-evolution: What features should the chatbot have to produce the users' desired outcome? **(IIIP3)** To what degree is the behavior of using the chatbot self-motivated? **(IIIP4)** Does the user need a tutorial on how to use the chatbot? **(IIP5)** How can a chatbot measure user satisfaction? **(IIP6)** Is the user experience improved by integrating gimmicks?	**(IIIA1)** How do the users formulate their requests? **(IIIA2)** Is a chatbot-driven or user-driven dialogue preferred? **(IIIA3)** What type of objectives do the users attempt to meet by using the chatbot? **(IIIA4)** Is the intent to use the chatbot more goal-oriented or non-goal-oriented? **(IIIA5)** How did a typical conversation between a customer and an employee look like before the chatbot? **(IIIA6)** What should the chatbot be able to do? What should the chatbot be unable to do for now? (core function) **(IIIA7)** What activities are measurable after implementation?	**(IIIC1)** In what way (text/speech/video) do users wish to communicate? **(IIIC2)** What type of context-awareness is needed by the chatbot? **(IIIC3)** How should the chatbot react if it cannot respond? **(IIIC4)** Is the emotional context explicitly of the users handled properly? (i.e., stressed or frustrated users)	**(IIIT1)** Are there already chat interfaces in the company that can be adapted or should the company start from scratch? **(IIIT2)** To what extent is it desired for the chatbot to present human-like features? (e.g., avatar, personality) **(IIIT3)** Which interfaces to further knowledge bases are required to provide the information requested by the users? **(IIIT4)** How should the UI look from a user viewpoint? **(IIIT5)** Are the users' desired chatbot features within the approved company budget? **(IIIT6)** Is the chatbot expected to have good speech recognition/ NLU? **(IIIT7)** Does the chatbot need an interface for pictures? **(IIIT8)** Are licenses/ permissions for access required? **(IIIT9)** Are there any data protection restrictions? **(IIIT10)** Does the chatbot need artificial intelligence?

Step 4 *"dialogue tree construction and content development"* deals with the development of the conversational flow by creating dialogue trees. Based on the decisions made in the previous steps, step 5 *"prototype development"* focuses on developing a chatbot prototype, which is why this step is the only one that does not raise any questions. This prototype is evaluated in step 6 *"acceptance testing"* by involving future users. Based on these outcomes, the chatbot is revised before release. Step 7 *"measuring added value"* concentrates on guiding how to monitor and measure whether a chatbot is accepted and successful from the end-user point of view. As the environment and requirements change, the chatbot must also be enhanced after release. Therefore, step 8 "*post-implementation*" focuses on constantly questioning whether the functionalities still satisfy the user's expectations. If they do not satisfy the user's expectations, the chatbot must be revised or another technology introduced. The guiding questions for steps 4, 5, 6, 7, and 8 are provided in Table 21 (p. 60).

Table 21: Guiding Questions for PACT Chatbot Implementation in Steps 4-8 (Own Representation based on Janssen et al. 2022)

People (P)	Activity (A)	Context (C)	Technology (T)
(IV) Dialogue tree construction and content development			
(IVP1) In which language specifications do the users wish to communicate with? **(IVP2)** What type of characteristics should the chatbot's response have from the user perspective? (e.g., long/short answers) **(IVP3)** Does my target group use multiple languages? Should the chatbot work with translating tools? **(IVP4)** Do answers include emojis, visualizations, and/or text? **(IVP5)** Will it be a B2B or B2C chatbot (technical or colloquial)?	**(IVA1)** Do the users prefer to use a pre-configured selection menu or would they prefer to formulate their own questions/requests? **(IVA2)** What do sample texts look like? **(IVA3)** What answers do users expect? **(IVA4)** Are there previous dialogue trees that can be used as a base? **(IVA5)** Do multiple formulations lead to the same result?	**(IVC1)** Does the chatbot match the intended context use and user's perceptions? (Exp15) **(IVC2)** How should the conversation start from the user's perspective for it to sound more human-like? **(IVC3)** What chatbot personality traits do the users expect? **(IVC4)** How should the chatbot react if it is not asked anything something out of context? (i.e., marriage proposal)	**(IVT1)** Which data are usable? **(IVT2)** Do these data still need to be strongly classified? **(IVT3)** Is there enough data or should data be purchased? **(IVT4)** How much training does a chatbot need to obtain enough data without overloading?
(V) Prototype development			
(VI) Acceptance testing			
(VIP1) Are the expectations of the end-users fulfilled in the test phase? **(VIP2)** Does the user perceive the chatbot as a serious communicator?	**(VIA1)** What questions do users have? **(VIA2)** Which questions can the chatbot not answer yet?		**(VIT1)** From an NLP perspective, does the chatbot interact as the users expected?
(VII) Measuring added value			
(VIIP1) What are the usage criteria for the users in the end?/What perceived value does the chatbot have to the user? **(VIIP2)** How often do the users leave the chatbot or stop writing and why?	**(VIIA1)** What is the average duration of a chat? **(VIIA2)** How profound is the response to the inquiry? **(VIIA3)** How often is the conversation surrendered to a human?	**(VIIC1)** Does the chatbot accomplish its primary task?	**(VIIT1)** How often is the chatbot used as an offer? **(VIIT2)** Does the chatbot do what it is supposed to do?
(VIII) Post-implementation			
(VIIIP1) Do we still reach the target group with the chatbot?	**(VIIIA1)** Does the chatbot still represent the activity requested by the user? **(VIIIA2)** Are there any conversational flows that led to a failure because the flow was not modelled?	**(VIIIC1)** Does the context in which the chatbot is used still fit the chatbot? **(VIIIC2)** Does the chatbot fit the company? **(VIIIC3)** Is the chatbot affected by legal changes?	**(VIIIT1)** How can the answer given by a human to a question that the chatbot cannot solve be built into the chatbot? **(VIIIT2)** What newfound technologies can be included? (Updates)

With this research, we contribute to the chatbot implementation field by providing researchers and practitioners comprehensive guidance through 102 questions on how to develop, deploy and manage chatbots. By using the user-oriented PACT classification of Benyon et al. (2005; 2014) a user-oriented implementation is now possible, including end-user characteristics, the activities to be fulfilled, the contextual environment, and the preferred technological specifications.

4.7. Conclusion

This chapter summarizes the results of five research papers in the chatbot research field. Even though the majority of the papers focus on chatbots in general, by analyzing chatbots from a wide variety of application domains, the following chapter presents initial attempts to determine what this implies for the B2B sector.

To answer RQ3 of identifying conceptually grounded and empirically validated design elements for chatbots, taxonomies were built in three papers, all of them with different foci, by analyzing scientific literature and real-world chatbots. Archetypes were formed based on Ward clustering and the use of K-means (Janssen et al. 2020; Janssen et al. 2021a) and a time-dependent formula was developed by the authors (Nißen et al. 2022). These archetypes, 11 in total, contribute to chatbot research and practice by assisting and facilitating decision-making in the development process of future chatbots by showing which characteristics are typical for specific intentions. Considering the results of all three papers, the majority of the 227 included chatbots noticeably still have rather rudimentary functions, and showing socio-emotional behavior does not yet play a major role in most of the analyzed papers. When abstracting the dimensions, all dimensions can be assigned to the three perspectives: intelligence, interaction, and context. However, it also depends extremely on the application area. Whereas 88% of B2B customer service chatbots offer the possibility of directly contacting a human employee (Janssen et al. 2021a), only 20% offered this possibility within the domain-superior study (Janssen et al.2020) in which the data was classified one year earlier. Although this is considered a very relevant topic in the scientific literature (Corea et al. 2020; Følstad & Skjuve 2019; Herrera et al. 2019), in practice, we could show that whether handoff to a human agent is provided depends very much on the application domain. The results also show that this depends on one's perspective toward chatbots. The meta characteristic plays a decisive role here, thus, the focus is exclusively on one aspect of chatbots.

The three taxonomies offer a wide range of possible design options that are currently used in the market and described in research. Particularly, when comparing the design elements currently used in B2B to the other two cross-application taxonomies, the taxonomies provide a wide range of options not currently visible in B2B. However, in the analysis of chatbot technology acceptance, exemplified by the study of insurance chatbots discussed in Chapter 3.5, it became apparent that not only do functionality aspects affect the intention to use an insurance chatbot but also, e.g., privacy concerns.

RQ4, in terms of what needs to be considered when implementing, deploying, and managing chatbots, was, therefore, covered in two papers in particular. According to Janssen et al. (2021c), one of the main reasons for failure is the lack of a suitable use case, instead, a chatbot is developed to jump on a technological trend. Especially, in an era where B2B activities are becoming increasingly digital (Paschen et al. 2020) and chatbots are marketed as a cost-effective and 24/7 available technology, this may sound tempting (Kushwaha et al. 2021).

The eight-step chatbot development model and the list of questions to be asked in the chatbot implementation presented in Janssen et al. (2022) and the list of CSFs in Janssen et al. (2021c) help and guide practitioners and researchers in structurally developing chatbots. This also includes the question of whether chatbot technology is suitable for the use case to be implemented.

Involving experts who have already developed and implemented chatbots in practice demonstrated that various aspects, such as top management support, the composition of the project team, and adequate budget and competencies after implementation for continuous support and improvement of the chatbot, contribute to the success of a chatbot, which were earlier either not mentioned or superficially done in the literature on chatbots. The results of the paper on chatbot failure endorse the need for user-centered design, instead of a company-centered one.

5. Overall Discussion and Implications

"Humans interact with information, technologies, and tasks; especially in business, managerial, organizational, and cultural contexts."

(Alan Hevner and Ping Zhang 2011, p. 56)

This cumulative dissertation includes ten scientific papers dealing with digital analytics, technology acceptance, and chatbots. By addressing four overarching research questions, the dissertation shows how the results of these papers can be applied within, interpreted for, and transferred to the industrial context. After presenting the results in the previous chapters, the goal of this chapter is to critically discuss the papers and identify relationships at an abstract level.

In building and deploying a technology, the end-user is crucial (Adam et al. 2021a). Whether a communication channel is successful is ultimately decided by the end-user, who uses, accepts, and prefers it to other channels. Therefore, most of the papers within this cumulative dissertation are user-oriented. Some of the papers develop frameworks and conduct surveys to monitor (potential) users or customers (Janssen et al. 2019; Klebansky et al. 2021; Rodríguez Cardona et al. 2020; Rodríguez Cardona et al. 2021), some analyze which design-elements of an object can be observed from an end-user perspective while interacting with them (Janssen et al. 2020; Janssen et al. 2021a; Nißen et al. 2022), and others focus on what needs to be considered to be successful while developing and managing a technology (Janssen et al. 2021c; Janssen et al. 2022).

In the chatbot environment, a special emphasis was laid on the B2B customer service area. However, it revealed that this sector is, until now, rarely investigated in IS and HCI research (Janssen et al. 2021a; Kushwaha et al. 2021). To provide an overview of the current state of academia and practice, domain-spanning research was conducted through several research projects (Janssen et al. 2020; Janssen et al. 2021) while always focusing on text-based, domain-specific chatbots (Diederich et al. 2019b; Gnewuch et al. 2017). This approach is meaningful to learn from and get inspired by other domains.

Even though the online survey on the acceptance, trust, and privacy concerns on the intention to use insurance chatbots (Rodríguez Cardona et al. 2021) was aimed at the B2C end consumer context, the insurance sector may have parallels to the B2B sectors in the industry. Both industries tend to be conservative and sell services and products that often require explanation, need to be customized, and ideally are used over a long period (Rodríguez Cardona et al. 2021; Janssen et al. 2021a). Therefore, information about the customer is crucial in the sales process to be able to tailor it to the customers. This may be why both industries had extremely high rates of additional human support availability in the data sets (insurance chatbots = 100%, B2B customer service chatbots = 89%) (Damnjanovic 2019; Janssen et al. 2021a; Riikkinen et al. 2018; Rodríguez Cardona et al. 2021). The online survey revealed that privacy concerns may negatively impact trust, which may be crucial when private, sensitive, or competitive data is exchanged in the human-to-chatbot dialogue. Whereas only two out of six insurance chatbots (33%) directly provided data protection information in the dialogue, further analysis of the dataset of Janssen et al. (2021a) revealed that 14 out of 40 B2B customer service chatbots (35%) provided information about data protection issues, which is very similar. Therefore, this information should certainly be communicated openly and clearly. Additionally, the analyses indicate how important it is to focus on the user and his or her added value, which, in customer service, is characterized in particular by the simplicity of handling and features that enable the user to achieve a goal (Rodríguez Cardona et al. 2021).

Examining a dataset of 103 chatbots twice, where 53% of them were no longer available or functioning 15 months later (Janssen et al. 2020; Janssen et al. 2021c), demonstrates how quickly this market is evolving. New chatbots are constantly being launched in the market, and the hurdle to develop them seems to be getting lower and lower due to many free programs, tools, and courses in which one can develop, e.g., a FAQ chatbot in a day (e.g., Nightingalehq 2021). Especially in the commercial context, however, it is essential that chatbots are further developed, improved and revised. This was also shown in the study of Janssen et al. (2021c), in which various experts reported that this was the reason chatbots failed.

Current text-based and domain-specific chatbots are often seen as an intermediate technology toward virtual AI-based digital assistants (Maedche et al. 2019) that can automatically adapt to end-user behaviors and perhaps even replace relationships. Looking at the chatbot analyses (Janssen et al. 2020; Janssen et al. 2021c; Nißen et al. 2022), it becomes clear that the majority is still designed to be rule-based and very simple in terms of functional capabilities. The chatbots need to be frequently trained by the chatbot development team to better recognize what the user wants, based on patterns, to provide the appropriate response. This leads to the result that chatbots are only as good as they are trained to be, which in turn requires knowing the end-user's needs, desires, and concerns. On the contrary, machine-based self-learning algorithms have been written recently, which learn based on user input and adjust their behavior accordingly. Microsoft's chatbot Tay, a self-learning chatbot that turned racist in a very short time, was taken offline (Brandtzæg & Følstad 2018; Zemčík 2020), showing the explosive nature that self-learning chatbots can develop. The question of the meaningfulness and dangerousness of comprehensive automation thus becomes apparent.

Technically, much more is already possible than what is being widely implemented. However, it turns out that in many fields, people themselves are not yet ready for this. For example, Sohn et al. (2021) found that users trust a human more than a chatbot in a live chat, which might be why some companies are currently turning their chatbot into a live chat, which we were able to observe in the analysis of chatbots after 15 months (Janssen et al. 2021). However, these preferences can change quickly when agents become part of everyday life. This change is also demonstrated by recent studies on the uncanny valley phenomenon, in that users trust a robot only up to a certain point, until it becomes too uncannily similar to a human being (Ciechanowski et al. 2019; Mori 1970), which, however, current studies disprove (e.g., Blut et al. 2021). The speed with which acceptance and market penetration can evolve can be seen in the adoption of voice assistants, such as Amazon Alexa or Google Assistant, which have caught on at an unprecedented rate, eclipsing annual growth rates of other technologies, such as tablets and smartphones (Taylor et al. 2018).

For many companies, it seems tempting to be pioneers in the use of emerging technologies (Janssen et al. 2021c; Janssen et al. 2022). However, it became apparent that just deploying technology is not effective, the benefit and acceptance for the end-user are what ultimately determines whether a chatbot is successful (Janssen et al. 2021c; Janssen et al. 2022; Rodríguez Cardona et al. 2021). This conclusion not only is relevant in the chatbot context but can also be transferred to various application areas. This is especially important, as chatbots will not be the last technology in the human-computer and human-robot interaction field. In this dissertation, chatbots as a digital communication channel were examined more deeply from different perspectives. To move from an isolated micro perspective to a comprehensive view, it is important that this communication channel fits into the overall strategy and that a holistic approach in the sales funnel is established. For this, obtaining a big picture of all communication channels and the analysis underlying is essential.

In Chapter 3, several approaches to analyze (potential) user behaviors and technology acceptance were presented and applied. The results give the opportunity to offer the user even more suitable products and services and, ideally, to maximize profits. In the context of this thesis, the focus was on demonstrating how analytics tools can be used to gain insights into user behavior. Business intelligence (BI) tools are utilized for countless other applications in addition to analyzing customer behavior and have become an indispensable part of many professionals' everyday lives (Passlick et al. 2020). The usage of various self-service business intelligence (SSBI) tools, such as Microsoft Power BI, Tableau, and SAP Analytics Cloud, has become a standard to flexibly visualize organization's information and to derive interpretations efficiently (Passlick et al. 2020; Srivastava et al. 2022). Even in this area, however, the developments of NLP and AI have the potential to revolutionize how data is analyzed and visualized in the future (Richardson et al. 2020). In recent years, several BI vendors have introduced Q&A features that allow users to obtain automated visualizations by formulating a query with spoken or written business terms (Bousdekis et al. 2021; Richardson et al. 2020; Srivastava et al. 2022). Richardson et al. (2020) predicted that "*by 2022, augmented analytics technology will be ubiquitous, but only 10% of analysts will use its full potential*." In practice, this feature of augmented analytics using NLP and AI-assisted data preparation and insight explanation is still little adopted in practice (Bousdekis et al. 2021; Oesterreich et al. 2021). However, this might change in the next years with generations Y and Z, who are increasingly entering the job market and changing the digital workplace (Gabrielova & Buchko 2021). Generations Y and Z have grown up as digital natives, and the use of technology has strongly shaped the way they learn, think, communicate, and search for information (Calvo-Porral & Pesqueira-Sanchez 2020; Silva et al. 2020; Vinichenko et al. 2021). The already widespread use of virtual assistants could also contribute to the circumstance that asking questions in a professional setting will become more widespread. However, for using this natural language query feature of augmented analytics in BI tools for analyzing data, an understanding of which questions could be useful and how they should be asked is required, which may be challenging.

Various approaches were presented, making it possible to analyze the behavior of users even without their precise knowledge. An example is the prediction of users' personality traits as shown in Klebansky et al. (2021), without users being aware of it. However, when analyzing user behavior, one should question the ethical aspects. How analyses can be exploited negatively is shown by the actions of Cambridge Analytica (Krotzek 2019), which has received great attention in recent years. This company used micro-targeting to target election advertising (Krotzek 2019). If, e.g., the personality mining method combined with new deep learning approaches were used to subliminally manipulate people through AI-based customized messages in the future by influencing opinions, this could be even more dangerous than Cambridge Analytica was in 2016 during the US presidential election (Lee & Quifan 2021). This shows that companies have a responsibility to handle information properly.

However, not only are end-users consumers of algorithms, but also companies themselves use services from other organizations for various purposes, such as for customer analysis or for the development of tools, such as chatbots. These tools are a black box for the end-users as well as for corporate users, and there might be no insight into the algorithms. Additionally, in the context of this cumulative dissertation, two tools (i.e., Google Analytics (Janssen et al. 2019) and IBM Watson Personality Insights (Klebansky et al. 2021)) were employed whose functioning and scope are not entirely transparent. Thus, this wide range of analysis options makes it easy to take on the role of the consumer without knowing what exactly is really being measured. It is, therefore, indispensable to question what I really need in order to be able to guide my decisions in a targeted and efficient manner, instead of being overrun by the flood of data (Janssen et al. 2019).

On the other hand, various tools, such as Google Analytics offer extensive analysis of, e.g., website user behavior, at no cost. However, these services are by no means free of charge. Rather, a huge treasure trove of data is established for the providers of these services, which, with enormous computing power, forms the basis for in-depth analyses transcending company boundaries and cross areas of life as well as deep-learning approaches (Spitz 2017). This centralization of data processing enables data companies such as Google and IBM to create a monopoly, allowing them to pick and choose the industries they want to target and disrupt (Spitz 2017). *"However, algorithms in themselves are not good or evil. It is how they are used that matters"* (Fry 2018, p. 3). It depends on how algorithms are interpreted and used. When companies develop technologies, write algorithms, and offer services, the primary focus is usually on economic calculations maximizing profit and impact (Yogeshwar

2019). However, the new technological developments bring an unprecedented impact on the human life of individuals, which makes responsible action and adherence to ethical standards necessary (Yogeshwar 2019). Critical questioning of organizational tasks and goals and the allocation of responsibilities is more important than ever in times when technological developments are advancing with new speed (Spitz 2017).

6. Overall Limitations

"Research is messy, and not always fully transparent or explicit."

(Jan Recker 2013, p. 7)

All papers aimed to provide the most global perspective and influence into the research by considering English language literature from internationally recognized conferences and journals in the field of IS, HCI, and related disciplines, such as marketing and data science. However, it cannot be ignored that the literature published in other languages has been missed. Research thrives from reading and building upon other scientific papers. However, due to licensing regulations, it is not possible to access all the literature. Even though a wide range of different scientific databases is accessible via university access, it may happen in individual cases that relevant literature could not be considered due to lack of access.

In this thesis, differing emphases were placed on the generation of knowledge within the papers. DSR (Janssen et al. 2019; Janssen et al. 2021c; Janssen et al. 2022), taxonomy development (Janssen et al. 2020; Janssen et al. 2021a; Nißen et al. 2022) and quantitative analysis (Rodríguez Cardona et al. 2020; Rodríguez Cardona et al. 2021; Klebansky et al. 2021) approaches were selected and employed to conduct research. The decision on which research design and methods should be employed can be seen as a landmark decision, each of which may also lead to limitations, which are outlined subsequently.

In three DSR papers (Janssen et al. 2019; Janssen et al. 2021c; Janssen et al. 2022), interviews were the preferred way to collect experiences and knowledge from experts. One paper (Janssen et al. 2020) concentrated on interviewing experts from an industrial automation specialist as well as involving them in a FGD, which may lead to a certain company's cultural bias, even though a deeper understanding was obtained by collecting different perspectives within one organization. Experts with different organizational and geographical backgrounds were searched for interviewing for Janssen et al. (2021c) and Janssen et al. (2022) as well as for FGDs in Janssen et al. (2020), Janssen et al. (2021c) and Janssen et al. (2022). However, it became apparent that the acquisition of interviews was challenging, depending on the topic. All companies whose chatbots no longer existed 15 months after analysis for Janssen et al. (2020) were contacted for the paper of Janssen et al. (2021c), whereupon no contact for an interview could be established with any of these providers. To talk about their experiences may be sensitive, especially when talking about failure, which may also impact the results. However, especially in a world where chatbots are being increasingly developed, deployed, and used, critical failure analysis is central and important. The interview partner and FGD attendee search processes in the papers of Janssen et al. (2021c; 2022) took a global approach, using LinkedIn, email, and practitioner conferences in the process. However, experts from six countries in the regions the Europe, Middle East, and America were involved in the research processes, which may result in a certain geographic and cultural bias.

Three papers (Rodríguez Cardona et al. 2020; Rodríguez Cardona et al. 2021; Klebansky et al. 2021) followed a quantitative approach to conduct research. In each of these three studies, hypotheses were tested based on previously defined constructs. The online surveys (Rodríguez Cardona et al. 2020; Rodríguez Cardona et al. 2021) involved between 199 and 215 respondents and were conducted in German whereas the study of Klebansky et al. (2021) had a geographical focus on British inhabitants, which is why potential cultural differences could not be investigated. The acceptance models TAM (Rodríguez Cardona et al. 2021), UTAUT2 (Rodríguez Cardona et al. 2020), and OCEAN personality traits (Klebansky et al. 2021), as well as moderators and variable extensions were carefully chosen but also affect the expected result. Other factors such as a social and cultural background were not included.

While the three taxonomies exclusively analyzed scientific papers as well as publicly available chatbots, it was not possible to examine chatbots that might be used in internal employee communication or customer service, which were behind a paywall or available only to existing customers. The B2B taxonomy analysis (Janssen et al. 2021a) in particular, on the other hand, revealed that 25% of the reviewed chatbots were usable only with registration procedures or by specifying one's email address and name. Chatbots available to customers in a secured environment may well be significantly more advanced in terms of information and interaction, as they can, e.g., read previous customer messages or analyze purchase histories. A total of 227 chatbots (103 chatbots (Janssen et al. 2020); 40 chatbots (Janssen et al. 2021a); 120–42 = 78 chatbots (Nißen et al. 2022); 6 chatbots (Rodríguez Cardona et al. 2021)) from all five continents were classified in the papers by using translation programs, even if they communicated in, e.g., Suaheli (Tanzanian chatbot eShangazi[15] in the dataset of

[15] https://m.me/eshangazibot

Janssen et al. 2020). However, translation errors cannot be completely prevented. These chatbots were identified in scientific papers, through blogs, internet research and chatbot databases, such as botlist.co and chatbots.org. However, some bias may be included here, as only chatbots that were marketed in some way were analyzed. All chatbots were analyzed in the period from May 2019 to December 2020, but no statement can be made about how old they are and to what extent they have been further developed in recent years. Furthermore, it is also unclear to what extent they are being used. The challenge here is that obtaining internal information is extremely difficult and that companies often close their doors. This may also be why there is a lot of single use case-based research in the chatbot area.

Several tools and technologies were used in papers of this thesis to conduct and to facilitate research: Mendeley for organizing scientific literature, Trint and Amberscript for simplifying and partly automating the transcript processes, MAXQDA for coding and analyzing interview transcripts, R for conducting statistical and clustering analyses, Python for automatically extracting Tweets from the Twitter Developer Account, Circle3 and Survey Monkey for conducting online surveys, SmartPLS for computing structural equation models and for validating the inserted measurement models, Google Analytics for analyzing website visitor behaviors, and IBM Watson Personality Insights for automatically predicting the OCEAN personality traits of Twitter users. To some extent, these tools must be seen as a black box, as they earn profit with their services, which is why they do not disclose their algorithms. Hereby, some factors not apparent from the outside may certainly influence the results, although this should be partially relativized because the papers focused more on how the tools and results can be used or to simplify the research processes than on drawing direct results from it.

All papers included in this cumulative dissertation, as well as the dissertation itself, have been researched to the best of the researchers' ability and knowledge to reflect the current state of research and practice and to contribute to the body of scientific knowledge. However, mistakes may have occurred during the research processes, which is why scientific work and results should always be critically questioned. Furthermore, technologies and their usage are constantly evolving, which is why all studies are only a snapshot of what was observed at the time of the study, but this also leads to further research opportunities, which will be described in the next chapter.

7. Further Research Opportunities

"The future doesn't just happen. We create it."

(Hannah Fry 2018, p. 4)

The papers presented in this dissertation as well as the considered research areas in IS and HCI offer diverse opportunities and enormous potential for further research. While the scientific papers describe these further research directions in detail with respect to the research foci within the papers, this chapter aims to provide an overview of further research opportunities across the papers.

In this cumulative dissertation, several papers focused on supporting implementation processes, for which frameworks (Janssen et al. 2019; Janssen et al. 2022; Klebansky et al. 2021) and CSFs (Janssen et al. 2021c) were developed, all of which were evaluated in FGDs and predominantly applied in one company to test the applicability. In the future, these artefacts should also be tested in other companies and industries to verify broad applicability. It would also be interesting, starting from the models, to find out, how to abstract and generalize them for other application areas.

Chapter 3 illustrated various approaches for isolated application areas, how potential and current customer behavior can be analyzed. In the future, the focus should be on transferring these approaches into a cross-channel analysis to support multi-channel marketing and sales activities. One example is the application of the personality trait prediction approach, for which a framework has been developed (Klebansky et al. 2021). Several articles address how social media marketing differs in B2B and B2C markets on social networks (e.g., Iankova et al. 2019; Swani et al. 2014; Rėklaitis & Pilelienė 2019). While Waheed et al. (2017) discovered that the personality traits of salespersons impact how they perform, an exciting approach would be to analyze the tweets of individuals who follow B2B or B2C corporate accounts to predict their personality traits using personality mining. Further, it would be interesting, to introduce this personality mining approach into the chatbot context. Personality trait expressions play a relevant but under-researched role in the chatbot context (Ahmad et al. 2022). Similar to the approach of Feine et al. (2020b), who identified a gender bias within the chatbot design, it would be interesting to analyze personality trait expressions of diverse chatbots to see whether certain traits are particularly pronounced, especially in between different application areas. Also, it would be exciting to observe whether there are personality trait patterns of users interacting with chatbots. In the future, one possible application area would be to use personality trait prediction within the human-to-chatbot dialogue so that the chatbot can adapt to the personality traits of the user (Ahmad et al. 2022).

The novel trend for handling big data in the BI domain through augmented analytics (Bousdekis et al. 2021; Oesterreich et al. 2021) combines themes of web analytics dashboard, and information generation, discussed in Chapter 3, and the natural question formulation as practiced in human-to-chatbot dialogues (see Chapter 4). The question arises as to what extent this new way of generating information using NLP will replace the previous rather rigid dashboards and herald a new era of information generation. However, as this is a very new subject area (Oesterreich et al. 2021), many open questions should be illuminated in the future. In the future, it would be interesting to investigate which factors influence the intention to use NLP features in analytics and BI tools. It would also be exciting to explore the extent to which the previous communication with chatbots and voice assistants impacts the intention to use NLP-based features in other technological systems such as web analytics and BI tools. Trust issues are also interesting to explore in this context, as users need to trust the tool to display the correct results based on their input, with the use of ML and AI.

Companies and developers have a large impact on how the socio-technical artefact in the form of, e.g., a chatbot is designed in terms of behavior, which may lead to stereotyping (Wambsganß et al. 2021). The technical possibilities are further strongly driven by the tremendous advances in NLP and AI, which opens entirely new possibilities in communication. However, for end-users, the tools remain a black box, offering no insight into the algorithms and the developers' and providers' real intentions for deployment. Especially when, chatbots are able, e.g., to adapt to the personality of the counterpart by using a huge amount of conversational data and to establish a relationship, which facilitates manipulation, the investigation of ethical aspects is enormously important (Wambsganß et al. 2021). It could be especially worthwhile to consider the cultural context in the ethical discussion due to, e.g., the cultural dimensions of Hofstede (1984), which has rarely been investigated before.

Within this cumulative dissertation, three chatbot taxonomies were presented, each with a different focus. The developed taxonomies are only a snapshot of what could be monitored in the moment of the real-world object classification, and the chatbot market is undergoing major changes in terms of, e.g., discontinuation, as a re-analysis of the Janssen et al. (2020) dataset after 15 months showed in Janssen et al. (2021c). However, currently, new taxonomies are developed repeatedly instead of reviewing and expanding existing ones. Based on a regularly performed, extended, and refined taxonomy with a constantly expanded dataset, recognizing trends and patterns after a certain interval would be exciting, which is also recommended by Kundisch et al. (2021) using the term ‘cumulative taxonomy design’.

We analyzed the literature and real-world objects worldwide and consulted experts from as many countries as possible to obtain the broadest possible perspective and avoid cultural bias. Experts confirmed that internationally operating companies develop tools and technologies across countries by translating the content 1:1 into the respective language (Janssen et al. 2021c). In the future, examining cultural differences, in particular, will be worthwhile, as cultural borders and law regulations were mentioned as one of the main reasons for chatbot failure. These cultural differences would also be exciting in a more global perspective for other communication tools along the sales funnel to investigate whether, e.g., corporate websites should be structured differently or social media channels should have varying speech.

In the context of various papers within this cumulative dissertation, chatbots were examined from the first consideration to introduce a chatbot to the development, deployment, acceptance testing, and failure. In the future, it might be interesting to examine the entire life cycle of chatbots in a study, for which the eight-stage implementation model (see Figure 14, p. 57) offers a first approach. By, e.g., conducting a multiple case study analysis, it would be possible to explore various life cycles of individual chatbots and identify patterns or design principles.

Even though the market volumes of the B2B and B2C sectors are more or less similar, the chatbot study (Janssen et al. 2021c), as already illustrated in marketing research by Lilien (2016) and Paschen et al. (2020), revealed extremely little research on the B2B sector compared to B2C to date. Just because chatbots are being used in B2B applications (Janssen et al. 2021c; Kushwaha et al. 2021), it does not necessarily indicate that they are useful and accepted from the end-user point of view. However, various B2B specific factors, such as complex products that require explanation, long decision-making periods with many involved entities, and the importance of personal contact may influence the success of a technology. Therefore, the B2B chatbot field offers diverse opportunities for further research in the form of chatbot acceptance studies, the analysis of application areas in B2B for which the archetypes in Janssen et al. (2021a) have already given first approaches, development of CSFs based on Janssen et al. (2021c), and the relevance of individual design elements, such as gamification and socio-emotional behavior (Janssen et al. 2020). The general appropriateness of chatbots in B2B should also be analyzed by comparing this form of communication with others.

To end with Hannah Fry's quote (2018, p. 4): "*The future doesn't just happen. We create it.*" Whatever is developed and researched in the future, the impact these developments may have on the end-user should not be forgotten.

8. Overall Conclusions

"Humans are more than just an algorithm that a robot can replace.
AI can enrich our human culture in extraordinary ways."

(Flynn Coleman 2019, pp. 235, 236)

Within this cumulative dissertation, ten research papers were presented with the objective of contributing to the research fields of digital analytics, technology acceptance and chatbots.

After summarizing the methodologies and methods for qualitative, quantitative, and taxonomy development research in Chapter 2, in the context of digital analytics and technology acceptance, Chapter 3 focused on answering two overarching RQs by presenting four papers. In this chapter, two frameworks that enable the development of target group-specific reports in an industrial context using a web analytics tool and to perform automated personality trait profiling of Twitter users were presented. The massively increasing amount of data provides huge potential for understanding customers and their patterns to even better supply them with optimal products and services at the decisive moment. However, only if this data is properly analyzed and translated into practical actions will added value result. To understand which factors influence whether a customer uses a technology, conducting surveys is still a valuable method. Therefore, two papers with online surveys were outlined, addressing technology acceptance of robo-advisors in finance and chatbots in insurance, whose industries are seen as similarly conservative and in need of product explanation as B2B industries. All four papers illustrated ways to analyze (potential) customers in complex industries to learn more about the target audience. As B2B has evolved in recent years from predominantly on-site sales to online-based information-seeking, this circumstance offers not only various opportunities for even deeper pattern and omnichannel analysis but also new opportunities when it comes to online-based communication in the form of, e.g., inserting conversational agents such as chatbots. Therefore, chatbots can be a great way to provide 24/7 availability to customers by answering product and sales questions that arise and by helping with troubleshooting as well as being a lead generation channel. However, it also became apparent that a human agent cannot be replaced universally, especially in the B2B sector. Much more, a meaningful and useful service automation with virtual assistants is to be strived for.

Chapter 4 contributed to the chatbot field by answering two overarching RQs by summarizing five research papers. To answer RQ3 on identifying the prevailing design elements from different application domains, three papers were presented, each with a different focus. Regarding the B2B sector, it became apparent that chatbots are primarily deployed for FAQ and lead generation purposes and in aftersales. Compared to the other taxonomies that included chatbots from several application domains, it revealed that there is still a lot of undiscovered potential in the B2B market, which is why we included domain-spanning chatbot knowledge to answer RQ4 within this dissertation. Two papers covered the issues to consider when developing, deploying, and managing a chatbot. Whether a communication channel is sustainably successful and accepted is decided by the target group, which is why it should be involved as early as possible. It became clear how important the use case being converted into a chatbot is and how crucial internal company conditions, such as the composition of the development team, as well as the support of the management and the maintenance of competencies after the introduction, are. Even though many self-service chatbot tools sound tempting, in which one can quickly build a rudimentary chatbot, a chatbot requires continuous support and improvement, which entails additional costs and efforts. Even though chatbots have been considered in detail in the context of this cumulative dissertation, it is important, especially in the B2B sector, where explanation-requiring complex products and services are marketed, to also offer other options for getting into contact by regarding chatbots as one touchpoint among others along the sales funnel. The B2B sector can convert knowledge from other industries, but the use case and the end-user acceptance determine success. Chatbots are a hype topic but with the rapid technological improvements of NLP, ML, and conversational AI, they can be also seen as a transitional technology changing the way we seek information and interact with technology.

The focus in this cumulative dissertation was on user-oriented approaches. Even with the adoption of future technologies, keeping the end-user in mind will always be important because if the end-user does not accept the technology, it will be useless.

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Appendices

Using Web Analytics Data: A Participatory Design Model for Individual Web Traffic Development

Citation: Janssen, A., Passlick, J., and Breitner, M. H. (2019). Using Web Analytics Data: A Participatory Design Model for Individual Web Traffic Development. In: Proceedings of the 25th Americas Conference on Information Systems.

Link: https://aisel.aisnet.org/amcis2019/adoption_diffusion_IT/adoption_diffusion_IT/21/

Abstract: Web Analytics (WA) tools offer an increasing amount of analysis options. This amount of possible data overwhelms business users who are not familiar with WA and therefore the potential of WA is not fully exploited. We address this demand of individual information needs with the development of an indicator selection process. By using participatory design methods future users from different business units are involved in order to adopt WA into their workspace through building individual WA reports. The developed iterative model consists of five main steps. After the presentation of the developed model, we demonstrate the applicability in a case study at an industrial company. The case study shows a greater adoption by the different users, as the dashboards are individually tailored to them.

Keywords: Web Analytics Key Performance Indicators, Web Traffic Report Development, Participatory Design, Individual Technology Adoption.

Appendix A2. Virtual Assistance in any Context: A Taxonomy of Design Elements for Domain-Specific Chatbots

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Virtual Assistance in any Context: A Taxonomy of Design Elements for Domain-Specific Chatbots

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Citation: Janssen, A., Passlick, J., Rodríguez Cardona, D. and Breitner, M. H. (2020). Virtual Assistance in any Context: A Taxonomy of Design Elements for Domain-Specific Chatbots. *Business & Information Systems Engineering* (BISE), (62:3), pp. 211–225.

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Abstract: Several domain-specific assistants in the form of chatbots have conquered many commercial and private areas. However, there is still a limited level of systematic knowledge of the distinctive characteristics of design elements for chatbots to facilitate development, adoption, implementation, and further research. To close this gap, the paper outlines a taxonomy of design elements for chatbots with 17 dimensions organized into the perspectives intelligence, interaction and context. The conceptually grounded design elements of the taxonomy are used to analyze 103 chatbots from 23 different application domains. Through a clustering-based approach, five chatbot archetypes that currently exist for domain-specific chatbots are identified. The developed taxonomy provides a structure to differentiate and categorize domain-specific chatbots according to archetypal qualities that guide practitioners when taking design decisions. Moreover, the taxonomy serves academics as a foundation for conducting further research on chatbot design while integrating scientific and practical knowledge.

Keywords: Chatbot Taxonomy, Design Elements, Domain-specific Chatbots, Human Computer Interaction.

Appendix A3. Nutzerakzeptanz von Robo-Advisor Systemen für das digitale Investitionsmmanagement in Deutschland

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Nutzerakzeptanz von Robo-Advisor Systemen für das digitale Investitionsmmanagement in Deutschland

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Citation: Rodríguez Cardona, D., Janssen, A., Uphaus, J., Fischer, J. and Breitner, M. H. (2020). Nutzerakzeptanz von Robo-Advisor Systemen für das digitale Investitionsmmanagement in Deutschland. IWI Discussion Paper #96.

Link: https://www.iwi.uni-hannover.de/fileadmin/iwi/Publikationen/DP/K_96_IWI_DP.pdf

Abstract: Das mit dem Diskussion Paper verfolgte Ziel ist es Einblicke bezüglich der Faktoren zu gewinnen, welche die Akzeptanz von Robo-Advisor Systemen im Kontext des Investitionsmanagement in Deutschland bestimmen. Zu diesem Zweck haben wir das Modell der Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) erweitert, um den Einfluss von drei Konstrukten des Automatisierungsgrades, der Kostenstruktur und der Risikowahrnehmung auf die Verhaltensabsicht der Nutzer gegenüber Robo- Advisor Systemen zu untersuchen. Die verwendeten Primärdaten wurden in erster Linie durch eine Fragebogenerhebung mit 250 Befragten gewonnen und mittels Strukturgleichungs-Modellierung (SEM) mit einem partiellen Ansatz der kleinsten Quadrate (PLS) analysiert. Die Ergebnisse der Analyse deuten darauf hin, dass der erwartete Nutzen und der Automatisierungsgrad entscheidende Schlüsselfaktoren sind, welche die Akzeptanz von Robo-Advisor Systemen in Deutschland beeinflussen. Darüber hinaus zeigten verschiedene sozioökonomische Moderatoren wie das Alter, Bildung oder Einkommen der Nutzer ebenfalls einen signifikanten Einfluss auf die Nutzung von Robo-Advisor Systemen. Die empirischen Ergebnisse zeigten jedoch einen geringen Bekanntheitsgrad von Robo-Advisor Systemen, sodass verschiedene Maßnahmen wie beispielsweise verstärkte Werbekampagnen aber auch Testversionen für Anwender dazu beitragen könnten, die Akzeptanz der Robo-Advisor Systeme in Deutschland deutlich zu erhöhen.

Keywords: Advisor, Benutzerakzeptanz, Digitale Investitionsverwaltung, UTAUT2.

Appendix A4. More than FAQ! Chatbot Taxonomy for Business-to-Business Customer Services

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More than FAQ!

Chatbot Taxonomy for Business-to-Business Customer Services

Citation: Janssen, A., Rodríguez Cardona, D. and Breitner, M. H. (2020). More than FAQ! Chatbot Taxonomy for Business-to-Business Customer Services. In: Følstad A. et al. (eds) Chatbot Research and Design. CONVERSATIONS 2020. Lecture Notes in Computer Science, vol 12604. Springer, Cham., pp. 175–189.

DOI: https://doi.org/10.1007/978-3-030-68288-0_12

Abstract: Chatbots are becoming increasingly important in the customer service sector due to their service automation, cost saving opportunities and broad customer satisfaction. Similarly, in the business-to-business (B2B) sector, more and more companies use chatbots on their websites and social media channels, to establish sales team contact, to provide information about their products and ser- vices or to help customers with their requests and claims. Customer relations in the B2B environment are especially characterized by a high level of personal contact service and support through expert explanations due to the complexity of the products and service offerings. In order to support these efforts, chatbots can be used to assist buying centers along the purchase decision process. However, B2B chatbots have so far only been marginally addressed in the scientific human-computer interaction and information systems literature. To provide both researchers and practitioners with knowledge about the characteristics and archetypal patterns of chatbots currently existing in B2B customer services, we develop and discuss a 17-dimensional chatbot taxonomy for B2B customer services based on Nickerson et al. [1]. By classifying 40 chatbots in a cluster analysis, this study has identified three archetypal structures prevailing in B2B customer service chatbot usage.

Keywords: Chatbot Taxonomy, Business-to-Business, Customer Services.

Appendix A5. A Matter of Trust? Examination of Chatbot Usage in Insurance Business

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A Matter of Trust?

Examination of Chatbot Usage in Insurance Business

Citation: Rodríguez Cardona, D., Janssen, Guhr, Breitner, M. H., and Milde, J. (2021). A Matter of Trust? Examination of Chatbot Usage in Insurance Business. In: Proceedings of the 54th Hawaii Inter-national Conference on System Sciences (HICSS) 2021, Maui, USA, pp. 556–565.

Link: http://128.171.57.22/handle/10125/70679

Abstract: Critical success factors such as trust and privacy concerns have been recognized as grand challenges for research of intelligent interactive technologies. Not only their ethical, legal, and social implications, but also their role in the intention to use these technologies within high risk and uncertainty contexts must be investigated. Nonetheless, there is a lack of empirical evidence about the factors influencing user's intention to use insurance chatbots (ICB). To close this gap, we analyze (i) the effect of trust and privacy concerns on the intention to use ICB and (ii) the importance of these factors in comparison with the widely studied technology acceptance variables of perceived usefulness and perceived ease of use. Based on the results of our online survey with 215 respondents and partial least squares structural equation modelling (PLS-SEM), our findings indicate that although trust is important, other factors, such as the perceived usefulness, are most critical for ICB usage.

Appendix A6. The Role of User Involvement: Relationship between Participatory Design and Design Science Research

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The Role of User Involvement:

Relationship between Participatory Design and Design Science Research

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Citation: Janssen, A., Rodríguez Cardona, D. and Breitner, M. H. (2021). The Role of User Involvement: Relationship between Participatory Design and Design Science Research. IWI Discussion Paper #97.

Link: https://www.iwi.uni-hannover.de/fileadmin/iwi/Publikationen/DP/IWI_DP97_k.pdf

Abstract: An important factor for the success of design-oriented processes is the involvement of the future users. However, there is a dispersed knowledge about how Participatory Design can be used in connection with Design Science Research to assess user preferences. Aiming to synthesize the existent knowledge on these both design-oriented approaches, this IWI discussion paper provides an overview of the relationship, similarities and differences on diverse Participatory Design methods used in the extant scientific literature either separately or embedded in Design Science Research processes.

Keywords: Design Science Research, Participatory Design, User Involvement, Research Design, Research Method.

See You Soon Again, Chatbot?
A Design Taxonomy to Characterize User-Chatbot Relationships with Different Time Horizons

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Citation: Nißen, M., Selimi, D., Janssen, A., Rodríguez Cardona, D., Breitner, M. H., von Wangenheim, F., and Kowatsch, T. (2021). See You Soon Again, Chatbot? A Design Taxonomy to Characterize User-Chatbot Relationships with Different Time Horizons. Computers in Human Behavior.

DOI: https://doi.org/10.1016/j.chb.2021.107043

Abstract: Users interact with chatbots for various purposes and motivations – and for different periods of time. However, since chatbots are considered social actors and given that time is an essential component of social interactions, the question arises as to how chatbots need to be designed depending on whether they aim to help individuals achieve short-, medium- or long-term goals. Following a taxonomy development approach, we compile 22 empirically and conceptually grounded design dimensions contingent on chatbots' temporal profiles. Based upon a classification and analysis of 120 chatbots therein, we abstract three time-dependent chatbot design archetypes: Ad-hoc Supporters, Temporary Assistants and Persistent Companions. While the taxonomy serves as a blueprint for chatbot researchers and designers developing and evaluating chatbots in general, our archetypes also offer practitioners and academics alike a shared understanding and naming convention to study and design chatbots with different temporal profiles.

Keywords: Conversational Agents Chatbots, Temporal Profile, Time-dependent Design, Taxonomy, Archetypes.

Appendix A8. We Know your Personality! An Automated Personality Mining Approach on Twitter Data

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We Know your Personality!

An Automated Personality Mining Approach on Twitter Data

Citation: Klebansky, M., Janssen, A. and Breitner, M. H. (2021). We Know your Personality! An Automated Personality Mining Approach on Twitter Data. IWI Discussion Paper #98.

Link: https://www.iwi.uni-hannover.de/fileadmin/iwi/Publikationen/DP/IWI_DP98_Kneu.pdf

Abstract: Twitter has become a globally relevant platform for political discussions. While social media analytics comprises various tools to identify important factors influencing political participation, the influence of personality traits in political discussions has only been investigated unsatisfactory. We begin to close this research gap by developing a framework to identify the prevailing "big five" personality traits of Twitter users. Our framework is based on hypotheses derived from political psychology. The application prototype then enables automated personality mining using IBM Watson Personality Insights. Our applicability check with UK-based Twitter users' data discussing the UK Brexit shows both practical applicability and interesting deviations from offline investigations for extraversion and neuroticism.

Keywords: Personality Mining, "Big Five" Personality Traits, Political Discussions, Twitter, UK Brexit.

Why do Chatbots fail?
A Critical Success Factors Analysis

Citation: Janssen, A., Grützner, L., and Breitner, M. H. (2021). Why do Chatbots fail? A Critical Success Factors Analysis. Proceedings of the International Conference on Information Systems.

Link: https://aisel.aisnet.org/icis2021/hci_robot/hci_robot/6/

Abstract: Chatbots gain more and more attention, both in research and in practice, and enter several application areas. While much research addresses technical or human-centered aspects, development, and adoption, little is known about Critical Success Factors (CSF) and failure reasons of chatbots in practice. Design Science Research oriented, we first analyze 103 real-world chatbots to examine the fluctuation rate of chatbots in 15 months. With a literature review and 20 expert interviews, we derive 12 specific CSF and identify failure reasons which are evaluated in a focus group discussion with chatbot experts, afterwards. We explain chatbots' failure in practice, improve chatbot knowledge in Information Systems (IS) and Human Computer Interaction (HCI), and finally deduce recommendations and further research opportunities.

Keywords: Chatbot, Conversational Agent, Failure Reasons, Critical Success Factors, Design Science Research.

How to Make Chatbots Productive - A User-Oriented Implementation Framework

Citation: Janssen, A., Rodríguez Cardona, D., Passlick, J., and Breitner, M. H. (2022). How to Make Chatbots Productive - A User-Oriented Implementation Framework. International Journal on Human-Computer Studies, 168, 102921, pp. 1—22.

Link: https://doi.org/10.1016/j.ijhcs.2022.102921

Abstract: Many organizations are pursuing the implementation of chatbots to enable automation of service processes. However, previous research has highlighted the existence of practical setbacks in the implementation of chatbots in corporate environments. To gain practical insights on the issues related to the implementation processes from several perspectives and stages of deployment, we conducted semi-structured interviews with developers and experts of chatbot development. Using qualitative content analysis and based on a review of literature on human computer interaction (HCI), information systems (IS), and chatbots, we present an implementation framework that supports the successful deployment of chatbots and discuss the implementation of chatbots through a user-oriented lens. The proposed framework contains 101 guiding questions to support chatbot implementation in an eight-step process. The questions are structured according to the people, activity, context, and technology (PACT) framework. The adapted PACT framework is evaluated through expert interviews and a focus group discussion (FGD) and is further applied in a case study. The framework can be seen as a bridge between science and practice that serves as a notional structure for practitioners to introduce a chatbot in a structured and user-oriented manner.

Keywords: PACT Framework, Chatbot Implementation Framework, Human Computer Interaction, Human-Centered Design.