ACCEPTANCE OF RECRUITING CHATBOTS: AN EMPIRICAL STUDY ON THE RECRUITERS' PERSPECTIVE

JUDITH DREBERT

**A Dissertation Submitted in Partial
Fulfillment of the Requirements for the Degree of
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ABSTRACT

Title of Dissertation	ACCEPTANCE OF RECRUITING CHATBOTS: AN EMPIRICAL STUDY ON THE RECRUITERS' PERSPECTIVE
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In economic history, there have always been changes and disruptions within market structures and established infrastructure. One eruptive technological development is the automation of business processes. Chatbots offer a way to automate processes in an interactive-laden way via dialogues with the human inquirer. The study at hand investigates factors influencing recruiter-sided chatbot acceptance within the recruiting process. The recruiting process step of candidate interviewing serves as a high-involvement use case for the target group of the quantitative survey: Participants are recruiters in human resource departments in companies from Germany (main focus), Austria and Switzerland with candidate interviews in their recruiting processes. The first chapter contains an introduction to the topic, states the objective of the study and shows the structure of the dissertation. In the second chapter, the recruiting process is being outlined and brought together with the aspect of digitization and automation before regarding the role of chatbots in recruiting. Acceptance research and the topic of chatbot acceptance are presented in the third chapter. The fourth chapter is about the formation of the research model: Based on research on acceptance and specifically the technology acceptance model (TAM), the Human-Robot Collaboration Model (HRCAM) is transformed into the novel Human-Chatbot Collaboration Model (HCCAM) for the non-physical case of chatbots and expanded via the chatbot-relevant constructs of perceived system transparency and inertia regarding chatbot technology. Main focus of the quantitative recruiter survey is the investigation of the antecedents of recruiting chatbot acceptance according to the HCCAM model, specifically regarding job-related automation concerns. It incorporates (1) the validated TAM2 (Venkatesh & Davis, 2000) items subjective norm, job relevance, result demonstrability, and output quality, (2) the validated TAM3 (Venkatesh & Bala, 2008) items self-efficacy,

perceptions of external control, and chatbot anxiety, (3) the ethical, legal and social implications (ELSI) and technology affinity items as introduced by Bröhl et al. (2019), (4) perceived system transparency (e.g., Peters et al., 2020) as well as (5) inertia (e.g., Polites & Karahanna, 2012) items adapted from related literature. The fifth chapter is about the quantitative survey for assessing the factors related to recruiters' chatbot acceptance presenting the methodological approach. Subsequently, the empirical study results are presented in the sixth chapter. Subjective norms and perceived usefulness are found as most relevant significant acceptance criteria for chatbots in recruiting. Overall, 13 significantly influencing factors are yielded, amongst them perceived system transparency and inertia. The dissertation concludes with a discussion of the findings, a display of the theoretical and practical contributions, a conclusion section, an examination of the limitations of the study, and an outlook on future research.

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JUDITH DREBERT

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LIST OF ABBREVIATIONS

Abbreviation	**Explanation**
A	Attitude (variable within acceptance research)
(Extended) AAM	(Extended) Automation Acceptance Model
Acc.	According
AGE	Age (variable within acceptance research)
AI	Artificial Intelligence
ANX	Anxiety (variable within acceptance research)
Approx.	Approximately
Art.	Article
AT	Austria
ATS	Applicant Tracking System
ATSD	Applicant Tracking System Currently Deployed (variable within this acceptance research)
AVE	Average Variance Extracted
Avg.	Average
BI	Behavioral Intention to Use (variable within this acceptance research)
BIG5	Big Five Theory
bn.	Billion
BU	Barriers to Recruiting Chatbot Utilization (variable within this acceptance research)
C.	Construct
CA	Cronbach's Alpha
CDEP	Chatbot Deployment in the Company (variable within this acceptance research)

CDEV	Chatbot Currently in Development (variable within this acceptance research)
CEXP	Chatbot Experience (variable within this acceptance research)
cf.	Confer = compare
CFA	Confirmatory Factor Analysis
CH	Switzerland
CHRO	Chief Human Resource Officer
CKNOW	Chatbot Knowledge (variable within this acceptance research)
CP	Company Position (variable within this acceptance research)
CPLAN	Chatbot Currently Being Planned (variable within this acceptance research)
CR	Composite Reliability
CRAM	Collaborative-Robot Acceptance Model
CTA-PLS	Confirmatory Tetrad Analysis in PLS-SEM
CV	Curriculum Vitae = resume
DACH	Region consisting of Germany (D), Austria (A) and Switzerland (CH)
DE	Deutschland (EN = Germany)
df	Degrees of Freedom
DOI(T)	Diffusion of Innovation (Theory)
DTPB	Decomposed Theory of Planned Behavior
DU	Drivers for Recruiting Chatbot Utilization (variable within this acceptance research)
ECT	Expectation Confirmation Theory
e.g.	Example given
e-HRM	Electronic Human Resource Management
EIMP	Ethical Implication (variable within this acceptance research)
ELSI	Ethical, Legal, and Social Implications
EN	English
et al.	Et alia/alii/aliae = and others

EU	European Union
EUR	Euro
EXP	Experience (variable within this acceptance research)
FAQ	Frequently Asked Questions
FAT(ES)	Fairness, Accountability, Transparency, (Ethics, and Security) of a Technology
FAU	Framework of Automation Use
GDPR	General Data Protection Regulation
GoF	Goodness-of-Fit Index
GSR	German-speaking Region
GUI	Graphical User Interface
HCCAM	Human-Chatbot Collaboration Model
HCM	Hierarchical Component Model
HCI	Human-Computer Interaction
HOC	Higher-Order Construct
HR(M)	Human Resources (Management)
HRC	Human-Robot Collaboration
HRCAM	Human-Robot Collaboration Acceptance Model
HRI	Human-Robot Interaction
IA	Industry Affiliation (variable within this acceptance research)
INA	Inertia (variable within this acceptance research)
INAAB	Inertia – affective-based (variable within this acceptance research)
INABB	Inertia – behavioral-based (variable within this acceptance research)
INACB	Inertia – cognitive-based (variable within this acceptance research)
i.e.	Id est = that is to say
IS	Information System
ISSM	Information System Success Model

IT	Information Technology
JRAC	Job-Related Automation Concerns
KIAM	Künstliche Intelligenz Akzeptanz Modell (EN: Artificial Intelligence Acceptance Model)
KMO	Kaiser-Meyer-Olkin Measure of Sampling Adequacy
LIMP	Legal Implication (variable within this acceptance research)
LOC	Lower-Order Construct
LVS	Latent Variable Score(s)
Mio.	Million
MOCI	Modus Operandi for Candidate Interviewing (variable within this acceptance research)
n	Number of the sample = sample size
N	Number of the population = population size
NFI	Normed Fit Index
NI	Number of Interviews (variable within this acceptance research)
NLP	Natural Language Processing
NLU	Natural Language Understanding
no.	Number
NOE	Number of Employees (variable within this acceptance research)
O	Original Sample
OUT	Output Quality (variable within this acceptance research)
Para.	Paragraph
PBC	Perceived Behavioral Control (variable within this acceptance research)
PC	Personal Computer
PCA	Principal Components Analysis
PE	Perceived Enjoyment (variable within acceptance research)
PEC	Perceptions of External Control (variable within this acceptance research)

PEOU	Perceived Ease of Use (variable within this acceptance research)
PI	Personal Innovativeness (variable within this acceptance research)
PLS	Partial Least Squares
PLS-SEM	Partial Least Squares Structural Equation Modeling
PS	Perceived Safety (variable within acceptance research)
PST	Perceived System Transparency (variable within this acceptance research)
PU	Perceived Usefulness (variable within this acceptance research)
R&D	Research and Development
RASP	Relevant Aspects During the Recruiting Process (variable within this acceptance research)
RCANX	Recruiting Chatbot Anxiety (variable within this acceptance research)
RCATS	Recruiting Chatbot Linked to Applicant Tracking System (variable within this acceptance research)
RCDEP	Recruiting Chatbot Deployment in the Company (variable within this acceptance research)
RCDEV	Recruiting Chatbot Currently in Development (variable within this acceptance research)
RCPLAN	Recruiting Chatbot Currently Being Planned (variable within this acceptance research)
RCSE	Recruiting Chatbot Self-Efficacy (variable within this acceptance research)
Reg.	Regular
REL	Job Relevance (variable within this acceptance research)
RES	Result Demonstrability (variable within this acceptance research)
RPA	Robotic Process Automation
RQ	Research Question

RSKILL	Relevant Skills During the Recruiting Process (variable within this acceptance research)
RWTH	Rheinisch-Westfälische Technische Hochschule (German name of the RWTH Aachen University)
SCT	Social Cognitive Theory
SD	Standard Deviation
SE	Self-Efficacy (variable within this acceptance research)
SEM	Structural Equation Modelling
Sig.	Significance
SIMP	Social Implication (variable within this acceptance research)
SmartPLS	Statistical analysis software by SmartPLS GmbH
SN	Subjective Norm (variable within this acceptance research)
SPSS	Statistical Package for the Social Sciences (Statistical analysis software by IBM)
SRMR	Standardized Root Mean Square Residual
SWE	Switching Efforts (variable within this acceptance research)
SWETE	Switching Efforts – Transition Efforts (variable within this acceptance research)
SWESE	Switching Efforts – Sunk Efforts (variable within this acceptance research)
SWEUE	Switching Efforts – Uncertainty Efforts (variable within this acceptance research)
TA	Technology Affinity (variable within this acceptance research)
TAM	Technology Acceptance Model
TOE	Technology-Organization-Environment Framework
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
TTF	Task-Technology Fit Model
TU	Technological Understanding (variable within this acceptance research)
U	Actual utilization (variable within acceptance research)

U&G	Uses and Gratifications Theory
UC	Use Case for Recruiting Chatbots (variable within this acceptance research)
US	United States (of America)
USD	US Dollars
UTAUT	Unified Theory of Acceptance and Use of Technologies
VIF	Variance Inflation Factor

CHAPTER 1

INTRODUCTION AND RESEARCH OBJECTIVES

1.1 Introduction

In today's times of globalization and digitalization, business processes are increasingly automated across different industries (Völkle & Planing, 2019) at a growing pace (Dudler, 2020). Focusing on interaction processes, communication is also subject to constant change and development with the central driving force being technological development (Jäger & Petry, 2021; Ternès, 2018). Without denying the persisting importance of personal communication, new means of communication are introduced and gaining significance – people tend to increasingly use messaging platforms and their possibilities (Accenture, 2017; Gentsch, 2017; Jäger, 2018). This communication with computer systems is shifted towards natural language interactions (Völkle & Planing, 2019) in the form of digital conversations (Rowley, 2004). Thus, the habits of interacting with companies are changing through new types of communication via novel kinds of technology. Such new communication possibilities have implications on the required means of interaction between companies and their stakeholders, who get accustomed to instant messaging: The increase in real-time messaging influences the preferences for interaction with businesses (Drift, 2018). Companies need to take these external stakeholder requirements into consideration whilst minimizing internally occurring implementation and overall process costs as expenditures in novel (information) technology are only justified if they benefit the business. These internal costs and efforts are closely intertwined with internal stakeholder requirements in the form of acceptance determinants: Only if they are willing to welcome these automation technologies into their business processes and tasks and accept it, they can effectively support the workflow and increase efficiency and thus unfold their expected benefits (Bhattacherjee & Sanford, 2006). Acceptance is essential for the further development of novel technologies (Taherdoost, 2018).

One recently trending technology seeking to automate formerly intricate processes while enhancing efficiency is the implementation of chatbots (Bastam, Bicker, Walf, & Nachtwei, 2020; Tawk, 2021). Those automated dialogue systems are implemented to take over structured tasks such as answering to frequently asked questions or collecting specific information and data. As outlined, a contemplation on the acceptance factors for new technology such as chatbots is imperative for a sustainably successful implementation into the company. Albeit they are no new phenomenon, research on chatbot acceptance is not overbearing. However, there are increasing tendencies concerning chatbot acceptance research studies (Rapp, Curti, & Boldi, 2021). Especially studies on important acceptance factors without special foci on technical setup, tonality or anthropomorphism are rare. This study examines such general acceptance factors concerning chatbots. As a special focus, job-related automation concerns are observed as well as their influence on the acceptance of chatbots: When looking at the advantages of automation technology, the human perspective on these developments needs to be considered. Acceptance of business process automation is not simply given as the concerned employees whose formerly self-performed process steps are being subsidized might oppose the idea of implementing such an automation technology. Reasons for that are vast – in this study, the influence of the aspects (1) perceived system transparency, (2) inertia defined as tendency to prefer familiar assumptions over new ones even after proven questionable (Polites & Karahanna, 2012), (3) ethical implications, (4) legal implications, (5) social implications, and (6) established acceptance constructs from adaptations of the Technology Acceptance Model (TAM) are examined.

As an area of application, chatbots in recruiting within companies in Germany are being regarded in this study because of the novel character alongside the high significance of automation technology in this industry: Recruiting is highly affected by digitalization (Lieske, 2018). New possibilities of communication are introduced to the recruiting process to comply with the changing habits and frequent Internet usage of the candidates in Germany (R. Hartmann, 2015). Chatbots could be a way to improve productivity (Majumder & Mondal, 2021), resulting in an efficiency and effectiveness enhancement of the recruiting process via automatization (Tawk, 2021). To effectively exploit these potential benefits, the chatbot would need to be integrated within the envisioned process steps as a facilitating and enabling entity, co-existing alongside recruiters as the ones traditionally in charge of all related tasks and now subsidized for certain process steps. For this take-over to work, such automated dialogue systems have to be accepted by the recruiters. Hence, acceptance is of vital importance and the main focus of this study. Recruiting chatbot are regarded as a recruiter substitution for first interview conduct[1] as exemplary use case for this study. Interviewing is a realistic, easily conceivable scenario potentially inducing job-related automation concerns as a high involvement task that is essential for the recruiting process and depictable in a dialogue-based process. It has a high practical value as it takes over a frequent task with a high workload for the recruiter. Unlike many other recruiting process steps, interview conduct is a process highly shapeable by the recruiter so that he can choose freely whether to implement the chatbot or stay in his traditional way of interview conduct.

1.2 Research Gap

This research offers several unique aspects new to the field of technology acceptance research regarding automated dialogue systems closing the associated research gaps: Chatbot utilization and performance from the specific front end-sided user view and specifically in the form of the company-external stakeholders' point of view has been subject to various studies (e.g., Buell, 2018; Ciechanowski, Przegalinska, Magnuski, & Gloor, 2019; Eißer & Böhm, 2017; J. Pereira & Díaz, 2018; Bayan A Shawar & Eric Atwell, 2007; Völkle & Planing, 2019). The firm-internal perspective however is a special one regarding the aspects of company-internal technology implementation as well as the expected end user behavior towards this technology. Regarding this internal sight, recruiting chatbot implementation is viewed as a recruiter project, which is in line with T. Bondarouk, Parry, and Furtmueller (2017), as recruiters hold the necessary knowledge of HR processes. Acceptance theories regularly share

[1] Interview conduct is defined as a first chatbot questioning and candidate answering process regarding the applicant's hard skills in the form of abilities, degrees and certificates for example. Such a two-step approach with a first focus on hard skills and a second one on soft skills has been suggested for recruiting (Litecky, Arnett, & Prabhakar, 2004).

one commonality: They analyze the acceptance of an innovation (innovative technology in most cases) that is being utilized by the investigated participants. In the study at hand, this assumption or rather basic trait is not present: The recruiters whose acceptance is evaluated do not use the technology of recruiting chatbots themselves (and thus do not perceive its level of ease of use) but rather implement it in their processes where it is being utilized by the candidates. By deploying a chatbot for interviewing, they authorize the automation system to replace them as conversation partner for the candidate. While organizational research on chatbot technology is already rare (e.g., Frommert, Häfner, Friedrich, & Zinke, 2018; Meyer von Wolff, Masuch, Hobert, & Schumann, 2019), studies regarding this company-internal perspective considering employees as technology collaborators or maintainers instead of sole technology utilizers have only seldomly been part of scientific research (e.g., Bröhl, Nelles, Brandl, Mertens, & Nitsch, 2019; Slater, Campbell, Stinson, Burley, & Briggs, 2017). In this study, the recruiters are investigated concerning their acceptance of chatbot implementation into their work processes. In a unique approach, both the recruiters' (1) own relationship with the chatbot system from an internal perspective (chatbots as a tool for task automation integrated into the recruiters' work processes), and (2) their assessment of the applicants' interaction with the chatbot in the frontend (outside perspective with chatbots as actual means of communication) are considered. Within this internal perspective, work process-related issues and facets of chatbot implementation arise bringing new aspects to the approach of acceptance investigation such as automation anxiety or inertia regarding established and potentially ingrained processes. Only few studies regarded the aspect of anxiety regarding potential job loss due to substitutability through automation technology (Dahm & Dregger, 2019; Eißer, Torrini, & Böhm, 2020; Laurim, Arpaci, Prommegger, & Krcmar, 2021). The concept of *job-related automation concerns* combining this anxiety with other potential automation apprehensions forming through the TAM aspects subjective norm, job relevance, output quality, self-efficacy, perceptions of external control, chatbot anxiety as well as potential ethical, legal and social implications is a novel approach and has not been scientifically investigated in this form yet. The thesis at hand shall close this gap. Furthermore, no existing quantitative acceptance study observed chatbots in recruiting for the specific use case of candidate interviewing to date. This scientific study aims at enriching the area of technology acceptance research while transferring the idea of technology collaboration from current studies focusing on physical technology automation (e.g., Bekier, 2013; Bröhl et al., 2019) to digital automation. In sum, to the knowledge of the author, research regarding (1) the recruiter-sided acceptance of chatbots for recruiting process improvement and enhancement of its efficiency and/or (2) the influence of job-related automation concerns of the ones affected by the automation technology has not been conducted so far. In this study, this research gap is sought to be closed. The findings will help to understand the relevant determinants of recruiter-sided chatbot acceptance and the role played by the job-related automation concerns that accompany the integration of the system into the recruiting process.

1.3 Study Objective and Research Questions

Chatbots can be a possible solution for recruiters to elevate efficiency within their processes while saving time and monetary expenditures amongst others. However, research concerning their integrability into recruiting processes is rare. The goal of this thesis is to assess imperative acceptance factors for recruiters that need to be considered when implementing chatbots in the recruiting process of a company in general as well as in the special interaction area of candidate interviewing as use case in focus. Potential support points via chatbots are evaluated before identifying recruiter-sided acceptance determinants. From that, theoretical and practical contributions are derived for a suitable chatbot implementation of high acceptance, which allows for a surmounting of these quandaries.

In the main part of the study, the statistical results of a cross-sectional in-between subjects quantitative survey will shed light on the determinants for individual recruiting chatbot acceptance by recruiters as relevant enabler figures of chatbots within recruiting. Furthermore, the status quo of chatbot acceptance will be assessed in the statistical analysis process via the identified influencing factors. Acceptance is a well-examined field of research with most according theories and models having been established and validated for several decades now such as the Technology Acceptance Model (Davis, Bagozzi, & Warshaw, 1989). Without modifications, these models cannot be brought into accordance with neoteric subjects (Quiring, 2006) such as elaborate chatbots and neglects their status as novel form of interactive communication. Thus, the recently formed Human-Robot Collaboration Model (HRCAM) by Bröhl et al. (2019), adapted to chatbots as non-physical business process collaboration technology, is suggested for the examination of acceptance factors for chatbots. In the HRCAM model, acceptance is expressed as system usage as common practice in acceptance research, which is influenced by perceived usefulness and perceived ease of use as suggested by most acceptance researchers such as Davis (1985) and Venkatesh, Morris, Davis, and Davis (2003). In their model, Bröhl et al. (2019) introduce novel independent variables such as social, legal and ethical implications as well as new relevant control variables like technology affinity to be considered when hypothesizing (physical) human-machine collaboration. In this study, the HRCAM model is expanded to form the novel Human-Chatbot Collaboration Model (HCCAM) to fit to the innovative technology of chatbots: *Perceived system transparency* is a highly important aspect concerning complex functionalities (e.g., Peters, Pumplun, & Buxmann, 2020; Shin & Park, 2019), especially for systems disclosing their processing techniques and decision-making rationale. In this thesis, system transparency refers to the explainability and interpretability of the behavior and decision-making of the system. *Inertia* as expression of a status quo bias formed to depict the potential influence of tendencies to cling to familiar assumptions instead of adjusting them when being exposed as questionable or wrong (Polites & Karahanna, 2012). Alongside the chatbot-fitting constructs of the HRCAM, perceived system transparency and inertia are brought together and related to *job-related automation concerns* potentially explaining a recruiter's intention to work with a chatbot or to keep from integrating such a system. Furthermore, the model is adapted to the non-physical nature of chatbots as a kind of software. All these beforementioned aspects represent novel aspects of investigation enriching the area of chatbot technology acceptance research. As a middle-ranged country concerning its state of digitalization,[2] Germany serves well as an average example when it comes to prerequisites and infrastructure for novel technology – i.e.,

[2] Germany holds Rank 12 among the 27 European countries in the Digital Economy and Society Index 2020 according to the European Commission (2020) and Rank 18 in the World Digital Competitiveness Ranking 2020 regarding 63 countries by IMD (2020).

chatbot – integration. For sampling quality reasons, Austria and Switzerland are added as suitable neighboring countries because of assumed like-mindedness (e.g., Vatter & Stadelmann-Steffen, 2013; Wagenhofer & Ewert, 2007). The aspect of cultural differences is not part of the dissertation at hand.

Based on the specific proposed exemplary use case of *candidate interviewing*, a focused investigation of appropriate recruiting chatbot acceptance prerequisites ensues. The interviewing process represents a relatable scenario for the participating recruiters as well as one stipulating a high level of involvement and – dependent on the kind of person – a certain sense of concern towards automation. Furthermore, this scenario is one hypothesized to be voluntary for the targeted sample – by virtue of their decision-making power, recruiters can choose to integrate a chatbot in the recruiting process or to refrain from this automation.

RQ_1: What are relevant determinants for recruiting chatbot acceptance amongst corporate recruiters in Germany?

a) Which general recruiter-sided factors might influence recruiting chatbot acceptance?
b) Which external variables influence the acceptance of chatbots in recruiting?
c) How strong do the identified factors influence recruiter-sided recruiting chatbot acceptance?

RQ_2: What are relevant job-related automation concerns of corporate recruiters in Germany regarding recruiting chatbots influencing their level of acceptance?

a) Which relevant factors related to *job-related automation concerns* exist and how can they be operationalized and measured?
b) What is the level of influence of *job-related automation concerns* on recruiting chatbot acceptance?

The overarching goal of this acceptance research study is to yield empirical data in order to evaluate the recruiting chatbot acceptance in Germany. This way, a focalized examination of recruiting chatbot acceptance within this framed field in the form of the defined core area of recruiting is executed. Special focus is laid on the introduced variables referred to as *job-related automation concerns* allowing for functional and academically validated insights.

In summary, the thesis at hand aims at establishing theoretical as well as practical findings concerning relevant elements influencing the acceptance level of recruiting chatbots as novel communication systems from the recruiters' perspective based on established technology acceptance frameworks adapted to the context of contemporary chatbot technology. This directly supports the deployment of recruiting chatbots for recruiting process automation and the enhancement of the business-to-candidate interaction during communication. Furthermore, it increases the efficiency of certain to be narrowed down recruiting process steps by substituting parts of recruiters' labor in the process chain and thus leaving them room to concentrate on strategic tasks and economize the whole recruiting process within companies. In the phase of object containment, the research subject of general chatbot acceptance is narrowed down to interviewing within the recruiting process.

In this context, a quantitative survey is conducted in order to answer the presented research questions. The theoretical and empirical findings shall be utilized to draw influencing factors concerning recruiting chatbot implementation in companies' recruiting processes. Based on the identified acceptance determinants, possible measures shall be proposed to support recruiter-sided recruiting chatbot acceptance in companies in Germany. Thus, practical relevancy will be established as researchers suggest that there is a causal relationship between acceptance in the form of utilization (intention) and business performance (i.e., Goodhue & Thompson, 1995; L. Liu & Ma, 2006; Son, Park, Kim, & Chou, 2012). Acceptance research will be advanced by presenting and validating an advanced Technology Acceptance Model that is timely and adapted towards current automation technology in a novel approach of regarding the company-internal view on employees as collaborators of digital automation technology.

1.4 Structure of the Dissertation

In compliance with the two research questions, the chapters are designed to give an overview of the research objective and exemplary use case, which are recruiting chatbots for first candidate interviews. An overview of the structure is presented in Figure 1.1.

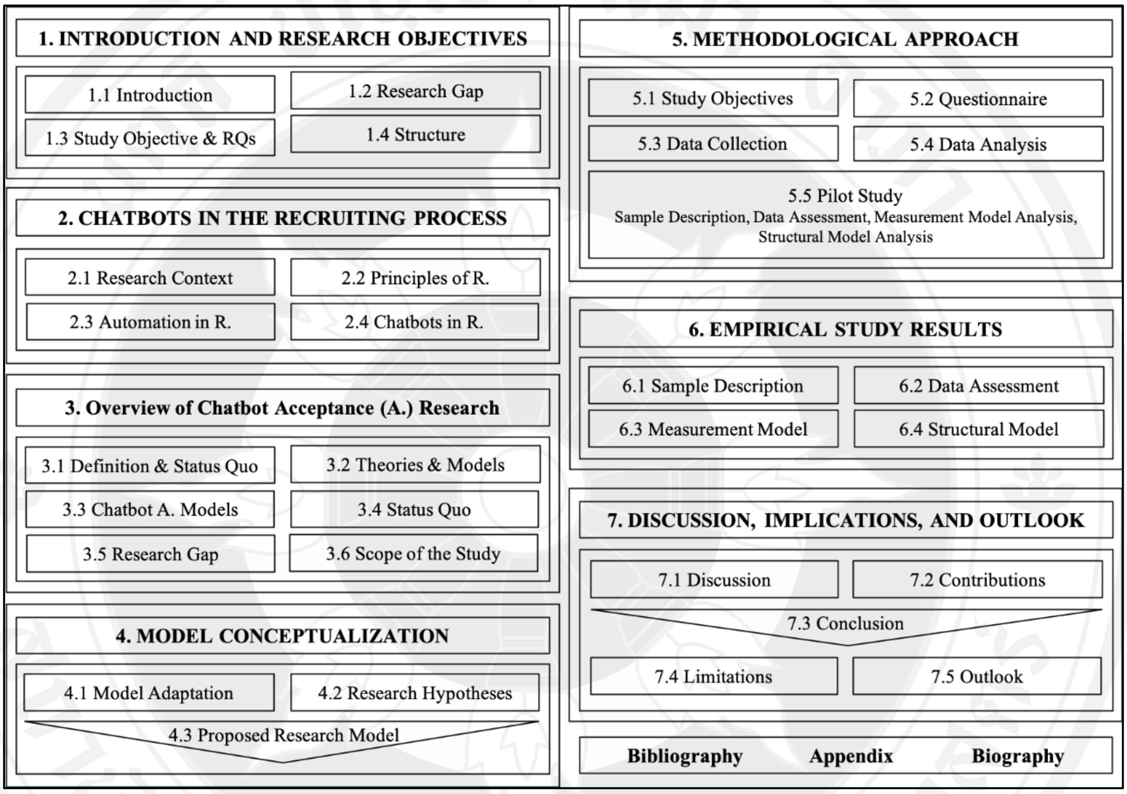

Figure 1.1 Organization of the Dissertation
Source: Own illustration.

An outline is given on chatbot acceptance research and then the model for the central part of the study, the quantitative survey, is developed and the according methodological approach is presented. The quantitative survey yields insights to answer RQ1 and RQ2. The results are presented, discussed and the theoretical as well as practical contributions are shown. In the end, a conclusion is drawn, the limitations are discussed and an outlook is given on possible future research.

CHAPTER 2

CHATBOTS IN THE RECRUITING PROCESS

For the understanding and preparation of the assessment of the current state of chatbot deployment in the recruiting processes of companies in Germany, the present situation of recruiting within a digitalized working world is outlined and the fundamental precepts of chatbot technology as well as implementation scenarios in general and specifically for the recruiting process are illustrated. Bringing together the technology and the area of application, chatbots in recruiting are examined for the German market focusing on the appropriability of the technology, suitable use cases, existent solutions, the status quo of its implementation, existent findings on the acceptance, limitations and rejection criteria, the role of recruiters, and implementation particularities.

2.1 Overview of Research Context

As its main goal, this study seeks to identify acceptance factors for automation technology, chatbots in the study at hand. Managers seeking to implement such technology within processes of their company need to be aware of these aspects: They are expected to close the gap between technical promise and achievement in the concerned process areas and may struggle with difficulties such as resistance to change (Leonard-Barton & Kraus, 1985). Prior to the acceptance investigation, the research subject is narrowed down. This study regards automation technology in the form of chatbots as automated dialogue systems in the context of recruiting for the specific use case of first applicant interviews. Step by step, the according theoretical fundamentals are presented regarding recruiting within human resources management and the implications automation technology has on the different tasks that are defined for the overall process. Process steps specifically suitable for automation are presented as a preparation for chatbot suitability analysis, which are evaluated based on the four developed criteria

1) occurrence frequency (automation of repetitive tasks),
2) volume in terms of fraction of the recruiter's workload contingent (freeing the recruiter to work on strategic tasks),
3) substitutability of human labor in task conduct (fitness for automation), and
4) amount of data conveyable in this task indicating that there is efficiency increase potential (volume of information, that can be yielded via automation).

The usage and role of chatbots in recruiting are analyzed in detail. Firstly, the inner workings, components, and features of chatbot technology are presented and general field of applications across industries are compiled to then develop a listing of recruiting tasks that are specifically appropriate for chatbot conduct. This list is developed along the four decision criteria

1) appropriateness concerning the representability of the task as a dialogue string,
2) practicability in terms of the size of the potential user group and the probability that the task is realistically conducted via a chatbot dialogue,
3) freedom of choice describing the choice of utilizing a chatbot for the task, which can either lay with the recruiter himself or with the general management without a possibility of influence for him, and
4) the recruiter's level of involvement in the task.

The market of chatbot solutions for and the status quo of chatbot application concerning the regarded target group, recruiters in Germany, are analyzed before presenting current utilization limitations, the role of the recruiters within chatbot implementation and particularities that require consideration regarding chatbot deployment.

2.2 Principles of Recruiting

In the following sections, the fundamentals of this business process are described in order to comprehend the subsequently termed impacts of and changes due to digitalization within the recruiting process of companies.

2.2.1 Recruiting in Human Resources

The concept of Human Resource or Human Resources (HR) refers to the overall remit of personnel within a company (Jung, 2017). Human Resources Management (HRM) describes the managing process within an organization to achieve its goals, which makes it an essential part of successful business operations (Bohlander & Snell, 2006). Recruiting is part of the overall HR process network consisting of the steering, operational and service-bound parts of HR processes. It belongs to the operational part alongside personnel planning, development, activation and liberation (Jäger & Petry, 2021). According to the International Organization for Standardization, recruiting "is designed to attract, source, assess and employ people to carry out an organization's activities." (ISO, 2016, para. 10) Distinguishable into the three parts *attraction* (personnel marketing), *selection*, and *integration* (Achouri, 2015), the main task of recruiting is personnel procurement, which comprises all measures concerning the search for, selection and hiring of potential employees in order to cover the predefined personnel requirements at the right time in the right place bringing in the required qualifications and competencies (Büdenbender & Strutz, 2012). According to Chhabra and Ahuja (2018), "[r]ecruitment is the process of identifying and hiring the right talent for a job in an organization, within a timeframe and by incurring the least expenses." (Chhabra & Ahuja, 2018, p. 24) Hence, the importance of time and cost management throughout the process becomes apparent. Task-wise, recruiting is intertwined with personnel or rather HR marketing – the latter describing the upstream process step of attracting candidates and enthuse them for the company while the former is about winning these candidates over (Holtbrügge, 2018). Examples of main elements of personnel marketing and recruiting are increasing a company's familiarity, employer branding, applicant generation and active sourcing (Jäger & Petry, 2021).

Demographical changes and the increasing need for technically adept, qualified and trained employees fueled a “war for talents”, which calls for intense recruiting activities in order to provide companies with sufficient and adequate workforce (e.g., Achouri, 2015) as well as appropriate tools to accompany these measures (Laurim et al., 2021). Where in former times, companies could pick their talents from a pool of candidates, many industries are now characterized by talent market structures with candidates picking their ideal employers (Dudler, 2020). Hence, these conditions of high competition among companies to acquire qualified and talented employees as well as rising the demand for such specialized workforce manifest the important position of recruiting within HR processes (Bollessen, 2014; Kulkarni & Che, 2019). Recruiting thus is a key element for companies as this business process takes responsibility for building and expanding the company and for generating success through the employment of efficient and competent workforce (Majumder & Mondal, 2021; K. Y. T. Yu & Cable, 2013). The importance of human resources intensifies in today’s times of digitalization (Laurim et al., 2021). Here, main predicaments are data overflows in terms of incoming questions and applications and a disrupted candidate experience. At the same time, recruiters are striving to acquire new potential employees at minimum expenses while considering that hiring a person unfit for the job is associated with very high costs (Korn et al., 2017; Ritter, 2010).

2.2.2 General Recruiting Process

The procedure of recruiting can be broken down into distinguishable parts. A recruiting process step definition overview yields three to eight steps (cf. Table 2.1).

Table 2.1 Recruiting Process Step Definitions

Ritter 2010	**Schottek 2016**	**Knapp 2017**	**Miebach 2017**	**Jäger & Böhm 2012**	**Teetz 2018**
Recruiter View				**Applicant View**	**Both Views**
	1. Labor Market Information			1. Employer Branding	
1. Personnel Demand Establishment		1. Personnel Planning	1. Personnel Planning	2. Relevant Set	

2. Job Profile Creation	2. Job Profile Creation				
	3. Media Selection for Job Posting	2. Search for Personnel	2. Personnel Acquisition	3. Employer of Choice	1. Job Advertisement Placement
					2. Job Search
3. Application Receipt	4. Application Preselection			4. Application	3. Application
4. Application Preselection		3. Candidate Selection	3. Candidate Selection	Post-Application	4. Candidate Selection
5. Detailed Applicant Selection	5. Contact with Selected Candidates				
6. Hiring Decision	6. Candidate Selection				
7. Hiring	7. Hiring (Employment Contract)	4. Personnel Deployment			
	8. Initial Training				

Source: Ritter (2010); Schottek (2016); Knapp (2017); Miebach (2017); Jäger and Böhm (2012); Teetz (2018).

The process step approaches are sorted chronologically and distinguished according to their point of view either of recruiters or applicants. While the most encompassing process chain includes eight steps (Schottek, 2016), the most concise one solely consists in personnel planning, acquisition and selection (Miebach, 2017). The study at hand focuses on the most prevalent steps while concentrating on the candidate-directional parts acquisition and selection, where digital technologies can take an influence on the interaction with applicants in order to examine the recruiter- and applicant-directional aspects of recruiting.

Hence, the recruiting process followed in this examination consists of the six steps (1) job profile placement, (2) job search, (3) application, (4) candidate pre-selection (based on application documentation assessment), (5) hiring decision (based on interviews or online assessments), and (6) hiring spread over the three parts pre-application, application and post-application (cf. Figure 2.1). The pre-application phase is defined as the personnel acquisition segment already including first applicant inquiries for example while the (post-)application phases encompass all aspects of applicant (documentation) management.

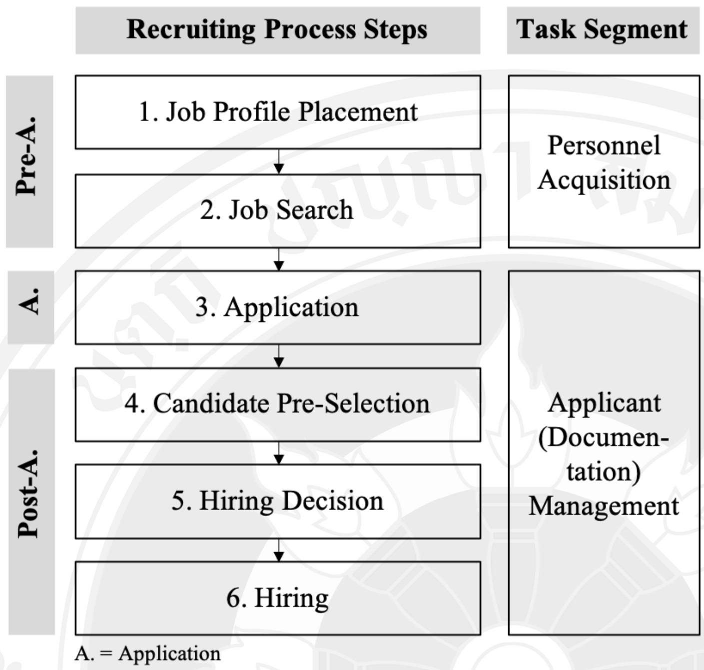

Figure 2.1 The Six Phases of Recruiting
Source: Own illustration.

Applicants and applications in this context refer to company-internally as well as externally directed interested potential candidates, whereby the main focus is on external candidates as most commonly occurring group of applicants. In this regard, kinds of potential candidates are discerned: (1) The ones seeking for work, and (2) the ones currently in a position elsewhere but interesting for other companies to headhunt, which results in two different cases. This study focuses on the first group of candidates, which make up the larger part of the pool.

Personnel acquisition plays an important role in this process. In the form of recruitment marketing, short-term measures are conducted: (1) Creation of a job profile, (2) identification of appropriate potential candidates, (3) selection of recruitment sources and media, and (4) job posting (Miebach, 2017). Miebach (2017) also positions the screening of applications within employer branding, whereas in the study at hand, this step is part of the applicant (documentation) management encompassing the post-application (Post-A.) process steps. In this task segment, all responsibilities directly relating to the candidates and their application documents are summarized.

2.2.3 Roles, Tasks and Touchpoints in Recruiting

The main actors within the recruiting process are the candidates, the recruiters, and the concerned departments of the company seeking to fill an open job position. The candidate wants to take up a job and acquires and evaluates information in preparation for the according decision while the company aims at filling their open job positions by identifying, attracting, assessing, and employing the right talents (Miles & McCamey, 2018) fitting to the company and especially to the department in search of new employees. Both parties provide certain information for each other with the common goal of filling the position. The roles are clearly defined: Generally, the company offers a job and the candidate can choose to accept the offered employment (Miles & McCamey, 2018). However, this depends on the situation in the job market; while the effort for companies are higher in a candidate-driven market, they increase for job seekers in an employer-driven market. In Germany as main focus and the also German-speaking DACH region consisting of Germany, Austria and Switzerland, the job market is in a candidate-driven state (e.g., Dudler, 2020) demanding for appropriate recruiting measures (Laurim et al., 2021).

Regarding the overall task allocation, the company (hiring department and recruiter) defines, communicates and offers the job to which certain conditions (e.g., skills, qualifications, working environment) are attached, while the job seeker is expected to inform himself and decide on the job position most suitable for his profile and his needs. In general, the recruiter has four kinds of tasks to manage (Holtbrügge, 2018): (1) Personnel management (e.g., employee administration), (2) consultation (e.g., coordination with the hiring department), (3) directive tasks concerning the human resource policies for the company, and (4) service (services for other departments of the company) tasks. As part of this workload, he manages the recruiting process and accompanies the candidates through it by supporting their journey, answering their questions, mediating between the department and the candidate, who applied to this unit, and overseeing the hiring process. His tasks are thus focused on the external interaction with the candidates and their data as well as on the internal recruitment process in collaboration with the job-advertising department. More specifically, the procedure of recruiting ranges from the job profile placement in accordance with the requirements and specifications of the hiring department to the actual hiring for recruiters and from the acquisition of company- and job-related information during the job search to the need for answers to (frequently asked) questions coming up in the post-application phase for candidates. All assignments have been checked for an appropriate level of complexity potentially suitable for automation since current HR automation still focuses on elementary tasks (Ternès, 2018). For the three introduced stakeholders, several touchpoints with each other exist, which are summarized in Table 2.2.

Table 2.2 Recruiter, Candidate, and Hiring Department Touchpoints within Recruiting

Step	**Specific Task**	**Applicant**	**Recruiter**	**Hiring Department**	**Perspective**
General	Answering General Questions Replies to (new) recruiters' questions concerning the applicant tracking system or chatbot usage for example	–	Provider	Receiver	Company Internal (Towards Recruiter or Department)
General	Answering General Questions Replies to applicants' general questions via different digital channels (frequently asked questions about the company, the open position, the technology of the application system or the application process itself for example)	Receiver	First/Second Provider	First/Second Provider	External (Towards Candidates)
1	Creation of Job Advertisement (Initialization) Creation of a job advertisement based on an according requirement profile	–	Provider	Receiver	Company Internal
1	Creation of Job Advertisement (Inspiration) Support of job advertisement creation via information extraction from existent advertisements (database)	–	Provider	Receiver	Company Internal
1	Creation of Job Advertisement (Formulation Suggestion) Support of job advertisement creation via intelligently proposed wording ideas/alternatives based on well performing phrases from the database	–	Provider	Receiver	Company Internal

Step	Specific Task	Applicant	Recruiter	Hiring Department	Perspective
1	Classification and Posting of Job Advertisements Job category assignment, application of key words fitting to target group	–	Receiver	–	Company Internal
1	Channel Identification Identification of promising job forms and boards as well as social media channels for specific job offers	–	Receiver	–	Company Internal
2	Job Selection Facilitation Helping potential applicants to find their ideal job position with distinguished, refined results	Receiver	First Provider	Second Provider	External
3	Assisted Application Form Fill-In Assisted filling in of application forms without the need of motivation letters or CVs in the form of information entry or self-selection via business/social networks or educational institutes for example	Receiver	Provider	–	External
3	Guidance Through the Application Process Handling parts or the whole application process as dialogue via the chatbot interface (e.g., assistance during information filling and document uploading)	Receiver	Provider	–	External
3	Answering Questions regarding the Application Process	Receiver	Provider	–	External
3	CV Inquiry Asking for data (information about the school education or studies) from the digital CV or online profile of an applicant	Receiver	First Provider	Second Provider	External
3	Missing Information Inquiry Asking for missing data from business platform profiles for example	Receiver	First Provider	Second Provider	External
4	Scheduling Arranging job interviews as an intermediary between the recruiter and the applicant	Receiver	First Provider	Second Provider	External
4	Interviewing Conduct of first pre-screening (video) interviews with the candidates	Receiver	Second Provider	First Provider	External
4	Candidate Matching Pre-screening by comparison of the candidates' profiles with the job profile under consideration of diversity management; hard skill matching based on information from the CV and motivational letter for example	–	First Receiver	Second Receiver	Company Internal (Provider: Database)
4	Extended Candidate Matching Referral of interesting potential candidates with inappropriate profiles for the job at hand to more fitting open spots within the company	–	First Receiver	Second Receiver	Company Internal (Provider: Database)
4	Candidate Pre-Selection Effective pre-selection of candidates based on relevant criteria; creation of a candidate pool	–	First Receiver	Second Receiver	Company Internal (Provider: Database)

Step	Specific Task	Applicant	Recruiter	Hiring Department	Perspective
5	Online Assessment Automated online assessment of the candidates' competencies, matching of these competencies to the ones of the potential future team and the overall job requirements	Receiver	Second Provider	First Provider	External
5	Personality and Soft Skill Analysis Automated creation of candidate personality profiles by analysis of the candidates' language, expressions, emotions, voice, etc. based on image/voice recognition technology; soft skill assessment and matching via cultural fit evaluation (in its early development phase), for example based on comparison with optimum values either from science or company-internal champions	–	First Receiver	Second Receiver	Company Internal (Provider: Database)
5	Elaborative Candidate Selection Effective selection of candidates based on detailed selection methods; preparation of decisive information for the recruiters based on algorithm examination	–	First Receiver	Second Receiver	Company Internal (Provider: Database)
5/6	Guidance through the post-application phase Guiding the candidate through the particular steps succeeding his application	Receiver	First/Second Provider	First/Second Provider	External
6	Employment Contract Creation of employment contracts containing all relevant applicant data from the database	Receiver	First Provider	Second Provider	External
6	Onboarding Structured information for new employees	Receiver	First Provider	Second Provider	External

Source: Own compilation based on Groß and Gressel (2016); Hollmann (2017); CHRIS (2017a); Böhm and Meurer (2018); Jäger (2018); Mülder (2018); Teetz (2018); Semet and Hilberer (2018); Corinna Maier (2018); Meurer, Eißer, and Böhm (2019); B. Hmoud and Várallyai (2019); Regber, Eißer, and Böhm (2019); Meurer, Drebert, and Böhm (2020); B. I. Hmoud and Várallyai (2020); Teetz (2020); Jäger and Petry (2021); Laurim et al. (2021).

Along the six defined recruiting process steps, certain tasks with touchpoints between at least two of the three actors are displayed and analyzed according to the associated information or rather conversational content provider(s) and receiver(s). The party providing the information and determining the database details for the recruiting process or candidate file is defined as provider while the receiver obtains the information specified by the provider. In certain cases, there is more than one provider given that several tasks need to be accomplished in coordination between different stakeholders i.e., the recruiting and the hiring department; some are without a provider as this would be a task where automated systems can give suggestions. While some of the presented tasks are directed towards the applicant or the hiring department, all of them involve the recruiter either as the one making available or the one collecting information concerning the talent or the hiring department of his respective company. Automation could be a way to enhance efficiency and effectiveness while disburdening the recruiter of some interaction activities for him to focus on strategic work. The next section analyzes the possibilities and implications of automation technology for recruiting.

2.3 Automation in Recruiting

Recruiting is key for a company's success in terms of competitive advantage (İşgüzar & Ayden, 2019). Digitalization transformed the recruitment of personnel in companies: E-recruitment, the electronic form of recruiting, allows for ubiquitous, collaborative hiring processes (Holm, 2012) affected by digitalization and automation. For the understanding and preparation of the assessment of the current state of chatbot deployment in the recruiting processes of companies in Germany, task automation as well as the present situation of recruiting within a digitalized working world are outlined and the fundamental precepts of chatbot technology alongside possible implementation scenarios are illustrated.

2.3.1 Digitalization and Automation Implications for Recruiting

Digitalization refers to technological changes within economy and society (Weigert, Bruhn, & Strenge, 2017), whereby technology is defined as "the use of systematic procedures to produce intended effects." (Kipnis, 1991, p. 62) According to the IMD World Digital Competitiveness Ranking,[3] Germany currently holds the 18th rank out of 63 analyzed countries regarding knowledge (e.g., talents, training, R&D expenditures), technology (e.g., regulatory framework, capital and technological framework) and future readiness (e.g., adaptive attitudes, business agility, IT

[3] The ranking held by the IMD World Competitiveness Center analyzing 63 economies calculated on the basis of 52 ranked criteria (IMD, 2020).

integration) (IMD, 2020). Hence, Germany shows room for improvement concerning its digitalization status. Digitalization can be divided into the parts automation, robotization and virtualization (Ternès, 2018). According to (Jäger & Petry, 2021), the pace of change concerning economic and market structures rapidly increased over the last years and defines the current technological development. Digitalization is a central part of the working environment in HR management today, which poses a challenge for many companies (Böhm & Meurer, 2018). Since its beginning stage, the Internet has become imperative in people's daily routine and increased their knowledge and consciousness (Civelek, İnce, & Karabulut, 2016). 94 percent of Germans ages 14 years and above utilized the Internet in 2020, which makes it a vital part of people's everyday life (ARD & ZDF, 2020).

Automation describes technology performing tasks formerly executed by humans (R. Parasuraman & Riley, 1997). Task automation is no new development and its establishment can be dated back to times even before the Industrial Revolution in the 18th and 19th century (Achouri, 2015; McClure, 2018; McKinsey Global Institute, 2017). In the course of this technical rationalization with an ongoing tendency of digitization, (1) certain human labor force has been substituted, and (2) the focus has shifted to creative human capital as production factor calling for optimization in the form of productivity increase (Achouri, 2015). Hence, there are two kinds of manifestations concerning automation in formerly human labor tasks: (1) The mere support of human labor, or (2) a complete substitution of human work in case of a full automation approach (Czarnecki, Bensberg, & Auth, 2019). Intelligent automation is feasible for process substitution supporting actual value creation such as automatic sorting and processing of unstructured data (Heinen, Heuer, & Schautschick, 2017). Automation is implemented for time-consuming and labor-intensive activities (R. Parasuraman & Riley, 1997). More specifically, automation is introduced for reasons such as cost reduction, permanent availability and a high level of reliability (Czarnecki et al., 2019). The implementing party mostly hopes for an increase in efficiency, overall progress, work result improvements and improved security while raising concerns such as potential surveillance, insensitivity, loss of control and lack of data protection (Bosch, 2020). In this process, human labor is shifted to technological systems. However, according to Ghazizadeh, Lee, and Boyle (2012), automation rather changes the structure of tasks and introduces new ones than replacing human labor altogether. This indicates a high importance of efficient recruiting for companies in these times of digitization in order to obtain the necessary creativity, skills and willingness to adapt to these innovative and potentially volatile circumstances. Recruiters need to obtain competences such as evaluation skills regarding the technologically acquired candidate data (Repova, 2020).

The implementation of information technology into HR management processes is called e-HRM (T. V. Bondarouk & Ruël, 2009). E-recruiting offers a wholly digitized process from candidate search via selection up to an accompanying communication and application management process (Laurim et al., 2021). Organizations implement e-HRM and -recruiting technology to profit from administrative as well as strategic benefits in the form of reduced costs, process improvements and a substitution of operative tasks leaving professionals to superior tasks (T. Bondarouk et al., 2017). Hence, in the course of digitization and automation, candidate assessment within recruiting shifted away from hard skills in the form of knowledge and experience towards soft skills and thus rather non-obvious abilities, which become more and more relevant within qualification assessment (Achouri, 2015). While hard skills, defined as knowledge and experience aspects, are evaluable via CV data, soft skills are qualifications and capabilities (e.g., communication capability, empathy, assertiveness), that are not as easily extractable from application data and need to be uncovered in interviews and assessment centers for example (Achouri, 2015). Hence, there are rather easily assessable information and complex kinds of information, which require either human assessment or advanced analysis technology. As a consequence, obvious and thus quickly verifiable hard skill information tends to be more suitable for automation than complex and non-obvious soft skill information. While already analyzable via AI-based technology (Laurim et al., 2021), soft skill assessments presuppose advanced technology not accessible to all recruiting departments because of monetary or other restrictions or technological inadequacies for example.

One popular way of automating processes is to implement functionalities, where the components of human thought, decision making, problem solving and learning, are being computerized (Bellman, 1978). Formerly, automation technology was mostly deployed in mass production scenarios with repetitive processes because of high configuration requirements. With the rise of AI technology, also unpredictable yet standardizable activities are expected to become automatable even though they might permanently change without rentability issues making it more versatile and cheaper (Heinen et al., 2017; Jha, Jha, & Gupta, 2020). Sophisticated digital instruments are already reality in recruiting today and will increase in numbers (Dahm & Dregger, 2019). Their level of acceptance regarding the hiring processes raises (Jha et al., 2020). One essential part of the hiring process is the communication between the company and the applicants. Communication needed to be adapted to the digital transformation and shifted towards conversational modes (Rowley, 2004). The digitalized working world is now characterized by conversational ubiquity, digital communication and interlinked systems (Kienbaum, 2016). In the context of automation, communication with computer systems is shifted to natural language interactions (Völkle & Planing, 2019). Inquiries formerly conducted on websites or apps can now be undertaken via consolidated natural language interfaces (Følstad & Brandtzæg, 2017). Drift (2018)[4] found that "[…] the rise of real-time messaging has led to a fundamental shift in how people prefer to connect with businesses." (Drift, 2018) Messaging app users do not only log in for chats with friends anymore but also to get in touch with companies (BI Intelligence, 2016): According to a study by Twilio (2016),[5] nine out of ten consumers globally are inclined to use messaging when they want to approach businesses. Digital communication can be automated via the introduction of an interface, for example in the form of a chatbot (cf. *section 2.4*), that interacts with the human requestor (i.e., interested party, candidate). In the course of technological advancement, a more complex dialogue management is possible considering contexts, historical data and unexpected natural language input. These tendencies changed and expanded the ways of communicative interaction resulting in also a larger variety of application possibilities via instant messaging for example changed the application process: Formerly limited to traditional application submission via postal letter, candidates have a broader range to choose from today. Sourcing and recruiting are seen as highest digitalized fields within HR management (Kienbaum, 2016); more and more steps of

[4] 2018 State of Chatbots Report by Drift (2018) (n = 1,051 US adults, conducted from 30.10.-06.11.2017 in the US).
[5] 2016 Global Mobile Messaging Consumer Report by Twilio (2016) (n = 6,000 adults from the US, UK, Germany, India, Japan, Singapore and South Korea).

the recruiting process become automated (Bastam et al., 2020). As a consequence, the requirements and problems of recruiting changed: More and more applications are submitted via e-mail and online form templates respectively while paper-based submissions decline,[6] which makes it easier for candidates to submit applications and allows for an overall higher number in submissions on average. Analyzing and evaluating those incoming application streams manually is a laborious task for recruiters (Anitha & Shanthi, 2021). The Top 1,000 companies in Germany[7] receive 32 applications for one open spot on average with 73.3 percent receiving up to 40 applications and 7 percent even up to 100 – all of them neglecting 60 percent of the submissions when sifting through the material (CHRIS, 2017b). In this context, recruiters necessitate ways to process and manage this overpowering data stream (Dahm & Dregger, 2019).

HR is a vocal starting point for productivity increase and cost saving measures as it impacts the whole staff. The automation of routine activities (e.g., payroll processing, maintaining employee data) is an obvious consequence of technology introduction to HRM (Bohlander & Snell, 2006). The foci are process harmonization and overall improvement for a more strategic alignment as well as an increase in efficiency (Ziebell, Albors-Garrigos, Schoeneberg, & Marin, 2019). Formerly, recruitment and candidate selection have been archaic with fragmented recruiting measures and selection procedures relying on managerial discretion potentially corrupted by inherent biases or subjectivity in selection (Jha et al., 2020). However, in spite of technological advancements, the costs of hiring, the risks or wrong hiring and the time necessary to acquire competent candidates continues increasing (Kulkarni & Che, 2019). One reason for this is that while time savings are yielded, questions, for example concerning the technology's levels of accuracy and their handling of privacy implications (Laurim et al., 2021) as well as suspicions of bias and discrimination arise (Ochmann & Laumer, 2019). Hence, measures to increase efficiency are sought to

[6] According to the 2017 CHRIS recruiting trends study (n = 2,300 German companies; 3,400 candidates), paper-based applications declined from 26.8% of all submissions (2010) to 17.0% (2016) with the prediction to fall to a mere 7.0% in 2021 while e-mail/form applications increased from 39.7% (2010) to 41.4% in 2016 with form applications predicted to account for the majority of applications (60.9%) in 2021 (CHRIS, 2017b).

[7] Ranked according to revenue (>50 Mio. EUR annual revenue; >250 employees).

counteract this with effective automation measures as one possible way. In the first stages of digitalization within HR, it was about automation of routine tasks such as reoccurring payroll accounting. Secondly, when PCs were introduced in the work place, the administrative work was more wholesomely automatized in the form of digital application management for example. With the further diffusion of the Internet, recruiters started to make use of the increasing accompanying possibilities such as the opportunity to advertise jobs via different platforms like job portals or own career websites with integrated application forms or social media. Thus, while at first, information technology served as a tool for automation and acceleration within HR processes, it then was assigned the roles of an enabler and amplifier of intelligence through its analysis and prognosis features (Mülder, 2018). However, in the current state of the industry, the focus is still on the gradual depletion of especially elementary tasks by rationalization, standardization and automation in order to free formerly bound resources within HR (Ternès, 2018). Hence, automation holds the potential for overall HR intelligence strengthening by computerizing routine work in order to leave the strategic and creative work to human recruiters while it is not mature for large-scale deployment in tasks of high complexity yet. This novel, changed and developed form of recruiting is called digital recruiting, also referred to and most commonly known as e-recruiting. It comprises all web-based measures for personnel advertisement, approach and selection as well as application processing (Salmen, 2012). It allows for time and cost savings as well as for a higher reach for potential applicants (I. Lee, 2011), especially when supplemented by sophisticated tools (Laurim et al., 2021). The mixture of software-assisted e-recruiting and algorithm application, also called robot recruiting, includes features like video recruiting[8] and big HR data as well as according HR data analytics to analyze formerly unutilized anonymous or personalized unstructured data of different sources and draw managerial implications (Mülder, 2018). However, successful automation projects depend on user acceptance (Laurim et al., 2021) as well as seamless integration into the existing structures (Hollnagel & Woods, 2005). Although well-suited for digitalization, HR is late concerning technology adoption

[8] Company-sided video recruiting: videos for employer branding or attractiveness enhancement; candidate-sided video recruiting: video interviews, personality assessment (Mülder, 2018).

(Mazurchenko & Maršíková, 2019), which is a basic prerequisite for successful and sustainable implementation.

In summary, digitalization has a strong impact on companies and their recruiting processes, which shifted to online touchpoints such as the company's website and instant messaging (Lieske, 2018). It takes influence on the communication between companies and their applicants as well as their way of applicant (documentation) management, since most or even all the data needs to be processed and managed digitally. Future-oriented, sustainable personnel files are maintained as digital files within such document management systems, part of Applicant Tracking Systems (ATS). Sources for such systems to draw information from can be application documents, employment contracts, performance assessments, certificates or related correspondence for example. They allow for quick, economic and consistent HR processes (Jäger & Petry, 2021). Furthermore, automation plays an important role for recruiting. Automation software is implemented to support the recruiting of prospects, the tracking of candidate information, the screening of their data by scanning CVs for example and the pretests of promising candidates (Bohlander & Snell, 2006). All such efforts are characterized by one common denominator: The need for recruiter acceptance in order to yield the expected advantages such as an increase in efficiency.

2.3.2 Task Automation in Recruiting

After regarding the impact of digitalization on the recruiting process and the role of technology as an automation tool, the established tasks and according touchpoints of the recruiting process from the company's and the applicant's side are now examined to evaluate their potential for automation. Jäger and Petry (2021) suggest that the whole recruiting process can be supported and steps taken over by automated systems. Laurim et al. (2021) support this view and offer information on possible application scenarios. However, a containment of the recruiting process steps is necessary based on the specific kind of the task: Task specification is defined as the combination of the (1) frequency, (2) volume, and (3) task-related automatability of a certain task. In recruiting, the two problems of handling of high amounts of information (in the form of applications and applicant data points) and producing relevant output for the high number of inquiries (task frequencies of applicant inquiries) are prevalent and need to be addressed. Information-intense recruiting tasks or those requiring coordination are apt for intelligent automation because of the saving potential. Hence, the task assumed to be of highest relevancy for recruiters are those of high frequency, high volume (in terms of level of interactivity regarding the interactions with the applicants), and a high level of automatability. Frequent and voluminous process steps are laborious. For example, the analysis and evaluation of incoming applications is strenuous work for recruiters (Anitha & Shanthi, 2021). Such time-consuming and labor-intensive work is specifically suitable for automation (R. Parasuraman & Riley, 1997). Within acceptance research, the role of the kind of task (e.g., Bekier, 2013) as well as impact of task frequencies (e.g., Degenhardt, 1986) have been examined. As stated before, high amounts of (applicant) information and high task frequencies (responses to applicant inquiries) are the main problems within recruiting processes with automation as a possible solution – given that it is appropriate from a technical and a process-step view. Regarding this task-related automatability, the distinction of Czarnecki et al. (2019) is considered, who differentiate between a mere support of task accomplishment and the overall substitution of human labor within this task. The task is also defined by its informative value regarding the amount of yieldable or conveyable information.

As specified, the following aspects are being drawn as criteria for selecting tasks suitable for automation with a three-scaled evaluation scheme that is applied to the average daily routine of recruiters (● = high extent; ◑ = medium extent; ○ = low extent):

1) Occurrence frequency (Frequency of the task during the recruiting process),
2) Volume (Task scope and influence on the workload within the recruiting process measured by level of interactivity regarding the interactions with the applicant and the achievable information),
3) Task-related automatability (Task-inherent suitability for automation in terms of (1) the degree of human counterpart substitutability, and

(2) the amount of information that is obtained from or transferred to the human enquirer)

Table 2.3 Task Automation Evaluation of the Recruiting Process

Step	**Specific Task**	**Occurrence frequency**	**Volume** (Scope, inter-activity)	**Task-related automatability** (Substitutability of human labor)	**Task-related automatability** (Amount of information)
General	Answering General Questions	●	●	●	●
1	Creation of Job Advertisement (Initialization)	○	◑	●	●
1	Creation of Job Advertisement (Inspiration)	◑	●	◑	●
1	Creation of Job Advertisement (Formulation Suggestion)	●	◑	◑	◑
1	Classification/ Posting of Job Advertisements	●	○	●	●
1	Channel Identification	●	○	◑	○
2	Job Selection Facilitation	◑	●	●	●
3	Assisted Application Form Fill-In	○	○	●	●
3	(Partial) Guidance Through the Application Process	●	◑	●	●
3	Answering Questions regarding the Application Process	●	●	●	●
3	CV Inquiry	●	●	●	●
3	Missing Information Inquiry	◑	●	●	●

Step	**Specific Task**	**Occurrence frequency**	**Volume** (Scope, inter-activity)	**Task-related automatability** (Substitutability of human labor)	**Task-related automatability** (Amount of information)
4	Scheduling	●	●	◑	◑
4	Interviewing	●	●	◑	●
4	Candidate Matching	●	●	●	●
4	Extended Candidate Matching	◑	●	●	●
4	Candidate Pre-Selection	●	●	●	●
5	Online Assessment	◑	◑	●	●
5	Personality and Soft Skill Analysis	●	●	◑	●
5	Elaborative Candidate Selection	●	●	○	●
5/6	Guidance through the post-application phase	●	●	●	◑
6	Employment Contract	●	●	◑	◑
6	Onboarding	●	●	◑	●

Source: Own compilation (cf. Table 2.2). The six steps are (1) Job profile placement, (2) job search, (3) application, (4) candidate pre-selection, (5) detailed candidate selection, and (6) hiring. Highlighted in grey color: Especially suitable tasks for automation according to the evaluation criteria (> 3 ●).

It is important to note that not all fields of application for automation technology technically implementable according to the presented criteria are practically feasible: As discussed before, the last decision concerning the recruitment of new personnel in the form of candidate selection remains in the hands of human recruiters and must not be executed by a technological system (Art. 22 Para. 1 GDPR). Thus, only pre-selection in the form of a first coarse filter is permissible under European law (Groß & Gressel, 2016). Hence, elaborate candidate selection is not executable via automation technology under current law. However, as it was not found to be as relevant over the four presented criteria, it is disregarded after this point.

According to the criteria-based evaluation in Table 2.3,

- FAQ-related tasks (general questions, questions regarding the application process),
- Inquiring CV and other missing information,
- Analysis tasks ((extended) candidate matching, candidate pre-selection, personality and soft skill analysis), and
- Overall process steps (job selection facilitation, interviewing, guidance through the application process or post-application phase, onboarding)

are best suited to be taken over by automation technology because they are of high occurrence frequency, of high volume regarding the recruiter's workload, and because the human factor can be best substituted while yielding high levels of informative value. The FAQ tasks represent a great relief for recruiters as they cover a large range of topics, are highly voluminous and well standardizable thus automatable given that the answers can be predefined while posing relevant content with high informative value for the applicant. CV inquiry regards the central information required from the applicant and is very time-consuming for the recruiter. Its automation presents an easement for the human employees formerly entrusted with this task. The complex task of interviewing also takes up a lot of time of the recruiter as the interview needs to be prepared, coordinated, held and debriefed. Alongside the CV information, the information drawn from the interviews are most valuable for the assessment of the applicant. Both kinds of candidate matching as highly laborious tasks are well automatable in case the requirements that are compared to the candidate's skills and abilities are clearly defined and the existent jobs are described and tagged precisely. The other analysis tasks, candidate pre-selection and personality and soft-skill analysis, are also frequent and time-consuming elements of the recruiter's workload that yield relevant information for the assessment of the candidates and that at first glance might be taken over by automation technology as long as the analysis criteria is predefined. However, in the case of personality analysis, current solutions in the form of sentiment (e.g., facial expressions, tone of voice) analyses are a nascent field of technology making human intervention imperative. Navigation through the (post-)application phase is another well automatable task as it is a routine, standard process step which needs to be performed for each hired employee in a similar way. Onboarding and the associated process steps are also highly frequent, occur for each new employee and in the case of structured onboarding plans is highly automatable. The study will focus on these presented 13 tasks as best suited for automation.

2.3.3 Job-Related Automation Concerns in Recruiting

Automation has an imminent effect on human labor. Alongside obvious benefits such as increases in productivity and economic growth, automation technologies might surpass their purpose as a tool of support and replace human workforce. According to the McKinsey Global Institute (2017), the extent of workforce substitution depends on the adoption of such technology. It states that 60 percent of all occupations existent today hold the potential to be automated by at least 30 percent. Heinen et al. (2017) aggregate different studies estimating between five and 83 percent (average: 36.21 percent) of all jobs to be at risk of automation or substitution through complex technology. 68 percent of the participants in a survey by E. A. Hartmann, Hornbostel, Thielicke, Tillack, and Wittpahl (2017)[9] think that jobs will be substituted in the future and 69 percent state that technological advances will destroy more human labor than it will create anew. In a study by Bundesverband der Personalmanager (2019), 27.1 percent of the respondents state that at least one job has actually been omitted because of intelligent technology.[10] In a study by Spiceworks (2018),[11] 40 percent say that automation can replace entry-level jobs not requiring creativity; only 17 percent perceive their own job being at risk because of it. However, according to Sarter, Woods, and Billings (1997), automation is a changing force to tasks and processes as well as responsibilities instead of a substituting element. In more recent times, Tawk (2021) states that human recruiting processes will not be replaced by chatbots but the

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[9] Survey concerning AI and the future of work of the Technology Review in cooperation with the Institute for Innovation and Technique (iit) (n = 3,219 German online magazine readers).
[10] Survey of the German Federal Association of HR Managers concerning their level of AI implementation (n = 1,032 HR managers).
[11] Spiceworks Survey 2018 (n = 529 IT professionals in North America and Europe).

technology will be increasingly utilized. However, Buell (2018) argues that while state-of-the-art automation technology is currently limited in its functionality making second-level support by humans still a necessity, this might change with technological advances and progress. As a result, the skill requirements change: The world of work is characterized by increased needs for work requiring high skill levels while substituting plain touch labor work with rather knowledge-driven work involving responsibility planning, decision making and problem-solving responsibilities for tasks (Bohlander & Snell, 2006; McClure, 2018). As Balasundaram and Venkatagiri (2020) put it: “The role of the human worker is being […] altered significantly and irreversibly. Economies and industries are moving from a workforce organized around manual labor to that organized around knowledge.” (Balasundaram & Venkatagiri, 2020, p. 1) Employees with sophisticated qualitative skills concerning aspects such as strategy, consultation and coaching are viewed as most employable whereas employees involved in currently automatable processes such as calculations and administration are endangered by potential substitution. Of course, this is a matter of technological advancements: In today’s times and with the current state of technology, a certain range of process steps is classified as automatable whereas this range might be different in the future. Presumably, fewer process steps are (mass-)automatable today than envisioned to be possible in the future. As a result, potential stakeholders in the form of employees currently performing potentially automatable activities might be held back from the acceptance of such technology because of job-related concerns and anxiety accompanying the implementation of it. This would have a tremendously negative impact on the potential that automation can unfold in the organization since the acceptance of such technology is a mandatory requirement for automation excellence (Ghazizadeh et al., 2012; Hollnagel & Woods, 2005). Even in case of substitution by automation technology for certain process steps, employees potentially stay involved in the process as a whole for those tasks that cannot be automated. Coined by Akst (2013), automation anxiety describes the fear people experience based on their impression that jobs are being automated thus causing unemployment for human workers. In their meta-analysis, Libert, Mosconi, and Cadieux (2020) found this aspect of fear of job loss to be one of the major HR-related challenges in recent research. It can be assigned to the work and relational anxiety forms of technology-induced anxieties as defined by Kummer, Recker, and Bick (2017): Work anxiety describes perceptions of a negative influence of technology on jobs while relational anxiety is defined as a perception of loss of the personal component within the interaction. (Thatcher & Perrewe, 2002) found a negative relationship between technology-induced anxiety and acceptance. Apart from such anxiety, employees might experience other related concerns regarding automation technologies such as perceptions of opaqueness (low level of transparency), potential biases (e.g., Følstad & Brandtzæg, 2017; Zierau, Engel, Söllner, & Leimeister, 2020) or inertia (Müller, Mattke, Maier, & Weitzel, 2019). In recruiting, sophisticated technology can take over various tasks and becomes an increasingly common part of recruiting processes as a way to increase efficiency while reducing costs and eliminating potential human errors and biases (B. Hmoud & Várallyai, 2019; B. I. Hmoud & Várallyai, 2020; Jha et al., 2020). Tawk (2021) for example expects recruiting jobs to be affected by technology-related substitution as well. Hence, recruiters are highly affected by changing processes and the implementation of automation technologies potentially causing concerns.

Alongside the presented internal struggles, there are different considerable macro-level aspects of innovative automation technology that are influential on the individual acceptance of it: Negative ethical, legal and social implications that might impact (recruiting) employees after implementation into organizational processes.

Ethically, there is the question of human workforce substitutability. Recruiting process step automation might lead to the replacement of human recruiters raising the area of tension between process optimization and the company's social obligation to their employees. Grasping an innovative technology's potential and relevance for the work processes and acknowledging its output quality, recruiters might become anxious about the own position within the company and see it threatened by this technology. Furthermore, the automatability of tasks is dependent on their specific kind. A problematic aspect is the containment and selection of suitable candidates for an open position for example: In Germany, as in the whole of the EU, the last decision is accredited to the human recruiters regardless of a potential subjectivity bias (gut feeling) known in human decisions (e.g., Gärtner, 2017; Corinna Maier, 2018; Scheller, 2016). As a consequence, for the time being, the final selection of the new employee remains in the hands of a human recruiter with automated systems as supportive assistants only – considering the flaws and limits chatbots still have concerning empathy and decision-making skills (Jäger & Petry, 2021; Semet & Hilberer, 2018). This example points out a gap between current and future technical possibilities of chatbots as well as the perceived level of capabilities, perceived transparency, reliability and overall acceptance. In general, the final decision must remain with human recruiters so that the selection procedure complies with European law (Groß & Gressel, 2016).[12] This is in line with the European Commission, which defines human agency and oversight as an essential requirement for trustworthy automation via sophisticated technology (European Commission, 2019). Thus, candidate selection tasks cannot be outsourced to automated analysis technology as of today. For now, chatbots are regarded as dialogue systems and not as decision-making systems. Another ethical and potentially legal aspect is the danger of racial differentiation and discrimination within elaborate automation (Fernández & Fernández, 2019). There are many more ethical aspects such as compatibility with moral principles. However, this thesis mainly focuses on the criteria defined by Bröhl et al. (2019).

A closely related topic is the area of data protection. Legal certainty is important regarding permitted data exchanges and processing via chatbot interfaces. All interactions need to be compliant to the European General Data Protection Regulation (GDPR). Recruiting chatbots within applicant tracking systems could contain data privacy flaws or execute unintended and even wrongly implemented manipulations for example. Data security in the form of network, device, software and algorithm protection from malicious behavior of third parties is also important (Wing, 2018). Furthermore, automated technology is not permitted to take hiring or lay off staff by law (Groß & Gressel, 2016). However, while concerns regarding the automated classification of candidates are justified, they are theoretical for now and will have to be discussed for future systems as today’s technology is not yet considered capable of making arbitrary decisions regarding the fate of potential new employees (Dudler, 2020).

[12] According to Art. 22 Para. 1 GDPR (EU regulation), people have the right not to be subjected to a decision based solely on automated data processing, which evaluates individual aspects of them as a person and potentially adversely to them (Hoeren & Niehoff, 2018), prohibiting final hiring decision-taking through automation technology.

In addition, the social impact needs to be considered: Recruiting is a highly interactive process with many touchpoints between recruiters and potential candidates for open job positions. Automating parts of these processes might cause a perceived loss of contact from the recruiters' point of view (Bröhl et al., 2019). The same can be hypothesized for the candidates, who might feel neglected or being kept away from human contact persons. This is not the focus of the study at hand, but might influence recruiters in their thinking. Tawk (2021) supports the idea that the applicants' responses might be affected by social and legal factors.

Condensing the related distresses as introduced above (converging in the research model of this study, cf. section 4.3), the concept of job-related automation concerns (JRAC) is presented in this study. These concerns and their influence on chatbots in recruiting specifically are object of this investigation. In a similar approach, Dahm and Dregger (2019) researched on a construct dealing with the fear of substitutability by the technology of artificial intelligence and found that the participants – students in their case – tend to think that AI will not substitute humans and that they do not predict to be substitutable in their own occupational activities but rather see it as a way to facilitate labor. Chatbots as a communication-focused automation technology represent an interesting topic to research the aspects of job-related automation concerns, for example on an ethical, legal, and social level, on.

2.4 Chatbots in Recruiting

Where in former times, company interaction was characterized by one-way communication, it is now shifted online and following a conversational approach (Rowley, 2004). When computer communication commenced, inserting input into computer systems via keyboards was novel and people needed to adapt to this new kind of conversation. Today, digital messaging is a standard procedure performed by most of the adult population in the developed world – conducted in a short and asynchronous way executable with several dialogue partners at once (Dale, 2016), which is now also performed with automated computer systems. Thus, vastly different conversations and service availments previously conducted via different websites or apps now merge into actions undertaken with the same natural language interface (Følstad & Brandtzæg, 2017). An automation technology allowing for digital interaction in natural language is the one of chatbots. Chatbots – also called (machine) conversation systems, virtual/digital agents, dialogue systems or chatterbots for example (Bayan A Shawar & Eric Atwell, 2007) – are topical and popular technological systems (e.g., Hien, Cuong, Nam, Nhung, & Thang, 2018; Schikora, Galster, & Högerl, 2020). Before examining their potential for implementation into recruiting processes, the term will be defined, delimited and technical foundations will be presented.

2.4.1 Definition of Chatbot

There are different kinds of bots: For one, there are chatbots, which are examined within this thesis. Tsvetkova, García-Gavilanes, Floridi, and Yasseri (2017) divide bots according to the tasks (1) information collection, (2) action execution, (3) content generation, and (4) human emulation. Other categories are web crawlers for search engines, content-editing bots, which can be integrated into online collaboration communities, and spambots compromising social media communication for example (Tsvetkova et al., 2017). Chatbots differ from bots in general, which can be linked together to botnets in order to be coordinated at large scale, often with malicious motivations concerning attacks for example (Radziwill & Benton, 2017). While initially invented and mostly deployed with good-natured intentions, this does not mean that chatbots are immune to misusage – they can be employed in a harmful fashion as well, for example for election propaganda and manipulation (Radziwill & Benton, 2017).

Regarding their role within process automation, chatbots belong to the software bot category of digital assistants (Horváth & Partners, 2018). As depicted in *Figure 2.2*, they are characterized by a high degree of automation as well as a rather high process complexity. While chatbots in the form of digital assistants are already performing on a high-level complexity and automation levels, autonomous agents are able to take over even more complex tasks and thus automate key functions, which chatbots are not capable of substituting human labor from yet. This potential can be exploited by integrating complex functionalities such as natural language processing (NLP) and context recognition for example.

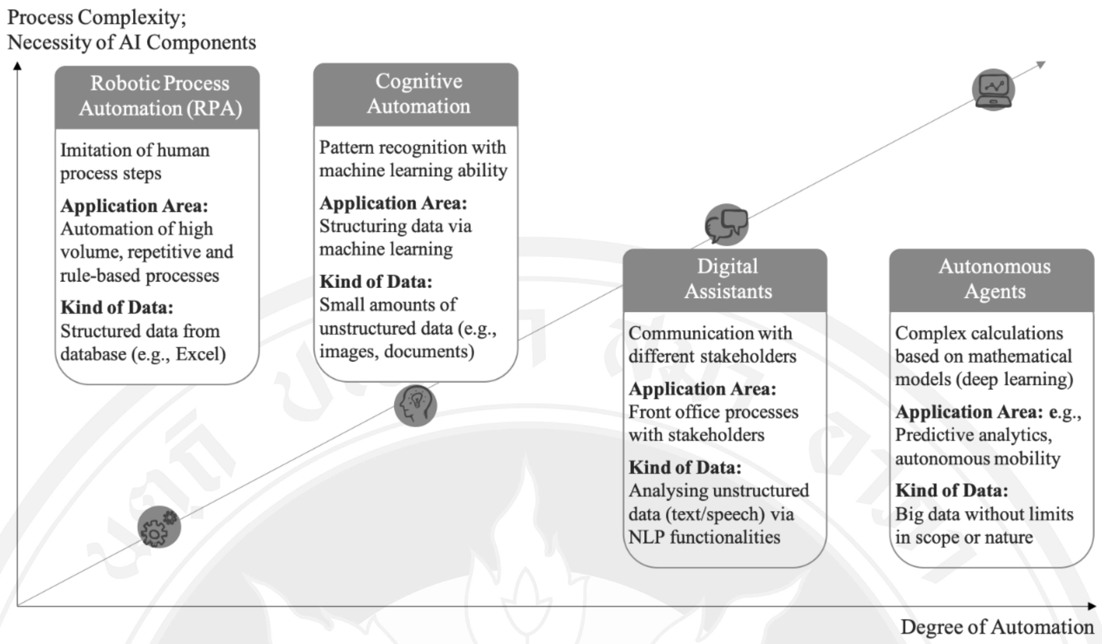

Figure 2.2 The Four Kinds of Bots for Process Automation

Source: Own illustration based on Horváth & Partners (2018).

Chatbot as a phrase comprises the terms chat, referring to the verb talking and bot as an abbreviation of robot (Stucki et al. 2018). They are conversational programs for effective interactive question-and-answer processes via interactions with human users based on pattern matching or artificial intelligence techniques and natural language processing methods (Eißer & Böhm, 2017; Mittal, Agrawal, Chouksey, Shriwas, & Agrawal, 2016; Quarteroni & Manandhar, 2007; Bayan A Shawar & Eric Atwell, 2007). Instead of the traditional information architecture of searching and finding, chatbots are dialogue-based and follow a logic of questioning and answering (Böhm & Meurer, 2018). The chatbot converses with their users without human intervention (Majumder & Mondal, 2021). One main driver of chatbot development was the users' desire to use their own language to speak to computer systems by expressing their interests, wishes and general queries in a direct and natural way in spoken or written form (Bayan A Shawar & Eric Atwell, 2007). As a specific kind of conversation agents, they refer to a class of dialogue systems. They mimic interactions with humans and are typically not embodied as avatars, humans or humanoid robots (Radziwill & Benton, 2017). One step further goes the field of robotics, where bot structures and algorithms are personified in a humanoid shape conveying additional features such as facial expressions and gestures in the form of avatars for example (Jäger & Petry, 2021). According to Tsvetkova et al. (2017), chatbots are persistent, autonomous and reactive computer programs with continuously running code and the possibility of self-activation in the form of individual decision-making and context perception as well as adaption. Schumaker, Ginsburg, Chen, and Liu (2007) make a further distinction between chatbots and dialogue systems: While according to them, chatbots only mimic conversations without profound understanding, dialogue systems are based on natural language processing and offer more elaborate automated conversation (M. J. Pereira, Coheur, Fialho, & Ribeiro, 2016; Schumaker et al., 2007). However, this thesis ascribes those intelligent attributes to chatbots in general. In contrast to general computer-mediated communication, chatbot communication is not technology-mediated but conducted by the computing system itself. Chatbots comprise the two essential features naturalness of interaction and the circumstance of sharing knowledge space with both the system and the user holding specific details so that both need to interact to form a solution for the user's problem (Morrissey & Kirakowski, 2013).

In short, a chatbot can be defined as a "computer program designed to simulate conversation with human users, especially over the internet" (Drift, 2018, p. 6). While this definition serves as a broad description of chatbots and allows for an inclusion of different kinds of chatbots, several researchers distinguish chatbots as text-based conversational agents from voice-based and -activated personal assistant such as the famous examples Alexa (Amazon), Siri (Apple) or Google Now (Dale, 2016; Lester, Branting, & Mott, 2004; Radziwill & Benton, 2017).

Table 2.4 Chatbot Definitions in Literature

Author	**Year**	**Definition**	**Key statement**
Quarteroni/ Mandandhar	2007	*"Question answering (QA) systems can be seen as information retrieval systems which aim at responding to natural language queries by returning answers rather than lists of documents."* (p. 83)	**Question answering** in **natural language**
Shawar/ Atwell	2007a	*"A chatbot is a software system, which can interact or "chat" with a human user in natural language such as English."* (p. 89)	**Interaction**/chatting in **natural language**

Author	Year	Definition	Key statement
Schumaker et al.	2007	*”Dialog Systems can be divided into two main groups* […]. *The Theoretical or High-level systems involve symbolic reasoning and a deep understanding of user input. The Performance or Low-level systems forgo syntactic analysis and understanding for a much simpler pattern-matching algorithm.”* (p. 2237)	Distinction of high-level (**natural language** processing) and low-level (simple logic) systems
Morissey/ Kirakowski	2013	*”Conversational agents, or chatbots, are systems that are capable of performing actions on behalf of computer users; in essence, reducing the cognitive workload on users engaging with computer systems. There are two key strategies used.* […] *[T]he use of a set of well-learnt communicative conventions: natural language and the accepted conventional structure of a conversation so that the user does not need to learn artificial conventions (such as* […] *query languages* […]*) The second is enabling the user and the computer to refer to broad shared classes of knowledge* […] [. N]*aturalness of interaction and sharing knowledge space are the two essential features of all conversational agents.“* (p. 87)	Natural **interaction** via **natural language** and shared knowledge space are the two essential features of chatbots
Mittal et al.	2016	*”A chatbot is a software that interacts with humans using natural language processing and pattern matching techniques to understand questions and give relevant answers.“* (p. 1055)	Understand questions and interact via **natural language** processing and pattern matching
Pereira et al.	2016	*”These are text-based services which let users complete tasks such as checking news, organising meetings, ordering food or booking a flight by sending short messages.* […] *Chatbots are a kind of bots that emulate user conversations. Their effectiveness very much depends on focusing on a specific domain.“* (pp. 912-913)	**Text-based** bots emulating conversations in specific domains
Radziwill/ Benton	2017	*”Chatbots are one class of intelligent, conversational software agents activated by natural language input (which can be in the form of text, voice, or both). They provide conversational output in response and, if commanded, can sometimes also execute tasks“* (p. 25)	Processing of **natural language** input in **text**, speech or both providing output or **task execution**
Drift et al.	2018	*”A computer program designed to simulate conversation with human users, especially over the internet.“* (p. 6)	Conversation simulation
Feine et al.	2019	*”Chatbots are software-based systems designed to interact with humans using text-based natural language and have attracted considerable interest in online service encounters.“* (p. 24)	**Text-based** interaction using **natural language**
Majumder/ Mondal	2021	*“A bot is considered to be an effective communication system which can be used among the employees as well as customers for performing some communication-oriented works within an organization without any human intervention.” (*p. 1) *“A chatbot is a software that helps to make the conversation easy with a user with the help of artificial intelligence (Dahiya, 2017). Chatbots use natural language with the help of messaging applications, mobile apps, websites, telephone etc. (Jain, Kumar, Kota, & Patel, 2018).”* (p. 2)	Conduct of communication-oriented tasks in messaging applications without human intervention while using artificial intelligence features

Table 2.4 summarizes the different types of definitions for chatbots leading to the definition chosen for this research. This thesis follows the distinction by Radziwill and Benton (2017) and Feine, Morana, and Gnewuch (2019) and defines chatbots as a mainly text-based form of cognitive systems. This is in line with current research that found text-based to be well-preferred over voice-based chatbots (aiaibot, 2021).[13] Thus, in this thesis, chatbots are defined as follows:

> Chatbots are text-based, non-embodied conversational systems for human-computer dialogue purposes allowing for an intuitive use of natural language for inquiries providing an answer to a question raised or initiating a requested action.

Hence, as opposed to voice-based or strictly rule-based non-natural language-based assistants, which mainly serve purchase processes and mimic conversations, chatbots are suitable of mapping moderately complex processes processing potentially unexpected natural language input and not just providing textual answers but also the possibility to initiate an action.

As visible in Figure 2.3, the most common appellation for chatbots[14] is chatbot itself, followed by chat bot with a hyphenation, which once again underlines the topicality and relevancy of chatbots (Google Trends, 2020). Accordingly, the term "chatbot" is chosen to be utilized predominantly throughout this thesis in accordance with the consolidated definition given above.

[13] Survey regarding the relevancy and perception of chatbots by aiaibot in cooperation with ZHAW and PIDAS AG (n = 910 end users from Germany, Austria and Switzerland).

[14] There are many different terms utilized in this context, which are chatbot, dialogue system, recruiting chatbot, cognitive system, virtual/digital assistant and conversation agent/program – referring to uniform or technologically slight variations of the system (incomplete listing; e.g., Schumaker et al. 2007; Radziwill/Benton 2017; Kreuzmann 2018; Alexandre et al. 2018).

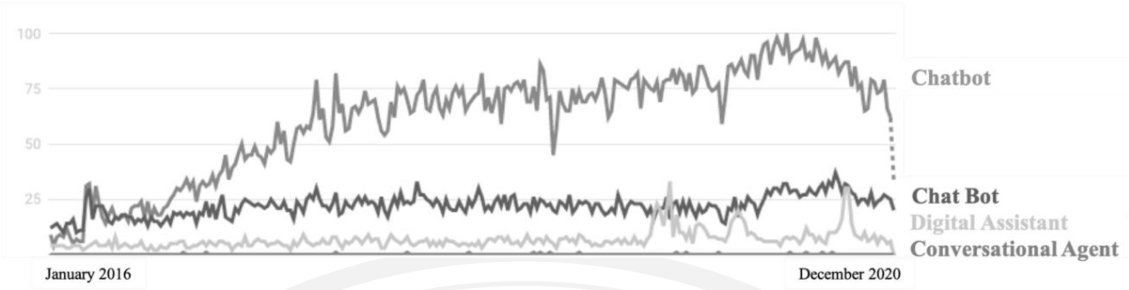

Figure 2.3 Google Trends Global Chatbot Denotation Comparison
Source: Google Trends 2020.

Central to chatbot conversations is the dialogue between the system and the human interlocutor. Chatbot dialogues consist of different segments. One is greeted by the chatbot with a welcoming message upon which the system offers one an introduction and an explanation of the possible kinds of conducible tasks or dialogue strings. Normally, the chatbot is then confronted with a question posed or a task demanded by the human inquirer (Stucki, D'Onofrio, & Portmann, 2018). In the actual conversation, the chatbot either pursues the goal of solving a problem or to successfully chat with the human conversation partner for his entertainment. In the end, the dialogue usually concludes with a farewell message by the chatbot. Regarding the content of the conversation, the chatbot aims at understanding the intention the human interlocutor has when talking to it as well as to sufficiently specify this intent by means of identification of the associated entities. While intents are defined as the purpose or objective of the inquiry posed by the human enquirer, entities are the contextual information given around the intent such as the desired time or date as well as the identity of the enquirer for example (Stucki et al., 2018). Adamopoulou and Moussiades (2020) describe intent mapping as a mapping between the user's input and the corresponding action of the chatbot. This information is crucial for the retrieval of the correct answer from the database and thus the satisfaction of the inquirer. In case of detected ambiguity or a misunderstanding, the chatbot demands a rephrasing of the enquiry.

2.4.2 Technical Foundations of Chatbots

A popular distinction industry experts utilize to describe chatbots are the two kinds of bases: Rule-based chatbots and generative chatbots offering natural language-based conversations, potentially based on natural language processing. In this section, the specifics of the chatbot setup are discussed as well as the general ecosystem.

2.4.2.1 Chatbots Complexity Levels

Chatbots conduct dialogues using natural language (Dale, 2016; Lester et al., 2004). By offering ubiquitous and thus time- and location-unbound services, they hold the potential to not only help to reduce the overall process (e.g., recruiting) costs, but also to extend the overall communication offer by digitalizing it and making it available in an omnipresent way.

Elliot, Baker, and Revang (2020) distinguish three kinds of chatbots based on their complexity: (1) low complexity chatbots for simple requests for pre-defined answers or actions in limited domains, (2) complex dialogue chatbots for larger scopes with multiple backend system integration possibilities, and (3) contextual chatbots with advanced architectures allowing the system to anticipate what the approaching human needs and wants requiring enormous efforts and a skilled team of specialists, which are relatively rare today. Hien et al. (2018) as well as Adamopoulou and Moussiades (2020) translate this logic into three technological states by labelling chatbots as either (1) rule-based offering services and dialogues of low complexity based on a predetermined set of rules, (2) retrieval-based relying on various available resources via APIs for a more comprehensive response selection, or (3) generative for context-specific inquiry handling of higher complexity. They offer either structured conversations in the rule-based – thus predefined and scripted – approach while generative chatbots enable unstructured, non-learned parts in the dialogues (Ayanouz, Abdelhakim, & Benhmed, 2020).

Rule-based approach: Pattern matching rule bases were the starting point of chatbot development with simple keyword matching techniques mapping users' input to database information (Bayan A Shawar & Eric Atwell, 2007). In this retrieval-based pattern matching approach, keywords, word roots and synonyms are searched for within conversational input while foregoing real understanding of the content. Prior to actual dialogues, such snippets are anticipated and predefined and written down in code to build possible conversation flows for future question answering (Dahlbäck, Jönsson, & Ahrenberg, 1993; Deryugina, 2010; Guerin, 2011; Reshmi & Balakrishnan, 2016). Rule-based pattern matching offers deterministic responses (Radziwill & Benton, 2017). Hence, no novel or non-domain output can be established as the chatbot only draws from a choice of predefined answers or statements. It may include natural language understanding features. Such simple, rule-based chatbots utilize menu structures as main conversation procedure. This way, the chatbot navigates through the conversation by solely offering pre-defined answer options such as yes/no, buttons for topics 1 to n or certain emojis for example. Rule-based systems can be seen as simple and cost-efficient solutions. However, the rules are sometimes not easily definable (e.g., more than one solution can be correct) and such systems cannot find solutions for novel or unexpectedly formulated problems. They offer no solutions for complex inquiries. In the future, Følstad and Brandtzæg (2017) predict chatbots to more and more rely on sophisticated natural language dialogues and thus make menu structure interaction mechanisms, for example via buttons, more and more redundant.

Generative approach based on AI: Chatbots allowing for more sophisticated natural language conversation contain features of artificial intelligence. Artificial intelligence with its increasingly improving processing power enables technology to conduct more and more tasks autonomously by supplementing physical machine performance with mental thinking and learning abilities (Heinen et al., 2017). It describes the automation of human thinking in the form of decision making, problem solving and learning (Bellman, 1978). AI enriches chatbots in a way so that they can analyze input and handle dialogues more efficiently than strictly rule-based chatbots. They also base on rules, but offer more. Semantic analysis for example enables an understanding of the meaning of words and texts by computers and a predictability of patterns (Vowinkel, 2017). Generative dialogue systems based on artificial intelligence go beyond the predefined logic of rule-based approaches by producing unique answers via the assembly of knowledge and analysis of the present context within learning processes based on algorithms (Guerin, 2011). This more complex approach is tailored to interactions with humans because unexpected written input in natural language can be understood and processed. Here, the inquirer steers the conversation by openly describing his intent without the stricter regulations and pre-definitions of rule-based chatbots. For sophisticated systems, this may result in easier interaction and facilitated utilization (Eißer & Böhm, 2017; Panetta, 2016). However, current chatbots only contain a weak form of artificial intelligence – features surpassing easy NLP functionalities are beyond the current state-of-the-art of AI-based chatbots (Schikora et al., 2020). Sophisticated NLP allows for elaborate question answering and is defined as the performance of natural language understanding and in turn the generation of natural language (Chandrasekar, 2014). Fields of applications other than NLP features for intent matching and answer generation lay outside of today's utilization points of AI within chatbot technology.

Kassibgi (2017) distinguishes three development stages for chatbots classifying them into (1) strictly rule-based ones solely processing input that exactly matches the predefined patterns, (2) rule-based chatbots incorporating AI features to classify a limited amount of arbitrary input, and (3) chatbots mostly based on AI able to learn new input classes and generating unique output.

Ayanouz et al. (2020) give an overview regarding the current technical limitations of chatbots which keep them from a highly complex, human-like natural performance:

1) Currently, fixed rules with entirely straightforward machine learning techniques are applied allowing the chatbot to understand natural language within a certain predefined domain but no capability of processing or answering entirely new topics and concepts
2) The systems' accuracy is limited to the domain and the dialogue strings they have been designed for; unexpected questions or sudden subject changes result in unsatisfactory responses
3) No ability to detect intent or entities in case of grammatical errors (as opposed to spelling mistakes), ambiguity or unknown language structures due to foreign translations for example
4) Non-recognizability of sentiment and emotions (however, first solutions are introduced enriching chatbots with sentiment analysis features such as IBM Watson (IBM, 2021))

As a conclusion, there are two logical foundations of chatbots in the form of a simple rule basis or a more complex yet narrowly defined structure. The necessity for one, for the other or even a combination of both as well as the degree of complexity depends on the specific use case and kind of questions or tasks the system is developed for. However, most chatbots currently on the market are rule-based (e.g., Meurer et al., 2019). As a consequence, mainly narrow and simple tasks are transferred to chatbots for now such as FAQ scenarios. This in turn requires an elaborate database filled with as many input and output variations as possible in order to offer the user a relevant tool for problem solving.

2.4.2.2 Chatbot Components and Ecosystem

Chatbots can be built in various ways mapping different levels of conversation complexity. At their core, they consist of mainly three parts: a knowledge base, a chat engine in the form of an interface and an interpreter program (Reshmi & Balakrishnan, 2016). The interface is presented to the users in different ways: Chatbots can be integrated into (company) websites, apps or messengers such as the Facebook messenger or WeChat for example. Furthermore, they can be deployed in developer productivity tools such as Slack or GitHub (Radziwill & Benton, 2017).

Figure 2.4 Exemplary Conversation Snippet of a Recruiting Chatbot

Source: Own illustration.

In the example shown in Figure 2.4, the chatbot is implemented to help the candidates find a job offer from the job pool of a company that suits them best. The process of searching for a job is translated into a dialogue sequence, which is navigated through by the chatbot. Questions regarding the kind of profession and the focused job title as well as the location the inquirer desires to work at determines the job offers he is shown as result of the conversation. In terms of interpreting, the system extracts the essence of nature language input such as statements and questions in the form of intents as well as the necessary entities to specify the intent. The ability to integrate this specifying information into their understanding and output generation is a highly important aspect of well-performing chatbots. Without this capability, many application points are omitted – in the context of recruiting interviews for example, asking for the salary of a certain position can only be answered correctly if this position is known to the chatbot (Adrion, 2017). This setting into context and linking of information also eradicates ambiguities within the input (Stucki et al., 2018). In the exemplary recruiting chatbot conversation snippet of Figure 2.4, the user's intent is to find a job while the entity of the first user input is the general profession (software developer) the position is searched in.

A typical chatbot architecture integrating the main parts of the above-mentioned elements is summarized in Figure 2.5, incorporating the two views of the frontend directed to the candidates and the backend facing inwards the chatbot system.

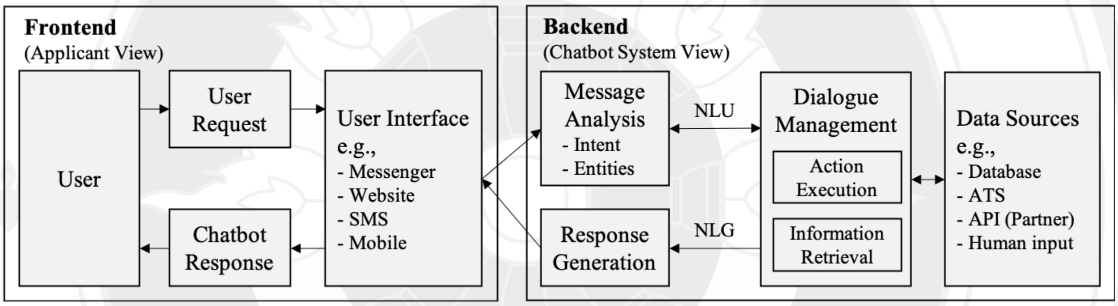

Figure 2.5 Basic Components of Chatbot Architecture
Source: Own illustration based on Adamopoulou and Moussiades (2020).

The user accesses the system via one dedicated (graphical) user interface (GUI) such as a chat widget or window implemented on the company's website and states his inquiry by submitting textual or voice-based language input. Following the stated definition of chatbots, a text-basis is assumed here. This input is then processed by the chatbot in the form of a message analysis consisting of a classification of the intent and an information or rather parameter extraction of the remaining contents to yield the necessary entities. Sophisticated chatbots offering unstructured conversations not only match the input to the predefined database but perform natural language understanding (NLU) in this step. This way, contents are made understandable and processable by the automated dialogue system while allowing the inquirer to use natural language, which he is accustomed to through interhuman interaction. NLU, broken down into analyses to identify the structure, logic, intent and the entities of the input, is the first part of natural language processing, which also encompasses natural language generation (NLG) for the output the chatbot issues (Ayanouz et al., 2020). Subsequently, the course of action – information retrieval/generation and/or action – is determined in the dialogue management component of the system based on the understanding of the input the system acquired, which also manages and updates the context of the current conversation and the dialogue itself by requesting missing information or asking follow-up questions for example (Adamopoulou & Moussiades, 2020). It is also referred to as decision engine and contains the underlying rules or algorithms the chatbot is built upon (Ayanouz et al., 2020). The output generation and distribution or the action (e.g., distribution or opening of a hyperlink, booking of a time slot or ticket) ensues either directly or by first integrating some kind of (user) history or data from a database. In order to generate output, the chatbot either accesses a dedicated database, is fed by data from an API with dedicated partners or incorporates NLG functionalities. NLG generates an understandable, linguistically correct response (Ayanouz et al., 2020), that is given to the human inquirer through the same interface he placed his inquiry in.

Companies can choose to build them in-house or to give such a project to third-party companies (Nguyen, 2017). In regards to self-construction, the development and implementation of chatbots becomes more and more straightforward (i.e., reduced or ceased coding effort) with the systems themselves gaining in power (Radziwill & Benton, 2017). There are tools enabling chatbot development, enhancement and deployment with specific features for the different most commonly used messaging platforms such as Pandorabots or the Microsoft Bot Framework (Dale, 2016; Microsoft, 2020; Pandorabots, 2020).[15] After creation, the bot testing process is split between service providers (inputs, outputs, action execution) and clients (ease of use, effectiveness of task accomplishment) (Radziwill & Benton, 2017) as per common practice in software development.

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[15] There are various comprehensive enlistings of contemporary chatbot companies and tools, for example provided by AIMultiple (2021) or (Trusted, 2021).

2.4.3 Chatbot Features and Fields of Application

Theoretically, chatbots encompass many useful traits and specific advantages compared to other means of interaction. The following listing is to be seen as a summary of important characteristics rather than an exhaustive account:

Chatbots offer

1) agility (IBM, 2017)[16],
2) an ubiquitous, time- and location-unbound, way of interaction (Majumder & Mondal, 2021),
3) a perceived quicker/instant question answering than apps or e-mails and the offering of 24-hour service seven days a week (e.g., Drift, 2018; Dudler, 2020; Personalmarketing2null, 2017),
4) an operating principle as an interface between information and users with the sent-out information being characterized by a consistently high delivery speed and quality (Stucki et al., 2018),
5) subsequently an inexhaustible and theoretically limitless labor and data processing capacity of multiple dialogue partners and inquiries at once (Reshmi & Balakrishnan, 2016),
6) a deployment in the form of already familiar and learnt interfaces of messaging platforms, which incurs only a small learning curve and foregoes any additional installations or compulsory log-ins (Jain et al., 2018; Personalmarketing2null, 2017),
7) savings in human agent employment costs (e.g., Dudler, 2020; YouGov, 2017),
8) a transfer of all decision-making power to the human inquirer, in this case applicants through the text-based approach where he is anonymous, can prepare his answers, can refer to conversations strings as they are saved in the dialogue window, and can decide about the length of as well as his degree of involvement in the conversation (Dudler, 2020).

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[16] Part of the IBM Institute for Business Value and IBM Smarter Workforce Institute Study (n = 400 Chief Human Resource Officers [CHROs]) concerning the assessment of their opinion on cognitive computing in the form of an information understanding, analysis result reasoning and knowledge/logic learning systems.

For sophisticated chatbot solutions, several more qualities supervene such as

9) the competency to understand and generate, thus process, natural language (NLP),
10) the aptitude to learn and thereby enhance its own knowledge and capabilities (machine learning),
11) the capability to actively engage in contextual conversations,
12) the skill to assess not only the meaning of natural language input, but also the unexpressed concomitant conversational circumstances such as components of the users' emotional state, personality, attitudes and behavior(al intention) can be esteemed,
13) a fact-based, emotionless deciding process free from bias (e.g., unconscious bias describing the involuntarily and undesirably occurring subjective opinion recruiters form when handling application cases (Dudler, 2020)) as opposed to the humans' subjective decision-making (Groß & Gressel, 2016; Corinna Maier, 2018) resulting in decisions with reduced discrimination based purely on job-relevant skills and capabilities.

Advanced recruiting chatbots could contain features such as individual screening questions for an improved job-matching or CV-filtering (Dudler, 2020).

Within real utilization scenarios, limiting effects and circumstances require consideration such as technological restrictions, data security issues and the users' overall willingness to interact with chatbots based on their perceived level of trust, past experiences and requirements regarding usability for example. Thus, a distinction is required between the technical possibilities/restrictions and appropriable features in real usage scenarios, which forms the boundaries of chatbot application and will be part of this study.

Chatbots are versatile and offer various fields of application in business and commercial context as well as for entertainment purposes (Reshmi & Balakrishnan, 2016). They can automate external communication between companies and stakeholders such as customers, but also serve as company-internal assistants (Czarnecki et al., 2019; Völkle & Planing, 2019). As an innovative dialogue interface, they can complement a company's digital communication strategy regarding the importance of communicational relationships to its stakeholders if implemented with the consent of the involved employees. In theory, any desired field of application can be created for a chatbot (Kusber, 2017), whereas careful consideration is needed when choosing to implement a chatbot into a process as use cases need to fulfil certain criteria to be fit for chatbot integration (Meurer et al., 2020). There are innumerable examples; a comprehensive overview of examples regarding text- and voice-based chatbots for different industries and processes is provided by Stanoevska-Slabeva and Lenz-Kesekamp (2018). However, according to a study by Brandtzaeg and Følstad (2017),[17] there are four main categories of motivation for chatbot utilization or rather application occasions: (1) Productivity (convenience, assistance, information retrieval), (2) entertainment (fun to use), (3) social/relational (strengthening of social interaction) and (4) novelty/curiosity (investigation of the system's capabilities). The most relevant motivation with the highest practical implication is the assistance in productivity. Related to productivity enhancement, Mason (2017), Conversation Offering Manager at IBM, divides chatbots into three distinct task types for deployment: (1) Support chatbots within one specific domain and thus context-sensitive environment, (2) skills chatbots reacting to commands such as the ones operating smart home applications, and (3) assistant chatbots, which execute both the role of a support and a skills system. The kind of chatbots regarded in this thesis can be grouped into the class of assistants for productivity enhancement.

More and more services are being partly automatized via chatbot technology (Seidl, 2020). However, chatbots can unfold their value potential especially in processes and for tasks characterized by interactional, repetitive, recurring or somehow onerous (e.g., time-consuming) procedures (Dudler, 2020; Majumder & Mondal, 2021; Sengupta & Lakshman, 2017). According to Kusber (2017), ideal scenarios for assisting chatbots are reoccurring tasks in the form of first level support (handling of simple inquiries and redirection of complex ones). In their position of easy-to-use messaging interfaces, chatbots can be utilized as a substitute for FAQs (e.g., Laurim et

[17] Academic study regarding motivational reasons for chatbot usage in general (n = 146).

al., 2021) and be utilized like search engines such as Google search: Compliant with the changed user behavior of questioning instead of searching (Eißer & Böhm, 2017), they can offer direct (instant and tailored) answers instead of links provided by a Google search for example and generate narrowed-down answers other than suggestions aggregated from different sources like Google searches do (Bayan A Shawar & Eric Atwell, 2007; Stucki et al., 2018). The aspect of natural language interaction offers business potential and is one of the reasons for increased chatbot implementation and utilization (McTear, Callejas, & Griol, 2016). According to Research and Markets (2021), the banking and healthcare sectors are among the most popular industries and one relevant use case is complaint resolution with 90 percent of the queried business reporting faster task accomplishments utilizing chatbots. During the outbreak and stretch of the global COVID-19 pandemic, chatbots are increasingly implemented to covey information and to reduce customer query workload for the now less available customer service employees (Research and Markets, 2021).

In the field of recruiting, chatbots can offer a more direct, comfortable and appealing way of application on every possible chat platform such as messaging services or the company's own career website (Dudler, 2020). Furthermore, it expands the range of communication interfaces and touchpoint possibilities for companies that reach out to their candidates.

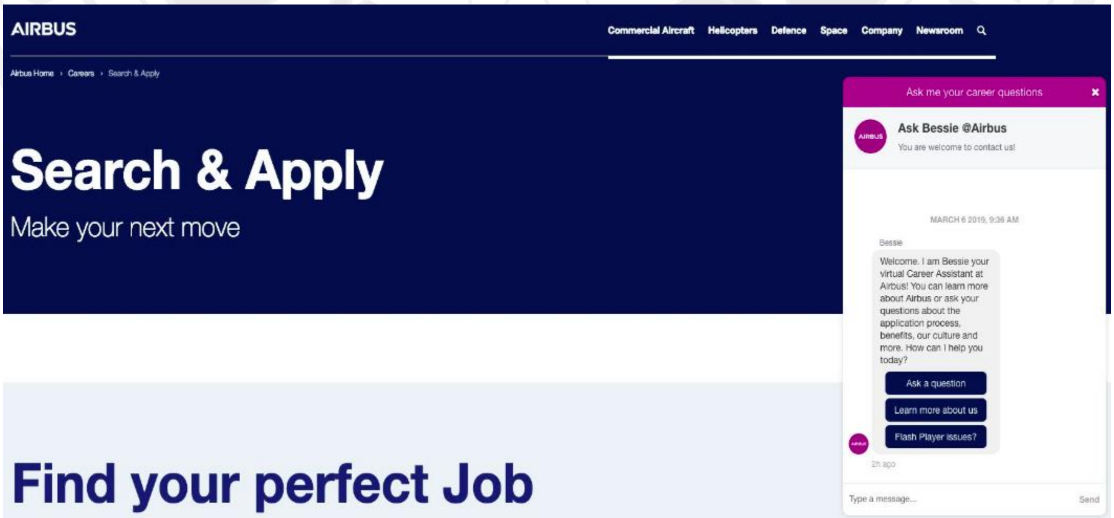

Figure 2.6 Exemplary Assistant Chatbot Bessie of Airbus

Source: Airbus (2020).

Figure 2.6 shows the practical example of Bessie, a recruiting chatbot for visitors of the Airbus careers site (Airbus, 2020; Dudler, 2020). It is implemented to welcome interested candidates and to answer their most frequent questions to facilitate their application choice and process. On the recruiters' side, the chatbot is supposed to reduce support tickets (Dudler, 2020) in terms of individual questions the recruiting team needs to answer. According to Airbus and Jobpal (2020), Bessie accounts for more than 12,000 interactions with potential candidates each month. In rush-hour times, the chatbot receives up to one message per second (Dudler, 2020). Especially helpful in times outside regular working hours and regarding frequently asked questions, the chatbot responds to 74 percent of all inquiries automatically thus forwarding only one fourth of the queries to a human second-level support team (Airbus & Jobpal, 2020). Hence, it reached its goal to decrease the number of inquiries and affiliated support tickets issued to the recruiters.

2.4.4 General Chatbot Implementation Stages and Status

Chatbots are no new technology (i.e., ELIZA by Weizenbaum (1966)) and no new phenomenon in companies (Rozumowski, Rellstab, & Klaas, 2019), but the establishment and improvement of the web as the universal communication channel, reliable linguistic functionality, availability (i.e., via cloud computing), computing and storage capacity enabling dialogue service delivery to large audiences as well as machine learning intelligence creation increased its attractiveness (Lester et al., 2004; Radziwill & Benton, 2017; Stucki et al., 2018). The first chatbots did not have sufficient technological possibilities to create humanlike behaving systems but rather acted mechanically or offered inadequate results, which initially lead to poor acceptance of computer-based dialogue systems (Stucki et al., 2018): There was a first peak in popularity in the beginning of the 2000s (e.g., ALICE between 1995 and 2000 (Wallace, 2003); SmarterChild from 2000 (TechnologyAdvice, 2002); GooglyMinotaur from 2001 (CNET, 2002); Ultra Hal from 2005 (Zabaware, 2022); Sergeant Star from 2006 (Chatbots.org, 2022)) because of advances in speech recognition technology and dialogue modelling frameworks (Dale, 2016). However, several chatbots were discontinued because of technological insufficiencies (Adrion, 2017). Accelerators for the new wave of popularity now are the recent increase in computational linguistics and AI efforts for human language parsing, understanding and modeling, which had not been too successful over the past fifty years but is on the rise now (Hill, Ford, & Farreras, 2015; Lester et al., 2004). Natural language conversations with technological systems in the form of short and asynchronous dialogues became mainstream (Dale, 2016; Følstad & Brandtzæg, 2017). A concomitant phenomenon is an increase in messaging services in popularity and user numbers (Gentsch, 2017). Messaging surpassed traditional social networks; a trend already visible in 2015 (BI Intelligence, 2016): While the number of active users of the five biggest messaging apps WhatsApp, FB Messenger, WeChat, QQ and Twitter worldwide adds up to 5.12 Bn., the five biggest social networking apps only hold a number of 4.58 Bn. active monthly users in 2020 (Hootsuite as cited from Datareportal, 2020). Conversational systems live off messaging platforms and with increasing messaging app activity, chatbots gain relevance as a way of facilitating messaging app usage (Nguyen, 2017). Hence, the platform technology requirement which exists for chatbot deployment in terms of an environment to present its interface does not pose a threat nowadays because of the high user bases of the most popular messaging apps and social networks. Certain target groups in Germany already expressed the willingness to utilize chatbots as means of communication with companies (e.g., CHRIS, 2017a). Businesses commence implementing chatbots for communicating with their stakeholders (Drift, 2018).

According to Kusber (2017), chatbots are in the same stage now that the world wide web was in 1995 or smartphone apps in 2008: a certain section has been reached but the technology is far from perfect (Kusber, 2017). Drift (2018) found that 15 percent of US adults consciously utilized a chatbot and 38 percent made use of an online chat as means of communication with a company during the past twelve months. With the increase in NLP functionalities, such automated dialogue systems are more and more categorized as human-like conversational partners as perceptions of humanness are attributed to them (Rzepka & Berger, 2018). For the case of smart personal assistants, NLP-enabled chatbots focusing on user assistance, Zierau et al. (2020) state that “[…] the boundary between man and machine becomes increasingly blurred from a user perspective […]”. (Zierau et al., 2020, p. 102) Consequently, although half of the

Germans state that they would notice whether they speak to a human or a chatbot (YouGov, 2017),[18] users might not always be aware of the fact that they conversed with a bot. Hence, the amount of chatbot users might differ and by that be even higher than stated by Drift (2018) (Cummings & Kunzelman, 2015).

While there were at least 100,000 chatbots implemented in the Facebook Messenger as most popular implementation platform at the time in 2017 (Johnson, 2017), the number rose to more than 300,000 chatbots on Facebook by 2018 (Johnson, 2018), which to the knowledge of the author is the latest published number of chatbots. A reason for this accumulation is the high estimated chatbot market volume: According to Research and Markets (2021), the global chatbot market was valued at USD 17.17 Bn. in 2020 and is anticipated to become USD 102.29 Bn. by 2026. Furthermore, a large savings potential is seen with a decrease in handling time up to 77 percent (Deloitte, 2019). These high figure estimations are backed up by the behavior of technological key players (e.g., Facebook, Google, Microsoft and Telegram), since they have been investing in the development of this technology for years now and also currently work on large-scale AI-bot projects (Nguyen, 2017).

Looking at the German market, people prefer human service agents for counselling or complaints but would be inclined to make use of digital contact possibilities for information retrieval, reservations and administrative inquiries for example according to (PIDAS, 2017).[19] Almost 85 percent of the respondents state that they can imagine using chatbots as such a digital contact possibility (PIDAS, 2017). However, in the study by YouGov (2017), it became apparent that Germans are not used to the term and idea of chatbots yet: 69 percent of the respondents stated that they have never heard of the word and 89 percent did not know the concept behind it (YouGov, 2017). This state seems to have changed: While in a 2018 study by aiaibot, only 40 percent of the respondents had already interacted with a chatbot, it has become 63 percent in 2021 (aiaibot, 2021). Nine percent of companies offer chatbots as of 2020

[18] 2017 Chatbot Communication Study by YouGov (n = 2,000 German adults [≥ 10 years old], conducted from 10.07.-17.07.2017 in Germany).
[19] 2017 Benchmark Study by PIDAS and ZHAW (n > 3,500 German end consumers; n = 100 German Service Experts from companies of different industries in Germany).

(PIDAS, 2020).[20] In general, Germany has a relatively low number of sites offering chatbots in relation to its population being on 7th rank (5.8 chatbots/1 Mio. inhabitants) behind the US (47.7 chatbots/1 Mio. inhabitants), Australia, the UK, the Netherlands, Canada, and France (Boomtown, 2019).[21] This shows that the German market offers untapped potential for the proposition of chatbots. In terms of interaction, chatbots are utilized mostly on websites as opposed to apps and while the experience is mostly perceived as neutral (42.3%), many users had positive encounters with the system (35.8%) so far and appreciate the easiness of the interaction (aiaibot, 2021).

2.4.5 Usage and Role of Chatbots in Recruiting

Companies are evolving around the constant changes in technology and the according implications, which causes top managers to attribute more relevancy to those technologies as an important external influence on their firms and predict a higher digital interaction with their stakeholders (IBM, 2016).[22] It affects businesses as well as the roles of management for example (Nell, Foss, Klein, & Schmitt, 2021). The large variety of interaction also applies to recruiting and the application possibilities of a company (i.e., via e-mail, SMS, website (form) and instant messaging as most recent communication habit adding to the traditional means in the form of written application submitted in person or postally) caused a change in the application process. Where in former times, the process was predefined and limited to the traditional submission channels, candidates can now benefit from a multitude of options. Recruiting is regarded as an exemplary field for chatbot implementation as it is key for a company's approach to growth, innovation and competitive advantage (B. Hmoud & Várallyai, 2019) and thus one of the main and most relevant business processes for a company.

Within electronic recruiting, there are the problems of (1) many – oftentimes congeneric – individually submitted questions incoming prior to and during applications and as well (2) a high amount of digitally submitted applications resulting in intensive recruiting labor in certain industries or for certain kinds of job positions. Task overload might ensue. Recruiters of the Top-1,000 German companies state that

[20] 2020 Benchmark Study by PIDAS And ZHAW (n > 210 customer service experts from companies from Germany, Austria and Switzerland).
[21] 2018 Study by Boomtown (n > 20,000 worldwide businesses utilizing chatbot tools).
[22] 2016 CEO Study by IBM Institute for Business Value (n = 5,247 C-suite executives).

their preferred way of submission is the online form (same for the responding candidates) and least preferred is the paper-based approach (CHRIS, 2017b), so they already demand automation solutions. As an imperative concomitant of technological development, also tasks and steps along the recruiting process become increasingly digitalized and automatized (Mülder, 2018). Chatbots can be a way to automate the problematic, labor intensive interaction with the candidates and the handling of application submissions in order to save time[23] and thus solve the problem of labor intensity through individual candidate inquiries and data (e.g., in the illustrated case of high application volumes for certain job positions such as flight attendants). As means to automatize recruiting processes, they belong to the currently most intensively discussed topics within HR (Adrion, 2017). A current hype is ascribed to job-related chatbots (Schikora et al., 2020). Haufe (2020) found FAQ in recruiting to be one of the two best scenarios for a chatbot in HR.[24] This is in line with the study by aiaibot (2021), which also found FAQ to be the most popular use case for the technology. Intelligent automated dialogue systems in the form of chatbots as means of e-recruiting can take over certain tasks to leave human recruiters to the more strategic part of the process (e.g., Dudler, 2020; Jha et al., 2020; Majumder & Mondal, 2021; Ternès, 2018; Ziebell et al., 2019). This advantage is also seen by HR employees (Haufe, 2020). Junker (2019) found that implementing automation technology in the form of decision-support-systems exploiting information structuring turned human employees towards more complex tasks or resulted in task shifts to other areas of activity.

In recruiting, the two problems of handling of high amounts of information (applications and applicant data points; e.g., Dahm and Dregger (2019)) and producing relevant output for the high number of inquiries (task frequencies of applicant inquiries) are prevalent and need to be addressed. Those problem areas are especially suitable for the implementation of chatbots in its role as automation technology. Recruiting and natural language processing, the basic core of elaborate chatbots, go well together

[23] As mentioned, only 40 percent of the submitted applications are being regarded and further analyzed by recruiters intensively, which is taking around eight minutes of their time with a mere two weeks of processing time until feedback with almost one third of the applicants claiming that they do not get feedback at all (CHRIS, 2017b). According to Magistretti (2017), the number of candidates not hearing back from potential employers after application goes up to 75 percent.

[24] Haufe survey 2020 regarding chatbots in HR (n = 105 employees in HR within different industries).

because of the candidate centricity and communication base of candidate-recruiter interaction (Suciu, Pasat, Balaceanu, Nadrag, & Drosu, 2018). Chatbots for recruiting can be called job bots, recruiting bots or career bots for example ((Kreuzmann, 2018)). However, recruiting-related designations are renounced throughout the dissertation and the term recruiting chatbot is utilized for clarification.

2.4.5.1 Chatbot Applicability to the Recruiting Process

Typically, HR processes and systems are perceived as over-sophisticated by the candidates (Jäger & Petry, 2021). Reasons for that may be outdated processes disregarding state-of-the-art general communication, authentication, or data collection methods. Hence, an important HR aspect is the simplification of processes and services. Digital technologies enable streamlined process perception, for example through simple menus and user interfaces in general. As introduced, one possible way of simplification by rationalization and automation are chatbots. Chatbots may offer companies the opportunity to not only automatize routine tasks like information compilation as mentioned before but to rather support decision making by also contributing to complexity reduction. Elliot et al. (2020) state that human resources offers particular appropriate use cases of apt complexity and sophistication for chatbot deployment. Holtbrügge (2018) states that recruiting methods need to be reliable and at the same time of minimum complexity in the form of time and cost effort. Chatbots as means of rationalization and automation of the digitalized recruiting process can be a tool of support here.

Tech-savvy online goers expect instant 24/7 service and do not tolerate waiting times (Kusber, 2017). The situation of applicants in particular is a similar one: They require fast and relevant information (Corinna Maier, 2018). A reason for this is the development of the interaction approach based on technological advances: 90 percent of the time spent with smartphones is said to be passed in e-mail programs and messaging apps (Kusber, 2017). The messages sent in instant messages are characterized by brevity (Kusber, 2017). According to a Kienbaum study,[25] social media and mobile applications are seen as biggest innovation potentials within HR (Kienbaum, 2016). Large technology companies such as Google, Facebook and

[25] Kienbaum Institut@ISM study 2016 regarding HR within digitization (n = 270 companies and their HR departments).

Microsoft confirm this consideration by predicting that digital interaction will move from websites and apps with graphical user interfaces to messaging platforms like the Facebook messenger (Følstad & Brandtzæg, 2017). Thus, especially younger candidates can be effectively and efficiently approached via (messenger) chatbots because of their seamless, frictionless, ubiquitous and intuitive way of communication (Dale, 2016; Hollmann, 2017) and their potentially higher retention rates. Supporting the recruiting processes, chatbots of some companies can already handle 70 percent of incoming questions from potential candidates (Dudler, 2020; Hollmann, 2017). According to İşgüzar and Ayden (2019), innovative technologies can save up to 80 percent of HR managers' time and increase productivity by up to 300 percent. Chatbots have also been found to help to reduce the time- and cost-per-hire (Majumder & Mondal, 2021). Thus, chatbots could be a feasible way to improve the recruiting process and to take all applications into consideration while shortening feedback time and be a relevant alternative to conventional channels such as e-mail or telephone touch points. They allow for quick interaction while handling the incoming (unstructured) candidate information (Dudler, 2020; Hollmann, 2017; Personalmarketing2null, 2017) and according to Drift (2018), they are already perceived to be faster in inquiry processing.

For successful recruiting in a digitalized HR environment, Semet and Hilberer (2018) suggest that companies shall expand their reach by sourcing potential new employees worldwide in international social networks and to adapt their application processes by dispensing with intricate, cumbersome and complex selection processes while exploiting advanced technological systems. Advantages in speed, accuracy, objectivity and cost-effectiveness are seen in technologically advanced recruiting (Jha et al., 2020). Dudler (2020) states that chatbots can contact candidates, answer their questions, help them with their applications, conduct screening interviews and by that presort the candidate pool, screen the submitted application data, support the onboarding process while being connected to the company's applicant tracking systems. In order to put these potential deployment possibilities to practical use, several other requirements need to be taken into consideration. Prior to deployment, the chatbots need to be trained with a suitable and sufficiently large set of training data in order to establish a neuronal network, which determines the performance quality of the chatbot (Personalmarketing2null, 2017; Teetz, 2018) and tested properly. Human intervention is necessary for chatbot configuration, training and optimization (Majumder & Mondal, 2021). Secondly, the types of candidates need to be chosen for whom chatbots can be a convenient alternative since different audiences have varying application requirements and criteria. While in theory, candidates for all kinds of job profiles can be offered a chatbot, the ones requiring several negotiation loops, being emotionally loaded or requiring loads of soft skills for example are hypothesized to not be as suited for chatbot deployment (for now regarding the current development phase of chatbots) as the ones primarily basing on hard skills. Also, from the applicants' point of view, it is questionable whether professionals for example want to interact with chatbots in such delicate matters as a job transition or might prefer human recruiters in this occasion. However, chatbots are discreet (e.g., Majumder & Mondal, 2021), theoretically free from bias, capable of learning from conversations and might be able to analyze and interpret the individual level of current willingness to take a certain position or to change the job in general for example (Jatsch, 2016). Thus, depending on the development of chatbot acceptance, this concern might diminish.

One fundamental question concerning the deployment of chatbots in recruiting is whether this technology is necessary and beneficial for companies and their HR departments in specific. For every new technology, HR managers need to evaluate its content, the kind of value that forms for employees, managers and customers (e.g., which existing HR processes can be optimized by implementation and how this can be realized), the resulting changes for the value chain architecture and overall structure of the industry on the company it operates in, potential competitors, customers, suppliers and others (potentially) using it. Central to this issue are the perceived pressure to use this special kind of technology and the specific level of applicability of the existing HR processes (Jäger & Petry, 2021). Eventually, both recruiters and applicants need to sense a benefit when utilizing such a system. The benefits of process automation via chatbot technology must be recognized and valued higher than possible implementation limitations by recruiters in order for them to successfully support their work in the recruiting processes. Neglecting the use of new technologies can have negative consequences such as economic disadvantages for the organization (e.g., Schnell, 2008; Schönecker, 1982). Regarding chatbot deployment in companies as such new technology, numerous advantages are notable. Especially in question-answering scenarios, chatbots provide a cost-effective solution (Lester et al., 2004; McTear et al., 2016). Furthermore, support services conducted by humans done for humans take time (Ranoliya, Raghuwanshi, & Singh, 2017). With chatbots, stakeholder interactions can be performed at twice the speed with only a fraction of the expense traditionally spent in the form of staff (Accenture, 2017). However, the success of recruiting chatbot implementation may depend on the specific applicants' readiness to utilize conversational systems (i.e., perceived quality and their potential barriers concerning chatbot application for example because of the complexity of their profession as interaction rejection factor). An additional aspect worth mentioning is reputation – in terms of employer branding, chatbots can be seen as a prestige feature for companies to express their innovativeness and their willingness to adapt to stakeholders' requirements (Brickwedde et al., 2016).

2.4.5.2 Chatbot Use Cases within Recruiting

With the help of chatbots as newly implemented features for electronic human resource information systems, the whole recruiting process[26] can be supported and improved: Examples for chatbot application fields are the first approach, assessments, pre-screening, evaluation of candidates' suitability, application and overall applicant communication (e.g., provision of real-time updates concerning the status quo of the individual application process) for example concerning application recommendations and tips, invitations and also internal processes such as document referral and appointment management (e.g., B. Hmoud & Várallyai, 2019; Personalmarketing2null, 2017; Stone & Dulebohn, 2013). In recruiting, the two problems of handling high amounts of information (in the form of applications and (unstructured) applicant data) and producing relevant output for the high number of inquiries (task frequencies of applicant inquiries) are prevalent and need to be addressed. Main user of the recruiting chatbot is the potential candidate or applicant, who wants to engage in a dialogue with the company he is interested in. While handling the chatbot's content (backend perspective), the recruiter can be relieved of a significant amount of workload by installing recruiting chatbots as automation measures.

[26] The process is defined as a six-step procedure regarding (1) Job profile placement, (2) job search, (3) application, (4) candidate pre-selection, (5) detailed candidate selection, and (6) hiring.

The task assumed to be of highest relevancy for recruiters and most suitable for this study is the one most appropriate and practicable for chatbot conduct, the one the recruiter can choose to let the chatbot handle and the one he is most involved with in his work effort-wise and regarding his closeness to the applicant. Task appropriateness is defined as the ability to construct the process as a dialogue string so that it can be conducted by a chatbot and processed by its component (e.g., language processor, database). Recruiting process steps need to be depictable via communicative, at best conversational interaction between recruiters and other stakeholders such as applicants in order to be suitable for chatbot deployment. Appropriateness is derived from the applicability and exploitability of the beforementioned features that chatbot technology (cf. section 2.4.3) offers beyond the properties of automated systems in general. In comparison to general automation technology, chatbots additionally represent a familiar looking and learnt mode of interaction in the form of a natural language interface between information, which they can convey instantly and with a consistently high level of quality all day, and the user. Sophisticated systems can engage in contextual conversations while taking into account unexpressed concomitant conversational circumstances such as components of the users' emotional state, personality, attitudes and behavior(al intention). Another relevant aspect is the actual applicability of the chatbot-supported use case to the recruiters' daily work: The chatbot's implementation only makes sense in case a large group of recruiters or their taskforce is involved in the task so that a chatbot would induce an effective change in the form of a noticeable increase in efficiency by saving otherwise necessary resources such as time and budget. An analysis is required as to how realistic it is to conduct the task within a chatbot dialogue and how large the size of potential users would be to see whether the transformation of the task into a dialogue string is reasonable. Furthermore, this study considers the recruiter's perspective. Hence, a use case is regarded that concerns him and lays in his direct sphere of influence regarding the actual process step conduct: The recruiter needs to be able to decide on the chatbot utilization or disregard in the instance at hand as opposed to a central decision made by the company's or HR management beyond their possibility of influence. This way, the study can assess the influence of the advantages recruiters see in chatbots concerning them and their work directly and that of the potential associated job-related automation concerns. As a fourth criterion, the recruiter's involvement in the task is assessed: The more the recruiter feels involved in the task regarding his mental capacity, his workload and his connection to the applicants, the more impact potential associated job-related automation concerns may influence his acceptance of the technology.

These considerations are now mapped to the presented 13 touchpoints recruiters and candidates have within the recruiting process, which have been found to be well suitable for automation (cf. *Table 2.3*). As specified, the following aspects are being drawn as criteria for selecting an apt recruiting chatbot use case to regard in the study at hand with a three-scaled evaluation scheme that is applied to the average daily routine of recruiters (● high extent ; ◑ medium extent ; ○ low extent):

1) Task appropriateness
   Appropriateness of the task structure for depiction in a dialogue process (dialogue orientation), appropriate complexity of the task for accomplishment via an automated dialogue system
2) Practicability
   E.g., size of the group of potential users amongst applicants or degree to which this process step is realistically conducted via a chatbot dialogue from the user's point of view
3) Recruiter's freedom of choice
   Freedom of choice, often considered as so-called discretionary use in acceptance studies (Ghazizadeh et al., 2012), means that the decision to utilize a chatbot for a certain task is taken anew every time the task is conducted and this decision lays with the recruiter himself – detached from any strategic decision for this type of task in general
4) Recruiter's involvement
   The level of involvement the recruiter subjectively takes in the particular task from a state of mental absence up to a full-scale involvement filling a significant amount of the recruiter's time

Table 2.5 shows a focused overview of automatable tasks that can be supported or substituted by chatbots which are suitable for dialogue conduct, of appropriate practical value, selectable for conduct via chatbot by the recruiter himself and bear a certain level of involvement leaving the recruiter as discharged party by substituting his workload. Within those use cases, the recruiter can be supported or substituted by a chatbot in letting applicants interact with the chatbot as an alternative way to their current method of executing certain tasks or offering information for the recruiter.

Table 2.5 Convergence of Suitable Tasks for Chatbot Implementation based on Automatable Recruiting Tasks

Step	**Specific Task**	**Appropri-ateness**	**Practi-cability**	**Freedom of Choice**	**Involve-ment**
General	Answering General Questions The chatbot replies to applicants' general questions (e.g., about the company, the open position) via different digital channels.	●	●	○	○
2	Job Selection Facilitation The chatbot supports potential applicants in their quest to find their ideal job position with distinguished, refined results.	◑	●	○	◑
3	(Partial) Guidance Through the Application Process The chatbot navigates the candidates through the process of applying and offers guidance via explanations for example in each process step.	●	●	○	○
3	Answering Questions regarding the Application Process The chatbot replies to applicants' questions regarding the application process and system via different digital channels.	●	●	○	◑
3	CV Inquiry The chatbot asks the applicant for CV information.	●	◑	●	○
3	Missing Information Inquiry The chatbot asks the applicant for missing information.	◑	◑	●	◑
4	Interviewing The chatbot supports the effective pre-selection of candidates via dialogue-based first interviews yielding relevant first (hard skill focused) information about the candidates.	●	◑	●	●

Step	Specific Task	Appropri-ateness	Practi-cability	Freedom of Choice	Involve-ment
4	Candidate Matching The chatbot guides the recruiter and/or line manager through the process of pre-screening the application by comparing the candidates' profiles with the job profile.	○	○	●	●
4	Extended Candidate Matching The chatbot guides the recruiter and/or line manager through the process of referring interesting potential candidates with inappropriate profiles for the job at hand to more fitting open spots within the company while running according analyses in the underlying database.	○	○	●	●
4	Candidate Pre-Selection The chatbot guides the recruiter and/or line manager through the process of pre-selecting candidates based on relevant criteria and creating a candidate pool while running according analyses in the underlying database.	○	○	●	●
5	Personality and Soft Skill Analysis The chatbot guides the recruiter and/or line manager through the process of creating candidate personality profiles by analyzing their data.	○	○	◑	●
5/6	Guidance through the post-application phase The chatbot navigates the candidate through the particular steps succeeding his application by offering necessary information, material and guidance.	●	●	◑	●
6	Onboarding The chatbot offers the chosen candidate onboarding information regarding the workflow, general questions or the issuance of documents or materials for example.	◑	◑	●	●

Source: Own compilation (cf. Table 2.3*)*. The six steps are (1) Job profile placement, (2) job search, (3) application, (4) candidate pre-selection, (5) detailed candidate selection, and (6) hiring. Highlighted in grey color: Especially suitable tasks for chatbot conduct according to the evaluation criteria outcome (> 3 ●).

While FAQ scenarios represent highly relevant and frequent occurrences for companies and the recruiting context, they encompass many distinct use cases. Focusing on a single FAQ situation would not do justice to this important field of application by producing only singular and non-generalizable results.

Furthermore, FAQ can mostly be seen as a centrally, management-wise decided on substitute rather for FAQ sections of (HR) websites than for recruiter-conducted tasks he feels involved in, which makes it a not well-suited use case to present recruiters querying potential job-related automation concerns regarding recruiting chatbot technology. The same applies to the (partial) guidance through the application process, which is centrally dictated by the management and not decided on case by case on the operational level. CV inquiry as well as missing information inquiry have a very low level of involvement and not a high practical value as dialogue process. The analysis-based tasks of (extended) candidate matching, candidate pre-selection, and personality and soft skill analysis are neither appropriate for chatbot conduct, nor of practical value for actual dialogue processing. Moreover, only around 30 percent of the candidates consider automated pre-selection a proficient way of recruiting (CHRIS, 2017a) thus leaving it unwanted by the candidates as concerned party. Job selection facilitation may be practicable and have decent levels of involvement and appropriateness for chatbot-based automation, but it is also centrally decided on by management and no voluntary support for the recruiters.

Two highly suitable use cases are interviewing and guidance through the post-application phase. Guidance through the post-application phase is relevant for successful candidates and may even be selectable for conduct by the recruiter himself in each instance – however, this process is often complex demanding personalization as it depends on the specific job, role and knowledge as well as experience level of the candidate. Thus, individual care is required rather than standardized automated processes. Furthermore, it is vaster and lengthier than the narrow, specific task of interviewing. As a result, this study will regard the scenario of interviewing in terms of a first skill interrogation (cf. Figure 5.1). Interviewing induces a realistic scenario for potential job-related automation concern formation as it is appropriate for depiction as a dialogue, practical, selectable by the recruiter himself, and possesses a high level of involvement from the recruiter. Repova (2020) reinforces this choice by classifying chatbots as an efficient tool for job interview conduct gaining popularity. In the study at hand, interviewing is defined as a first questioning and answer interpreting process regarding the hard skills of the candidate. This kind of first hard skill interrogation is suggested for recruiting as a first step before assessing the soft skills of the candidate

(Litecky et al., 2004). Such a first skill assessment can be utilized as a filtration method to narrow down the candidates for the subsequent in-depth face-to-face interviews (e.g., Bateson, Wirtz, Burke, & Vaughan, 2013; Indeed, 2020; Toggl Hire, 2022), especially for jobs of high recruitment volumes with a well-defined skill set, repetitive tasks and no intensive management responsibility (e.g., parcel delivery service). This definition containment is crucial as the automatability and substitutability of the complete acquaintance interaction between the candidate (of every profession) and the company is questionable (Bastam et al., 2020). Furthermore, it would involve aspects such as perceived humanness and emotionality, which is no focus of this study. Interviewing is considered as suitable scenario as it

1) represents a potentially relevant workload reduction with high frequencies easily conceivable for recruiters when being confronted with the use case,
2) can be seen as the quintessential part of the recruiting process,
3) is hypothesized to induce profound job-related automation concern tendencies in recruiters when being automated,
4) would be able to completely substitute the recruiter's perspective within the dialogue, reinforcing the hypothesis of 3),
5) encompasses the delicate issue of skill assessment, which brings in the aspect of advanced chatbot technology,
6) represents a chatbot functionality, which is treated as an element of voluntary use[27] for recruiters as they can alternatively choose to stay with their current interviewing method in person for example as opposed to a management-induced central decision for utilization.

It does not involve final decisions. However, the task potentially contains data processing (data administration, interpretation, and handling in the ATS) and is generally of high importance for the recruiting process. Selecting the most suitable candidate(s) can be seen as the core responsibility within the recruiting process. Interviewing is a relevant use case as it reflects the technologically advanced nature

[27] Voluntariness is a vital aspect within acceptance research (e.g., Arromdee & Suntrayuth, 2020; Bröhl et al., 2019; Gattiker, 1984; J. Wu & Lederer, 2009) and often considered in acceptance studies as discretionary use (Ghazizadeh et al., 2012), which is thus considered in this study (cf. items of Appendix D).

that chatbots can have: They can help the company to get acquainted to the candidate without a need for human intervention and by thus add substantial value to the recruiting process by reducing labor costs and time efforts via automation. Hence, interviewing as a high-involvement task is chosen for this investigation. In the empirical part of this research, the beforementioned facets of the interviewing use case such as hard skill assessment and data processing are being examined: The participants are asked to evaluate potentially relevant aspects of the interviewing process (e.g., relevancy of efficient candidate handling, data analytics, relevancy of soft skills in comparison to hard skills and other traits) as well as potentially relevant recruiter skills during interviewing conduct such as ethical practice or transparency (cf. section 5.2.1.5).

2.4.5.3 Recruiting Chatbot Solutions in the German Market

Regarding chatbots, there are different kinds of solutions suited for different cases of implementation into the company. A distinction can be made between (1) chatbot frameworks, (2) stand-alone chatbot solutions, (3) integrated chatbot modules for talent acquisition software and applicant tracking systems in general, and (4) individual solutions developed entirely by the company. Bot frameworks enable companies to develop mostly small own solutions for quick implementation or creating an individual solution together with the framework provider (e.g., Chatbot4U (2022) and JobAI (2021) as German providers). Some of the major players in the international market are IBM Watson (IBM Corporation) and Dialogflow (Google), among others (Research and Markets, 2021). Stand-alone chatbot solutions are mostly standardized yet adaptable designed for high-volume application and are integrated into the business processes via certain interfaces (e.g., USU Software (2022) and MessengerPeople (2021) as German providers). As an example, the popular US-based recruiting chatbot vendor *XOR* claims that a recruiting chatbot allows businesses to recruit 33 percent faster and screen 85 percent more resumes with the same budget while spending 50 percent less per hire (XOR, 2021). Mya of Mya Systems, a San Francisco based AI-chatbot manufactory, offers streamlining processes for applicant sourcing, screening, question answering and scheduling with a self-proclaimed rate of 79 percent decrease in time-to-interview alongside an increase in recruiter productivity of 144 percent after implementation of a chatbot in the recruiting process steps (Mya Systems, 2021). In a case study with a global cosmetics company, the chatbot of Mya was deployed for candidate screening to fill > 5,000 vacancies and reduced the time spent per interviewee by 40 minutes while saving $250,000 in recruiter costs (Tawk, 2021). There are functionalities that can be added to chatbot systems for further elaboration such as content databases, advanced NLP engines or sentiment analysis tools. Furthermore, there are agencies developing chatbots on demand as an individualized version of a stand-alone chatbot solution (e.g., kiko by 1000° Digital (Kiko, 2022) and Chatbot Fabrik (Digital Affin, 2022) as German providers). Another alternative are comprehensive and ready-to-use solutions already integrated into the ATS solution from the same provider which companies who start their digital recruiting process anew or simply upgrade to this solution then (e.g., d.vinci (2021) and Haufe (2022) as German providers).

Table 2.6 shows a collection of exemplary recruiting chatbots that can be accessed and implemented by companies on the German market. The collection is not exhaustive by far but gives an overview of the available features in the form of covered task of the recruiting process regarding German recruiting chatbot solutions. In case none of the presented providers in Table 2.6 offer a dialogue-based automation solution for a certain task, the author could not find any concluding that no solution is currently presented for it to the German market. At the same time, features occurring only once in the table are not necessarily rare on the German market but further examples are simply left out of observation for simplification reasons. Only those solutions or rather providers are presented that are accessible in the German market. Hence, companies which are not operating in the German market such as the popular American automated interviewing company HireVue are disregarded. Certain solutions offer process automation but without a dialogue component chatbots are defined by and are not considered as well. For example, Prescreen offers diverse automation features along the recruiting funnel such as guidance through the application process and candidate pre-selection concerning their hard skills but with internal processes such as status changes in the system or an automatic mail send out (Prescreen, 2021).

Table 2.6 Exemplary Recruiting Chatbot Solutions Available on the German Market

Company/ Product Head office		**Assono** Germany	**BOTfriends** Germany	**e-bot7** Germany	**HR4You** Germany	**Joboti, Recruitee** Netherlands	**Jusmeum** Germany	**ONLIM** Austria	**Softgarden e-recruiting** Germany	**VIER Precire** Germany
Kind of Software[a]		3	2	1	3	3	2	2	3	2
Task considered for chatbot conduct along the recruiting process[b]	Answering questions (FAQ)	X	X	X	X	X		X	X	
	Creating/ Posting job ads									
	Job selection facilitation	X	X	X				X	X	
	Assisted application form fill-in				X				X	
	Guidance through the application process					X		X	X	
	CV inquiry				X				X	
	Missing information inquiry				X			X	X	
	Scheduling	X	X			X				
	Interviewing								X	X
	(Extended) candidate Matching		X						X	
	Candidate pre-selection					X				
	Online assessment									
	Personality and soft skill analysis					X Registers emotion				X
	Elaborative candidate selection									X Decision basis
	Guidance through post-application phase							X		
	Employment contract						X			
	Onboarding		X	X				X		
Level of elaboration		AI basis	AI basis	AI basis	AI basis	AI basis	AI basis	AI basis	AI basis	AI basis
Source		(Assono, 2022)	(BOTfriends, 2019, 2021)	(e-bot7, 2022)	(HR4YOU, 2022)	(Recruitee, 2021a, 2021b)	(Jusmeum, 2022)	(ONLIM, 2022)	(Softgarden, 2022b)	(Precire, 2022c)

[a] Kind of software: 1 = chatbot framework, 2) = stand-alone chatbot solution, 3 = chatbot module integrated in ATS. [b] Kinds of automated tasks: Classification taken from Table 2.2. Indicated in grey color: Tasks currently not offered for automation via recruiting chatbots in the German market based on the collection of found solutions.

As apparent in Table 2.6, all tasks are offered as automated chatbot dialogues in the German market except for job advertisement creation and posting as well as online assessment conduct. While job ad preparation is envisioned to be depicted via chatbot conversation (Teetz, 2020), no solution was found by the author on the German market offering such a service yet. However, there is a solution on the French market (Joonbot, 2021) and there are automation modules implemented in ATS systems but without dialogue process conduct (Softgarden, 2022a). Online assessment is also a conceivable task for chatbot deployment and there are examples on the US market such as chatbot “Casey” for automated case study interviews focusing on skills such as problem structuring, quantitative rigor, and the candidate’s judgement at BCG (Boston Consulting Group, 2020). However, none is currently offered for the German market. The other tasks are all automatable as purchasable dialogue strings in Germany with FAQ scenarios as most frequent tasks. Numerous case studies document the increasing utilization in German recruiting departments: James, the FAQ chatbot for AUDI created by e-bot7 (2022), Ferry, the Porsche recruiting chatbot by BOTfriends, which records a workload reduction of 25 percent for the involved recruiters (BOTfriends, 2021), and WhatsMeBot of the German Federal Employment Agency by MessengerPeople (2020) are prominent examples. An example of software utilizable for personality and soft skill analyses is Precire, a German language analysis tool that identifies and recognizes behavioral and interactional tendencies (Precire, 2022b) for elaborate candidate pre-selection.

This study focuses on the specific task of interviewing. Interviewing chatbots provide a high level of support for recruiters by saving a substantial amount of time as pre-selection is one of the most time-consuming tasks for recruiters (Holley, 2018) and gives companies the opportunity to regard each and every application and to do this with a constantly high level of rigor, which otherwise might not be possible due to time restraints for example. Human recruiters can be entirely left out of the process via full automation if implemented as a preparatory step for the main interviewing process that is then held analogously. There are numerous international chatbot solutions (e.g., Olivia (Paradox, 2021); XOR (2022); Mya (Mya Systems, 2022); and Vera (Holley, 2018)) that screen candidates via first – mostly hard skill focused – interviews. Offers range from interviewing modules only (e.g., Mya Systems, 2022) to integrated recruiting tools encompassing candidate matching, potential candidate classification, and interest identification to see whether the regarded talent is actually searching for new employment (e.g., Vera (Holley, 2018)) prior to the actual interviewing for candidate pre-selection based on the interview findings. They take over a profound number of preliminary interviews that would otherwise require human time and labor – in case of Vera, up to 1,500 interviews are automatically held per day (Holley, 2018). Today's solutions contain NLP functionalities and thus potentially offer high quality conversation experiences. However, they are mostly limited to hard skill assessments with no means of soft skill analyses to yield the cultural fit of the candidate to the company he is applying to. This is in accordance with the defined use case of the interviewing chatbot suggested for the research at hand, which is supposed to increase efficiency by assessing hard skills prior to an in-depth face-to-face interview. An example would be the Interview Chatbot by Tars Technologies (2022): It collects information regarding their skill sets and experience and then matches the candidate with the right interviewer for the subsequent in-person interview based on the assessed hard skills. While there are first attempts to tap into this field, there is no sophisticated, emotionally intelligent solution yet that could substitute the human component needed for in-depth candidate interviews. Recruiters can equip the chatbot with pre-defined questions from the provider's database, own questions tailored to the specific company or a combination of both. The outcome of chatbot interview conduct are raw information provided by the candidates concerning the questions asked. Through either an automated or a recruiter-led filtering process, a pre-selection is then performed to create a short list of candidates with the best fit for the regarded job position. Recruiters need to implement and recurrently adjust the associated filter criteria, verify the results offered by the chatbot and further process the proposed best suitable applications.

On the German market, sophisticated interviewing chatbots for automated recruiting are rare (e.g., ARTS, 2022). PitchYou is an interviewing chatbot on WhatsApp that conveys pre-defined questions, checks the given answers for plausibility and if desired parses the information to the ATS it is integrated in (d.vinci, 2021). According to d.vinci (2021), the completion rate is 87 percent, which makes automated conversations a successful candidate interviewing alternative for pre-screening purposes. The chat profiler by Precire is a module that can enrich interviewing chatbots by adding a psychological language evaluation component to it (Precire, 2022a, 2022c). This way, the chatbot can learn during the actual conversation to spontaneously adapt and react according to the inquirer's individual needs and expectations (Precire, 2022c). A third example it Emplobot, an interviewing chatbot that can be utilized for job selection facilitation and interview process itself (Softgarden, 2022b). Implementable into ATS systems to retrieve job openings or parse information from the interviews to the database, it offers quick interviews of up to five minutes and yields a increase in effectiveness of 40 percent on career pages (Softgarden, 2022b).

2.4.5.4 Status Quo of Chatbot Application in Recruiting in General and Germany

Conversational agents become common features for large companies: They can now be found in all parts of daily life, where they become a popular communication system in various contexts (e.g., Reshmi & Balakrishnan, 2016; Bayan A Shawar & Eric Atwell, 2007). The interest in chatbots is imminent (e.g., Schikora et al., 2020 for job-related ones). On a global scale, several corporations report having 30 and more separate chatbot projects running within their different business processes (Elliot et al., 2020). In a study regarding the European German-speaking market (DACH), 72 percent of the companies ascribe increasing importance to chatbots in the future and state recruiting as the fourth most prominent field of application (PIDAS, 2020).

While early chatbot solutions focused on pattern matching and single dialogue threads concerning simple question-and-answer scenarios, current solutions can increasingly be used for more elaborate tasks such as in-depth dialogues with users and function as assistants offering either information or performing their destined processes. In the field of HR, examples for such complex assignments are applicant interview conduct (e.g., Repova, 2020; Tawk, 2021) or personal consultancy in the form of suitable training modules selection (Semet & Hilberer, 2018; Stucki et al., 2018).

Gartner (2020) expects 35 percent of organizations to turn the job application process into conversation strings containing natural language processing interaction by 2022. However, while nowadays widely deployed in recruiting (Laurim et al., 2021), as a new technology and use case, the majority of chatbots in this field are sparse and on a simple, rather rule-based level: Most recruiting chatbots are rule-based without elaborate functionalities, are not integratable to databases within the HR departments of companies and are overall in an immature state (Meurer et al., 2019).

Since only limited work is available, the author conducted an own examination regarding the status quo of chatbot implementation within the 100 largest companies in Germany to create an overview of the currently existing solutions focusing on recruiting (cf. Appendix A). The author examined the chatbots wherever published by the specific company (e.g., own career website, Facebook Messenger) by analyzing the companies' own statements and press releases as well as a practical testing of the chatbot in focus (cf. Appendix B regarding the sources). The field of application (HR or recruiting coverage), the quality of NLP integration and the features were assessed during a structured test of the chatbot within a conversation utilizing (1) natural language to pose the question (general FAQ-related or job-related in case of connection to HR), (2) intentional spelling and grammar mistakes, and (3) unexpected intents and entities to elicit the system's response to such behavior and to check for the uniqueness of the answer. The examination yielded 48 candidate-sided recruiting chatbots, most of which (64 percent) are individual solutions customized for one specific company and area of application. Their main task is job search (47 percent) followed by candidate selection (13 percent). A mere 11 percent of the chatbots are integrated solutions for deployment prior, during and after application and chatbot modules for implementation into ATS are only offered twice. While 18 percent at least implemented NLP features enabling free and unstructured natural language input that was understood and processed, only seven percent offer an automated candidate interview analysis. Only 10 percent stated themselves that they implemented NLP functionalities and another 10 percent claimed utilizing AI in general (PIDAS, 2017). Of the nine percent of all companies utilizing a chatbot in 2020, 11 percent have incorporated AI functionalities and 16 percent claimed offering purely sophisticated chatbots; hence, the majority offered rule-based ones (PIDAS, 2020).

From the applicants' point of view, the relevance of chatbots is apparent: Chatbots are gaining importance as an intuitive and oftentimes open (in terms of independence from certain social media services) interface between humans and computers and they hold the potential to become the next generation of search engines (Ranoliya et al., 2017; Stucki et al., 2018). The intuitiveness derives from the possibility to transfer human-human communication with natural language to human-computer communication, which humans call for (Bayan A Shawar & Eric Atwell, 2007). Thus, candidates are able to communicate with potential future employers in an innovative, efficient way without missing the ability to converse in natural language.

Concerning artificial intelligence, a study by Boston Consulting Group (2020) found that in 2019, 20.9 percent of HR managers already utilized AI functionalities in the field of personnel recruiting and 11.3 percent already implemented them into the candidate selection processes. In the next three years, the biggest changes through AI are expected in the area of personnel recruiting (Bundesverband der Personalmanager, 2019). Regarding this increasingly technology- and evidence-based approach to HRM within companies, Hollmann (2017) prophesizes chatbots to become indispensable. IBM (2017)found that at least half of the CHROs (1) see significant value in cognitive computing (= processing of unstructured information by understanding language patterns, reasoning and learning as potential backbone for a chatbot to draw from) for HR (66 percent or the respondents), and (2) think that cognitive computing will affect key roles in HR (54 percent). Within this global view, this thesis regards Germany. According to the German 2017 study by (CHRIS, 2017a), half of the respondents stated that the digitalization of tasks empowers the effectiveness and efficiency[28] of recruiting. Thence, recruiting companies in Germany consider process automation to be advantageous.

In general, career specific chatbot content is offered by 10 percent of the largest German employers (Meurer et al., 2019). A study mentioned by Böhm and Meurer (2018)[29] showed that only three percent of the regarded German HR departments offer automated suggestions for fitting jobs via chatbots (job matching),

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[28] Effectiveness refers to the accuracy and completeness of goal achievement while efficiency is defined as the quality of resource application to achieve these goals (Radziwill & Benton, 2017).
[29] Recruiting Department Study cited in Böhm and Meurer (2018) (n = 240 of the biggest and most popular German employers).

two percent propose suitable career recommendations and below one percent of the companies implemented career or job bots for career specific information retrieval or job searches (Böhm & Meurer, 2018).This offer is in contrast to the momentary candidate-sided demand: According to CHRIS (2017a), more than one third of the applicants in Germany would like to use digital career assistants when searching for open positions. From the recruiters' personal point of view, Regber et al. (2019) found that only 43.3 percent of German recruiters (predominantly the younger respondents) already had one or more experiences with a chatbot. 19 percent (mostly large corporations) stated that they already employ a chatbot – 38 percent of which are applied to the recruiting process. Only one third of the recruiters with already established chatbots stated that they were linkable to the ATS system (Regber et al., 2019). As a result, chatbots cannot be utilized regularly by candidates interacting with different companies as there is no sufficient supply yet. aiaibot (2021) who looked at all three German-speaking focus countries of the DACH region, found 88 percent of the respondents stating that they seldomly or only every now and then interact with chatbots. Hence, chatbot solutions are still sparse although just as cognitive computing and digitalization technology in general, they are seen valuable impacting HR in general as well as recruiting.

2.4.5.5 General Level of Recruiting Chatbot Acceptance in Germany

In light of this diversity of application points of chatbots within the recruiting process, the question of recruiting chatbot acceptance arises. Aside from necessary technological and legal orchestration, chatbots can only take over tasks in recruiting and thus develop relevancy when they are sufficiently accepted by both parties, which is a mutually undetermined aspect in the field of HR. This makes it a vital part of recruiting chatbot examination and a relevant study focus. From a practical perspective, acceptance is an essential prerequisite for the successful and sustainable implementation of a technology (e.g., Dahm & Dregger, 2019; Mazurchenko & Maršíková, 2019)).

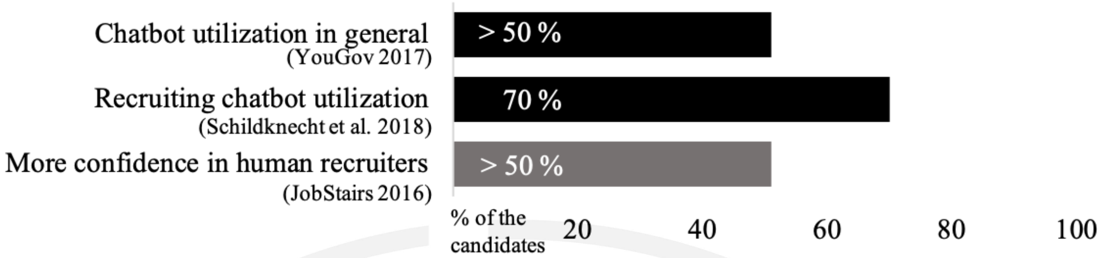

Figure 2.7 Chatbot Utilization Intention in Germany in Figures
Source: JobStairs (2016), Schildknecht, Eißer, and Böhm (2018)[30]; YouGov (2017). Indicated in black: In favor of utilizing a chatbot. Indicated in grey: Not in favor of utilizing a chatbot.

Figure 2.7 shows three facts regarding (recruiting) chatbot utilization in Germany: At least every second German can envision himself using chatbots in the future in specific situations such as information retrieval or scheduling (YouGov, 2017) while around 70 percent of the responding applicants in a study by Schildknecht et al. (2018) state that they can imagine utilizing a recruiting chatbot in the future. However, the majority of the candidates do not project as much confidence into technological systems as they do in human recruiters altogether (JobStairs, 2016), which indicates a potential utilization intention hindrance. In case they do utilize automated dialogue systems, candidates state that chatbots on the companies' own career sites are more trustworthy in comparison to those on internet-based job platforms or in career networks like XING or LinkedIn (CHRIS, 2017a). That is remarkable as chatbot interaction in sales contexts is perceived equally as warm, competent and trustworthy as human sales agent interaction (Rozumowski et al., 2019). Hence, chatbots are seen as feasible means of communication with a company by applicants with different points of view concerning their trustworthiness.

Regarding recruiter-sided acceptance, 35 percent of the Top 1,000 companies state that automated recommendation systems such as chatbots are capable of suggesting qualified candidates (CHRIS, 2017a). The 2017 IBM study regards the differences in (1) current, and (2) future decision-making, (3) feeling of being sufficiently informed, and (4) trust concerning cognitive systems as understanding,

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[30] Applicant study with n = 213 German potential candidates.

learning and reasoning complex technology, which advanced chatbots can be assigned to, with a sample of 8,600 employees (IBM, 2017). A recruiting-specific scenario was included asking whether as a hiring manager, cognitive approaches would be used in order to enhance the candidate selection process. Respondents stated that on average, they would

1) not change their behavioral intention but rather make similar decisions when advice is received from conventional sources or from cognitive solutions,
2) intent to also use the advice of cognitive systems in the future concerning decision making although the intent to reuse was more distinct for traditional HR advice sources,
3) receive sufficient information from cognitive solutions, and
4) overall trust cognitive systems – especially concerning more complex and less personal decisions with a higher trustworthiness perceived than information from conventional sources (IBM, 2017).

They conclude that employees seem to have short learning curves concerning cognitive system usage behavior and thus understand how to exploit its features (IBM, 2017). According to Schildknecht et al. (2018), recruiters mostly see aspects like time savings, effort savings, ubiquitous 24/7 accessibility, faster candidate pre-selection and cost savings as possible implementation reasons for chatbots (sorted by response frequency). Remarkably, they see accessibility as the most important factor within the procedure with high applicant reach on the second place (Regber et al., 2019). As requirements for willingness to deploy a recruiting chatbot, recruiters state that question-answer functionalities, integration possibility within the website, connectivity with the ATS, suggestion possibility of job postings with application option, scheduling, and integration into social media channels, possibility to switch between the chatbot and human recruiter within the chat are most important (Regber et al., 2019).

2.4.5.6 Current Recruiting Chatbots Limitations and Rejection Criteria

Potential hindrances concerning chatbot usage according to Drift (2018) can be a preference of real-life assistants or normal websites, the fear of mistakes by the system or the perception of unfriendliness. YouGov (2017) mentions additional reasons against chatbot utilization such as a perceived handling incapacity of individual/complex inquiries, an endangerment of jobs, a deficit in data security, and a lack of technological sophistication. Schildknecht et al. (2018) show that chatbots' advantages such as ubiquitous accessibility, promptness of reaction and answering, easiness of operation and bias/discrimination free interaction are seen and perceived as positive by most respondents while the highest perceived usage barriers are the chatbots' ascribed inability to comprehend complex contexts, a high failure rate during interaction and perceived lower competencies compared to human counterparts. Surprisingly, data security issues were not seen as usage barriers. This corresponds with the findings of aiaibot (2021) showing that 60 percent of the respondents express trust that their data is safe during chatbot conversation. However, their lack of common history or shared experience as opposed to fellow humans (Hill et al., 2015) makes them appear inhumane and potentially less approachable, which is another current challenge necessary to be overcome. The amount of information applicants may consign to chatbots differs according to their individual personality – younger candidates with a higher digital self-confidence might be more willing to share their information than the older generation (Corinna Maier, 2018).

The currently highest limitation of recruiting chatbots is their ongoing contained, narrow task scope. A certain lack of flexibility is ascribed (Lamprecht, 2018), which is caused by their mostly applied rule basis. Many researchers agree on and defend the paradigm that the final hiring decision after interaction and pre-selection support needs to remain with the human recruiters of the HR department instead of automation systems (e.g., Buell, 2018; Mülder, 2018; Semet & Hilberer, 2018; Bayan A Shawar & Eric Atwell, 2007; Ternès, 2018). According to Mülder (2018), especially the social-psychological complexities within HR decisions are neglected by the fact- and hard-skill-based, rather non-emotional chatbots, which makes them inadequate for recruiting decisions based on soft skill assessment. Researchers of his stance argue that chatbots lack certain sensitivity for candidates' competencies as well as their personal strengths and weaknesses, have an adjudged lack of moral/ethics and inherit the risk of high candidate selection failure rates (Ternès, 2018). Furthermore, they are ascribed a lack in rapport, which is important to build relationships and ultimately to build trust.

This shapes the limits as to how far chatbots can come into play within recruiting – certain candidates or circumstances might prohibit chatbot application. Another limiting factor is the system's level of suitable and matching answers and the according failure rate when it cannot help the users to solve their problems. Chatbots capable of learning are constantly reducing this limit, but it is still considerable comparing it to the human way of handling unknown problems. Then again, there is no aspiration for perfect human conversation imitation (Bayan A Shawar & Eric Atwell, 2007). Thus, while sophisticated chatbots base on the human logic of neural networks, they are not necessarily built to become as human as possible. One stream of researchers and industry experts shares the opinion that chatbots are not required to do an impression of a human or to pass the Turing test[31] but rather support human conversation (e.g., Radziwill & Benton, 2017; Wilson, Daugherty, & Morini-Bianzino, 2017). In case they reach their limit, users of course would like to be connected to a human counterpart (Drift, 2018). Regarding the case of recruiting, chatbots are installed to support the candidate in his application process while increasing its efficiency and thus relieving the recruiter of workload. While they might not be expected to appear human when answering simple company- or application-related questions, humanlike qualities might be expected or searched for when candidates ask sensible questions or take an automated hard-skill interview for example. Furthermore, chatbots are not applicable to every recruiting scenario and every type of candidate: While they can extensively unfold their potential in high-volume standard scenarios (e.g., delivery drivers, ground staff at the airport), they might not be appropriate in fiercely competitive hiring scenarios for highly qualified talents (e.g., general managers, specialized senior IT experts).

One of the major challenges for companies working with elaborate automation functionalities within HR is the identification of suitable training data since a high amount of data sets is needed for training and formerly rule-based logic cannot be applied (Böhm & Meurer, 2018). Only when high data quality is ensured, the chatbot is capable of performing in a value adding manner (Hollmann, 2017). Recruiters need

[31] The Turing Test was introduced by Alan Touring in 1950 in order to evaluate a machine's (digital computer) ability to think and by this appear human (Turing, 1950); it was turned into an annual practical competition of chatbots first by Hugh Gene Loebner and the Cambridge Center for Behavioural Studies in 1991 (Shieber, 1994).

to eradicate and correct possible errors within the system, which is vital to prevent inaccuracy spreading and – explicitly as well as implicitly – homogenous candidate selection causing in a diversity degression for example (Teetz, 2018). Advanced abilities to assess candidates' personal and social competencies or capacity for teamwork for example are viewed critically (e.g., Groß & Gressel, 2016; Laurim et al., 2021 (accuracy)). Thus, chatbots need to gain acceptance amongst candidates and recruiters apart from further technological advancements in order to become suitable for complex tasks such as soft skill assessment.

2.4.5.7 Role of Recruiters Concerning Chatbots in Recruiting Processes

In this study, recruiters are regarded as object of investigation focusing on their perspective on recruiting chatbot acceptance. They are the ones utilizing it in the sense of deploying it for first candidate interviews but are not the ones interacting with it from an end user perspective as it is offered to the applicants of the company. These candidates would normally interact with the recruiter, who is substituted by the chatbot in this process step. Concerning the recruiters' position within the company, the ones most affected by automatization via chatbots are part of the administrative staff. They will most likely be experiencing job-related automation concerns as opposed to recruiting managers, who take general decisions but are not the ones collaborating with the technology themselves. Chatbots as communication technology are usually implemented into the technical backbone of the recruiting process, which is the applicant tracking system. If existent in the company, the ATS serves as database for the chatbot and is necessary to enter and maintain recruiting-specific data such as applicant information or appointment dates as well as to answer related questions.

Several factors are highly relevant for the context of chatbot dialogue systems from the recruiters' perspective such as regulations (e.g., Art. 22 Para. 1 GDPR prohibiting final hiring decisions through automated machines), industry trends (past trends such as e-mail applications had an impact on the process of application), and critical mass in terms of incoming inquiries and data. Recruiters might be in favor of recruiting chatbots if they believe that such means of business-applicant interaction actually supports their work by augmenting the level of recruiting process efficiency.

Job-related automation concerns could be an interfering force concerning the acceptance of chatbots as recruiting process step automation technology.

Recruiters are extensively involved in the chatbot implementation process. As for the implementation phase, it is either them or their managers, who decide whether to deploy a chatbot for the application funnel. In case they decide, they have to educate themselves regarding the potential advantages and disadvantages of the technology regarding their specific situation in the company and the HR department. They need to choose a fitting solution for the existing needs and use case they have to select as well according to the requirements at hand. Subsequently, they need to configure the chatbot regarding its appearance and provide the contents for it to convey or the inquiries to pose to the end users. Constant attending is needed to keep the database up to date, correct mistakes and alter the contents as deemed necessary. In his daily business, the recruiter then has to decide on whether to utilize the chatbot for the tasks he can choose it for (e.g., CV processing, candidate matching, interviewing; cf. section 2.4.5.2). He is the one to monitor the performance of the chatbot and the response from the candidates: The technology can only work and have the desired positive outcome when it is accepted and effectively utilized by them. Thus, the recruiter also needs to frequently check the relevancy of the implemented automation system and consider a shut off in case the endeavor is not profitable anymore.

2.4.5.8 Implementation and Usage Particularities of Recruiting Chatbots

Thinking about chatbot integration into the recruiting process, certain utilization requirements and peculiarities have to be taken into consideration. Just like in other application scenarios, recruiting chatbots need to solve applicants' problems and not create new ones, for example due to bad performance. They are no solution for every kind of automatable process (Meurer et al., 2020). Every interaction needs to be thought through and generate benefits (Kusber, 2017). The system needs to be capable of solving a real problem (Drift, 2018). In line with Buell (2018), automation technology needs to support employees instead of interfering with their work process. For the case of recruiting chatbots, solutions are necessary which facilitate the recruiters' work stream while still allowing for and supporting the human connection between recruiter and applicant.

Applicants have four distinct motives for applying: (1) Attractive employer, (2) appealing position, (3) attractive place of work, and (4) the possibility to apply easily and in a trouble-free way (Jäger, 2018). Chatbots need to add value in this regard as well by supporting the company's overall HR strategy – especially concerning the aspects of employer branding and application management. According to a recruiting study by ManpowerGroup Solutions (2017),[32] German applicants take job-related decisions mostly based on salary, kind of professional activities, location and career advancement opportunities followed by brand and image of the company, flexible organization or working time and special benefits (all sorted by priority). Hence, an associated FAQ chatbot needs to offer insights to these kinds of information in order for the applicants to take an informed decision and opt in favor of the company. Since natural language is already the standard mode of online interaction (Følstad & Brandtzæg, 2017), conversing with a system capable of natural language exchanges and receiving the above-mentioned information accordingly might be a natural and thus effective way of conversing with stakeholders as a company. In cases of conversational breakdown, they need to be designed to provide acceptable responses (Følstad & Brandtzæg, 2017). To establish high usability within the interaction of applicants with a recruiting chatbot, the former need to be suggested what he might expect from the service and the input needs to be adequately interpreted (Følstad & Brandtzæg, 2017). Thus, expectation management needs to match the actual technical capabilities of the implemented system.

From the recruiters' point of view, chatbots need to be assessable and dirigible, which means that content change maneuvers must be simple enough so that non-technical HR personnel can perform it without the need of elaborate coding. The systems need to provide personnel policies and other relevant HR information (Lester et al., 2004). Regarding the data recording, collection and storage of (personal) data, data security issues arise. Companies need to prioritize data security management and abide by the according laws and regulations – for example the newly inaugurated European General Data Protection Regulation, which introduced rights of access and of oblivion for example (Semet & Hilberer, 2018). Other aspects are the topic and the

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[32] 2017 Recruitment Report by ManpowerGroup Solutions (n = 785 German adults (18-65 years old), part of the "Global Candidate Preferences Survey" with n = 14,000 working adults.

accompanying level of data sensitivity within chatbot conversations. In a study by Bhakta, Savin-Baden, and Tombs (2014), the likelihood to share sensitive data with a chatbot is affected by the discussion topic as well as the lengths of interaction.

Content-wise, the chatbot needs to be carefully conceptualized according to the use case and its requirements. Fitting areas of application for simple, low-threshold chatbot solutions are standardized ones with mostly repetitive general questions, so that the database of the chatbot can be centered around the most relevant and thus predictable questions covering most of the incoming inquiries. This is the case for FAQ depictions as well as explanations of or a walk through certain pre-defined processes for example. In non-standardized and rather complex scenarios, the chatbot setup needs to shift towards the rather specialized, potentially contextual questions it then needs to answer. High volume cases would be necessary to justify the implementation effort and expenses to enable the chatbot to process and react to such specific and variable questions. Examples for such variable questions are the status of an individual's application or a specific job opening.

In sum, there are many existent aspects concerning to consider when deploying a chatbot in a distinctive chatbot application point within the recruiting process with different levels of acceptance for state-of-the-art chatbots in this context. Their dissemination is restricted by current usage hindrances and limitations, which need to be overcome to yield the potentials of this technology.

CHAPTER 3

OVERVIEW OF CHATBOT ACCEPTANCE RESEARCH

According to Wixom and Todd (2005), there are two dominant streams in information technology research: Research regarding the user satisfaction (e.g., Bailey & Pearson, 1983; DeLone & McLean, 1992; Ives, Olson, & Baroudi, 1983; Melone, 1990; Seddon, 1997), which focuses on system and information design attributes such as information accuracy, and studies dealing with technology acceptance (e.g., Davis et al., 1989; Hartwick & Barki, 1994; Szajna, 1996; Venkatesh et al., 2003), which predict usage behavior mainly based on attitudes and beliefs (see also Forsgren, Durcikova, Clay, & Wang, 2016).[33] While earlier information system (IS) research focused on behavioral traits such as involvement (B. Pérez, 2010), more recent studies integrate more technical aspects, for example the different characteristics and qualities a system requires in order to perform successfully (e.g., DeLone & McLean, 2003; Goodhue & Thompson, 1995). The study at hand follows this technology-driven approach and focuses on acceptance research within the field of human-computer interaction (HCI; e.g., Dillon & Morris, 1996). The overarching goal of this study is to yield theoretical and practical findings on the factors influencing recruiting chatbot acceptance and the impact of job-related automation concerns. Theoretically, a collection of significant acceptance criteria is compiled and according research gaps are closed. Practically, managerial implications are derived in the contributions and recommendations for action for companies, which seek to improve their recruiting process via implementation of a recruiting chatbot, are developed.

In this section, acceptance research in general is outlined regarding its status quo before focusing on chatbot acceptance research alongside relevant research theories and models in this field. For example, the Technology Acceptance Model (TAM) as

[33] While originally applied in the context of data warehousing systems by Wixom and Todd (2005), Forsgren et al. (2016) for example applied it to system administration.

well as its associated foundations and the Unified Theory of Acceptance and Use of Technology (UTAUT) are discussed. In a subsequent step, the suitable chatbot technology acceptance research model with the best fit for the study at hand is presented in detail. A research gap is drawn based on the presented current state and existent research as well as the scope of the study at hand is specified.

3.1 Definition and Status Quo of Acceptance Research

Users undergo certain psychological processes while making decisions about technology usage with acceptance as possible outcome (Dillon & Morris, 1996). User acceptance can be defined as “the demonstrable willingness within a user group to employ information technology for the tasks it is designed to support.” (Dillon & Morris, 1996, p. 9) For acceptance, the subject needs to embrace the object in question within the context of the prevailing circumstantial conditions with a vast number of influencing factors such as usability, task suitability, self-efficacy and subjective norm (Schäfer & Keppler, 2013). This already evinces the complexity of the construct of acceptance and its multiple dimensions.

The basic idea of the economic standard model is that individuals act rationally and in accordance with their own needs. From a behavioral economist point of view, deviations from this standard are either the expression of certain preferences or wrong decisions (Holzapfel, 2019). A link can be drawn between such preferences and the level of acceptance an individual has for the object or process in focus (Pantano & Di Pietro, 2012). According to Schäfer and Keppler (2013), acceptance encompasses different perspectives: It ranges from a simple absence of resistance towards a certain technology or a benevolent acquiescence of it up to a readiness for action (Schäfer & Keppler, 2013). In this regard, technology acceptance research investigates motivators for information system utilization (J. Wu & Lederer, 2009). Factors favoring or hindering acceptance are identified so that recommendations for action can be derived fostering high acceptance levels for newly implemented technologies (Schäfer & Keppler, 2013).

While Brown, Dennis, and Venkatesh (2010) state that the two terms adoption and acceptance can be utilized interchangeably but suggest staying in accordance with originally utilized terms for different models, others differentiate between both: Adoption describes the decision to initially accept an innovation (Brandon-Jones & Kauppi, 2018), for example in an organizational context. Thus, technology adoption is defined as the single event of the decision to accept eventually leading to the acceptance or first use of an emerged technology or product (Alexandre, Reynaud, Osiurak, & Navarro, 2018; Khasawneh, 2008; K. C. Lee, Lee, & Kim, 2004). Technology acceptance however is a subjective, affirmative attitude of an individual towards a certain issue or a particular technological innovation with a possible action-oriented motivation (Niklas, 2015). It can be further defined as an individual's psychological state concerning their voluntary intention to utilize a technological innovation (e.g., Arromdee & Suntrayuth, 2020; Gattiker, 1984). Alongside these attitudinal and behavioral components, acceptance also encompasses a value dimension (Schäfer & Keppler, 2013). In general, acceptance refers to the long-term commitment to innovation utilization (Conboy & Morgan, 2012; Gallivan, 2001; Stoeckli, Uebernickel, & Brenner, 2018) at micro, hence, on an individual level (Brandon-Jones & Kauppi, 2018; Quiring, 2006). Consequently, both terms acceptance and adoption are related to overall technology reception and vary only in their chronological sequence with acceptance succeeding adoption. Acceptability is defined as the a priori prediction of usage intention (Rad, Nilashi, & Mohamed Dahlan, 2018). It describes the willingness to use a certain technology (Dillon & Morris, 1996). Chronologically, it precedes actual adoption leading to acceptance. The dissertation at hand focuses on acceptance going beyond the decision-oriented concept of binary adoption decision as often applied in research (Conboy & Morgan, 2012): The recruiters' actual commitment to utilize chatbots in their recruiting processes is investigated while identifying important influencing factors for the acceptance of such dialogue systems. Hence, the recruiters shall be queried about their degrees of actual or envisaged utilization to distil fine-granular levels of acceptance instead of presenting a dichotomous (yes/no) adoption choice to integrate the idea of utilization intensity as proposed by C.-F. Shih and Venkatesh (2004). Emphasis in this research is on individual acceptance focusing on the attitude- and behavioral-oriented aspects traditionally investigated for managerial implication deduction (e.g., Davis et al., 1989; Gefen & Straub, 2000; Niklas, 2015; Rengelshausen, 2000; Venkatesh et al., 2003). Complementary rather than opposite terms of acceptance and adoption are resistance and rejection; added to this is the concept of postponement (Nabih & Poiesz, 1997). Both notions acceptance (regarded variable: behavioral intention to use, cf. section 5.2.2) and resistance (regarded variable: inertia, cf. section 5.2.2) are investigated in this research.

Social science in terms of social and cognitive psychology and sociology (Dillon & Morris, 1996) as well as economic research perspectives concerning acceptance research can be distinguished (Schäfer & Keppler, 2013). It is influenced by different science streams and theories such as media research, technology genesis research, sociological innovation and diffusion research, behavioral theory or norm activation theory (Schäfer & Keppler, 2013). There are two perspectives regarding acceptance established by innovation diffusion theory: (Dillon & Morris, 1996) distinguish (1) organizational acceptance (e.g., Zaltman, Duncan, & Holbek, 1973) from (2) individual acceptance applying the concept of acceptance to the personal context (e.g., Rogers, 1962). Schäfer and Keppler (2013) supplement this categorization by general societal acceptance of technologies (e.g., energy technology). In general, information technology research can be performed at macro-economic level (e.g., review by Panko, 1991), micro-economic or firm level (e.g., review by Banker, Kaufman, & Mahmood, 1993), or at individual level (e.g., Davis et al., 1989). This study investigates the specific acceptance of recruiters at the individual level. Their personal associations with chatbots are being queried detached from organizational, possibly authoritarian technology implementation decisions. Hence, this work focuses on determinants for user acceptance directly as suggested by Dillon and Morris (1996) rather than on acceptance at a high level in the form of broad theoretical innovation diffusion analyses.

Several researchers state that there is a causal relationship between acceptance in the form of utilization (intention) and business (system) performance (i.e., Goodhue & Thompson, 1995; L. Liu & Ma, 2006; Son et al., 2012), which underlines the importance of system acceptance for the implementation of new technology. As a consequence, the dependent variables in acceptance research are mostly either operationalized as behavioral intention/intention to use as a predictor of (usage) behavior or use/utilization itself (e.g., Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019; Venkatesh et al., 2003). This concept will be applied in this study focusing on the overall term of acceptance, as well. Some research also incorporates the influence of expressed encouragements, mandates and reward/incentive systems on the acceptance of innovative technology (e.g., Dillon & Morris, 1996; J. Y. Lai, 2009). This can be seen as the subsequent research step after regarding general acceptance determinants of the regarded technology, as conceptualized for recruiting chatbots in the present study.

Low acceptance might lead to inefficient utilization performance negating the attributed benefits of a certain technology (Dillon & Morris, 1996). Hence, business level adoption is not adequate for implementation success: Brandon-Jones and Kauppi (2018) state that organizational adoption of technology alone is insufficient regarding performance benefits (Jeffers, 2010) through innovative technology as it may risk gaps between investments in and returns on these technologies (Autry, Grawe, Daugherty, & Richey, 2010; Finger, Flynn, & Paiva, 2014). A reason for this may be the circumstance that in organizational contexts, managers decide on the new technology while not being the ones actually working with it. Besides this organizational/managerial adoption, individual-level acceptance is important, which is no natural consequence but needs to be built by understanding the antecedents of employee acceptance (Brandon-Jones & Kauppi, 2018). In this study, individual acceptance is regarded from the recruiters' point of view as exemplary group of employees exposed to the technology in their business processes.

3.2 Overview of Technology Acceptance Research Theories and Models

The investigation of acceptance for information systems and technologies is a broad field of research. In the beginning of acceptance research, studies concentrated on the identification of factors facilitating system implementation in organizations before shifting towards the development and empirical testing of models predicting system use (Legris, Ingham, & Collerette, 2003). Technology diffusion and adoption are key areas within IS research (Tscherning & Damsgaard, 2008). Within these two streams of diffusion of innovations (DOI) and acceptance/adoption research and the two perspectives concerning the organizational and the individual level, several theories and a broad range of according models formed over the past six decades of in-depth acceptance research.[34] There are diverse theories, models and frameworks established to assess and evaluate the acceptance of computer systems by their users (Venkatesh et al., 2003). In this chapter, the predominant concepts, examples and potential theoretical fundamental structures for individual technology acceptance are being presented and then narrowed down to those relevant for chatbot acceptance. Subsequently, the research gap is presented as well as the according scope for the research at hand.

Rad et al. (2018) examined 330 IS technology adoption studies and identified 21 main theoretical foundations for acceptance/adoption from institutional theory, sociology, (social) psychology and economics (cf. Table 3.1).

Table 3.1 Theories Utilized in IT Acceptance/Adoption Studies[35]

Theoretical Foundation	**Main Contributing Author(s)**	**No. of papers**
Technology Acceptance Model (TAM)	Davis et al. (1989)	160
Diffusion of Innovations (DOI)	Rogers (2003)	44
Unified Theory of Acceptance and Use of Technologies (UTAUT)	Venkatesh et al. (2003)	38
Theory of Planned Behavior (TPB)	Ajzen (1991)	31
Technology-Organization-Environment Framework (TOE)	Tornatzky and Fleischer (1990)	22
Theory of Reasoned Action (TRA)	Fishbein and Ajzen (1975)	19
DeLone/McLean IS Success Model (ISSM)	DeLone and McLean (1992)	12
Task-Technology Fit Model (TTF)	Goodhue and Thompson (1995)	12
Expectation Confirmation Theory (ECT)	Oliver (1977)	8
Uses and Gratifications (U&G) Theory	Ruggiero (2000)	5
Big Five Theory (BIG5)	Tupes and Christal (1992)	4
Extended Techn. Acceptance Model (TAM2)	Venkatesh and Davis (2000)	4
Extended Techn. Acceptance Model (TAM3)	Venkatesh and Bala (2008)	4
Social Cognitive Theory (SCT)	Bandura and Walters (1977)	4
Trust Model	Kipnis (1996)	3
Six Other Theories	Various	13

Source: Rad et al. (2018, p. 365).

[34] The definitions of all abbreviations and acronyms can be found in the LIST OF ABBREVIATIONS**Error! Reference source not found.** – this refers especially to the different models and according variables within acceptance research in this section.
[35] The meta study encompasses n = 330 articles from IS research between 2006 and 2015.

It can be deducted that the main theories are DOI, TPB, TRA and the ones based on them (TAM and their extensions as most prevalent ones, UTAUT). This thesis also utilizes the TAM model as basic foundation for the acceptance study at hand (cf. sections 3.2.2 and 4.3). Schmaltz (2009) summarized the most relevant acceptance models into a form of genealogical tree (cf. Figure 3.1).

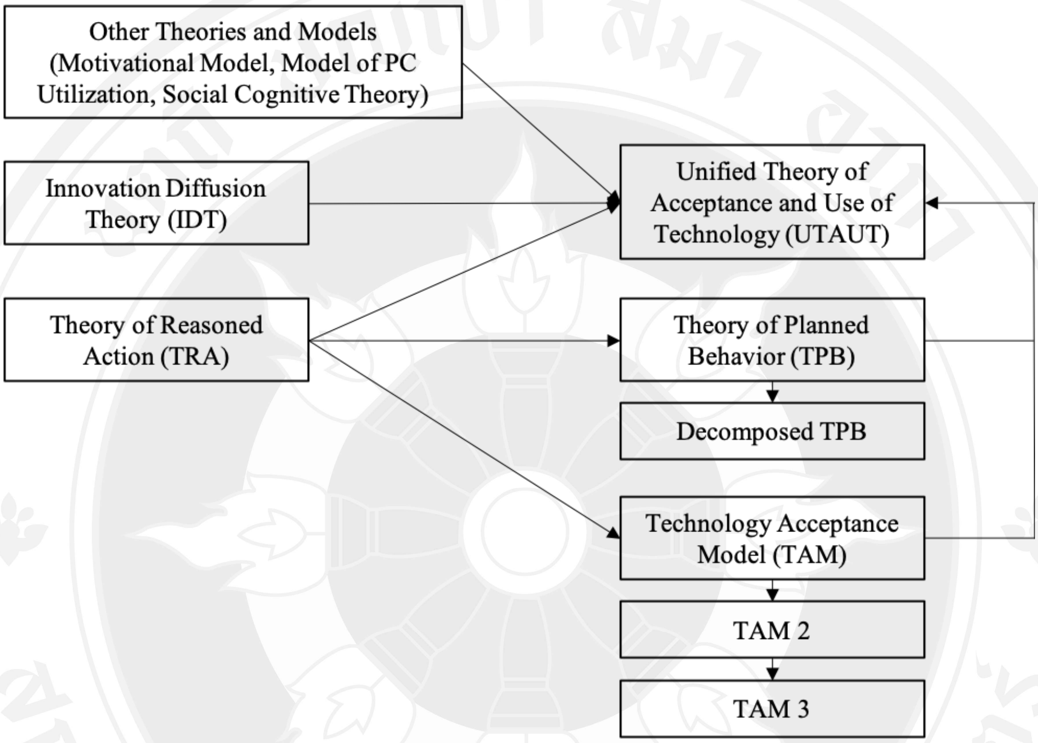

Figure 3.1 Overview and Formation of the Most Prominent Acceptance Models
Source: Own illustration based on Schmaltz (2009, p. 41).

The theory of reasoned action is being presented as well as its derivates TBP, TAM and UTAUT alongside their expansions Decomposed TBP, TAM 2 and TAM 3.

3.2.1 Theory of Reasoned Action and Theory of Planned Behavior

Fishbein and Ajzen (1975) formed the Theory of Reasoned Action (TRA) to identify the main reasons for the behavior of individuals. TRA stems from social psychology (Davis et al., 1989; Dillon & Morris, 1996; Taherdoost, 2018). Focusing on voluntary use, it predicts human behavior via the cognitive components attitudes, subjective norms, intentions and actual behavior (Dillon & Morris, 1996; Taherdoost, 2018). The model is shown in Figure 3.2.

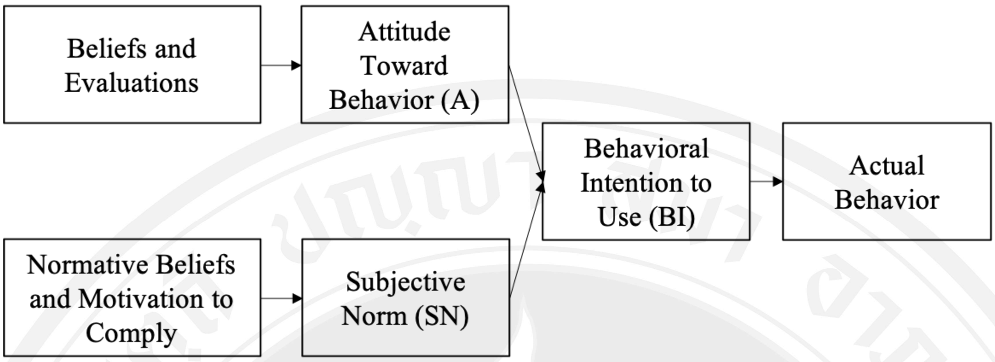

Figure 3.2 Theory of Reasoned Action (TRA)
Source: Davis et al. (1989, p. 984).

According to this theory, the conduct of a particular action unequivocally depends on the degree to which an individual has the intention to actually perform it (Schottek, 2016). Research objects are the influences of an individual's attitude (A) and the subjective norm (SN) concerning a certain behavior in the form of technology use or rejection (Dillon & Morris, 1996). Attitude refers to an individual's positive or negative feelings concerning the behavioral intention to use and actual technology usage as target behaviors, while subjective norms is defined as the perception an individual has about important influential persons to him concerning their opinion on this target behavior (Davis et al., 1989). Both constructs are influenced by certain beliefs (= an individual's perceived subjective probability of a certain consequence to performing the target behaviors), evaluations (= an evaluative reply to the believed consequence) or normative beliefs (= expectation perceptions of certain individuals or groups) and the motivation to comply to those (Davis et al., 1989). Those beliefs need to be identified for each research subject individually (Davis et al., 1989).

The TRA is "one of the most fundamental and influential theories of human behavior." (Venkatesh et al., 2003, p. 428) It was considered useful for strategy identification concerning behavioral changes in favor of technology utilization and further developed over time (Tscherning & Damsgaard, 2008). The main constructs behavioral intention to use (BI) and actual behavior in the form of use (U) have found their way into many other acceptance models such as the TAM and UTAUT and has been utilized in many research studies up to today. It has been expanded into various directions over the next decades. However, it is criticized to not explain behavioral reactions influenced by subconscious processes, impulses or emotions for example (Hale, Householder, & Greene, 2002).

The Theory of Planned Behavior (TPB) by Ajzen (1991) succeeded the TRA. In the TPB, perceived behavioral control (PBC) is added to the TRA and thus extends it via the introduction of aspects such as self-efficacy (Taherdoost, 2018; Venkatesh et al., 2003). The model tries to increase the explanatory power of TRA regarding situations without complete behavioral control (Königstorfer, 2008). Based on A, SN and PBC, the behavioral intention and finally the usage behavior is sought to be explained within the TPB (Fishbein & Ajzen, 1975; S. Taylor & P. A. Todd, 1995). TPB is a psychosocial theory (Taherdoost, 2018). Like the TRA, the TPB evinces high explanatory power (Königstorfer, 2008). As opposed to the rather theoretical DOI, both models are suitable for empirical validation as they exhibit straightforward definitions, operationalizations and causal relationships (Königstorfer, 2008). The TPB was expanded via explanatory external variables impacting the three variables A, SN, and PBC within the Decomposed Theory of Planned Behavior (DTPB by S. Taylor & P. A. Todd, 1995).

The prediction of intention in the DTPB is similar to the original TPB: In the DTPB, the three main constructs are broken down by revealing the underlying belief structure (Venkatesh et al., 2003) and thus making it even more applicatory to empirical research. According to S. Taylor and P. A. Todd (1995), the DTPB provides a good understanding of intention determinants while adding complexity to the model, whereas the TAM is a slightly better predictor of system use.

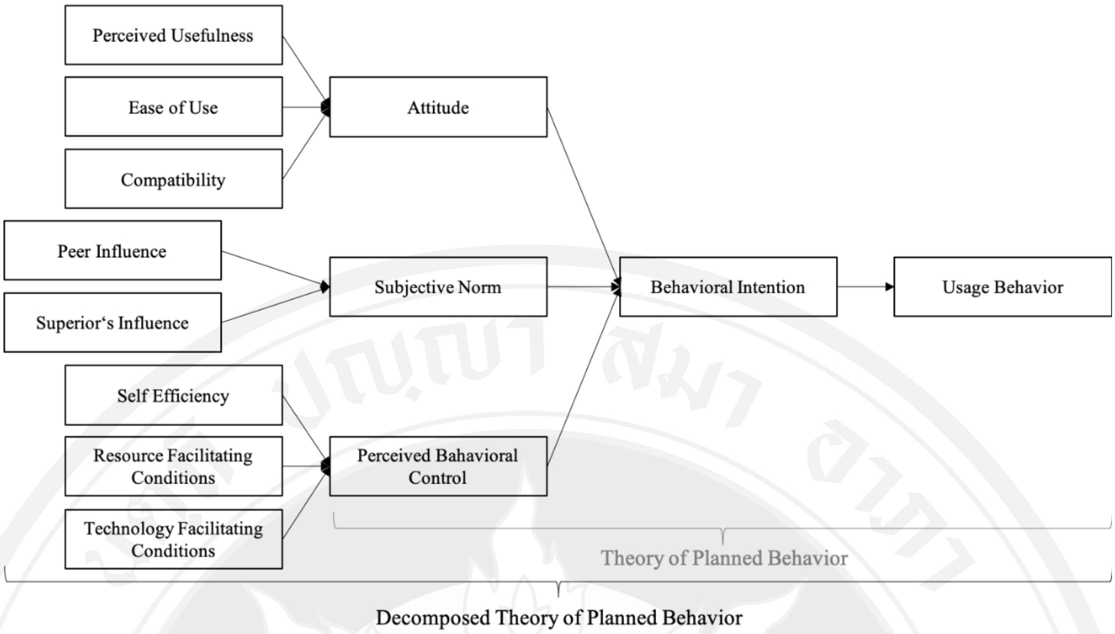

Figure 3.3 (Decomposed) Theory of Planned Behavior (TPB)
Source: Own illustration based on S. Taylor and P. A. Todd (1995, p. 146).

Figure 3.3 shows an overview of the (D)TPB components.

3.2.2 Technology Acceptance Model

The most popular model of the last several decades predicting system use is the substantially empirically supported Technology Acceptance Model (TAM; Gefen, Karahanna, & Straub, 2003; Taherdoost, 2018; J. Wu & Lederer, 2009). It is an adaptation of the TRA to suit information technology (Davis et al., 1989; Königstorfer, 2008; S. Taylor & P. A. Todd, 1995). Manifold adaptations have been established as well as combinations with other theories to enhance its explanatory power (Schmaltz, 2009). The TAM was established by Davis (e.g., Davis, 1985; Davis et al., 1989) to identify factors motivating individuals to utilize information systems (Y. Lee, Kozar, & Larsen, 2003; J. Wu & Lederer, 2009). The model implicates particular suitability for user acceptance prediction as well as explanation of information systems in the form of end-user computer technologies (Davis et al., 1989) and is tailored to job usage (Venkatesh et al., 2003). Main assumption of TAM is that actual, planned behavior is dependent on the behavioral intention to do so (Dahm & Dregger, 2019; Venkatesh et al., 2003). It has been object of diverse acceptance studies with various scenarios i.e., types of technologies and users (Venkatesh et al., 2003).

Based on the motivational paradigm of Stimulus (system features and capabilities) – Organism (user's motivation to use the system) – Response (actual system use), the TAM intends to describe the motivational processes in between these aspects (Davis, 1985). The TAM model is shown in Figure 3.4.

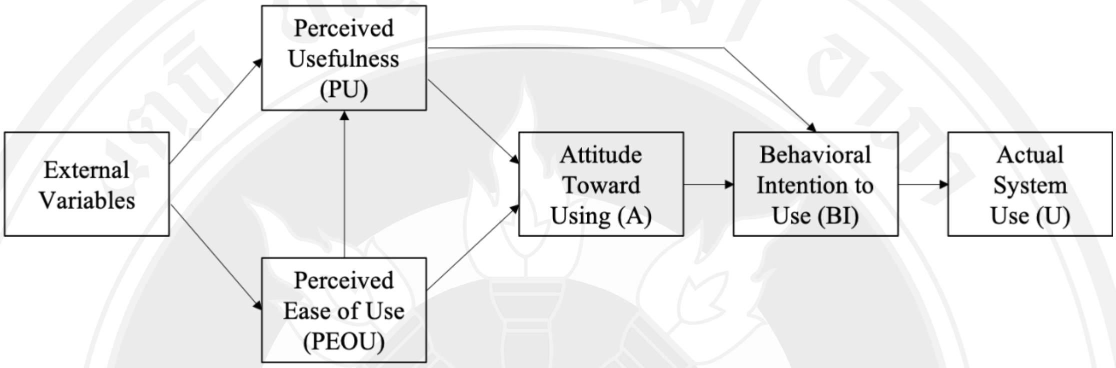

Figure 3.4 Technology Acceptance Model (TAM)
Source: Davis et al. (1989, p. 985).

The TAM brought practical use to acceptance research since its main aspects, perceived ease of use (PEOU) and perceived usefulness (PU), are factors of a technology that can be influenced and thus controlled by system designers (S. Taylor & P. A. Todd, 1995). PEOU is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320); PU refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989, p. 320). Both aspects are based on system features and capabilities, which in turn are dependent on the configuration and design of designers, developers and managers (Davis, 1985). According to L. Liu and Ma (2006), PU and PEOU explain between 30 and 70 percent of the variance in technology acceptance via BI and U. The TAM can be utilized in individual and organizational contexts. However, most empirical research investigates voluntary use cases with voluntariness as a prerequisite (e.g., Thim, 2017; Venkatesh, 2000; J. Wu & Lederer, 2009). The model is extensively empirically supported (e.g., Dadayan & Ferro, 2005;

Gefen & Keil, 1998; Ghazizadeh et al., 2012; L. Liu & Ma, 2006; Pires, Costa Filho, & Cunha, 2011). It gained popularity because of its scales' high levels of reliability and validity (Königstorfer, 2008; Venkatesh & Davis, 2000). Being a robust model in itself (e.g., King & He, 2006), the TAM has been extended by other crucial factors for IT adoption and use (J. Wu & Lederer, 2009). Extensions evolve around (1) individual dimensions concerning attitude, (2) technological dimensions, for example concerning its complexity, or (3) organizational dimensions regarding aspects such as motivation (H. Sun & Zhang, 2006). Criticized aspects are the hypothesized innovation positivism of the potential users (Scheuer, 2020) and a lack of practical relevancy for organizations because of missing instructions for intervention in the form of measures to increase PU and PEOU (Gefen & Keil, 1998).

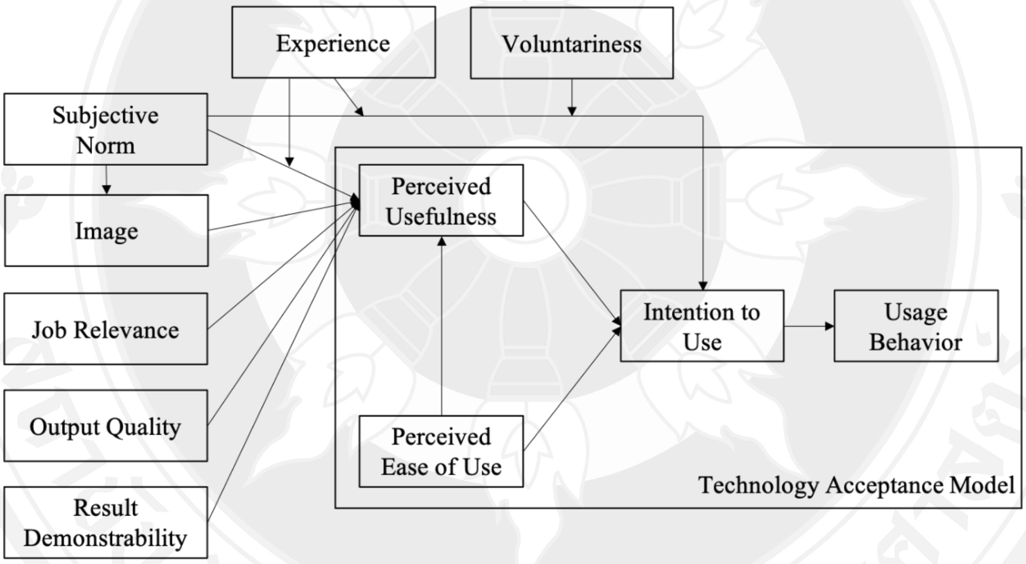

Figure 3.5 TAM2 as Extension of the Technology Acceptance Model
Source: Venkatesh and Davis (2000, p. 188).

The TAM2 (cf. Figure 3.5), mainly based on the original TAM, takes SN of TRA as well as other social (voluntariness, image) and cognitive instrumental processes (job relevance (REL), output quality (OUT), result demonstrability (RES)) as additional aspects (Park, 2009; Venkatesh & Davis, 2000).

Attitude has been omitted for better and more parsimonious explanation of intention (Venkatesh et al., 2003). The model seeks to better explain specifically the two constructs of perceived usefulness and behavioral intention to use (Venkatesh & Davis, 2000). Perceived usefulness is set into relation with job performance and it is hypothesized that even when individuals dislike a technological system personally, they may still use it as it is perceived to increase their job performance (Dillon & Morris, 1996). In their examination across four studies, Venkatesh and Davis (2000) found that the TAM2 accounts for 40-60 percent of the variance in usefulness perceptions and 34-52 percent of the variance in the intention to utilize a system. This is a considerable improvement to the original TAM (Alexandre et al., 2018; Park, 2009) beginning at 30 percent of variance explainability.

In the TAM3, the TAM 2 and the model of the determinants of PEOU developed by Venkatesh (2000) are combined by Venkatesh and Bala (2008) to form an even more elaborative and integrated model including further aspects such as computer self-efficacy (SE), perceptions of external control (PEC), computer anxiety (ANX) and perceived enjoyment (PE) (cf. Figure 3.6). The moderating effects of experience and voluntariness are hypothesized to affect the newly introduced variables as well. Classified into anchor variables (general beliefs concerning a certain technology and its utilization) and adjustment variables (related to system characteristics), there are six determinants of perceived ease of use (Venkatesh & Bala, 2008). Perceived usefulness is influenced by the five predictors as introduced in TAM2 (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). The TAM3 explains 43-52 percent of the variance in perceived ease of use while 40-53 percent of the variance in behavioral intention and 31-36 percent of the variance in use are explained across various time periods (Venkatesh & Bala, 2008). Hence, a slight improvement was achieved by further developing the TAM2 model. The capacious TAM3 model encompasses a significantly higher number of constructs than its predecessors TAM and TAM2. It serves as a welcome and often applied base for acceptance studies in various contexts (e.g., Claßen, 2012; Lotz, Himmel, & Ziefle, 2019; Scheuer, 2020; Schmaltz, 2009).

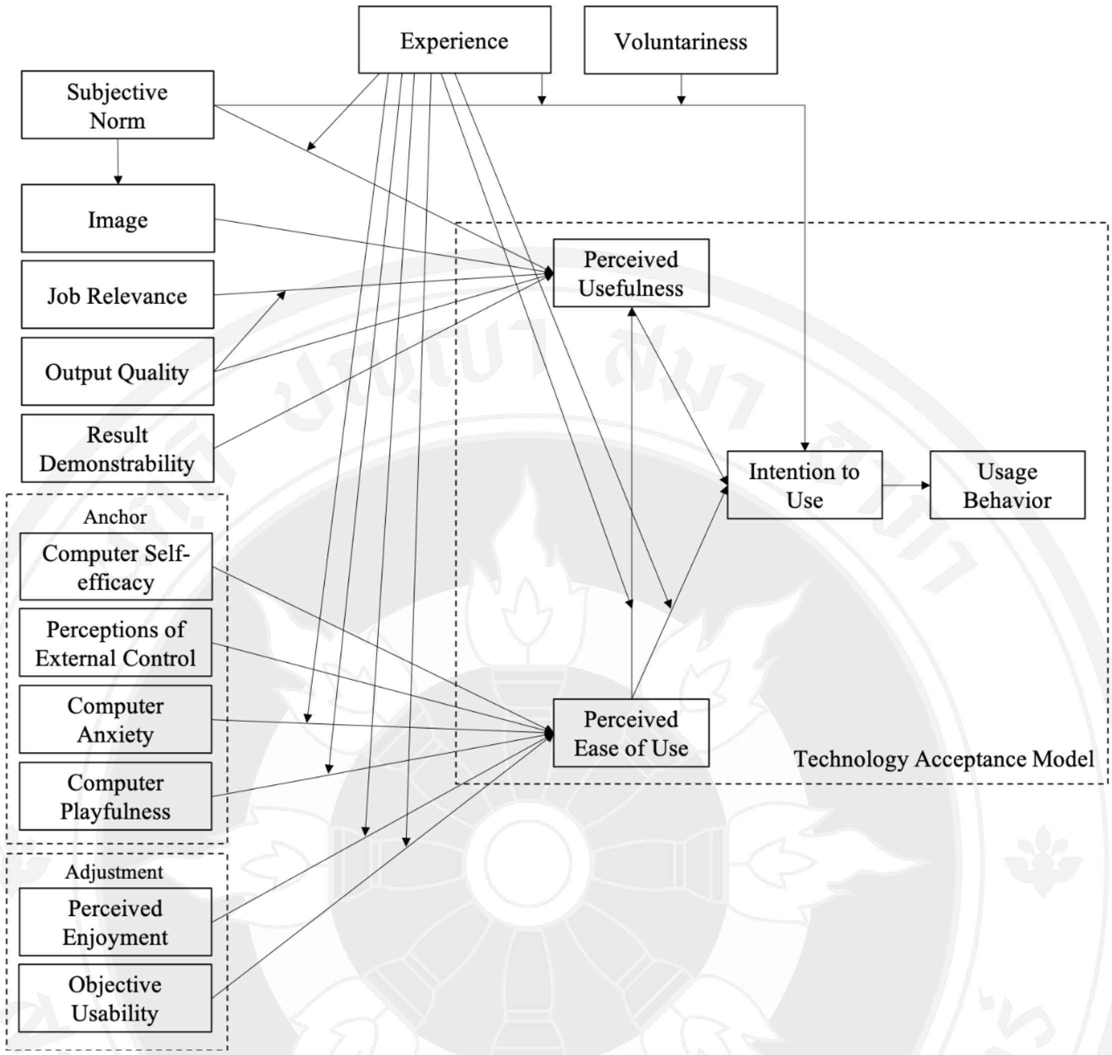

Figure 3.6 TAM3 – a Combination of TAM2 and the Model of the Determinants of Perceived Ease of Use

Source: Venkatesh and Bala (2008, p. 280).

In 2018, two meta-studies extracted 142 (Alexandre et al., 2018) and 26 (Rad et al., 2018) relevant acceptance criteria from literature, both of which show that the TAM-related perceived usefulness and perceived ease of use are most relevant for acceptance investigation.

3.2.3 Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) combines elements of eight established preceding acceptance models and theories (cf. Figure 3.7): TRA, TAM, Motivational Model (regarding extrinsic and intrinsic motivation), TPB, Combined TAM and TPB, Model of PC Utilization (investigation of the factors job-fit, complexity, long-term consequences, affect towards use, social factors, facilitating conditions influencing usage behavior directly based on Thompson, Higgins, and Howell (1991)), DOIT and Social Cognitive Theory as established by Bandura and Walters (1977) based on expectations, self-efficacy, affect and anxiety (Venkatesh et al., 2003). The four key concepts performance expectancy, effort expectancy, social influence, and facilitating conditions are regarded as influencers of the behavioral intention to use and ultimately utilize a certain technology. Furthermore, the four control variables age, gender, experience and voluntariness of use are included. Venkatesh et al. (2003) identified performance expectancy, effort expectancy, and social influence as direct determinants of intention to use while intention and facilitating conditions influence usage behavior. Experience, voluntariness, gender, and age are utilized as moderators. Altogether, UTAUT explains 70 percent of the variance in intention to use (Venkatesh et al., 2003), which substantially surpasses the explanatory power of the TAM3 model.

With the UTAUT2, Venkatesh, Thong, and Xu (2012) brought the concept out of the organizational and employee-focused perspective into the end consumer use context. For that, they regard the four key constructs from a consumer’s point of view and add three more: Hedonic motivation, price value and habit while omitting usage voluntariness as former moderator (Venkatesh et al., 2012). The model explains 74 percent of the variance in consumers’ behavioral intention to utilize a certain technology while accounting for 52 percent of the variance in consumers’ actual technology use (Venkatesh, Thong, & Xu, 2016).

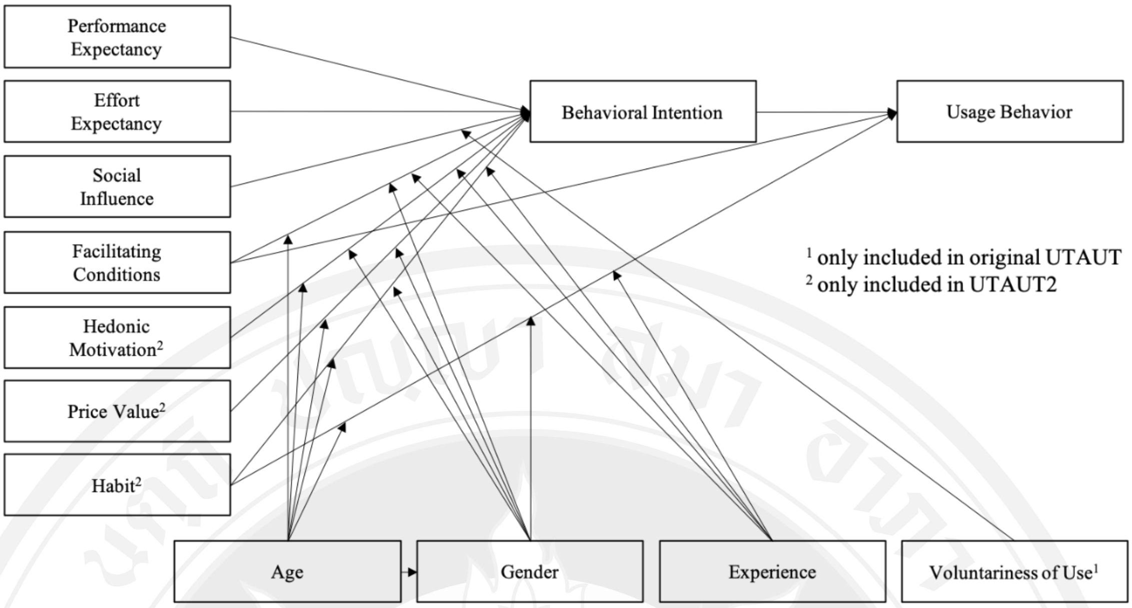

Figure 3.7 (Extended) Unified Theory of Acceptance and Use of Technology (UTAUT(2))

Source: Venkatesh et al. (2003, p. 337); Venkatesh et al. (2012, p. 160).

Despite its comprehensiveness, the suitability of the original model is questionable regarding the types of aspects investigated to predict and explain the acceptance of recruiting chatbots as novel information technology: As stated by C. Kim, Mirusmonov, and Lee (2010), the TAM constructs and extensions are considerably more specific than the generalized constructs utilized in UTAUT. The UTAUT2 shifted its perspective from an employee to a consumer viewpoint making it unsuitable for this research.

3.3 Chatbot Technology Acceptance Research Models

With productivity- and social psychology-oriented technology approaches, more specifically the TAM (Davis, 1985; Davis et al., 1989) as most prevalent one, many adaptations and demergers of such basic models established. In 2019, the author conducted a structured literature review to find a suitable adaptation of a traditional technology acceptance model considering the requirements and specialties of chatbot technology. 141 related papers as well as additional literature from relevant cited researchers of the found papers amassed a total of 349 papers resulting in 49 distinct acceptance models and 24 acceptance-related theories as well as many adaptations and combinations. As basis for the literature search, papers listed in the Social Science Citation Index and Google Scholar related to the term "acceptance" in relation to the terms "technology model/theory" (17,141/6,435 papers), "innovations" (5,866 papers), "automation" (3,530 papers), "recruiting" (5,348 papers), "HR" (7,763 papers), and "chatbot" (20 papers) were regarded. Those below the degree of Ph.D. were dismissed and the remaining papers were sorted prior to reduction according to content-related fitness (actual relation to at least one of the aspects chatbots or another innovative digital technology, recruiting or HR, and (new) acceptance theory/model) concerning the title, abstract, display of information about the utilized theoretical foundation and results. Appendix C shows an overview of the yielded 49 models of the structured literature review, many of which include parts or adapting the traditional acceptance models as introduced in *section 3.2*. A model posing a theoretical foundation for the examination of chatbot technology acceptance as exemplary automation technology for recruiting in HR was not found in the literature review. Hence, the most suitable model is identified for subsequent adaptation to the research subject at hand.

According to the preconditions as set by the research object-related parameters of the research study, the compiled research models are further analyzed for content-related fitness. Only the models setting focus on automation technology will be taken into consideration. Furthermore, an assessment of their empirical research applicability and feasibility is conducted (loosely based on selection criteria by Schmaltz (2009)) to ensure usefulness for the research at hand:

1) Chatbot research fit (adaptability to general chatbot technology acceptance thus suitable to (1) the recruiters' perspective in general (not focusing on one particular area such as looks/design or personality), and (2) chatbot technology directly or indirectly (e.g., automation research, dialogue reference, referral to features such as NLP)),
2) Empirical data/validation (e.g., related empirical studies of (sub-) model(s) available),

3) Overall operationalizability (existent items adaptable to chatbot research, external variable modelling),
4) Investigation at the individual level (as opposed to the organizational level), and
5) Specific automation focus in accordance with the established idea of job-related automation concerns.

Consistent with Schmaltz (2009), a four-scaled evaluation scheme is utilized:

● Requirement is fully met ◑ Requirement is partly met

◕ Requirement is met to a large extent ◔ Requirement is (mostly) not met

In Table 3.2, the five models meeting the binary criteria (4) (on the individual level) and (5) (automation focus) are evaluated according to the remaining three criteria (1)-(3) via investigation of the corresponding literature as well as additional context-related research.

Table 3.2 Criteria-based Evaluation of the Eligible Acceptance Models

No.	Model Name	Author	Year	(1) Chatbot Fit	(2) Empir. data	(3) Operat. (items)
29	**Framework of Automation Use (FAU)**	Dzindolet, M. T. et al.	2001	◔	◔	◔
42	**Automation Acceptance Model (AAM)**	Ghazizadeh, M. et al.	2012	◕	◔	◑
44	**Adjusted Automation Acceptance Model (AAAM)**	Bekier, M.	2013	◕	◔	◑
47	**Human-Robot Collaboration Acceptance Model (HRCAM)**	Bröhl, C. et al.	2019	◕	●	●
48	**Collaborative-Robot Accept. Model (CRAM)**	Lotz et al.	2019	◕	●	◔
49	**Künstliche Intelligenz Akzeptanzmodell (Artificial Intelligence Accept. Model) (KIAM)**	Scheuer, D.	2020	◕	◕	●

Source: Own evaluation based on Appendix C and loosely based on Schmaltz (2009, p. 52). Highlighted in grey color: Most suitable tasks for automation according to the evaluation criteria outcome (> 2 ●).

The concentration on research with automation focus is crucial as all conventional acceptance models such as the TPB, TRA, TAM, TAM2, TAM3, UTAUT and UTAUT2 have been established way before the sophistication of intelligent systems formed and do not consider certain aspects: Facets of automation technology such as the (1) increasingly elaborate abilities, (2) broader range of amenable tasks, and (3) users' heterogeneity in the form of different ideologies or levels of confidence (Castelo, 2019) are elided. However, they are hypothesized to evoke a certain level of perceived job-related automation concerns and thus represent the main focus of the study at hand.

3.3.1 Framework of Automation Use

The Framework of Automation Use (FAU) model was developed by Dzindolet, Beck, Pierce, and Dawe (2001) to predict the use, misuse, and disuse of automation technology mainly in military contexts based on user-sided cognitive, motivational, and social processes to better understand the rationale of end users relying or refusing to rely on automation technology. Regarded cognitive factors are the reliability of the automation technology, the reliability of manual operation, and several cognitive biases, which altogether form the perceived utility of the system (Dzindolet et al., 2001). Hence, in contrast to the traditional TAM approach, this model defines utility based on perceived reliability and the existence of biases such as the self-serving bias or the bias toward automation. This aspect of reliance does not fit to the use case at hand regarding chatbots as voluntary substitution possibility for candidate interviews. High perceived utility then leads to trust in the system and a feeling of dispensability (Dzindolet et al., 2001). Alongside the user's personal levels of fatigue, interest and his take on potential penalties for task failure as well as rewards for task completion, the perceived level of dispensability has an impact on the effort as main variable regarding the motivational process (Dzindolet et al., 2001). The social processes are broken down into the moral obligation to rely on oneself, relative trust, and feelings of control and directly influence the use of automation technology. While the model contains many relevant considerations such as the variable of feeling of control, the workload and the intrinsic interest in the particular task, it regards several variables not in focus of the scenario at hand, for example rewards as well as penalties for (un-)successful task completion. Overall, the FAU regards the likelihood of reliance on the automation system in the different manifestations (1) misuse indicating overreliance, (2) use showing reliance, or (3) disuse defined by a lack of reliance. This classification would shift the focus of this study away from acceptance research towards a reliance assessment.

3.3.2 Automation Acceptance Model

The Automation Acceptance Model (AAM) is an extension of the TAM model that was adapted to automation technology considerations by Ghazizadeh et al. (2012). They propose an inclusion of the aspects compatibility, defined as the consistency of the technology with the operator's values, experience, and needs, and trust. Both variables influence perceived usefulness as well as perceived ease of use and the external variables subjective norms, voluntariness, and experience in turn influence the beforementioned ones while compatibility is also hypothesized to be influenced by the level of automation (Ghazizadeh et al., 2012). The model contains interesting aspects, especially regarding the idea of trust and can be utilized for chatbots as automation technology. However, it is fairly straightforward lacking of constructs depicting potential automation-related job concerns and Ghazizadeh et al. (2012) have neither operationalized the proposed variables nor conducted a quantitative study to validate their theoretical considerations and the TAM adaptation. Bekier (2013) utilized this theoretical foundation in his dissertation on the specific use case of air traffic management automation and adjusted the AAM by developing the novel Adjusted Automation Acceptance Model (AAAM). Here, the aspects attitude towards change, job satisfaction, the quality of the automation technology, the type of the technology and the type of user (Bekier, 2013). These ideas offer research opportunities, for example for comparative studies regarding different types of users or different kinds of automation technologies. As this study aims at a cross-sectional in-between subjects study approach, these aspects are out of scope and would thus need to be disregarded. Analogous to the AAM, the AAAM has not been validated in a quantitative study yet and does not offer operationalized items for the respective variables.

3.3.3 Human-Robot Collaboration Acceptance Model

The HRCAM was invented by researchers of the Institute of Industrial Engineering and Ergonomics of RWTH Aachen, who introduced the HRCAM as a method to assess the acceptance of industrial process automation via physical robots. In a collaborative way, an automated physical system is introduced to work alongside the human employee and take over certain tasks of his. Building on the TAM model and its extensions, it incorporates fifteen independent variables exerting an influence on the core aspects of perceived usefulness, perceived ease of use and behavioral intention to use leading to actual system use (cf. Figure 3.8). Bröhl et al. (2019) utilize the well-established TAM2 variables subjective norm, image, job relevance, result demonstrability, and output quality. Furthermore, they include the TAM3 variables self-efficacy, perceptions of external control, anxiety, and perceived enjoyment. The authors then expanded this originally TAM-based model by considering technology affinity (TA) and perceived safety (PS) aspects as well as Ethical, Legal, and Social Implications (ELSI). Summarized as ELSI framework, those latter three facets initially stem from genome research (Biller-Andorno, 2001) and seek to explain organizational factors of influence. As discussed before, ethical, legal and social implications, for example potential job loss, play an important role in the research of automation technology acceptance. However, ELSI variables implications are new to technology acceptance research and were first introduced to the field within the HRCAM by Bröhl et al. (2019), who adapted those initially organizational aspects to the individual perspective of technology acceptance. The ELSI framework adds valuable information to the research agenda: (1) social (concerning potential social contact losses as defined by Kummer et al. (2017) and found to be influencing acceptance (Thatcher & Perrewe, 2002)), (2) legal[36] (focus here on data and the job processes it is utilized for), and (3) ethical (concerning potential job losses) implications of automation technology deployment within business contexts are considered. It allows for a more fine-grained examination of the introduced concept of job-related automation concerns.[37]

[36] The legal repercussions of automation technology implementation into recruiting processes are vast; see Freyler (2020) for example for an extensive discussion on automated recruiting.
[37] A similar study to the one on HRCAM by Bröhl et al. (2019) but with sole focus on TAM3 was developed by Lotz et al. (2019), who identified job-related automation concerns concerning safety and potential job loss to be most troubling for employees dealing with collaborative automation technology.

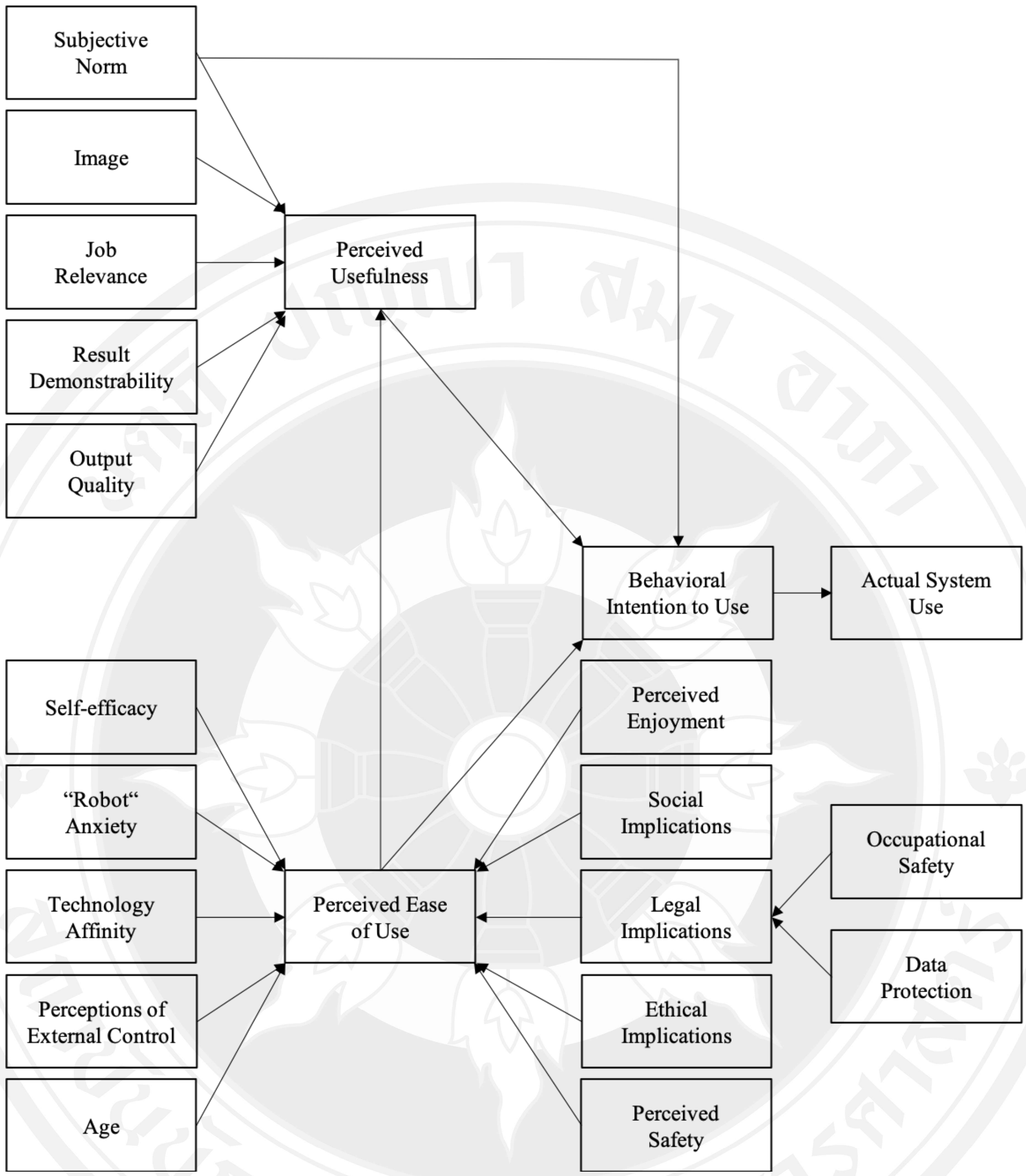

Figure 3.8 Human-Robot Collaboration Acceptance Model (HRCAM)
Source: Bröhl et al. (2019, p. 715).

Although the comparative aspect it contains regarding two different behavioral scenarios (active/passive behavior) is out of scope of the study at hand, the HRCAM is the most comprehensive one concerning the regarded external variables influencing technology acceptance among the identified automation acceptance models (cf. Table 3.2). It has been found highly performant in the empirical validation study by Bröhl et al. (2019), who had 1,326 subjects from four countries complete their online survey, which is accessible and shows the operationalization of the items. The underlying idea of collaboration between humans and technological systems poses a pertinent concept, which is suitable for the study at hand regarding recruiters as enablers and profiteers of chatbot implementation: The chatbot appears as a tool of support for the recruiter, who is involved in the configuration process of the dialogue system as well as the data maintenance and selective utilization of technology for certain tasks of his. Variables that have newly been introduced to the TAM environment such as ELSI can be adapted to the use case of chatbots. The aspect of anxiety fits the intended investigation of job-related automation concerns. However, with a focus on physical robots, the perspective needs to be adapted to the study at hand, which examines the technology of digital, non-physical chatbots. There are only few studies that investigated human-technology collaboration regarding technological process automation in the context of human resources management as most focus on design and programming aspects (Libert et al., 2020). The study at hand may expand this line of research. For this, aspects relevant for the discretionary deployment of automated dialogue systems in recruiting need to be included in the model.

3.3.4 Collaborative Robot Acceptance Model

The Collaborative Robot Acceptance model (CRAM) is a human-robot framework by Lotz et al. (2019), which similarly to the HRCAM regards a context of physical labor and is also derived from TAM3. It contains the TAM3 variables perceived usefulness and perceived ease of use as well as subjective norm, job relevance, output quality, computer playfulness, perceptions of external control, enjoyment, computer anxiety, image and computer self-efficacy as independent variables (Lotz et al., 2019). Furthermore, the locus of control, the experience regarding robots and manufacturing as use case, the age and gender are considered to explain the variance in the behavioral intention to use an automated robot (Lotz et al., 2019). In their own validation study with 159 participants, all variables were found to be significant except image, computer self-efficacy, and gender (Lotz et al., 2019). Considering the users level of anxiety and their fear of losing the job, this model contains relevant aspects important for the study at hand. However, it also contains certain factors specifically regarding the users own use, for example their level of computer playfulness and perceived enjoyment. This is not applicable to the study at hand, which regards the recruiters' perspective as implementers but not the end users of the recruiting chatbot. While there is empirical data from the study of Lotz et al. (2019), where they introduce the model and validate it, there is no information about the operationalization of the variables and the items utilized for TAM3 adaptation, the demographics, and the experience level as well as the newly introduced variable locus of control. No other study took up the model and re-evaluated or rather operationalized it. Hence, an alteration to the use case at hand is not feasible.

3.3.5 Artificial Intelligence Acceptance Model

The Artificial Intelligence Acceptance Model (German: Künstliche Intelligenz Akzeptanzmodell, KIAM) by Scheuer (2020) combines an adapted TAM (perceived usefulness and perceived ease of use as dependent variables; differences of the individual users, system characteristics, social influence, general conditions) for technology acceptance, AI specific extensions (level of human embodiment of the system, the level of intelligence of the system, the output reliability, perceived transparency, perceived trust) for specific AI technology acceptance, and the interpersonal acceptance-rejection theory (reciprocity, sympathy and affection) for AI personality acceptance to holistically explain the overall acceptance of AI. Regarding intelligent automation technology, it may seem suitable regarding the research object in focus and could be adapted to elaborate recruiting chatbots. It contains many pertinent variables, which can be applied to this study as well such as the variables transparency and technological understanding or the TAM basis. However, the model is closely linked to the broad term of AI, which complicates the transferability to the specific automation technology of chatbots. It combines different theories and models to form an overarching framework, which makes it comprehensive and relevant, but also too broad and too extensive for the purpose at hand asking recruiters for their opinion in a quantitative survey. Scheuer (2020) conducted a quantitative study to validate the model. However, it consists of only 42 participants reducing the significance or rather general validity of the empirical data – a limitation that is mentioned by Scheuer (2020) himself.

3.3.6 Model Confinement

The most proficient suitability for the study at hand according to the evaluation criteria as derived from Table 3.2 is accredited to the HRCAM. In contrast to the Framework of Automation Use (FAU), the (extended) Automation Acceptance Model (AAM), the Collaborative-Robot Acceptance Model (CRAM) and the Artificial Intelligence Acceptance Model (German: Künstliche Intelligenz Akzeptanzmodell, KIAM), it is not only suited best in terms of empirical validation and operationalization in terms of available items, but also the most comprehensive model in the area of automation research. As explained in section 3.2, TAM, TAM2 and TAM3 aspects are important cornerstones of acceptance research. Amongst scientific researchers, the TAM model as one of the productivity-oriented approaches, is considered a parsimonious and powerful theory (e.g., King & He, 2006; Y. Lee et al., 2003; Lucas Jr & Spitler, 1999; Venkatesh & Davis, 2000). It is considered one of the most popular and often applied models concerning acceptance at the individual level (e.g., Dennis, Venkatesh, & Ramesh, 2003; Esen & Özbağ, 2014; Venkatesh & Bala, 2008; Westin, Borst, & Hilburn, 2015). The model has been applied to various technologies and use cases and it has been enhanced by numerous variables (Y. Lee et al., 2003; Legris et al., 2003); their amendments TAM2 and TAM3 have been utilized extensively as well. It has been empirically tested and supported through numerous validation studies (e.g., Esen & Erdogmus, 2014; Venkatesh, 2000; Venkatesh & Bala, 2008). Especially the TAM aspects perceived usefulness and the behavioral intention to use have been identified as reliable measures utilizable in various contexts (King & He, 2006). Alongside the other essential acceptance research core variable of perceived ease of use, they have been incorporated within the highly performant HRCAM (cf. Figure 3.8 for full structural model), which is thus regarded as most suitable research model basis for the study at hand. It regards innovative technology as a way of cooperative process automation. In the case at hand, chatbots can be seen as co-workers to recruiters, who implement them into their work processes for efficiency enhancement.

However, a lack of practical relevancy for organizations is ascribed to TAM-related research in terms of a shortage in directives for measures increasing the perceived usefulness and the perceived ease of use (Gefen & Keil, 1998). While extensively expanded, changed and shaped over the years, the author found no encompassing, entirely suitable model that is sufficiently adapted to digital automation technology in terms of chatbots and that would consider relevant constructs important for recruiting chatbot acceptance to a satisfactory extent. Even the comprising HRCAM lacks important features such as a focus on non-physical automation technology and accompanying aspects like such a system's level of transparency towards its users. With an own acceptance model based on the core constructs of TAM and building on its adaptation HRCAM, this research adapts the presented concepts to the research object at hand – recruiting chatbots for first candidate interviews.

3.4 Status Quo of Chatbot Acceptance Research

Chatbots serve as technological dialogue partners for humans seeking assistance or certain information. Hence, research on this technological system is part of human-computer interaction (HCI). HCI refers to the communication and interaction between humans and computers. In the context of chatbots, HCI is also called human-robot interaction (HRI) (Liao et al., 2018). Here, the human counterpart treats the system not as a computer but also ascribes human attributes to it and thus treats it as a human (Nasirian, Ahmadian, & Lee, 2017). Over the past years, the focus of HCI changed from graphical user interface design towards natural-language user interfaces with textual input as means of interaction instead of the learnt scrolling or clicking of buttons for example (Følstad & Brandtzæg, 2017). The current premise in HCI is that interaction with technology via natural language textual or spoken in-/output is becoming relevant and feasible (Dale, 2016). AI researchers have underestimated the complexity of human language understanding and language generating for many years (Hill et al., 2015). As a consequence, main current fields of research within HCI are (1) the understanding and recreation of conversational processes, (2) the now possible analysis of high volumes of user data to improve the technology, (3) ethics and privacy of this novel technology and (4) the challenge of digital divides and biases (Følstad & Brandtzæg, 2017).

Acceptance of IS technology is an extensively researched area (e.g., S.-C. Chen, Shing-Han, & Chien-Yi, 2011; King & He, 2006; Krauße, Eißer, & Böhm, 2019; Tamilmani, Rana, Wamba, & Dwivedi, 2021). Many IS acceptance studies are set in e-commerce, e-government, and e-learning contexts (Rad et al., 2018). Particularly popular research objects are mobile technology in general, social media, Internet banking technology, and cloud computing (Rad et al., 2018). As established, most acceptance studies are based on TAM, DOI or UTAUT models. Often, the utilized research model is expanded via combination with other theories or integration of other variables (e.g., Agarwal & Prasad, 1998; Krauße et al., 2019), for example concerning the aspect trust (e.g., Gefen et al., 2003; L. Wu & Chen, 2005).

Focusing on chatbot research in particular, the number of scientific studies is increasing. There are many scientific studies embedding the automated dialogue system mainly in contexts such as healthcare (e.g., Fan et al., 2021; Kamita, Ito, Matsumoto, MunaNata, & Inoue, 2018; Laumer, Maier, & Gubler, 2019), education (e.g., Almahri, Bell, & Merhi, 2020; Chocarro, Cortiñas, & Marcos-Matás, 2021; J. Q. Pérez, Daradoumis, & Puig, 2020; Ranoliya et al., 2017), general customer and IT support scenarios (e.g., Goot & Pilgrim, 2019; Völkle & Planing, 2019) and e-commerce (e.g., Araújo & Casais, 2020; Chai, Horvath, Kambhatla, Nicolov, & Stys-Budzikowska, 2001; Kasilingam, 2020; Qiu, 2006; Rese, Ganster, & Baier, 2020). Other studies focus on particular aspects such as the perceived trustworthiness via warmth and competency during interaction (Rozumowski et al., 2019), design specifics (Abdul-Kader & Woods, 2015), or analyses of the humanness of the technology (e.g., Svenningsson & Faraon, 2019; Westerman, Cross, & Lindmark, 2019). A study by Rapp et al. (2021) found chatbot acceptance to be one of the five main topics of chatbot research in general; other focus topics are the general chatbot experience, emotional experience and expression, conversational issues, as well as humanness. Regarding their theoretical underpinnings, chatbot acceptance studies mostly draw on the TAM and its successors (e.g., Araújo & Casais, 2020; Kasilingam, 2020; M.-S. Lee & Kim, 2017; Qiu, 2006; Rese et al., 2020; Scheuer, 2020; Völkle & Planing, 2019), or the UTAUT(2) (e.g., Almahri et al., 2020; Laumer et al., 2019; Tamilmani et al., 2021). Some research yields results on chatbot acceptance based on DOI (e.g., Cardona, Werth, Schönborn, & Breitner, 2019).

In accordance with Libert et al. (2020) and Laurim et al. (2021), the author found that regarding the context of HR, only few acceptance research studies exist (e.g., Voermans & van Veldhoven, 2007; Yusoff, Ramayah, & Haslindar, 2010). TAM research for example is relatively new to human resource management (Schottek, 2016). El Ouirdi, El Ouirdi, Segers, and Pais (2016) for instance applied the UTAUT model to identify acceptance factors for social media in employee recruitment inspiring Rad et al. (2018) to apply their framework to HR social networks for recruiting. Dahm and Dregger (2019) set up a research study to investigate the acceptance of elaborate recruiting tools and to identify beneficial as well as inhibiting factors posing a similar research approach to the one introduced here. However, this research is broad in nature and does not focus on a specific technology, which the study at hand does with chatbots. Hence, acceptance studies are vast in the field of HR and recruiting. Also, chatbot acceptance studies gain in numbers (e.g., Rapp et al., 2021). First chatbot considerations in scientific research are also being conducted in the context of HR (e.g., Balachandar & Kulkarni, 2018; Hristova, 2019; Majumder & Mondal, 2021; Nawaz & Gomes, 2019; Schildknecht et al., 2018). However, HR-related chatbot acceptance studies based on scientific acceptance models are seldom (only three studies found: Eißer et al. (2020); B. I. Hmoud and Várallyai (2020)[38]; Laurim et al. (2021)). A research gap becomes apparent concerning factors influencing the acceptance of innovative automation technology in the form of dialogue-based chatbots in the HR-related field of recruiting.

3.5 Specified Research Gap

Advanced chatbot technology stands at its very beginning while coming into focus of extensive research (e.g., Hill et al., 2015; Lester et al., 2004; Radziwill & Benton, 2017; Stucki et al., 2018). Extensive chatbot studies of broad nature have been conducted (e.g., Liao et al., 2018; Mittal et al., 2016; Radziwill & Benton, 2017; Ranoliya et al., 2017; Reshmi & Balakrishnan, 2016; Stucki et al., 2018), some focusing on characteristics such as motivations for general private utilization and favorable aspects such as the naturalness of the system (e.g., Følstad & Brandtzæg, 2017;

[38] B. I. Hmoud and Várallyai (2020) solely mention chatbots as a possible example while mainly regarding AI measures for information systems in the context of human resources in general.

Morrissey & Kirakowski, 2013; Bayan Abu Shawar & Eric Atwell, 2007; Stoeckli et al., 2018). As seen in section 3.4, acceptance-related research studies for chatbot technology in HR contexts are a new field of research with few insights to draw from.

Research needs to evaluate how chatbots can help to increase efficiency in companies in the form of current and future possibilities. An essential prerequisite for successful chatbot implementation is the acceptance of this technology. Acceptance examination is vital for the novel innovation of elaborate chatbots in recruiting. This aspect will be investigated in the study at hand. While the concept of acceptance has been largely regarded for HCI and IS (Dillon & Morris, 1996), especially empirical account of HCI with conversational agents offering free text input are rare (Liao et al., 2018). Only little research has regarded chatbot acceptance in the context of HR communication.[39] The overall combination and application to the HR and more specifically the recruiting context for dialogue systems in communicative interaction contexts is new. While Yakkundi, Vanjare, Wavhal, and Patankar (2019) present a practical study in which they built an interviewing chatbot, no existing quantitative acceptance studies are known to the author where chatbots in recruiting have been the object of investigation for the focused use case of "candidate interviewing". This study aims at contributing to this nascent research topic and yields recommendations for action regarding the most relevant acceptance determinants out of the primary data.

The growing importance of automation technology, fueled by rising levels of application domains as well as capacity (Ghazizadeh et al., 2012; Scheuer, 2020) calls for scientific examination of human-technology relationships. Substituting human labor through software robots (bots) for standardizable tasks is generally called robotic process automation (Verhoeven & Goldmann, 2020). According to Horváth & Partners (2018), four kinds of software robots can be distinguished according to their automation and process complexity specifications (cf. section 2.4.1): (1) robotic process automation, (2) cognitive automation, (3) digital assistants, and (4) autonomous agents. Depending on their level of complexity, chatbots may fall into the second or third category. Areas of physical co-agency of technological and human workforce can be

[39] Deficiencies become apparent especially regarding integrated considerations of the whole recruiting process chain from first approach via employer branding up to candidate interviewing and analysis as well as the ultimate proposal of the most appropriate candidate(s) to the recruiter (for theoretical considerations in this regard e.g., cf. Majumder and Mondal (2021)).

summarized as human-robot collaboration. Human-technology collaboration, also called human-technology co-agency, is defined as the linkage between humans and machines (Hollnagel & Woods, 2005). As a novel kind of co-agency with a different relationship than in human-human interaction, it is interesting to study in scientific research. Consequently, it has already been subject of investigation (Ajoudani et al., 2018; Bröhl et al., 2019; Libert et al., 2020; Lotz et al., 2019). However, this research is principally centered on human-robot collaboration (HRC) in industrial contexts examining physical robots (e.g., Bahrin, Othman, Azli, & Talib, 2016; Brauer, 2017). In former times, research mainly focused on technological aspects of automation rather than on human aspects regarding technology collaboration (R. Parasuraman & Riley, 1997). This human perspective is regarded in more recent research (e.g., Bastam et al., 2020; Bauer, Wollherr, & Buss, 2008), also concerning acceptance factors (e.g., Beer, Prakash, Mitzner, & Rogers, 2011; Bröhl et al., 2019; Ghazizadeh et al., 2012). In a study regarding abstract digitalization scenarios but also collaboration with algorithms and robots by Bastam et al. (2020),[40] recruiters predict automation technology to rather function as a collaborating tool than as a substitution measure. The aspect of human-digital technology system collaboration however is a novel stream of research with a lack of investigation regarding human-chatbot collaboration and a study examining chatbots as collaborative task automation systems has yet to be done. While design features have been the object of investigation (Bittner, Oeste-Reiß, & Leimeister, 2019), to the best knowledge of the author, no study has sought for acceptance factors in this context of non-physical automation technology collaboration within organizations yet. Regarding the internal component of technology implementation in the recruiters' work processes as well as the external aspect of utilization by applicants, it is a relevant, novel research object and will enrich the field of acceptance research.

In conclusion, no study transferred the existing technology acceptance frameworks in the context of human-computer collaboration to chatbots in HR and in that regard, except for a case study by Eißer et al. (2020), no quantitative acceptance research is known to the author at this point regarding the recruiters' perception of recruiting chatbots as party working with this automation technology in their processes.

[40] Survey regarding "Digitalization in Recruiting" discussing future scenarios concerning the state of digitization in 2030 (n = 106 recruiters in German SMEs or corporations).

This gap will be closed by the dissertation at hand, providing new insights for theoretical acceptance research regarding digital automation technology as opposed to physical robotics and practical contributions in terms of relevant acceptance requirements that must be met to ensure successful chatbot implementation in recruiting processes. With the practical example of candidate interviewing, a novel use case is regarded not considered for chatbot conduct in scientific research yet. The focus construct of job-related automation concerns offers a new object of investigation potentially crucial for recruiter-sided chatbot acceptance.

3.6 Scope of the IS Research Chatbot Study

Main goal of the study is to empirically identify relevant acceptance factors for the novel and not yet sufficiently considered recruiters' perspective regarding chatbots as innovative recruiting automation technology. Exemplary field of application for the system is the recruiting-related task of candidate interviewing as established in the use case analysis. Reflections of the applicants' point of view rather than the recruiters' have been object of scientific research already (e.g., Dahm & Dregger, 2019; Langer, König, & Papathanasiou, 2019) and will not be in focus here. However, the recruiters' assessment of end user utilization is part of the investigation as their perception of the candidates' handling of the dialogue system potentially influences their acceptance. Concerning chatbot acceptance from the recruiters' point of view, the aspect of this technology specifically functioning as collaborator for the recruiting-related task of candidate interviewing is of special interest within this study: Are there any job-related automation concerns which are of significant influence on their level of recruiting chatbot acceptance? An examination of the underlying variables allows for theoretical and practical insights resulting in managerial implications. The resulting recommendations for action for companies will give indications for chatbot acceptance enhancement directives in terms of general management and prioritization measures of the identified factors resulting in recruiting process improvement via the implementation of a recruiting chatbot.

While at the organizational level, IT research assesses the relationship between technology expenditure and firm performance (Banker et al., 1993), the study at hand investigates the antecedents of recruiting chatbot acceptance at the individual level regarding expectations and perceptions of recruiters concerning the technology and does not focus on initial (binary) adoption decisions within the organization as depicted in Figure 3.9.

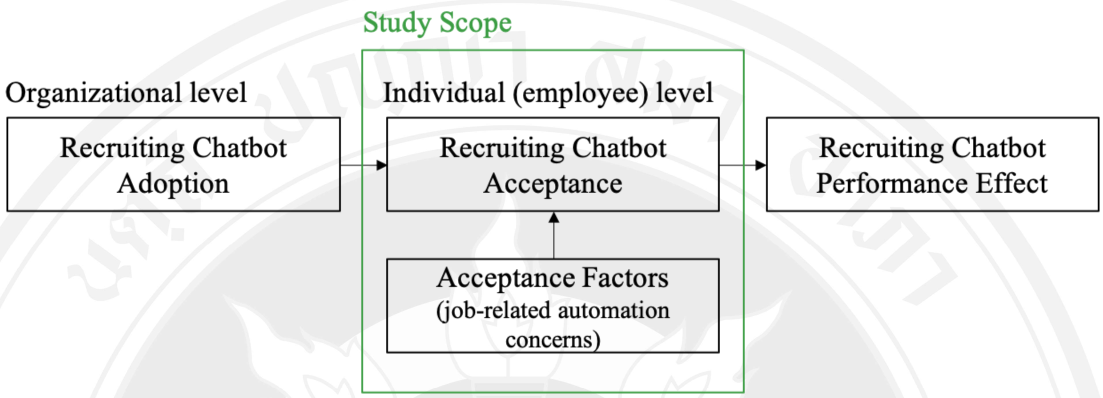

Figure 3.9 Scope of the Study for Examining Individual Recruiting Chatbot Acceptance Factors

Source: Own illustration based on Brandon-Jones and Kauppi (2018, p. 24).

The adoption decision for recruiting chatbots is taken by recruiting managers, who are typically not the ones collaborating with the technology within their daily work process. The study at hand investigates the latter group of non-managerial recruiters being directly affected by the implementation of a recruiting chatbot. This is in line with T. Bondarouk et al. (2017), who conducted a meta-study on electronic human resource management effectiveness research from 1970 to 2010 and found that people factors, as they call acceptance determinants on the individual level, are most relevant for successful e-HRM implementation. However, the organizational perspective is not neglected altogether as in this case, the recruiters in their role as collaborators with the chatbot technology within the recruiting process determine the success of the whole technology deployment operation within the organization. This applies at least to the scenarios he holds a freedom of choice in the form of discretionary utilization possibilities for. This study concentrates on the German market because of the current topicality of this area of research and the already obtained and imminently attainable market insights accessible to the author of the study. As established in section 1.3, the following research questions are sought to be answered:

RQ_1: What are relevant determinants for recruiting chatbot acceptance amongst recruiters in companies in Germany?

a) Which general recruiter-sided factors might influence recruiting chatbot acceptance?
b) Which external variables influence the acceptance of chatbots in recruiting?
c) How strong do the identified factors influence recruiter-sided recruiting chatbot acceptance?

RQ_2: What are relevant job-related automation concerns of recruiters in companies in Germany regarding recruiting chatbots influencing their level of acceptance?

a) Which relevant factors related to *job-related automation concerns* exist and how can they be operationalized and measured?
b) What is the level of influence of *job-related automation concerns* on recruiting chatbot acceptance?

Like Dillon and Morris (1996), this research does neither regard the design of the utilized interface (which in this case is to be seen as an enabling function for chatbot conversation from a back- and a frontend perspective) nor evaluates the performance of the system concerning its usability, but instead seeks to analyze the facilitators and impediments in the form of acceptance determinants concerning innovative technology on the example of recruiting chatbots. This way, the study is not bound to one single prototype alongside the linked lack of generalizability.

In order to provide relevant insights both for academics and practitioners, the study refrains from complex abstract model building and rather aims at validating established TAM and HRCAM considerations while integrating other vital concepts from chatbot research to propose a way of researching acceptance aspects concerning sophisticated recruiting chatbots. Hence, a synoptic conceptual model for analysis will be built and validated. Acceptance determinants for this kind of technology shall be reconciled. This way, practice-oriented managerial implications for companies with recruiting departments in need of such a solution can be derived from the research, which contemporary literature is lacking of by only discussing perfunctory restrictions such as the present non-capacity of automating atypical conversations and decision-making (e.g., Corinna Maier, 2018; Reilly, 2018).

CHAPTER 4

MODEL CONCEPTUALIZATION

As a theoretical foundation, this research incorporates the Human-Robot Collaboration Model (HRCAM) for process automation as proposed by Bröhl et al. (2019) based on TAM-related and ELSI variables. In this section, the HRCAM will be applied to the technology of chatbots as well as adapted from physical robot to digital chatbot technology workplace collaboration: The basic logic concerning the relationships between certain TAM-variables and the interrelationships with ELSI-variables are included as originally intended. In addition, it will be adapted from physical robot to digital chatbot technology workplace collaboration through (1) variable adaptation, and (2) extension by necessary variables for chatbot acceptance assessment as opposed to robot technology investigation. All changes and adaptations will be done in accordance with the underlying theoretical foundation. The factors most relevant for recruiting chatbot acceptance and susceptible to influence by companies in order to implement chatbots in their recruiting processes will be distilled. As a result, the specific constructs best suitable for acceptance research on chatbot technology will be consolidated and observed in this study. Closely related suitable variables withdrawn from the HRCAM model concerning human robot interaction and acceptance research in general (e.g., Alexandre et al., 2018; Davis et al., 1989; DeLone & McLean, 1992; Fishbein & Ajzen, 1975; Goodhue & Thompson, 1995; Kipnis, 1996; Rogers, 2003; Venkatesh et al., 2003), providing the basis for fear of substitution through technology (e.g., Mokyr, Vickers, & Ziebarth, 2015; Venkatesh & Bala, 2008), will complement the model and adapt it to the nascent topic of recruiting chatbot acceptance. Derived from literature and similar studies in other areas of focus already conducted, they all strike as relevant and worth including in the scope of the study.

With an extensive collection of TAM2- and TAM3-inherent variables, the HRCAM model contains many relevant aspects to examine in an investigation of chatbot acceptance with a focus on automation concerns, which are presented and embedded into the research context of this study. However, not all variables are suitable for the research object at hand because of a focus on physical robot technology for example or because of other specializations that are not considered of this acceptance study. In accordance with the focus of the study and in order to reduce complexity, those non-necessary or non-applicable variables of the HRCAM model are removed and no longer considered in the proposed HCCAM research model. The following variables are taken out of consideration:

1) Image: As a concept regarding the prestige of a certain innovative technology and investigating the interrelation with or rather opinions of other peers, it is no suitable object for the focused analysis of recruiter-internal job-related automation concerns. In this study, the individual perspective of the recruiters is examined while disregarding the general view on the technology, which a company might have from an organizational perspective alongside the potential impact on its image as a potential employer. Furthermore, Lotz et al. (2019) found it to be insignificant in the evaluation of their human-robot collaboration acceptance model.
2) Perceived enjoyment: While potentially important for applicants regarding recruiting chatbot utilization (Laurim et al., 2021), hedonistic effects are not in the focus of this recruiter study. It rather aims at yielding information on perceived job-related automation concerns that potentially trouble recruiters in their handling of chatbot technology. The element of perceived enjoyment is thus disregarded and removed from the model.
3) Perceived safety: In virtual contexts, safety in the form of harmlessness is different from physical safety concerning the collaborating human workforce. Hence, perceived safety concerning physical aspects of human-technology collaboration is not considered

in this research as chatbots belong to the digital kind of technologies incapable of physically impairing the well-being or actively harming the utilizing party (recruiters in this case). This is in accordance with Osswald, Wurhofer, Trösterer, Beck, and Tscheligi (2012), who proclaim that desktop-computer systems and the like offer comparably safe surroundings as opposed to risky physical situations such as operating a vehicle. However, they could cause harm in the form of data privacy flaws or unintended/wrongly implemented manipulation for example. Related to the aspect of safety, *security* in the form of protection from malicious behavior of third parties plays an important role (Wing, 2018). Where in materialistic scenarios, machines have to be guarded physically, digital security measures are necessary to protect the system from adverse intrusion. A popular example of a tampered chatbot system is Tay, an AI-based chatbot by Microsoft, which learnt to produce racist, sexist and anti-Semitic statements through Twitter conversations (Wolf, Miller, & Grodzinsky, 2017). Data science makes way for novel security flaws – networks, devices, software, underlying algorithms and data need protection (Wing, 2018). Security is an essential element of recruiting chatbots as they not only represent the company and thus the company's image, but also might deal with personal applicant data. In the HCCAM model of this research, it is included as the variable of legal implications focusing on data protection (security). Implicitly, it is also part of variable perceived system transparency, which is newly introduced to the model in this study.

4) Occupational safety: Alongside perceived safety, occupational safety as the institutionalized protective authority concerning technology in physical work processes is superfluous for this study.

5) Technology affinity: While regarded as a control variable, the personal trait of technology affinity it is not kept as focal point of the study. However, as it may impact the individual's perceptions

regarding exemplary innovative technology, it will be controlled alongside other relevant control variables.

6) Age: Age will be considered as a control variable as it is no main focus of the study but might be related to aspects like chatbot anxiety or the perceived ethical implications of chatbot implementation into the recruiting process.
7) Actual Usage: In this study, recruiters with and without previous recruiting chatbot utilization experience are queried about their opinion on the technology. Hence, some of them cannot be inquired about their utilization behavior but rather only on their behavioral intention to utilize such a dialogue system. Since considerable validation research found that behavioral intention to use predicts actual behavior (e.g., Davis et al., 1989; Sheppard, Hartwick, & Warshaw, 1988; Venkatesh & Davis, 2000; Venkatesh et al., 2016), behavioral intention is considered for the acceptance examination instead of the partially unanswerable question regarding actual usage.

4.1 Adaptation of the Human-Robot Collaboration Model towards Chatbot Research

In the following, the original HRCAM is adapted to the research context at hand. It is enhanced via suitable other variables and complemented with fitting control variables.

4.1.1 Model Extension

Regarding the contribution of the TAM to the field of IS research, Davis states that this model, in his opinion favorable to others in the field of acceptance research, serves as a profound base for extensions and elaborations (Y. Lee et al., 2003). This is in line with other researchers who claim that existent models shall be integrated with new models and theories (e.g., Dahm & Dregger, 2019; Fichman & Kemerer, 1999; Millman, 2012; Miltgen, Popovič, & Oliveira, 2013). In accordance with Dillon and Morris (1996), other relevant aspects are sought to improve the explanatory power of the model as single-variable answers are not likely to explain the acceptance level of a certain technology. In the research at hand, the model is adapted from the automation technology of physical robots to the virtual context of chatbot acceptance through extension: The chatbot-essential and context-specific aspects of perceived system transparency and inertia based on pertinent literature are introduced and items are adapted to the context of chatbots in recruiting processes.

4.1.1.1 Inertia

Talke and Heidenreich (2014) argue that in adoption and acceptance research, a common misconception, for example by Rogers (2003), is that users are generally open to change and consequently interested in experimenting with new technology. They label this assumption as pro-change bias, which needs to be overcome to facilitate innovation acceptance (Talke & Heidenreich, 2014). Hence, a point of criticism being articulated against acceptance research, e.g., the original TAM, is its innovation positivism approaching innovative technology with a categorically positive attitude and thus leaving reasons for potential rejection out of consideration (Scheuer, 2020; Talke & Heidenreich, 2014). Swanson (1988) and Davis et al. (1989) for example stress the importance of considering those users who might be unwilling to use a certain system as their inclusion yields potentially significant gains in performance. With the inclusion of inertia (INA), a notion associated with status quo bias (e.g., Polites & Karahanna, 2012; Sillic, 2019), attention is paid to this relevant aspect.

The status quo bias theory by Samuelson and Zeckhauser (1988) states that individuals tend to prefer the maintenance of the status quo when being presented alternatives to it. Based on economics, psychology, and decision theory and validated via a series of decision-making experiments, it describes the effect of decision-makers clinging to the status quo when being presented with decisions offering alternatives to the current situation. Possible explanations are transition costs, uncertainty, cognitive misperceptions or psychological commitment based on misperceived sunk costs, regret avoidance or a drive for consistency (H.-W. Kim & Kankanhalli, 2009; Samuelson & Zeckhauser, 1988). It is object of acceptance (e.g., Bagozzi & Lee, 1999; Polites & Karahanna, 2012) and resistance (e.g., H.-W. Kim & Kankanhalli, 2009; Moldovan & Goldenberg, 2004) research. Müller, Mattke, Maier, and Weitzel (2019) utilized the status quo bias perspective to investigate patients' resistance to use chatbots for medication. They found that many patients resisted the use of chatbots, mainly because of a lack of trust leading to anticipated regret. H.-W. Kim and Kankanhalli (2009) ascribe status quo-induced transition costs also to the technology acceptance items effort expectancy and perceived ease of use. A related concept is resistance to change, which describes a negative behavioral response in association with change (Müller, Mattke, Maier, & Weitzel, 2019). Talke and Heidenreich (2014) distinguish passive (generic resistance to innovations in general prior to actual system utilization) and active (negative outcome of an actual usage assessment) change resistance. The concept of change resistance has been extensively examined in organizational contexts (e.g., Au, Ho CK, & Law, 2014; Davidson & Chismar, 1999; Lucas, Lucas, Ginzberg, Schultz, & Schultz, 1990) and also specifically with HR focus (e.g., T. Bondarouk et al., 2017; Kossek, Young, Gash, & Nichol, 1994; Reddick, 2009). Investigated in chatbot context, it has been found to be the result of a low compatibility with the prevalent technical and social environment and to increase with perceived financial, psychological and privacy risks (Cardona et al., 2019). In the context of recruiting chatbot research, it can be considered as the recruiters' unwillingness to embrace such technology into the recruiting processes of their department in favor of the status quo of not utilizing automated conversation systems for their applicant communication. Uncertainty factors accredited to sophisticated automation systems based on algorithms causing a low level of perceived transparency because of their image as obscure "black box" (Ochmann & Laumer, 2019) may add to a desire of preserving the status quo.

In organizational contexts, inertia can be defined as "the strong persistence of existing form and function". (Rumelt, 1995, p. 103) According to Nam, Dutt, Chathoth, Daghfous, and Khan (2021), an employee's inertia is his resistance to accept changes novel technologies might bring while preferring the status quo. At the individual level, inertia is the human tendency to preserve familiar assumptions while being unable to adapt them even when proven questionable (Polites & Karahanna, 2012). Polites and Karahanna (2012) distinguish affective (concerning emotional attachment; INAAB), behavioral (regarding the habit of utilization; INABB), and cognitive (considering mental tendencies to hold onto a decision in spite of novel information; INACB) components, which all significantly influence inertia. Ku and Hsieh (2019) confirm the practicability of splitting inertia into affective, behavioral and cognitive components as suggested by Polites and Karahanna (2012). Hence, the composition of the construct and its three parts are applied to the measurement model at hand.

Inertia has been found to positively moderate factors of technology resistance such as loss aversion (Li, Liu, & Liu, 2016) as well as to directly negatively influence the perceived ease of use of a system and the intention to use it (Polites & Karahanna, 2012). Hence, inertia is not to be confused with low levels of intention to use a system but is rather a factor fostering utilization resistance (Polites & Karahanna, 2012) and thus preventing technology acceptance. It is rather to be understood as the conscious decision to maintain familiar concepts or dwell in learnt processes and prefer those over new ones on principle. According to a study by Horváth & Partners (2018), employee resistance is the main challenge regarding the implementation of automation technology such as chatbots, which – through the seemingly easy deployment and induced changes in activities and job profiles – arouse the job-related automation concern of fear of substitution.[41]

4.1.1.2 Perceived System Transparency

The increasing complexity of technology (e.g., J. D. Lee & See, 2004; Ochmann & Laumer, 2019) results in perceptions of opaqueness and a potential lack of trust culminating in decreasing levels of acceptance. These perceptions intensify in virtual environments where processes and operations of automation technologies are executed in the backend, invisible from frontend user perspective, with algorithmic operations that show results without disclosing their task-completion and decision-making (if applicable) process in an easily understandable way. Users then fail to comprehend the modus operandi of such systems. Consequential perceptions of uncertainty or high transition costs for example favor a status quo bias (H.-W. Kim & Kankanhalli, 2009; Samuelson & Zeckhauser, 1988). Regarding process step automation, the affected individual (recruiter in this study) might sense a loss of control and a resulting feeling of inferiority (Seeber et al., 2020).

[41] 2018 Next Generation Process Automation Report by Horvath & Partners (n > 180 corporate decision makers from twelve industries from Germany, Austria, Switzerland, Portugal and Romania).

As Weyer, Fink, and Adelt (2015) pointed out, advances in human-machine interaction relate to perception of loss of control. Alongside overreliance in and misplaced contentment with automated technological systems, inabilities to understand its inner workings result in control loss (Weyer et al., 2015), as evident for the states of status quo bias as well. Especially in IS and automation research, the aspect of loss of control is object of extensive investigation (e.g., Dix, 2017; Perrow, 1984; Sharkey & Sharkey, 2012; Weyer et al., 2015). It describes the perceived feeling (even if illusory) of having a decreasing level of control over a certain activity or technology in this case (loosely based on Perrow (1984)). Eidelman and Crandall (2012) ascribe loss aversion to the status quo bias, thus link the two perspectives. Individuals reluctant of loss of control exposed to innovations are likely to perceive such loss of control (Bagozzi & Lee, 1999). Li et al. (2016) found that loss aversion is positively related to technology resistance. According to Dix (2017), especially invisible computations and thus digital technological advancements are exposed to perceptions of loss of control. Loss of control is a common issue concerning automation technology (Perrow, 1984). Seeber et al. (2020) raise an according research agenda discussing loss of control because of task substitution by automated technology (machines) and resulting feelings of inferiority and a perceived limitation to nominal control. They call for an investigation of the level of authority given to machines in cases it has better answers than humans or can process more information (Seeber et al., 2020). In recruiting chatbot research, loss of control refers to the recruiters' perceived loss of control over certain recruiting process steps or formerly steered tasks after chatbot implementation. Reason for the perceptions might be a perceived lack of transparency, a perceived high level of job relevance or a high level of chatbot anxiety. Especially regarding the use case of first candidate interviews, potential loss of control strikes relevant: The interview is taken by an automated dialogue system, which has been configured but still performs a whole process with a chain of steps by itself.

Transparency is necessary to counter such perceptions of loss of control. It is demanded by stakeholders in processes involving algorithms (e.g., Ochmann & Laumer, 2019). Laurim et al. (2021) found that stakeholders in the recruiting process have an urge to understand how algorithms work and learn their mechanisms since those are essential aspects for gaining confidence in the technology.

In their examination of AI technology in general, they found that the individuals need the results of AI analyses to be understandable for them based on transparent and conjointly specified weighting and selection criteria (Laurim et al., 2021). Understanding the reasoning underlying a certain system-made decision, for example an applicant rejection or selection suggestion, is associated with higher levels of insight and flexibility ultimately resulting in higher levels of acceptance (Laurim et al., 2021) leading to successful implementation of the technology into the recruiting process. Furthermore, transparency can mitigate automation bias expressed as overconfidence in computer-based assistance such as advice (Bond et al., 2019). Transparency is one of the three widely discussed and researched on aspects of (1) fairness, (2) accountability, and (3) transparency of complex technology such as AI (summarized as FAT; e.g., Choudbury, Lee, & Kurenkov, 2019; Peters et al., 2020; Shin & Park, 2019; Sinha & Swearingen, 2002); extendable by (4) ethics, and (5) security (FATES; Wing, 2018). While fairness and accountability considerations mostly concern the initial implementation of such technology, transparency affects the day-to-day handling of it and thus can be well incorporated into longer term acceptance investigations.

Transparency is defined as “being open and clear to the end user about how an outcome, e.g., a classification, a decision, or a prediction, is made.” (Wing, 2018, para. 15) System transparency is the level of provision and accessibility of information regarding a systems’ reasoning (Zhao, Benbasat, & Cavusoglu, 2019). However, this research suggests that alongside the provision and accessibility of information, the users’ capability to understand and comprehend this information is closely related to the concept of system transparency thus following the definition perspectives of Sinha and Swearingen (2002) and Zhao et al. (2019). Zhao et al. (2019) state that the users’ ability to process and comprehend information needs to be taken into consideration. This is essential since plain transparency without successful understanding lacks the important component of explainability necessary for complex systems such as AI (Bond et al., 2019). Thus, the level of perceived transparency of recruiting chatbot behavior is associated with the explainability-affiliated aspects of the recruiters’ personal level of technology affinity and specific technological understanding of such systems, which are taken into consideration as control variables in this research. People with higher levels of technology affinity and technological understanding (expressed as profound knowledge) have a higher tendency to assess technology such as AI as generally positive for example (Bosch, 2020). The transparency of a systems' processes significantly influences the behavior of its users, also regarding their level of acceptance (Rzepka & Berger, 2018). For example, the European Commission proclaims transparency (including traceability, explainability and communication) as one of seven requirements of trustworthy AI (European Commission, 2019). A whole scientific stream has dedicated itself to research on principles of explainable AI (Seidl, 2020). While already studied extensively in terms of technical realization, IS research only recently took up the examination of transparency and its effect on user behavior (Peters et al., 2020). Research on the relationship between transparency and the acceptance of recommender agents and advice-giving assistants is vast (e.g., Arnold, Clark, Collier, Leech, & Sutton, 2006; Brunk, Mattern, & Riehle, 2019; Gedikli, Jannach, & Ge, 2014; Zhao et al., 2019). Studies incorporating the aspect of transparency in the research of sophisticated technology is on the rise (e.g., Ochmann & Laumer, 2019; Rzepka & Berger, 2018; Shin, 2021); chatbot research considering transparency however is still scarce (e.g., Wuenderlich & Paluch, 2017).

4.1.2 Variable Adaptation

In the study at hand, the Human-Robot Collaboration Acceptance Model by Bröhl et al. (2019) as most suitable theoretical foundation is sought to be adapted to the context of recruiting chatbots. The following acceptance factors have been taken over from the original HRCAM to form the hypothesized job-related automation concerns and – in their specific formulation – adapted to the modified human-chatbot collaboration acceptance model:

1) Subjective norm (the opinion of peers and supervisors concerning recruiting chatbots),
2) Job relevance (relevancy of chatbots for conducting recruiting tasks concerning its capabilities to enhance job performance),
3) Output quality (quality of recruiting chatbot performance and match with job goals; part of the concept of trust),

4) Self-efficacy (recruiters' judgement of their own competency to implement certain skills to handle recruiting chatbots),
5) Perceptions of external control (facilitating conditions within the organization concerning recruiting chatbot handling (e.g., supporting time, money, and IT resources)),
6) Chatbot anxiety (feel of eeriness, unease or fear concerning recruiting chatbots),
7) Ethical implications in the form of job substitution (fear of losing the own position in favor of the recruiting chatbot; reversely coded also known as perceived indispensability (Doe, Van de Wetering, Honyenuga, & Versendaal, 2019)),
8) Legal implications (influenced by data protection (data security perception of the chatbot; part of the concept of trust)),
9) Social implications (the influence of recruiting chatbot implementation on social contacts in the form of applicant touch points)
10) New: Perceived system transparency (the level of perception of the recruiting chatbot content to contain available and understandable information), and
11) New: Inertia (the recruiters' level of attachment to their traditional recruiting process handling even if they are aware of the incentives recruiting chatbots hold for these processes).

Regarding the two points of view (the recruiters' (1) own evaluation of a chatbot system from an internal perspective, and (2) assessment of the applicants' interaction with the chatbot in the frontend), most variables refer to the first perspective. The second perspective comes into play in the form of recruiter-sided estimations of the applicants' perception of perceived ease of use, which might affect their own opinion and thus levels of acceptance. This perspective is necessary because of the recruiters' role as enablers and implementors of the chatbot. They are capable of evaluating all above stated factors as well as the system's usefulness for example from their point of view. However, the perceived ease of use refers to the perceptions during end user and thus candidate-sided system handling. For this one variable, the recruiters are asked to empathize with the candidates and imagine a recruiting chatbot interview conduct from their point of view while answering the associated items of the questionnaire (cf. Appendix D). Since regularly, employees have a job because of successful own applications, this is a case of easy imaginability for the recruiters queried in this study.

4.1.3 Control Variables

Apart from the aspects directly associated with recruiting chatbot acceptance, several control variables are considered in order to reflect upon individual differences amongst the recruiters within the intended sample. They differ from other variables as they are not linked to the main hypotheses and theories that are being tested and are assumed to result in distortions concerning the hypothesized variable relationships to ultimately explain those main variable relations (Spector & Brannick, 2011). Control variables are either experimental or statistical control factors included to find additional explanations for findings, reduce error terms and at the same time increase statistical power (Becker, 2005). In this research, statistical control factors are considered. This kind of control variables has the power to adjust the relationships between the main variables of the research (Spector & Brannick, 2011). Becker (2005) argues that control variables are as important as any independent and dependent variable included in the model. Although they are not of primary interest for the research, their relationships are considered (Atinc, Simmering, & Kroll, 2012). Utilizing the inclusion technique, the variables are implemented in the survey to consider different manifestations at once and account for the variance caused by the specific aspect as opposed to the elimination method where only respondents of one of those manifestations are included (Atinc et al., 2012).

In the context of chatbot utilization, age might be an important aspect (e.g., Steinbauer, Kern, & Kröll, 2019). As suggested by Peters et al. (2020), it is treated as control variable. Along with personal innovativeness (PI; e.g., Agarwal & Prasad, 1998; Polites & Karahanna, 2012; Richad, Vivensius, Sfenrianto, & Kaburuan, 2019), technology affinity (TA; Bröhl et al., 2019), technological understanding (TU)[42] and

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[42] The concept of technological understanding could be partly related to the concepts of personal innovativeness and self-efficacy. However, it will be operationalized as a standalone, proper variable with an individual item set as suggested by Karrer, Glaser, Clemens, and Bruder (2009) for their variable of technological competency.

(chatbot) experience (EXP; Polites & Karahanna, 2012), it will be regarded as potentially relevant influencing factors of subordinate importance. Concerning the relationship between age, personal innovativeness and technology affinity, Steinbauer et al. (2019) found younger employees to be more open to chatbot testing than their older colleagues. Hence, a negative influence is expected between age and the behavioral intention to use a recruiting chatbot. Technology experience refers to the extent of familiarity based on practice within utilization. Computer experience was found to have positive effects on self-efficacy, perceived ease of use, perceived usage and usage (Igbaria & Iivari, 1995). According to T.-K. Yu, Lin, and Liao (2017), media experience is the ability to use a specific type of information and communications technology influencing their perception of this technology. In the case at hand, chatbot experience is about the recruiters' familiarity with chatbot utilization and their resulting expertise. Chatbot experience is expected to be positively related to the behavioral intention to use.

Several other interesting aspects that might play a role and are thus included in the survey are (1) demographical traits (i.e., gender, position in the company), (2) company characteristics (i.e., size of the company by number of employees, industry affiliation, no. of recruiting-related interviews per year, modus operandi for candidate interviewing in the company – especially asking for the respondents' own level of involvement in the interviewing process, chatbot deployment), and (3) existing chatbot-related knowledge (knowledge apart from previous experience). In accordance with De Battisti and Siletti (2019), this study complies with the criterion of parsimony, which dictates careful inclusion of control variables to avoid overcrowding and overcomplexity of interpretation. Hence, the beforementioned aspects are not taken up as control variables per se, but they will be observed and mentioned in the analysis in case significant relationships and findings emerge. One assumption might be that those recruiters being exposed to large amounts of staff requisitions in their company which need to be processed (e.g., clerks/administrative staff, auxiliary staff, servants) are more in favor of chatbots as a tool to automate than recruiters from small companies.

4.2 Development of Research Hypotheses

Out of the previously stated extension and adaptation considerations, the hypotheses for the research model of this study are formed. Firstly, the hypotheses regarding the established job-related automation concerns, especially the newly developed concepts inertia and perceived system transparency, are introduced before presenting the hypotheses ascribed to the remaining variables of the HRCAM by Bröhl et al. (2019).

Subjective norm, also known as social influence (S. Taylor & P. Todd, 1995; Venkatesh et al., 2012) or social pressure (Venkatesh & Bala, 2008), describes individuals' perception about persons influential to them regarding their opinion on the behavior that is in focus (Davis et al., 1989). Relationships between subjective norms and the perceived usefulness of a technological system as well as the behavioral intention to utilize it were established by Venkatesh and Davis (2000) and further investigated by researchers following up on their idea regarding automation technology acceptance (e.g., Bröhl et al., 2019; Fernandes & Oliveira, 2021; Laumer, Gubler, Maier, & Weitzel, 2018; M.-S. Lee & Kim, 2017; Scheuer, 2020). Hence, subjective norms is a relevant factor to observe in acceptance research context when examining the usefulness and behavioral intention to use a technology. Huang and Kao (2021) found that social norms significantly influence the perceived usefulness of service chatbots. This was confirmed by Laurim et al. (2021) in the context of recruiting. In a study by Brachten, Kissmer, and Stieglitz (2021), subjective norm was found to be the second most relevant influencer of the intention to use a chatbot. Following this line of research, direct relationships with perceived usefulness as well as the behavioral intention to use are hypothesized:

H_{1a}: Subjective norm has a positive influence on the perceived usefulness of recruiting chatbots.

H_{1b}: Subjective norm has a positive influence on the behavioral intention to use a recruiting chatbot.

Defined as an individual's perception of applicability of the technology to the job based on the importance of the process steps it can support (Venkatesh & Davis, 2000), job relevance can be seen as a vital part of acceptance models as it yields perceptions of the individuals' ascribed significance of the technology in terms of perceived usefulness (Schottek, 2016). It has been part of various automation technology-related studies (e.g., Lotz et al., 2019; Wewerka, Dax, & Reichert, 2020). In the study of Bröhl et al. (2019), job relevance turned out as the most important predictor of perceived usefulness. This finding has been confirmed in chatbot research as well, where job relevance has been found to be the most relevant and highly significant influencer of perceived usefulness (Eißer et al., 2020; Sonntag, Mehmann, & Teuteberg, 2022). Regarding the context or recruiting, job relevance is one of the most frequently affecters of perceived usefulness (Laurim et al., 2021). In this light, the second hypothesis is stated as follows:

H_2: Job relevance has a positive influence on the perceived usefulness of recruiting chatbots.

The result of an individual's assessment of the task performance through a certain technology is defined as its output quality (Venkatesh & Davis, 2000). In the context of recruiting, it is about the support of work-related task results to yield best recruiting results (Schottek, 2016). It has been subject of various general innovative technologies (e.g., Claßen, 2012; Schottek, 2016) and specifically automation technology acceptance studies (e.g., W.-H. Lee, Lin, & Shih, 2018; Lotz et al., 2019). Lotz et al. (2019) found output quality to be the best variable to explain the observed variance in the behavioral intention to use automation technology alongside perceived enjoyment – conjointly they explained 63.7 percent and thus stress reliable output quality as a relevant workplace requirement. Moussawi (2016) found a significant positive effect from output quality as part of perceived intelligence on the perceived usefulness of personal intelligent agents in the form of natural language-based recommender systems. The perceived or also predicted output quality is expected to affect the perceived usefulness of chatbots as well:

H_3: Output quality has a positive influence on the perceived usefulness of recruiting chatbots.

Self-efficacy describes an individual's control beliefs regarding the personal utilization capabilities regarding the technology (Venkatesh & Bala, 2008). It is the individual's self-confidence in his or her ability of certain behavior performances (Bandura & Walters, 1977). As Bandura (2006) puts it, the efficacy belief system is a set of self-beliefs linked to specific aspects, which vary in their distinct levels since an individual possesses a finite amount of capability mastery. Igbaria and Iivari (1995) found self-efficacy to generally affect the perceived ease of use and perceived usefulness. An acceptance meta-study by Abdullah and Ward (2016) confirmed the relationship between self-efficacy and the perceived ease of use. Turja, Rantanen, and Oksanen (2019) and Latikka, Turja, and Oksanen (2019) for example validated this finding in the context of automation technology. van Bussel, Odekerken–Schröder, Ou, Swart, and Jacobs (2022) found self-efficacy to be a highly significant positive antecedent of effort expectancy (which is a synonym for perceived ease of use as it consists of strictly PEOU-related items), which in turn positively influences the behavioral intention to utilize a chatbot. In accordance with existent acceptance research (e.g., Venkatesh & Bala, 2008; Zheng & Li, 2020), the self-reported level of recruiting chatbot self-efficacy (RCSE) is expected to positively relate to the perceived ease of use of a technology:

H_4: Self-efficacy has a positive influence on the perceived ease of use[43] of recruiting chatbots.

Perceptions of external control refer to an individual's control beliefs concerning the availability of facilitating resources and structures within the organization the technology has been implemented for (Venkatesh et al., 2003). According to Venkatesh and Bala (2008), perceptions of external control determine the perceived ease of use. Automation acceptance research picked up on this notion and validated this relation (Bröhl, Nelles, Brandl, Mertens, & Schlick, 2016; Wewerka et al., 2020). Bröhl et al. (2019) state that especially perceptions of external control as a

[43] It has to be noted that unlike the other considered variables, the *perceived ease of use* in this context is to be regarded from the candidates' point of view since they are the ones interacting with the dialogues system. In the study at hand, the recruiters are asked to imagine and assess the *perceived ease of use* from the applicants' perspective (cf. section 5.2.2.2).

variable highly influential to automation acceptance can be influenced by managerial measures to improve employee attitude in the long term. This goes together with H_1 and the hypotheses stated for subjective norms as managers are the ones capable to directly influence both the perceived subjective norm and the external control of the respective employed recruiter. The study at hand proposes the following hypothesis:

H_5: Perceptions of external control have a positive influence on the perceived ease of use[43] of recruiting chatbots.

The term for an individual's feeling of fear when confronted with a certain technology – primarily established for computers in general – is (computer) anxiety (Venkatesh et al., 2003). This also applies to future utilization (Igbaria & Parasuraman, 1989). Anxiety is a frequently included part of acceptance research (e.g., Abdullah & Ward, 2016; Brown, Fuller, & Vician, 2004; Claßen, 2012; Igbaria & Parasuraman, 1989; Venkatesh & Bala, 2008; Zheng & Li, 2020), also concerning automation acceptance (e.g., Beer et al., 2011; Bröhl et al., 2016; Eißer et al., 2020). Bröhl et al. (2019) found robot anxiety to be among the highest influential concepts on robot acceptance. Also for chatbots, (computer) anxiety was found to be a relevant factor as it significantly positively influenced the perceived ease of use of the automated dialogue system (Sonntag et al., 2022). For the context of recruiting, Laurim et al. (2021) identified anxiety as a relevant automation technology acceptance factor. Following the presented previous research, computer anxiety, in this case adapted to automated dialogue systems as recruiting chatbot anxiety (RCANX), is expected to negatively affect PEOU:

H_6: Chatbot anxiety has a negative influence on the perceived ease of use of recruiting chatbots.

Nelles et al. (2017) introduce (1) ethical, (2) legal, and (3) social implications to automation technology acceptance research dealing with the potentially disadvantageous aspects of automation technology deployment in business processes accompanying the benefits. This is an innovative approach, as traditionally, these three aspects have been regarded individually (e.g., Rességuier and Rodrigues (2020) and Munoko, Brown-Liburd, and Vasarhelyi (2020) concerning ethics; H.-Y. Liu et al.

(2020) and Schneeberger, Stöger, and Holzinger (2020) regarding legal implications; Parson, Fyshe, and Lizotte (2019) and Hohenstein et al. (2021) focusing on social implications) or in a two-fold manner (e.g., Carrillo, 2020; Vesnic-Alujevic, Nascimento, & Polvora, 2020). Subsequently, the inclusion of ELSI aspects has been taken up, especially in AI (e.g., Carter et al., 2020) and robotics research (e.g., Kapeller, Felzmann, Fosch-Villaronga, & Hughes, 2020; Wullenkord & Eyssel, 2020). Only few acceptance studies have considered these aspects yet (e.g., Fink, Börner, & Eibl, 2020; Kraetsch et al., 2021) with only Bröhl et al. (2019) found to implement it into a scientific technology acceptance research model. While Bröhl et al. (2019) originally propose a relationship of the ELSI factors with perceived ease of use, other research suggests that there rather is a significant influence of the ELSI factors on the perceived usefulness: Xiao and Kumar (2021) for example argue that ethical aspects and legal implications are the costs of technology adoption influencing the benefits-costs calculation relatable to ascribed usefulness in this study. Horst, Kuttschreuter, and Gutteling (2007) implicitly regard legal implications via system risk while Koenig-Lewis, Marquet, Palmer, and Zhao (2015) and Y.-H. Lai (2020) focus on social influence in this context. This focus on the perceived usefulness is seen as most suitable for the study at hand because if anything, ethical, legal, and social concerns are seen to influence the subjectively ascribed general usefulness of recruiting chatbots as opposed to the rather technical- or labor-sided perceived ease of use of such technology. In accordance with Bröhl et al. (2019), ethical implications have a positive influence on the perceived usefulness as comprehensible from the recruiters' point of view. Understandably, fearing that a recruiting chatbot works with higher productivity and on a higher quality level as well as a fear of losing one's own job because of such an automated dialogue system lets them ascribe a high level of usefulness to the technology. Recruiters who fear a substitution by the automated system are convinced of the fact that they are useful for the task in question. Integrated in the concept of legal implications is the aspect of data protection. It is considered in the study at hand alongside the aspect of breach of duty (cf. Nelles et al., 2017) to jointly form the formative variable legal implications. A negative effect is hypothesized opposing the study by Bröhl et al. (2019), as while the aspect not minding the chatbot to collect personal information can be seen as a relevant support feature of the technology rendering it useful, it can also be seen negatively: The more the recruiters do not care about whether the chatbot collects applicant data, the less relevant (as well as performant) they might assess it to be. The rationale behind it might be that it does not matter whether the system collects the data – it will not make a difference as the chatbot does not embody a useful support tool anyways for the ones seeing it this way. A potential breach of duty, representing the second aspect of legal implications, is also hypothesized to have a negative impact on the recruiters' view on the systems usefulness as it cannot be practically deployed when there is a danger of breach of duty linked to the system. It is derived from the potentially seen breach of duty of care an employer might have in physical human-robot collaboration workplaces (Nelles et al., 2017), which was adapted to the scenario of digital recruiting chatbot. Here, breach of duty of care would be the security-related danger of wrongful data handling in the form of mis-management and -treatment. Compliant with Bröhl et al. (2019), a positive influence is ascribed to social implications on perceived usefulness since recruiters who fear a loss of contact to the candidates through chatbot implementation would naturally find chatbots to be a suitable and thus useful alternative compared to direct, human communication. Hence, the following hypotheses are formulated:

H_7: (Negative) ethical implications have a positive influence on the perceived usefulness of recruiting chatbots.

H_8: (Negative) legal implications have a negative influence on the perceived usefulness of recruiting chatbots.

H_9: (Negative) social implications have a positive influence on the perceived usefulness of recruiting chatbots.

Trust, defined as the expectation that the party chosen to be trusted does not take advantage of the situation and behaves in a way that is dependable, ethical, socially appropriate and not opportunistic (Gefen et al., 2003), has been recognized and considered in various technology acceptance studies (e.g., Kipnis, 1996; Müller, Mattke, Maier, & Weitzel, 2019; Venkatesh et al., 2016). Ghazizadeh et al. (2012) suggest trust to be included in automation acceptance research, especially frameworks evolving around the TAM. Their work is based on findings of Muir (1987) and (J. D.

Lee & See, 2004), who found trust to play an important role in automation acceptance. In terms of human-robot collaboration, a dedicated trust scale has been established by Charalambous, Fletcher, and Webb (2016). However, this scale is not applicable to non-physical, electronic technology systems such as chatbots. In the context of e-HRM, extensive research has examined the impact of trust (e.g., Reddick, 2009; Tansley & Watson, 2000; Wilson-Evered & Härtel, 2009). Laumer et al. (2018) examined this aspect in the context of recruiting and found trust to be one of the most important determinants of applicants' acceptance in job recommender systems. Trust has also been object of extensive chatbot research (e.g., Cardona et al., 2019; Müller, Mattke, Maier, Weitzel, & Graser, 2019; Völkle & Planing, 2019). Especially sophisticated chatbots face trust-related acceptance issues (Jensen, Lowry, Burgoon, & Nunamaker, 2010; Zierau et al., 2020): Elaborate automation technology may be perceived as complex, opaque, biased and potentially risky, also in terms of data security, if relied upon without reflection from recruiter-perspective (Zierau et al., 2020). Trust is fundamental to counter these perceived complexities and uncertainties as humans fail to comprehend the operating principles of sophisticated automation technologies (J. D. Lee & See, 2004; Zierau et al., 2020). Against this background, the study at hand follows Rozumowski et al. (2019) by considering the aspect of trust as an acceptance factor concerning automated dialogue systems. Völkle and Planing (2019) operationalize trust in the form the two aspects (1) reliability, and (2) data protection and found a low level of trust in chatbot's data security performance to be one of the main reasons for utilization resistance. This research follows their approach: In the context of recruiting, recruiters are hypothesized to need to trust implemented automated recruiting chatbot systems to reliably produce a satisfactory level of output quality and to act in accordance with data protection legislations/company regulations in order to accept it within their work processes. In the measurement model, it is thus considered within the variables of output quality and legal implications and the recruiters' according perceptions of them regarding recruiting chatbots (cf. hypotheses H_3 and H_8).

Other variables of the HRCAM taken over from TAM3 aside from the job-related automation concern aspects are (10) result demonstrability, (11) perceived ease of use, (12) perceive usefulness, (13) behavioral intention, (14) use, (15) tech affinity,

(16) age, (17) image, (18) perceived enjoyment, and (19) perceived safety. The variables (10), (11), (12), (13), (15), and (16) are applied to this empirical study as well (tech affinity and age as control variables), while image, perceived enjoyment, and perceived safety will be omitted because of absent suitability for the research focus at hand.

Result demonstrability is defined as the individual’s perception of a technology to be tangible, measurable and communicable and the ability to understand the consequences of using it as well as to communicate the (dis-)advantages of its utilization (Moore & Benbasat, 1991). Laurim et al. (2021) stress the importance of result affirmability yielded by a chatbot. In accordance with traditional acceptance (e.g., Venkatesh & Bala, 2008; Venkatesh & Davis, 2000), automation (e.g., Wewerka et al., 2020) and chatbot researchers in particular (e.g., Laurim et al., 2021), result demonstrability is expected to positively affect the perceived usefulness of recruiting chatbots:

H_{10}: Result demonstrability has a positive influence on the perceived usefulness of recruiting chatbots.

As established by Davis et al. (1989) and validated for example by Venkatesh and Davis (2000) and Venkatesh and Bala (2008), perceived ease of use is positively related to perceived usefulness and perceived usefulness in turn affects the BI to utilize a technology. Perceived ease of use also influences the behavioral intention to use (e.g., Venkatesh & Bala, 2008) and this behavioral intention affects actual system use (e.g., Davis et al., 1989; Venkatesh & Bala, 2008). The last relationship between the behavioral intention to use and actual use is not included here since respondents without actual utilization experience are included in this research (see also Nordhoff, Van Arem, and Happee (2016); Erdenebold, Kim, Rho, and Hwang (2020) and Cher et al. (2020) for example). In order to also incorporate the opinions and perceptions of potential non-users for observations on the influence of job-related automation concerns and to also include those individuals who were not exposed to and did not experience the collaboration with this nascent technology in its topical complexity, the concept of behavioral intention spans both perceptions (1) on actually planned usage, and (2) hypothesized planned utilization on occasion. Diverse studies have been found which support and highlight the relevance of perceived ease of use as well as perceived usefulness for the examination of chatbot acceptance (Huang & Kao, 2021; Laurim et al., 2021; Sonntag et al., 2022; Völkle & Planing, 2019). Therefore, as originally proposed and re-evaluated numerous times, relationships from perceived ease of use to perceived usefulness and the behavioral intention as well as from perceived usefulness to the behavioral intention to utilize a recruiting chatbot are hypothesized for this study:

H_{11a}: Perceived ease of use has a positive influence on the perceived usefulness of recruiting chatbots.

H_{11b}: Perceived ease of use has a positive influence on the behavioral intention to use a recruiting chatbot.

H_{12}: Perceived usefulness has a positive influence on the behavioral intention to use a recruiting chatbot.

Further parts of the HRCAM are the variables tech affinity, age, image, perceived enjoyment, and perceived safety. Table 4.1 gives an overview over their definitions, their handling in acceptance research and their occurrence in the study at hand as previously discussed.

Table 4.1: Remaining HRCAM Variables

Variable	**Definition**	**Exemplary occurrence in acceptance research**	**Treatment in study at hand**
Tech affinity	Technology affinity is a personal trait expressed for example through a positive attitude, enthusiasm and trust towards the technology (Karrer et al., 2009).	Bröhl et al. (2019)	Included as control variable
Age	Age can generally be defined as the span of years of an individual’s life.	Claßen (2012); Laumer et al. (2018)	Included as control variable
Image	In the context of technological innovation, image is “the degree to which use of an innovation is perceived to enhance one’s […] status in one’s social system” (Moore & Benbasat, 1991, p. 195).	Moore and Benbasat (1991); Venkatesh and Davis (2000); Venkatesh and Bala (2008)	Omitted

Variable	Definition	Exemplary occurrence in acceptance research	Treatment in study at hand
Perceived enjoyment	Regarding technology utilization, it is the extent to which “the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use” (Venkatesh, 2000, p. 351).	Venkatesh and Bala (2008); Claßen (2012); Kasilingam (2020)	Omitted
Perceived safety	Osswald et al. (2012) yielded thirteen categories from an empirical survey impinging on perceived safety with the two main characteristics *distraction* caused by the system and *safety* describing the system’s level of danger to the operator.	Osswald et al. (2012); Haring, Silvera-Tawil, Takahashi, Velonaki, and Watanabe (2015); Bröhl et al. (2019)	Omitted

The omitted concepts have been discussed in the introductory part of chapter CHAPTER 4; the control variables are discussed in section 4.1.3.

Despite its high level of comprehensiveness, a lack of consideration of digital automation technology becomes apparent. Whilst regarding an extensive number of external variables and already considering the above-mentioned concern aspects, the HRCAM is not tailored to digital scenarios such as automated dialogue system application as it was applied to physical robot collaboration and it does not contain chatbot-relevant variable adaptations. Hence, an adaptation from physical robots to digital chatbot technology is compulsory. The recruiter might be inclined to stick with his traditional way of conducting first interviews with candidates when presented with the choice of deploying a chatbot for it. The chatbot solution itself might be perceived as opaque and lacking of transparency. Based on suitable theories regarding job-related automation concerns, the variables of inertia and perceived system transparency are introduced that are imperative to the investigation of recruiting chatbot acceptance.

In the context of recruiting, aspects like data security compliance regarding personal data handling is crucial, which demands high levels of transparency. According to Dahm and Dregger (2019), the construct of transparency is closely intertwined with trust and data security. A low level of perceived system transparency (PST) may lead to sensations of discomfort and insecurity in handling innovative technologies. Both discomfort and insecurity have been found to negatively influence the perceived ease of use of e-HRM technology, while discomfort also negatively influences perceived usefulness (Esen & Erdogmus, 2014). According to Laurim et al. (2021), “many Human Resource (HR) professionals still doubt algorithms’ recommendations and decisions.” (Laurim et al., 2021, p. 5495) Cramer et al. (2008) discovered that transparency concerning a system’s decision-making process increases user acceptance. Al-Jabri and Roztocki (2015) found a significantly positive relationship between perceived system transparency and perceived ease of use with the latter influencing the adoption via the TAM-specific attitude towards system use. Oldeweme, Märtins, Westmattelmann, and Schewe (2021) also found a mediated relationship between perceived system transparency and the behavioral intention to use via trust. This finding was confirmed by T.-W. Chen and Sundar (2018). Hebrado, Lee, and Choi (2013) propose a direct relationship between perceived system transparency and the behavioral intention to use. Hence, relationships between these variables are suggested:

H_{13a}: Perceived system transparency has a positive influence on the perceived ease of use of recruiting chatbots.

H_{13b}: Perceived system transparency has a positive influence on the behavioral intention to use of recruiting chatbots.

Within acceptance research, inertia is closely linked to a certain status quo bias (Y. Sun et al., 2017). Inertia has already been regarded in the context of chatbot research, for example by Seo (2022), who found inertia to be a central negative behavioral outcome of chatbot communication failure and dissatisfaction with the system. While inertia has been part of general IS acceptance (e.g., Haag, 2014; Y.-Y. Wang, Wang, & Lin, 2018), automation (e.g., Baksi & Parida, 2012) and chatbot research (e.g., M. K. Lee & Park, 2019), no study exists incorporating both perceived system transparency and inertia as antecedents of chatbot acceptance within an empirical study to the best of the author’s knowledge. Inertia can be seen as an exogenous variable (e.g., Y.-K. Lee & Li, 2016; Y. Sun et al., 2017). Recker (2014) suggests that there is an influence from inertia on perceived usefulness. This relationship is transferred to the study at hand:

H_{14a}: The recruiter’s level of inertia has a negative influence on the perceived usefulness of recruiting chatbots.

Furthermore, Samuel and Joy (2018), Y.-Y. Wang et al. (2018) and Lucia-Palacios, Pérez-López, and Polo-Redondo (2016) found that inertia has a significant negative effect on the behavioral intention to use. This is in accordance with H.-J. Kim, Lee, and Rha (2017), who established a positive relationship between inertia and the resistance to use a system. Ku and Hsieh (2019) confirmed that there is indeed a significant negative impact from inertia on the behavioral intention to use. Inertia has been identified as a relevant acceptance factor in the context of chatbot research, for example by M. K. Lee and Park (2019). In this study, the identified and confirmed negative relationship between inertia and the behavioral intention to use a system in general is transferred to the technology of chatbots as exemplary automation technology in the context of recruiting. Hence, the following hypothesis is proposed:

H_{14b}: The recruiter’s level of inertia has a negative influence on the behavioral intention to use recruiting chatbots.

According to Polites and Karahanna (2012), inertia forms via (1) perceived transition costs, (2) perceived sunk costs, and (3) incumbent system usage habit. The subconscious formation of incumbent system usage habit (Polites & Karahanna, 2012) opens a whole other research topic and is left out of scope of this research. The implementation of a recruiting chatbot is in focus of the study and not the potential tendencies to rely on the incumbent system prior to chatbot availability, which is expected to be their direct contact in terms of communication with the applicants during interview conduct. Ghazali, Nguyen, Mutum, and Mohd-Any (2016) argue that switching costs consist of manifold aspects such as learning costs, artificial costs (principle of attractive pricing to make switching prohibitively costly), uncertainty costs, search and evaluation costs as well as brand relationship loss. While artificial cost, learning and evaluation costs and brand relationship loss do not make sense in this setting of corporate chatbot implementation, the aspect of uncertainty definitely plays an important role. This is in line with the idea of status quo bias theory, based on which switching costs encompass all three aspects transition, sunk and uncertainty costs (H.-

W. Kim & Kankanhalli, 2009). In this research, they are seen as efforts rather than costs as the recruiters themselves do not bear the costs of recruiting process conduct but have certain efforts in the form of time contributions for example when learning a certain procedure. The concept of uncertainty is closely related to risks such as performance-, finance-, convenience-, and security-related perceived risks (Colgate & Lang, 2001; Ghazali et al., 2016). Uncertainty efforts occur due to the affected person's precariousness and anxiety about the changes resulting from switching a process (H.-W. Kim & Kankanhalli, 2009). Lucia-Palacios et al. (2016) found inertia to be significantly impacted by switching costs. The following hypotheses concerning switching efforts (SWE) are postulated:

H_{15a}: Perceived switching efforts (transition efforts) have a positive influence on the recruiter's inertia concerning recruiting chatbots.

H_{15b}: Perceived switching efforts (sunk efforts) have a positive influence on the recruiter's inertia concerning recruiting chatbots.

H_{15c}: Perceived switching efforts (uncertainty efforts) have a positive influence on the recruiter's inertia concerning recruiting chatbots.

The taken over, the adapted and the newly introduced hypotheses for the suggested HRCAM model as presented in the previous sections are summarized in Table 4.2.

Table 4.2: Underlying Hypotheses of the HCCAM

Variable	**Hypotheses**
Subjective Norm	H_{1a}: *Subjective norm* has a positive influence on the perceived usefulness of recruiting chatbots. H_{1b}: *Subjective norm* has a positive influence on the behavioral intention to use a recruiting chatbots.
Job Relevance	H_2: *Job relevance* has a positive influence on the perceived usefulness of recruiting chatbots.
Output Quality	H_3: *Output quality* has a positive influence on the perceived usefulness of recruiting chatbots.
Self-Efficacy	H_4: *Self-efficacy* has a positive influence on the perceived ease of use of recruiting chatbots.

Variable	**Hypotheses**
Perceptions of External Control	H_5: *Perceptions of external control* have a positive influence on the perceived ease of use of recruiting chatbots.
Chatbot Anxiety	H_6: *Chatbot anxiety* has a negative influence on the perceived ease of use of recruiting chatbots.
Ethical Implications	H_7: *(Negative) ethical implications* have a positive influence on the perceived usefulness of recruiting chatbots.
Legal Implications	H_8: *(Negative) legal implications* have a negative influence on the perceived usefulness of recruiting chatbots.
Social Implications	H_9: *(Negative) social implications* have a positive influence on perceived usefulness of recruiting chatbots.
Result Demonstrability	H_{10}: *Result demonstrability* has a positive influence on the perceived usefulness of recruiting chatbots.
Perceived Ease of Use	H_{11a}: *Perceived ease of use* has a positive influence on the perceived usefulness of recruiting chatbots. H_{11b}: *Perceived ease of use* has a positive influence on the behavioral intention to use a recruiting chatbot.
Perceived Usefulness	H_{12}: *Perceived usefulness* has a positive influence on the behavioral intention to use a recruiting chatbot.
Perceived System Transparency	H_{13a}: *Perceived system transparency* has a positive influence on the perceived ease of use of recruiting chatbots. H_{13b}: *Perceived system transparency* has a positive influence on the behavioral intention to use a recruiting chatbot.
Inertia	H_{14a}: The recruiter's level of *inertia* has a negative influence on the perceived usefulness of recruiting chatbots. H_{14b}: The recruiter's level of *inertia* has a negative influence on the behavioral intention to use recruiting chatbots.
Perceived Switching Efforts	H_{15a}: *Perceived switching efforts (transition efforts)* have a positive influence on the recruiter's inertia concerning recruiting chatbots. H_{15b}: *Perceived switching effort (sunk efforts)* have a positive influence on the recruiter's inertia concerning recruiting chatbots. H_{15c}: *Perceived switching efforts (uncertainty efforts)* have a positive influence on the recruiter's inertia concerning recruiting chatbots.

Hypotheses$_{1a\text{-}12}$: Bröhl et al. (2019) based on TAM2 and TAM3; Hypotheses$_{13a\text{-}15c}$: Own work.

Once compiled, these hypotheses will be tested by either falsification or support through the application of the model in the form of a quantitative recruiter survey. Main areas of interest are (1) decisive acceptance influencers in recruiters' opinion, (2) their perceived manifestations of the variables regarding current recruiting chatbot technology and (3) their willingness to utilize or state of utilization of such dialogue-based communication technology. Corresponding data on their perspective on recruiting chatbot acceptance will be collected and analyzed.

Most recruiters do not possess the position and power in their company to decide on chatbot implementation or omittance for their recruiting processes as this is a managerial task. Instead of an implementation based on their own decision, it is imposed by their organization or HR management respectively. However, premise for the study at hand and the stated hypotheses is that chatbot deployment for the use case of candidate interviews can occur voluntarily leaving recruiters with an explicit choice. This way, the respondents' assessment authentically displays their desire to collaborate with chatbots as opposed to repressed thoughts due to a lack of decision-making power.

4.3 Proposed Research Model

In the prior sections, the HRCAM model and its variables have been presented as well as the expansion via the two newly introduced variables perceived system transparency and inertia. In a second step, adaptations have been made by defining the existent variables for the use case of recruiting chatbot interview conduct and by eliminating unfit variables to suit the digital automation technology of recruiting chatbots.

As a result, the established HRCAM model is modified into the Human-Chatbot Collaboration Acceptance Model (HCCAM), which is shown in the structural model displayed in Figure 4.1. It depicts the proposed research model for the study at hand. Considering the special interest concerning job-related automation concerns, the related TAM2/3 variables (1) subjective norm, (2) job relevance, (3) output quality, (4) self-efficacy, (5) perceptions of external control, (6) chatbot anxiety, and (7) ethical (fear of potential job loss), (8) legal, and (9) social implications are combined in the modified human-chatbot collaboration acceptance model.

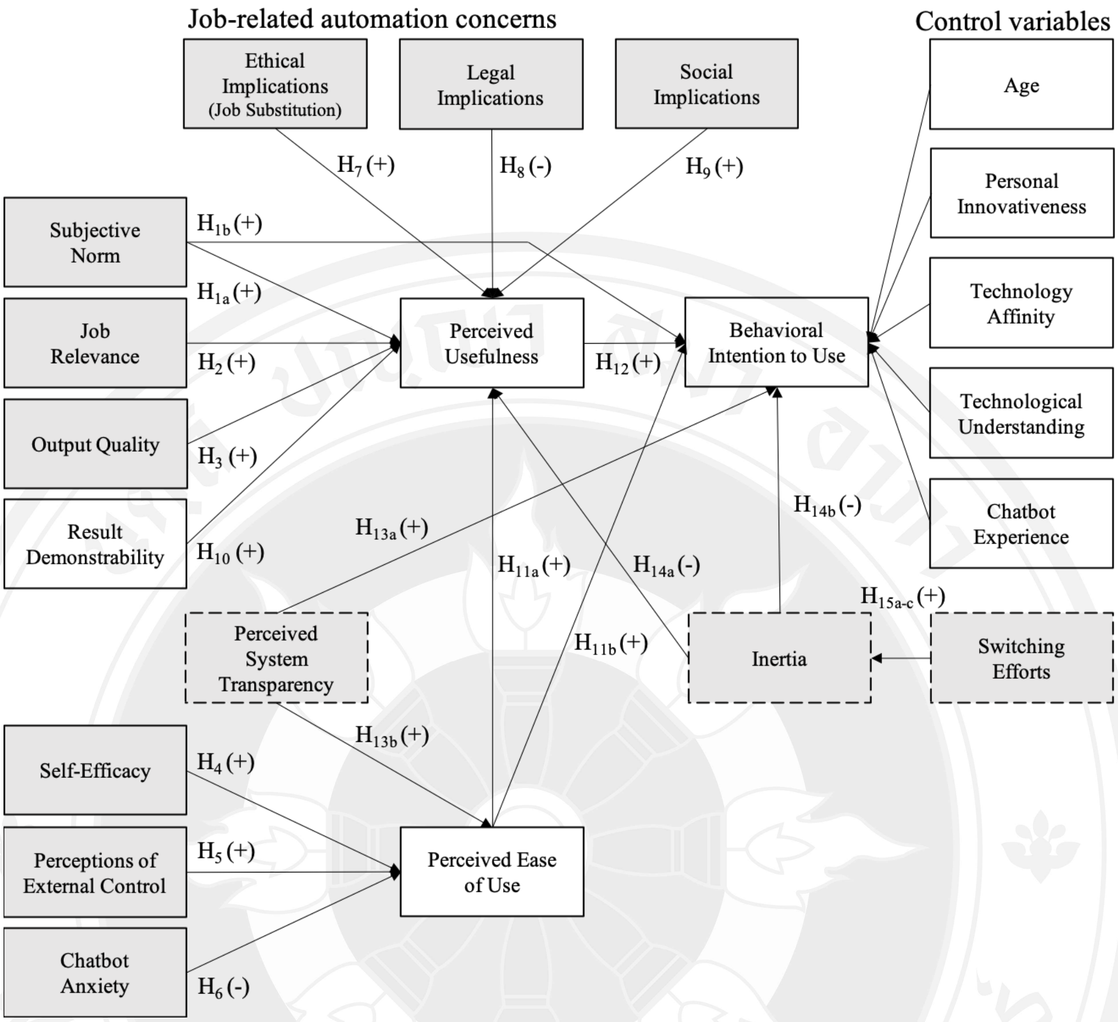

Figure 4.1 HCCAM Structural Model for Recruiting Chatbot Collaboration Acceptance
Source: Own illustration partly based on HRCAM by Bröhl et al. (2019, p. 715); hypotheses cf. section 4.2. Grey color = part of job-related automation concerns; dotted lines = variables newly added to the model.

The dotted lines indicate deviations from the original HRCAM in the form of the proposed new concepts of (10) perceived system transparency and (11) inertia. These variables belonging to the encompassing group of job-related automation concerns are highlighted in grey color in Figure 4.1. Originally suggested for measurement of human-robot collaboration acceptance by Bröhl et al. (2019), it is adapted to the subject of chatbots and according human-chatbot collaboration scenarios within the recruiting process.

Two perspectives are brought together in the model:

1) The recruiter-sided usage of the chatbot in the sense of implementing it in the process of candidate interviewing is considered. Here, the recruiters report their perceptions and assessments when deploying a chatbot into their interviewing processes.
2) Concerning the aspect of perceived ease of use, utilization from the candidates' front-end perspective is regarded as well. The recruiters are asked to assess the ease of use of a recruiting chatbot from the candidates' point of view as the applicants are the ones hypothetically conversing with the chatbot in the interviewing process. For all other aspects, the recruiters' own perspective is considered.

While inertia, perceived ease of use, perceived usefulness, and the behavioral intention to use are endogenous variables being explained by other variables of the model, all others are exogenous and thus explain the beforementioned endogenous variables (Hair Jr, Hult, Ringle, & Sarstedt, 2017). The high number of exogenous variables (12, not considering the five control variables) in relation to the small number of endogenous ones (four) defines the measurement model as focused model (Joe F Hair, Sarstedt, Ringle, & Mena, 2012). The hypotheses correspond with both the established ($H_{1a\text{-}12}$) and newly derived hypotheses by the author ($H_{13a\text{-}15c}$).

In the following chapter, the methodology of the study will be explained by embedding the study into the research context, explaining the formation of the questionnaire including the development of all operationalized items and scales. The data collection technique is presented as well as the data processing and analysis approach. Prior to the actual survey, a pilot study with a first 60 respondents is conducted to ensure best possible questionnaire fitness for the study.

CHAPTER 5

METHODOLOGICAL APPROACH

This study will quantitatively validate the proposed research model HCCAM and empirically test the according hypotheses. In this chapter, the rationale of the study conduct is described by explaining its objectives prior to a description of the study design. Subsequently, the composition of the questionnaire and the scaling of the specific survey items as well as the sampling technique of this study as foundations for the empirical validation of the HCCAM are explained. All necessary steps for this validation in form of the data processing and analysis methods are shown and justified. Prior to actual study conduct, a pilot study is run to control for scaling issues such as the existence of undesired consistencies (e.g., Johanson & Brooks, 2010), instrument applicability in the form of logic, answerability, ambiguity, and accuracy flaws.

5.1 Objectives of the Empirical Study

After an initial literature study in the form of desk research concerning the theoretical foundation and the current situation of digitalized HR, chatbots in general and chatbots in HR in Germany as exemplary country, relevant use cases for chatbots in recruiting have been compiled and narrowed down. The participating recruiters will be served the use case of candidate interviewing as a standard procedure and thus easily relatable part of the recruiting process and the research object, which was identified as most suitable for the investigation at hand.

A theory-based quantitative approach regarding established constructs from the HCCAM and variables not yet implemented into technology acceptance research frameworks (HRCAM model adaptation as described in chapter CHAPTER 4) is chosen. It is contributing to the scarce research field of chatbots (Stoeckli et al., 2018) and the novel context of recruiting, where no acceptance study under consideration of chatbot deployment are known to the author except for one recent foray (Swapna & Arpana, 2021). The quantitative survey is conducted to specifically investigate the influence of the adapted HRCAM-related acceptance factors on the behavioral intention to utilize recruiting chatbots for first applicant interviewing. Focus of the quantitative recruiter survey is the investigation of the antecedents of recruiting chatbot acceptance and the according relevance of the determinants (in the form of variance explained) according to the adapted HRCAM model. The according items are adapted from related literature (cf. section 5.2.2). Target participants are recruiters of different positions in HR departments of companies in Germany.

In accordance with Joseph F Hair, Risher, Sarstedt, and Ringle (2018), a systematic PLS-SEM analysis is conducted by (1) specifying the measurement model (cf. Figure 5.2) concerning the relationships between the latent and manifest variables (De Battisti & Siletti, 2019), (2) specifying the structural model (cf. Figure 4.1) regarding the relationships between the theoretical constructs (De Battisti & Siletti, 2019), (3) collecting and examining the data, (4) estimating the PLS path model, assessing the PLS-SEM results of (5a) the reflective measurement models, (5b) the formative measurement models and (6) the structural model as well as (7) thorough interpretation of the results and conclusion drawal.

5.2 Questionnaire Content and Scale Development

The survey comprises a multitude of relevant topics related to recruiting chatbots and the acceptance of such assistant technology. The queried kinds of subjects and questions as well as structure of the item batteries are presented in the following sub-sections.

5.2.1 Considered Topics and Recruiting Chatbot Aspects

For the assessment of recruiting chatbot acceptance, manifold potential subjects, kinds of questions and items might prove relevant and could be drawn for this research. After an initial assembly of all potentially relevant aspects derived from literature, they have been evaluated and either taken up in the questionnaire because of a high suitability for (1) generally answering the research questions, and (2) specifically validating the HCCAM model or discarded because of too little relevancy to create a questionnaire as concise as possible. After condensation and focusing, the questionnaire has been logically structured and divided into the following six sections: (1) Demographics and approach towards technology, (2) introduction to the research object, (3) recruiting process infrastructure, (4) recruiting chatbot use cases, utilization drivers and barriers, (5) relevant interviewing aspects and recruiter skills, and (6) HCCAM model-related questions. The proposed measurement item list with the original or modified items from the HRCAM and added validated items for inertia and perceived system transparency as well as for the other questions of the questionnaire can be seen in Appendix D.

5.2.1.1 Demographics and Approach Towards Technology

The participants are asked about their demographic and company specific background in the form of age (included as control variable), gender, no. of employees in the company for company size assessment and the sector the participant is working in. Work experience or tenure with the organization are intentionally left out of consideration to include all stages of seniority and potentially ensuing different views on recruiting chatbot technology. In a second step, the three technological control variables personal innovativeness, technological affinity and technological understanding are queried. As per common practice in research (e.g., Lotz et al., 2019; T.-K. Yu et al., 2017), the demographical traits form the first part of the questionnaire.

5.2.1.2 Introduction to the Research Object

To give all respondents the same baseline of information concerning chatbots and recruiting chatbots in particular, they are provided with an **introduction to the technology of recruiting chatbots** regardless of their experience or knowledge concerning recruiting chatbots or chatbots in general. They receive a brief, profound definition of the topic derived from recruiting chatbot literature (cf. section 2.4): “Chatbots are automated dialogue systems. Users can insert input and the chatbot will process it and answer to this automatically. Advanced chatbots based on artificial intelligence can make use of components such as natural language processing and machine learning as methods to match, process and respond to incoming queries. In this exemplary scenario, we imagine implementing the chatbot for first applicant interviews (in the following: interviews).” The shown dialogue is accompanied by exemplary chatbot conversation snippets for the three potential candidate interviewing situations (1) general inquiry, (2) hard skill assessment, and (3) soft skill assessment, which can be seen in Figure 5.1.

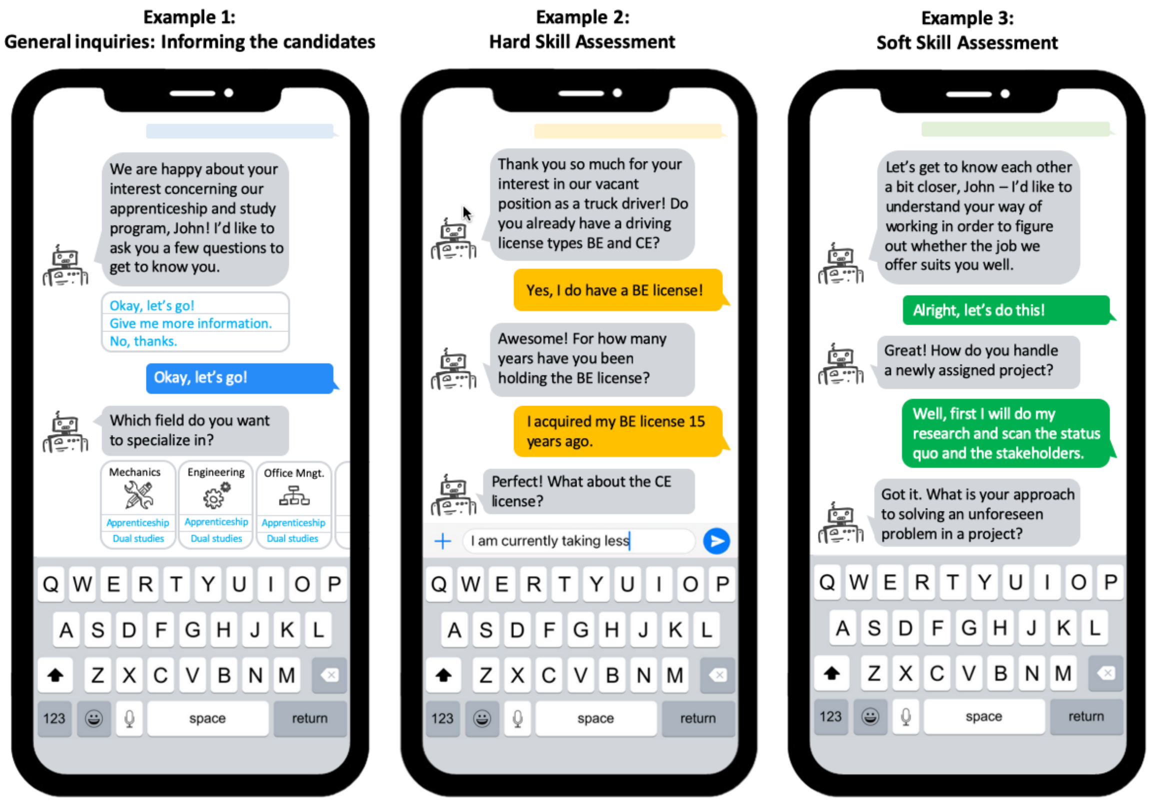

Figure 5.1 Chatbot Conversation Examples for Candidate Interview Scenarios in the Study

Source: Own illustration.

The three situations are introduced to give the respondents a comprehensive overview concerning potential recruiting chatbot deployment scenarios from both the recruiters' and the candidates' perspectives concerning information retrieval. The explanation is enwoven in between the demographical and technology approach variables and the ones with relation to the topic of (recruiting) chatbots.

5.2.1.3 Recruiting Process Infrastructure

In the third section, the recruiting-specific technological background is queried. Firstly, the number of interviews conducted in the company is inquired. In practice, there are statistically 250 resumes per job (Inc., 2015) and the interview-to-hire ratio varies between 2 to 15 (e.g., CareerSidekick, 2021; Workable, 2018; Zety, 2021). Knowing the number of interviews conducted in the companies of the participants can provide potential insights on the size of the respective companies and the relevancy an interviewing chatbot might hold for the situation of the participant in focus.

As a second step, the recruiters' present modus operandi in terms of their current method for interviewing is being investigated as a contrast to the (hypothetical) chatbot interview conduct. Introducing this aspect, both perspectives of acceptance research question types can be covered: Concerning the HCCAM-related aspects, there are (1) general questions regarding recruiting chatbots per se, and (2) those that are use case specific as commonly done in acceptance research. The second type of questions could be more difficult to answer for those participants not being involved in the interviewing process of the company as those involved in the process might think differently about the topic. Hence, a question is inserted asking whether the respondent is involved with interviewing him- or herself to control for possible effects and to assess potential differences in answer behavior to questions like job relevance of fear of substitution based on the fact that the respondent is not involved in the process in general.

The participants are not required to utilize applicant tracking systems in their recruiting processes, but as this facilitates integrative chatbot inclusion, this trait is being included in the questionnaire. The respondents' levels of chatbot experience and knowledge are assessed to yield their level of familiarity with the technology.

Furthermore, questions relating to the current state of chatbot infrastructure within the premises of the company are included:

1) Deployment status of a chatbot within the company
   (1) Is there a chatbot implemented within any process of the company?
   (2) In case no chatbot has successfully been implemented yet:
      a. Is a chatbot currently being developed for the company?
      b. Is there a plan to implement a chatbot within the processes of your company in the next two years?

2) Deployment status of a chatbot within the recruiting process of the company;
   (1) Is there a chatbot implemented within the recruiting process of the company?
      a. Is the chatbot linked to the company's ATS?
   (2) In case no chatbot has successfully been implemented yet:
      a. Is a chatbot currently being developed for the recruiting processes of your company?
      b. Is there a plan to implement a chatbot within the recruiting processes of your company in the next two years?

5.2.1.4 Recruiting Chatbot Use Cases, Utilization Drivers and Barriers

In this section, the respondents are asked for their recruiting-specific opinions regarding chatbots. Derived from theory (cf. Table 2.5; Meurer et al. (2019)) and questionnaire trials with scientific and recruiting experts in the course of questionnaire creation as well as validation within the pre-study (cf. section 5.5), a long-list of thirteen potentially relevant use cases for recruiting chatbots formed out of Table 2.5. It is given to the respondents to be rated concerning their relevancy. They have an option to add and specify an additional use case not mentioned in the list.

Alongside relevant use cases, the recruiters are asked to assess twelve drivers and ten barriers of recruiting chatbot implementation that were compiled from literature (adapted from Schildknecht et al. (2018); Mazurchenko and Maršíková (2019); Regber et al. (2019)) regarding aspects concerning cost, time, efficiency, quality, interaction, image, and technological/ company/recruiter implications. The results will complement the ones assembled in the HCCAM regarding the factors influencing recruiting chatbot acceptance.

5.2.1.5 Relevant Interviewing Aspects and Recruiter Skills

The respondents are asked to rank certain potentially relevant aspects and necessary skills for the interviewing process within recruiting. While 68 percent of recruiters of the LinkedIn Talent Solutions (2019) study state to assess soft skills based on social cues during an interview, 57 percent state that they struggle to accurately assess soft skills and only 41 percent of the companies have a formal process to assess soft skills potentially countering subjection and bias. Hence, questions are raised concerning a chatbot’s fit to this assessment. This aspect is taken up in the questionnaire. Eight traits each are ranked by the respondents to yield the most important characteristics loosely based on the works of Mazurchenko and Maršíková (2019) on human resource skills for a digitalized human resource management. They have been adapted for this study to particularly fit to recruiting. The participants of this study are asked to rank the traits of (1) efficient candidate handling, (2) hard skill assessment, (3) soft skill assessment, (4) social cue/cultural fit assessment ("human factor"), (5) relationship management, (6) digital communication possibility/possibilities, (7) data analytics, and (8) offering diverse communication channels. The relevant skills offered to the participants for ranking are (1) ethical practice, (2) application of expert knowledge and skills during selection, (3) diversity management/cultural awareness, (4) critical thinking, (5) transparency, (6) multitasking, (7) working in an agile way/creativity, and 8) problem-solving.

5.2.1.6 HCCAM Model-Related Questions

After the demographical and recruiting chatbot-related background questions, the main part of the quantitative study is formed by aspects included in the proposed HCCAM that are investigated to answer the research questions. This part incorporates the validated TAM2 (Venkatesh and Davis (2000); adaptations e.g., to recruiting by Cho, Lee, and Liu (2011) and to chatbots by Zarouali, Van den Broeck, Walrave, and Poels (2018)) items image, job relevance, result demonstrability, output quality, and subjective norm and TAM3 (Venkatesh & Bala, 2008) items self-efficacy, perceptions of external control, chatbot anxiety, and perceived enjoyment as well as the ELSI and technology affinity items as introduced by Bröhl et al. (2019). Furthermore, the levels of inertia and perceived system transparency are assessed. Inertia is included following the distinction by Polites and Karahanna (2012) into affective, behavioral and cognitive components as confirmed by Ku and Hsieh (2019). For perceived system transparency, the general concept view of W. Wang and Benbasat (2016) is adopted and preferred over the controllability items for transparency as proposed by Weyer et al. (2015) because they presume usage prior to question response (e.g., “I am always in full control over the recruiting process step and all its inherent functions albeit the implementation of the recruiting chatbot.” or “recruiting chatbot is frequently generating situations which I can not fully comprehend.”). The job-related automation concern aspects and other HCCAM variables as introduced before (subjective norm, job relevance, output quality, recruiting chatbot self-efficacy, perceptions of external control, recruiting chatbot anxiety, switching efforts, inertia, perceived system transparency, ethical/legal/social implications) are operationalized according to existent literature with adjustment for suitability to the case of recruiting chatbots. An overview of the regarded constructs and the origin of the items can be seen in Table 5.1 (a detailed overview on item-level is shown in Appendix D).

Table 5.1 Origin of the Operationalized HCCAM Constructs

Construct Abbreviation	**Construct Name**	**Source**
SN	Subjective Norm	Venkatesh and Bala (2008); translation according to Olbrecht (2010), Bröhl et al. (2019), and loosely Schmaltz (2009)
REL	Job Relevance	Venkatesh and Bala (2008); translation according to Schmaltz (2009) and Bröhl, Nelles, Brandl, Mertens, and Schlick (2017)
RES	Result Demonstrability	Venkatesh and Bala (2008); translation according to Schmaltz (2009)
OUT	Output Quality	Venkatesh and Bala (2008); translation according to Schmaltz (2009), Egger and Pühl (2010), and Rambusch (2012)
RCSE	Recruiting Chatbot Self-Efficacy	Venkatesh and Bala (2008) (modified according to Bröhl et al. 2019); translation according to Schmaltz (2009) (examples by Wellmann (2014) and Claßen (2012))
PEC	Perceptions of External Control	Venkatesh and Bala (2008); translation according to Claßen (2012) and the author of the study
RCANX	Recruiting Chatbot Anxiety	Venkatesh and Bala (2008); translation according to Claßen (2012) and the author of the study
PST	Perceived System Transparency	W. Wang and Benbasat (2016); translation according to Scheuer (2020) and the author of the study

Construct Abbreviation	Construct Name	Source
INAAB	Inertia (Affective based)	Polites and Karahanna (2012); H.-J. Kim et al. (2017); translation according to the author of the study
INABB	Inertia (Behavioral based)	Polites and Karahanna (2012); translation according to the author of the study
INACB	Inertia (Cognitive based)	Based on Polites and Karahanna (2012); translation according to the author of the study
SWETE	Switching Efforts: Transition Efforts	Moore II (2002); Polites and Karahanna (2012); translation according to the author of the study
SWESE	Switching Efforts: Sunk Efforts	Moore II (2002); Polites and Karahanna (2012); translation according to the author of the study
SWEUE	Switching Efforts: Uncertainty Efforts	Ghazali et al. (2016); H.-W. Kim and Kankanhalli (2009); translation according to the author of the study
EIMP	Ethical Implication (Job Substitution)	Bröhl et al. (2019); Nelles et al. (2017); translation according to Bröhl et al. (2017) and the author of the study
LIMP	Legal Implication	Bröhl et al. (2019); Nelles et al. (2017); translation according to Bröhl et al. (2017) and the author of the study
SIMP	Social Implication	Bröhl et al. (2019); translation according to Bröhl et al. (2017)
PU	Perceived Usefulness	Venkatesh and Bala (2008); translation according to Olbrecht (2010)
PEOU	Perceived Ease of Use	Gefen and Straub (2000); Pavlou (2003); Venkatesh et al. (2003); Venkatesh and Bala (2008); Polites and Karahanna (2012); Samuel and Joy (2018); translation according to Schlohmann (2012); Olbrecht (2010); Claßen (2012), and Schmaltz (2009)
BI	Behavioral Intention to Use	Venkatesh and Bala (2008); translation according to Schlohmann (2012); Diers (2020), and Schmaltz (2009)

While most questions regard the recruiters' perspective, perceived ease of use is queried requiring recruiter-sided estimations of the applicants' perception. Chatbot current limitations laying in its nature as a new and not yet diffused means of communications such as the boundaries in the form of trust issues based on potential lacks in transparency and output demonstrability for example are taken into consideration.

5.2.2 Measurement Item Operationalization

All hypothetical constructs in the form of latent variables not measurable directly are measured via indicator variables. Items are observed measures that make the underlying constructs examinable (Spector & Brannick, 2011) while a measure is defined as a quantifiable score, which is obtained via self-report or observation for example (Edwards & Bagozzi, 2000) based on certain rules (Hair Jr et al., 2017). Most of the items, especially the ones stemming from validated acceptance research models such as the TAM (e.g., Venkatesh & Bala, 2008; Venkatesh & Davis, 2000) and the HRCAM, are measured via the originally attributed and published seven-point balanced multi-item Likert-scales (1 = strongly disagree, 2 = moderately disagree, 3 = somewhat disagree, 4 = neutral, 5 = somewhat agree, 6 = moderately agree, 7 = strongly agree; cf. Appendix D for details). Typical of these Likert-scales, the HCCAM-related variables are queried as closed questions. Since it has been part of so many research studies, especially the concise and empirically sound TAM offers a wide range of validated questions of high reliability (Kasilingam, 2020), which are taken over for this research. The others items are adaptations from the respective literature, modified to fit to the case at hand with seven-point Likert scales as well (e.g., Bröhl et al., 2019; Polites & Karahanna, 2012; W. Wang & Benbasat, 2016). Likert scale batteries are formed for each variable of interest. Apart from their role within existent research, utilizing Likert-type scales result in higher reliability (e.g., Churchill Jr & Peter, 1984) and form an integral requirement for SEM measurement analyses (Kock, 2015). All measurement items have been taken over from existing research as indicated in Appendix D.

As suggested by Raaijmakers, Van Hoof, t Hart, Verbogt, and Vollebergh (2000), an “I don’t know” option is added where suitable. Since the original items were formulated in English language, a translation into German for understandability by the targeted respondents (recruiters in German-speaking companies) was required prior to questionnaire distribution, which was conducted in accordance with existing technology acceptance research regarding the field of recruiting in Germany (e.g., Diers, 2020; Prein, 2011; Wellmann, 2014). Furthermore, the adaptation or rather further development of several items was necessary for fitness to the innovative concept of recruiting chatbots and to make them comprehensible even for those participants, who have never interacted with a recruiting chatbot before. The author paid attention to preservation of value neutrality of the formulation and comprehensibility for all items, especially during translation. This translation has been tested in a pre-study with ten first respondents, who paid special attention to the general questionnaire setup, logic and item formulation (cf. section 5.3.2).

Many items are worded as unidirectional variables of positive polarity. However, certain items of popular TAM-related variables included in this research intentionally face in the opposite direction as common for self-report measures (Woods, 2006). Negatively polarized items are included to prevent distortions due to acquiescence bias (the respondents' tendency to rather agree than disagree) occurrences in the data (Swain, Weathers, & Niedrich, 2008; Woods, 2006). Prior to measurement model analyses such as reliability analysis, these items need to be reversed (Sarstedt & Mooi, 2014). In their order of occurrence in the questionnaire, the following items are reversely coded and have been recoded prior to statistical analysis to achieve uniform polarity in the form of general positive or negative assertion: PI03, TU02, RES04, PEC04, RCANX01, PST04, and LIMP01. The recoding was necessary to ensure suitability of the items for Likert scale score computation (e.g., Józsa & Morgan, 2017; Suárez Álvarez et al., 2018) for the ensuing analyses such as the Cronbach's Alpha investigation. In this case, average (mean) scores are formed as there are different numbers of items for each variable requiring average scores for comparison. This is a common practice to control for multicollinearity (e.g., Venkatesh, Brown, Maruping, & Bala, 2008). The transformation was conducted with SPSS 27.

The latent variables are divided into endogenous/dependent, exogenous/independent and control variables according to their role in this research. Within the path model, exogenous latent variables explain others while endogenous variables represent the ones that are being explained (Hair Jr et al., 2017). The items for each latent variable form scales of two to four individual items per construct with an exception of perceived system transparency comprising eight items as proposed by W. Wang and Benbasat (2016). Latent variables that are composed of measures representing the effects of a certain construct are defined as reflective while formative measurements combine non-interchangeable causal indicators, which form the construct (Hair Jr et al., 2017). Reflective scales are utilized for variables composed of indicators representing manifestations of the variable all expectedly highly correlated with the latent variable score (Edwards & Bagozzi, 2000). All variables in this study are designed reflectively composed of interchangeable indicators with four exceptions: The three variables of switching efforts (higher-order) and legal implications are composed of formative indicators because of their non-interchangeable nature. As such, they need special treatment during analysis, for example via a two-step approach concerning the higher-order constellations (Gaskin, Godfrey, & Vance, 2018).

5.2.2.1 Dependent Variables

First of all, the dependent variables or endogenous variables respectively are presented. Usually, the main dependent variable would be recruiting chatbot utilization as indicator of the acceptance of such technology. Acceptance research (e.g., Davis et al., 1989; Venkatesh et al., 2008; Venkatesh et al., 2003) distinguishes three key conceptualizations of system use: duration, frequency, and intensity. In this research, it is proxied by its predecessor variable behavioral intention as recruiters not yet utilizing chatbots for the recruiting process are involved, who would not be able to give an answer and state any actual utilization behavior. Disregarding actual usage behavior and rather concentrating on the behavioral intention to use is common practice in acceptance research (e.g., Cher et al., 2020; Erdenebold et al., 2020; Nordhoff et al., 2016). This also eliminates the problem of self-reported utilization assessment within acceptance studies: Self-reported usage is considered as a limitation for acceptance research, as it relies on assumptions and reflections on actual usage (Y. Lee et al., 2003). However, the study at hand considers the current opinion and outlook on potential usage scenarios as well as assumed usage. For behavioral intention, the standard item set by Venkatesh and Bala (2008) is taken and adapted to the exemplary use case of interviewing (e.g., BI01: "Assuming that I had access to a recruiting chatbot, I intend to use (use in the sense of implementing it into the interviewing procedure of my recruiting process) it.").

Table 5.2 Endogenous Variables of the Dissertation Survey

Construct/Topic	**No. of items**	**Affiliation**	**Source**
Inertia	9	N/A	Polites and Karahanna (2012)
Affective-based inertia	3		
Behavioral-based inertia	3		
Cognitive-based inertia	3		
Perceived usefulness	4	TAM	Venkatesh and Bala (2008)
Perceived ease of use	4	TAM	e.g., Venkatesh and Bala (2008)
Behavioral intention to use	3	TAM	Venkatesh and Bala (2008)

All items are measured via a seven-point balanced multi-item Likert scale.

A summary of all endogenous variables influenced by other latent variables, including the main dependent variable of behavioral intention to use, can be seen in Table 5.2. The items for affective-based inertia regard emotive factors (e.g., INAAB01: “I will continue using my existing recruiting methods for interviewing because it would be stressful to change.”). Behavioral-based inertia is about the customs of the participant (e.g., INABB01: “I will continue using my existing recruiting methods for interviewing simply because it is what I have always done.”). Cognitive-based inertia on the other hand covers mental aspects about this factor (e.g., INACB01: “I will continue using my existing recruiting methods for interviewing even though I know it is not the best way of doing things.”). For perceived usefulness and perceived ease of use, the standard item sets developed and validated in the TAM model and various its extensions are utilized and adapted to recruiting chatbots (e.g., PU01: “Using a recruiting chatbot improves my performance in my job.”) while considering the change of view from the recruiters’ own situation to imagining the applicants interacting with it. As explained, the recruiters are asked to take on the candidate’s perspective regarding perceived ease of use as the latter group is the one actually engaging with the chatbot (e.g., PEOU01: “The applicant’s interaction with the recruiting chatbot will be clear and understandable.”). The complete questionnaire including all items for the presented construct is summarized in Appendix D.

5.2.2.2 Independent Variables

Numerous independent variables derived from literature and added to the core of the HRCAM as foundation for this research have been integrated in the study to explain the highest possible amount of variance of behavioral intention to use recruiting chatbots. A list of all utilized variables according to the different constructs and topics, sorted by their chronological questionnaire position, can be seen in *Table 5.3* while the complete questionnaire broken down to item level is presented in Appendix D.

Table 5.3 Independent Variables of the Dissertation Survey

Construct/Topic	No. of items	Affiliation	Source
Subjective norm	4	TAM3	Venkatesh and Bala (2008)
Job relevance	3	TAM3	Venkatesh and Bala (2008)
Result demonstrability	4[a]	TAM3	Venkatesh and Bala (2008)
Output quality	3	TAM3	Venkatesh and Bala (2008)
Recruiting chatbot self-efficacy	4	TAM3	Venkatesh and Bala (2008)
Perceptions of external control	4[1]	TAM3	Venkatesh and Bala (2008)
Recruiting chatbot anxiety	4[1]	TAM3	Venkatesh and Bala (2008); Eißer et al. (2020)
Perceived system transparency	8[1]	N/A	W. Wang and Benbasat (2016)
Switching efforts[b]		N/A	Moore II (2002); Polites/Karahanna (2012)
Transition efforts	2		
Sunk efforts	2		
Uncertainty efforts	3		
Ethical implications	3	HRCAM	Nelles et al. (2017); Bröhl et al. (2019); Laurim et al. (2021)
Legal implications	2[a, b]	HRCAM	Nelles et al. (2017); Bröhl et al. (2019)
Social implications	1	HRCAM	Bröhl et al. (2019)

[a] The scale for one item in the item set is reversely coded; the scales were taken over from the original sources and left as intended. For further analyses, the correspondent items were recoded to ensure uniform polarity; [b] Composed as formative variable. All items are measured via a seven-point balanced multi-item Likert scale.

Most independent variables originate from the TAM3 model by Venkatesh and Bala (2008). Their standard item sets are considered and adapted to the technology and use case at hand (e.g., SN01: “People who influence my behavior think that I should use a recruiting chatbot for interviewing.”; REL01: “In my job, usage of a recruiting chatbot is important.”). The items for the newly introduced construct of perceived system transparency are adapted from the item set of W. Wang and Benbasat (2016), who regarded different aspect of technology clearness (e.g., PST01: “A recruiting chatbot makes its reasoning process clear to me.”). As suggested by Barroso and Picón (2012), the concept of switching efforts is viewed as a formative construct. Just like inertia with affective, behavioral and cognitive bases, switching efforts form a higher-order construct considering three kinds of efforts: Uncertainty efforts, transition efforts, and sunk efforts, all operationalized in a reflective way. The ELSI aspect of ethical implications, operationalized as the automation concern of potential job loss (EIMP01: “I fear that I will lose my job because of a recruiting chatbot.” In accordance with Bröhl et al. (2019)), it has been complemented by two further items also related to the concern of job loss, (1) the productivity level (EIMP02: “I fear that a recruiting chatbot works with higher productivity than me.”), and (2) the quality level (EIMP03: “I fear that a recruiting chatbot works with a higher quality level than me.”) as suggested by Nelles et al. (2017). The legal implication of data protection within ELSI (LIMP01: “I do not mind if a recruiting chatbot records personal information about the applicant.”) has been expanded via the danger of breach of duty concerning wrongful data handling (LIMP02: “I sense a danger of breach of my duty of care when implementing a recruiting chatbot into the interviewing procedure in my company’s recruiting process.”), resulting in a formative construct. The social dimension is also considered regarding the relationship of the recruiters to their candidates (SIMP01: “I fear that I will lose the contact to the applicants because of a recruiting chatbot.”).

5.2.2.3 Control Variables

Control variables are added to causal models to “rule out alternative explanations for findings or to reduce error terms and increase statistical power.” De Battisti and Siletti (2019, p. 1) In this research, it was controlled for age (AGE01: “Please state your age.” with the answer options 1 = under 20 years old, 2 = 20-29 years, 3 = 30-39 years, 4 = 40-49 years, 5 = 50-59 years, 6 = 60-69 years, 7 = 70 years or older) as well as the levels of personal innovativeness (e.g., PI01: “If I heard about a new information technology, I would look for ways to experiment with it.”), technology affinity (e.g., TA01: “I inform myself about technological systems, even if I have no intention to buy it.”), technological understanding (e.g., TU01: “I know most of the functions of the technological systems I own.”), and chatbot experience (CEXP01: “Please state the degree of your chatbot experience regarding the past three years.” with the answer options 1 = I do not have any chatbot experience, 2 = I have heard about chatbots prior to this questionnaire, 3 = I have already used a chatbot before, 4 = I have used more than one chatbot before, 5 = I am/was part of a chatbot development project) (cf. Table 5.4).

Table 5.4 Control Variables of the Dissertation Survey

Construct/Topic	**No. of items**	**Scale**	**Affiliation**	**Source**
Age	1	Ratio	N/A	Bundeszentrale für politische Bildung (2020); Eißer et al. (2020)
Personal innovativeness	4[a]	7-point Likert scale	Various	Agarwal and Prasad (1998)
Technology affinity	5	7-point Likert scale	HRCAM	Bröhl et al. (2019)
Technological understanding	4[a]	7-point Likert scale	TA-EG[b]	Karrer et al. (2009)
Chatbot experience	1	Nominal	N/A	Author of the study

[a] The scale for one item in the item set is reversely coded; the scales were taken over from the original sources and left as intended. For further analyses, the correspondent items were recoded to ensure uniform polarity. [b] TA-EG is utilized as an abbreviation for “Technologieaffinität Elektronischer Geräte” (EN: Technology affinity of electronic devices; Karrer et al. (2009)).

While age and technology affinity are adapted from the HRCAM model, personal innovativeness, technological understanding and chatbot experience are added for a more insightful analysis result (cf. section 4.1.3). For statistical control, these variables are measured and included in the analysis to examine their effect (De Battisti & Siletti, 2019).

5.2.2.4 Further Recruiting Chatbot Specific Aspects of Interest

Other aspects are included that are seen relevant for the study at hand. Abbreviations are assigned to each one, which is not to be confused with aggregable variables names but to be understood as topic identifiers. Regarding the demographical part of the questionnaire, the sex of the respondents (SEX), the number of employees in their company (NOE), their industry affiliation (IA), and their position in the company (CP; categorization into one of different roles of diverging responsibility and hierarchical standing) are included. Concerning the respondents' recruiting process infrastructure, their current recruiting situation in the form of the yearly number of interviews within their recruiting processes (NI), their modus operandi for candidate interviewing (MOCI), the technological infrastructure of their company in the form of applicant tracking system implementation (ATSD), their personal chatbot knowledge and experience (CEXP; different levels from no experience to actual development of a chatbot), and their company's general and recruiting chatbot situation (CDEP: chatbot deployed, CDEV: chatbot in development, CPLAN: chatbot planned within the next two years) are assessed.

Of special interest are the levels of relevance of potential recruiting chatbot use cases (ranking of the use cases UC_1 to UC_{13}) in the recruiting process as seen by the respondents as well as their view on potential drivers (level of agreement to the potentially ascribed chatbot implementation drivers DU_1 to DU_{12}) and barriers (level of agreement to the potentially ascribed chatbot implementation barriers BU_1 to BU_{11}) concerning the utilization of recruiting chatbots. Specifically focusing on the exemplary use case of candidate interview, the recruiters are asked to rank certain aspects of the interviewing process (RASP) and expected recruiter skills (RSKILL) according to their relevance. A summary of all mentioned variables can be seen in Table 5.5.

Table 5.5 Further Collected Variables of the Dissertation Survey

Construct/Topic	No. of items	Scale	Source
SEX	1	Nominal	Eißer et al. (2020)
NOE	1	Ratio	Loosely based on Eißer et al. (2020)
IA	1	Nominal	Destatis (2022); Statistisches Bundesamt (2008)
CP	1	Nominal	Author of this study
NI	1	Ratio	Author of this study
MOCI	1	Nominal	Author of this study
ATSD	1	Nominal	Author of this study
CKNOW	1	Nominal	Eißer et al. (2020)
Chatbot situation (CDEP, CDEV, CPLAN)	3	Nominal	Author of this study
Recruiting chatbot situation (RCDEP, RCATS, RCDEV, RCPLAN)	3	Nominal	Author of this study
UC	13	7-point Likert scale	Meurer et al. (2019)
DU	12	7-point Likert scale	Adapted from Mazurchenko and Maršíková (2019)
BU	10	7-point Likert scale	Adapted from Mazurchenko and Maršíková (2019)
RASP	8	Ordinal (ranking)	Partly adapted from Mazurchenko and Maršíková (2019)
RSKILL	8	Ordinal (ranking)	Partly adapted from Mazurchenko and Maršíková (2019)

The questionnaire containing all beforementioned latent variables as well as regarded topics and rankings was assembled and made available via the scientific web application SoSciSurvey in German language.

5.2.2.5 Proposed Measurement Model

In total, there are 25 variables (including the five control variables), which altogether form the proposed, operationalized HCCAM model. The path model, visually presenting the hypotheses and variable relationships investigated in partial least squares structural equation modelling (PLS-SEM) analysis, consists of a structural model and a measurement model (Hair Jr et al., 2017). The structural model for the

HCCAM has been introduced in section 4.3 (cf. Figure 4.1). Measurement models, also called outer models of the path model, visualize the indicators and their relationships with the respective constructs formerly combined in the structural model (Hair Jr et al., 2017). They specify the direction of these relationships (Christian Maier, 2014). The measurement model proposed for this research around the structural model of the HCCAM is presented in Figure 5.2.

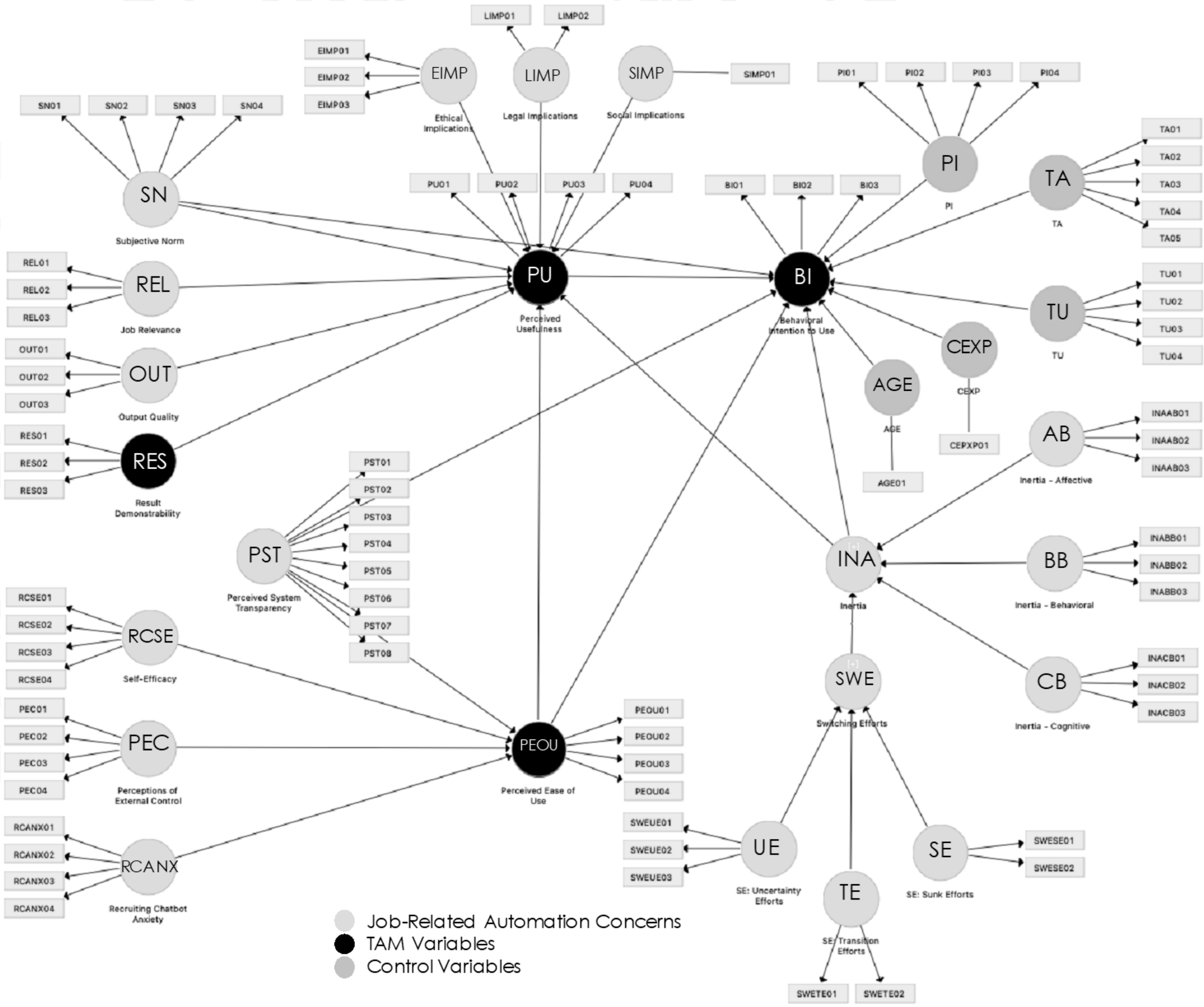

Figure 5.2 HCCAM Measurement Model
Source: Own illustration.

It consists of the presented measurement items for each construct. The variables indicated in light grey color belong to the group of aspects regarding job-related automation concerns, while the black variables stem from traditional acceptance research (TAM) and have been integrated in the HRCAM by Bröhl et al. (2019) serving as foundation for the HCCAM. Perceived system transparency (PST) and inertia (INA) alongside the switching efforts (SWE) impacting inertia extend the original HRCAM. The other grey variables represent the five control variables.

The precedents of inertia are modelled in a reflective way because of the content-related equivalence regarding the three distinguishable but also summarizable aspects (affective-based, behavioral-based, cognitive-based) of inertia. Switching efforts (uncertainty efforts, transition efforts, sunk efforts) however are integrated in a formative way as they regard different kinds of efforts with differently, even oppositely operationalized items (cf. Appendix D).

With inertia and switching efforts, the HCCAM model includes a top-down type of hierarchical components model (HCM) constellation with three lower-order and one higher-order construct each (Hair Jr, Sarstedt, Ringle, & Gudergan, 2018): The HCCAM includes a reflective-formative HCM concerning the effect of switching efforts as antecedent latent variable $Y_{exogenous}$ impacting inertia as higher-order construct (HOC) with the three lower-order constructs (LOC) affective, behavioral and cognitive inertia (Hair Jr et al., 2018). An overview of the HCM components can be seen in Figure 5.3.

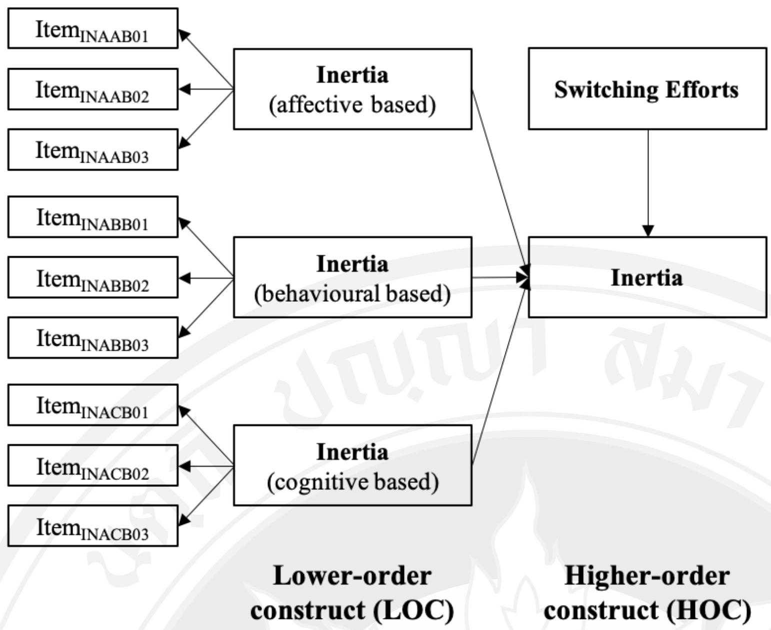

Figure 5.3 HCCAM Reflective-Formative Endogenous HCM Constellation
Source: Own illustration based on Hair Jr et al. (2018).

Inertia is an endogenous variable with its variance hypothetically being explained by its affective, behavioral, and cognitive characteristics. With the high R^2 resulting from this explanation, any further path coefficients such as the one of switching costs, would be doomed to be small and insignificant (Hair Jr et al., 2018; Ringle, Sarstedt, & Straub, 2012). As a counter measure, the total effects analysis of collect-type HCMs as suggested by Hair Jr et al. (2018) is conducted. Hence, the relationships between the antecedent construct of switching costs and the LOCs affective, behavioral and cognitive inertia are specified in the measurement model.

5.3 Data Collection

In this study, primary data is collected in the form of a quantitative survey. The data is collected to allow for model parameter estimation (Sarstedt & Mooi, 2014) to ultimately answer the research questions of this study. In the following, details are provided regarding the sample of recruiters selected for the study and concerning the method of questionnaire distribution.

5.3.1 Sample Setup

Regarding the unit of analysis of this cross-sectional in-between subjects study, recruiting employees of different positions, company sizes and industries from Germany are defined as population (N) for this study. With more than 12.7 Mio. vacant positions offered online (PHOENIX GIR, 2022), the German recruiting market is relevant to examine regarding digital recruiting measures. In 2020, the total number of employees in HR in Germany was 231,359 (Bundesagentur für Arbeit (2020); EN: Federal employment agency 2020). Assuming that 15 percent of the HR employees work in recruiting,[44] there are around 34,704 recruiters in Germany. A meaningful sample for hypothesis testing is drawn from this population.

The sampling frame consists of recruiting professionals in the form of recruiters in companies in Germany. Recruiting professionals are defined as employees (this includes recruiters, recruiting managers, HR administrators, HR officers, HR managers, and general managers in charge of HR (e.g., CHRO)) in the recruiting department of a German company with at least a half-year of experience within a related field. This way, it can be made sure that they are knowledgeable of the recruiting processes within their company. Furthermore, they are selected according to their affiliation with a recruiting department thus sorting out those types of companies too small to incorporate an own department for recruiting and those without distinct and profound recruiting processes. Hence, only those recruiters are sampled who have at least half a year of recruiting experience. Furthermore, the respondents' expertise is assessed via their common work tasks: Only those recruiters with actual recruiting-related job positions who explicitly state that they work on HR-related tasks are considered for this study. The recruiters are acquired based on their level of HR experience to gain insights concerning their assessment of chatbots for the recruiting processes in their work environment. Prior chatbot utilization or the deployment of an own recruiting chatbot within their companies is not made a mandatory prerequisite for study participation, as the focus is on their perceptions – may it be on a future potential novelty to their processes or on already established technology in the form of an up and running

[44] In their Talent Acquisition Benchmarking Report with n=1,708 recruiters from the US, China, India, and the United Arab Emirates, the Society for Human Resource Management (SHRM, 2017) found that 15 percent of the HR-related expenses in a company (including advertising costs, third-party agency fees and related costs) are allocable to recruitment activities.

recruiting chatbot. Furthermore, the technology of recruiting chatbots is not yet as prevalent as would be necessary to consider this eligibility criterion for participation in this study. However, the demographic control variable chatbot experience is regarded to examine a potential influence on the acceptance of recruiting chatbots. A high hierarchical position is not set as a requirement for participation because expertise in the operational recruiting work is asked for and inquired on in the survey, which includes all kinds of recruiters and especially those with lower ranks in the recruiting departments working in these operational environments.

The participating recruiters are sought to be working in a German company with German as corporate language. An international comparison and the examination of the influence of different company nationalities and thus corporate cultures for example on acceptance are not in focus of the study at hand. Concerning the industry or company size in focus, the recruiting professionals are chosen according to fitting industries and thus companies with expectably high numbers of potential candidates for certain positions presumably prone to or willing to make use of chatbot application and as a result high amounts of data, which make recruiting chatbot deployment (for first interviews) reasonable. Examples for suitable industries and positions are trade/transport/hospitality (e.g., salesman, driver or cabin crew positions), service providers (e.g., stewards, waiters), and manufacturing (e.g., assembly line workers). The participants are not required to have implemented a chatbot in their department/company altogether or have interacted with a chatbot before as this would prevent those individuals from participating, who are new to this technology or might have consciously decided to not make us of it, which can yield further relevant insights. More generally, recruiters may participate regardless of their technical infrastructure; they are not obliged to have deployed an ATS system in their HR processes for example.

As hypotheses are tested, an adequate sample size (n) needs to be determined to ensure sufficient precision as well as statistical power (Johanson & Brooks, 2010). Yamane (1967) provides a simplified formula to calculate the sample size:

$$n = \frac{\mathrm{N}}{1 + \mathrm{N}(e)^2}$$

N is the population size, n the sample size and e is the level of precision; the underlying assumption is a 95 percent confidence level (Israel, 2013). With a population size of 34,704 (calculated no. of recruiters in Germany), n = 34,704 / (1 + 34,704) * $(0.05)^2$) so that n = 395.44. Hence, at least 395 participants are sought to acquire for the study at hand to ensure precision and statistical power for the statistical analyses.

5.3.2 Survey Distribution

The quantitative survey for recruiting professionals is created and distributed digitally in order to make use of the high reach (Kjeldskov & Graham, 2003; Wynekoop & Conger, 1990) and the simplified circulation possibilities while the respondents profit from high levels of convenience and usability. Furthermore, online surveys are characterized by lower costs and time efforts as well as a better quantifiability than regular surveys (Röbken & Wetzel, 2016). In contrast to other methods such as paper, telephone or personal surveys, online surveys yield high levels of (1) data precision, (2) generatable data per study,(3) flexibility, and (4) representativeness while requiring only little time investments and a negligibly low level of interviewer bias (Kaya, 2009). Thus, the web-based survey is digitally distributed.

Prior to exposal of the questionnaire to the pilot study sample, the questionnaire has been tested technically and content-wise by ten industry as well as academic experts within a preliminary pretest. As suggested by Schmaltz (2009), the experts were asked to assess the survey concerning its comprehensibility as well as appropriateness regarding the questions from a respondent's point of view. Minor adjustments ensued to the wording of certain questions as well as the explanatory addendums to the questions for ambiguity reduction. Certain blatant comprehension problems occurred (1) in the section of recruiting chatbot introduction concerning understandability and comprehensibility, (2) with the item concerning the recruiters' current modus operandi for candidate interviewing (the number of answer options was overwhelming and imprecise), and (3) with the items of output quality and perceptions of external control, which were lacking explanations of recruiting chatbot output and utilization support respectively. Those error-prone sections and items were rigorously adapted to the needs and exigencies of the target group and tested again for assurance of maximum fit to the sample. After this second test, which did neither reveal any remnants of these issues nor any new problem areas, the now unambiguous survey proceeded into the distribution phase.

As sampling techniques, non-probability sampling in the form of judgement purposive sampling with an access panel as well as via recruiting-related message boards (practice in research, see Forsgren et al. (2016) for example) within the business networks XING and LinkedIn are conducted. In total, the questionnaire was posted in 13 HR-related forum groups of these business networks each reaching 2,840 HR experts on average alongside posting in an access panel. Strict quality control was applied concerning the access panel sampling as well as the business network distribution. The cross-sectional study was distributed online from March 17th to May 15th 2021 via SoSci Survey, a German online survey creation tool for scientific study conduct allowing for programmable filter and thus screen out routing (SoSci, 2021). Multiple responses could be ruled out via IP address verification within SoSci Survey by allowing each address to access and conclusively answer the survey exactly once. At some point, it became foreseeable that the desired sample size could not be satisfied via the access panel with survey distribution in Germany alone, so the sampling region was expanded to Germany and the adjacent German-speaking countries Austria and Switzerland (subsumable as DACH region) to fulfil the sample size requirements while ensuring cultural and mindset-related proximity of the respondents.

5.4 Data Processing and Analytical Methods

Six data analysis process steps are applied to the collected data for a thorough examination to ultimately answer the research questions $RQ_{1\text{-}2}$: (1) Data screening and cleansing to prepare the data for analysis, (2) sample description assessing the basic information of the respondents, (3) data assessment concerning the adequacy, distribution, and common method bias of the data set and (4) hypothesis testing via structural equation modelling (SEM) divided into (5) measurement model evaluation and (6) structural model evaluation.

5.4.1 Data Screening and Cleansing Approach

The data of this study is processed ensuring a retention of confidentiality and anonymity. No personal data is collected or processed ensuring data privacy. This circumstance can help reduce social desirability bias since the participants can be assured that their answers will not be linked to them personally. Estimations of structural equation models require complete data sets without missing values (Weiber & Mühlhaus, 2014). A data cleansing process is necessary to comply with this obligation. Data sets with missing information will be excluded from further analysis and outliers within the data will be handled. Specifically, the data set is being cleansed by removing all (1) screen outs, (2) general drop outs, and (3) quality dropouts prior to data analysis. The control question for screening out unfit participants was: "Please state the role that you have within the company that you currently work for:" When answer option 7 "My tasks are unrelated to HR" was selected or an HR-unrelated task was stated in the free-text input option, the respective participant was deemed inapt for the study at hand and screened out. Dropouts could be eliminated by ruling out all data sets containing an inacceptable amount of missing values in the form of incomplete answers and no correct completion of the survey (i.e., no answer to the last questions in the set, no reach of the farewell page). Quality dropouts were identified by either having left answer sections to more than ten items blank[45] or having needed less than ten minutes for completing the questionnaire. While experienced recruiters capable of speed reading are hypothesized to be quite fast in capturing textual contents, assessing the 149 to 152 items (depending on the inclusion of conditional questions) in under ten minutes is classified as non-attentive and inconsiderate survey filling behavior deemed inappropriate for this research study. Hence, all records with more than ten missing values or exhibiting answering times of under ten minutes were deleted in disregard for

[45] Several sections rendered left blank on purpose because the questionnaire contains certain conditional questions only queried when the preceding question was answered in a certain way. Other items were provided for qualitative textual supplements that could be added voluntary. The threshold of ten items was installed to consider these potentially missing conditions as well as voluntary additions and furthermore gave the respondents the possibility to leave out up to seven more of the queried items. Hair Jr et al. (2017) allow observations with up to 15 percent of missing data to remain in the data set, which would be 15 items according to the 152 queried items in this study (total content of the questionnaire). However, the author decided on up to ten missing values to achieve a high level of informative value. This threshold was simultaneously applied to identify general dropouts alongside those quality dropouts with > 10 missing items = (quality) dropout.

further analyses. Missing values that are expectable in case of conditional questions or voluntary input are not further processed. Data sets with otherwise missing values are deleted and excluded from further examination. As a result, only finished questionnaires with complete answer sets (≤ 10 missing values) are being counted and analyzed.

In accordance with Orr, Sackett, and Dubois (1991), the data was then checked for apparent errors such as answers that were not provided for by the pre-defined questionnaire coding (e.g., options > 7 for items with a seven-point Likert scale due to technical faulties or errors in data transferral). To check for anomalities, the data is subjected to standard deviation examination for detection of unengaged response patterns in the form of non-differentiation via IBM SPSS V27. Extraordinary response behavior is sought to identify unengaged response patterns via examination of the standard deviation for all cases. In accordance with Barge and Gehlbach (2012), unengaged response behavior because of non-differentiation is assumed for cases of a standard deviation (SD) = 0 concerning the HCCAM-related 7-point Likert scale items with same answers for at least 66 of the 68 items. The according case is disregarded from further analyses by deletion from the data set.

5.4.2 Data Assessment Approach

Data assessment establishes the level of appropriateness of the collected data for the subsequent analysis techniques. In a first step, the sampling adequacy is examined via the Kaiser-Meyer-Olkin (KMO) index and the Bartlett's test of sphericity. The KMO index describes the explainability of correlations between variables by other variables in the dataset; for sufficient adequacy, the KMO measure needs to be > 0.5 (Sarstedt & Mooi, 2014). The Bartlett's test of sphericity is used to see whether the correlation matrix is a diagonal matrix in the population. This null hypothesis needs to be rejected ($p < 0.01$) as high correlations are aimed for in principal components analysis (Sarstedt & Mooi, 2014).

Secondly, the distribution of the data is assessed via the three aspects (1) normality, (2) skewness, and (3) kurtosis. Normal distribution is assumed and required for statistical analysis via the traditional SEM method of maximum likelihood covariance-based SEM (Hair Jr et al., 2017). PLS-SEM analysis via SmartPLS however does not require a normal distribution of data (Hair Jr et al., 2017; Christian Maier, 2014). Nevertheless, data distribution is examined to yield the level of (non-)normality as too extreme deformations complicate the evaluation of the parameters' significances by inflating standard errors while bootstrapping for example resulting in decreased statistical power (Joe F Hair et al., 2012; Hair Jr et al., 2017). As suggested by Sarstedt and Mooi (2014), Kolmogorov-Smirnov and Shapiro-Wilk tests of normality are conducted. However, skewed distributions are expected as negative behaviors are generally assumed to result in skewed data distributions (Turel, Serenko, & Giles, 2011). This might the case for the variables of inertia and recruiting chatbot anxiety and will be examined both in the pre-study and in the main empirical study. The skewness and kurtosis values are reported to assess the shape of the data distribution at hand with values > |1.0| indicating non-normal data distribution (Hair Jr et al., 2017). While skewness represents the level of symmetry in the variable's distribution, kurtosis assesses the peak behavior of the distribution in terms of its narrowness towards the center (Hair Jr et al., 2017). Items with skewness or kurtosis levels > |2.0| are deemed unacceptable (George & Mallery, 2010) and removed from the data set. However, the variance underestimation does not pose a problem with samples of n = 200 and more (Waternaux, 1976), which is strived for in this study.

Common method bias is defined as a phenomenon that results from the measurement method utilized in SEM analysis while not being explained by the system of causes and effects associated with the latent variables themselves (Kock, 2015). Examples are ambivalent survey instructions or social desirability within the answering pattern causing a certain amount of shared variation among the concerned indicators and potential path coefficient inflation or deflation effects (Kock, 2015). While discriminant and convergent validity tests are not suited for common method bias detection, a collinearity test is proposed for common method bias detection (Kock, 2015): Full variance inflation factor (VIF) values are calculated for all latent variables in the model with VIF > 3.3 as an indication of pathological collinearity and thus possible contamination with common method bias (Kock, 2015). Hence, all inner VIF values are examined via Smart PLS3 for common method bias indication.

5.4.3 Hypotheses Testing Technique

After a descriptive analysis, PLS-SEM via the tool SmartPLS3 applying ordinary least squares regression (Hair Jr et al., 2017) is chosen for analysis as this research aims at predicting and explaining the constructs of the adapted HRCAM model and finding answers to RQ_1 (relevant recruiting chatbot acceptance determinants) and RQ_2 (relevant job-related automation concerns influencing recruiting chatbot acceptance) through statistical analysis. SEM enables the observation of unobservable, latent variables via indirect indicator variables (Hair Jr et al., 2017). It is a multivariate technique to empirically test hypotheses in quantitative research (Christian Maier, 2014). In contrast to other multivariate analysis methods such as regression-based analysis, SEM allows the inclusion of latent variables (Joe F Hair et al., 2012; Christian Maier, 2014). As defined before, latent variables are unobservable theoretical constructs in structural models (Hair Jr et al., 2017) in need of observable, manifest indicator measures (Christian Maier, 2014). With the help of SEM, a model test and individual hypotheses tests can be conducted as well as model fit criteria examinations (e.g., B. Pérez, 2010). PLS-SEM is one of the most popular approaches to estimate measurement and structural models (De Battisti & Siletti, 2019). "PLS-SEM determines the parameters of a set of equations in a path model by combining principal component analysis to assess the measurement models with path analysis to estimate the relationships between latent variables." Hair Jr et al. (2018, p. 3) Thereby, it succeeds covariance-based (CB-)SEM (Hair Jr et al., 2018). It is applicable to research settings dealing with small sample sizes (however, the precision in the form of consistency increases with larger sample sizes (Hair Jr et al., 2017)) while providing high statistical power (Joe F Hair et al., 2012). Furthermore, it can be utilized to estimate complex models and there is a possibility to measure reflective as well as formative latent variables (Joe F Hair et al., 2012). In this study, formative measurement is necessary for the latent variable of legal implications inhibiting different legal aspects as well as for switching efforts (higher-order construct) in this study. To control for a potential swamping out effect, which might occur for higher-order constructs – in this case inertia and switching efforts – as they are composed of the respective contained items of the lower-order variables, a two-stage approach is applied in Smart PLS calculating and analyzing the respective latent variable scores. Other advantages are the suitability of PLS-SEM for focused model prediction and examination (Joe F Hair et al., 2012) as well as its ability to handle complex models with various structural model relations, which applies to the proposed HCCAM model. PLS-SEM supports constructs measured with single- and with multi-item measures and thus suits the study at hand deploying both (Hair Jr et al., 2017).

While the main part of the analysis will be regarding the structural paths between the constructs, the relationship between measures and constructs is also important and will be evaluated as suggested by Edwards and Bagozzi (2000) and Petter, DeLone, and McLean (2008). Hence, prior to hypothesis testing and ultimately yielding the amount of explained variance of behavioral intention and actual use of recruiting chatbots based on PLS-SEM, confirmatory factor analysis (CFA) is conducted. It is utilized to test the expected variable structure while the subsequent structural equation modeling is used for an evaluation of the relationships between the observed variables (Sarstedt & Mooi, 2014). All tests are performed with the electronic statistical analysis packages SmartPLS3 (version 3.3.3) and IBM SPSS27 according to the available test metrics. In the symmetric and equidistant form, interval scale property can be attributed to the Likert scales calculated from the applied 7-point Likert scale items (Hair Jr et al., 2017), which enables the conduct of all necessary statistical analyses.

PLS-SEM results are yielded of the reflective and formative measurement models as well as the structural model. Figure 5.4 gives an overview of the applied procedure and comprised process steps. The factor analysis is run twice for the (1) lower-order, and (2) higher-order measurement model, to correctly capture the results of the endogenous higher-order factor of inertia (cf. Figure 5.3) via a two-stage approach (e.g., Gaskin et al., 2018). This two-step approach allows for HCM investigation eradicating the problems that occur when the higher-order construct is composed and completely explained by lower-order variables and then endogenously influenced by other antecedent latent variables (Hair Jr et al., 2018). The new data set formed by the latent variables scores is scanned for skewness and kurtosis issues prior to further processing.

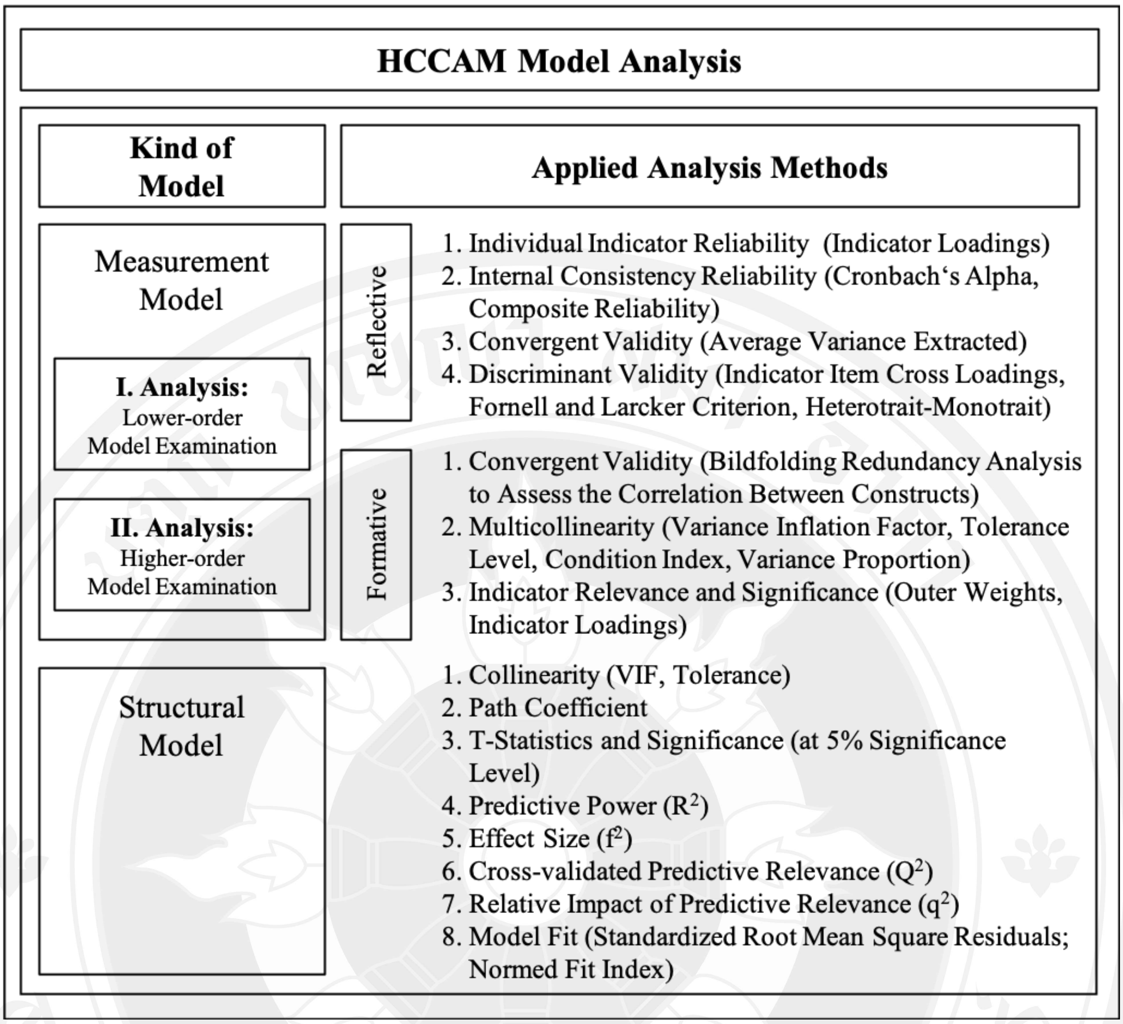

Figure 5.4 HCCAM Measurement and Structural Model Analysis Steps
Source: Own illustration based on Joe F Hair et al. (2012); Hair Jr et al. (2017); Joseph F Hair et al. (2018); Henseler, Ringle, and Sinkovics (2009); Christian Maier (2014); Sarstedt and Mooi (2014); PLS (2020); Smart PLS (2021).

A discussion of the findings and the according theoretical and practical implications ensues to answer RQ_1 and RQ_2. Those of the newly established variables are identified that are statistically significant predictors of the behavioral intention to use recruiting chatbots to answer RQ_1. In a subsequent step, it is analyzed which variables classified as job-related automation concern are significant predictors of the behavioral intention to use a recruiting chatbot to answer RQ_2 according to Hair Jr et al. (2017). For the measurement model, factor weighting is applied while path weighting is used for structural model analysis.

5.4.4 Measurement Model Assessment Method

For reflective measurements, factor analysis with reliability estimations is conducted (Edwards & Bagozzi, 2000). Specifically, individual indicator reliability, internal consistency reliability regarding the composite of measures for each construct, and the measures' convergent as well as discriminant validities are examined during measurement model assessment (Joe F Hair et al., 2012). Validity is as important as reliability, as both ensure unbiased data showing relevant, significant relationships, which otherwise might be overlooked (Joe F Hair et al., 2012) and ensure sufficient data and overall research quality (e.g., Straub, Boudreau, & Gefen, 2004). Whereas reliability refers to the consistency of the findings retrievable from the data set, validity regards the causality and causal direction of the relationships between variables (Saunders, Lewis, & Thornhill, 2009). The data is analyzed in Smart PLS3 with 5,000 iterations for each PLS algorithm analysis round.

Confirmatory Factor Analysis

Confirmatory factor analysis is applied to test the determined factors and their according indicators (Hair Jr et al., 2017). Specifically, it is conducted to (1) validate the established scales in the form of the implemented variables composed of individual variables and to (2) provide construct validity evidence of the self-reported scales. For the overall reflective measurement model, the beforementioned reliability and validity analysis methods are applied (cf. Table 5.6).

Table 5.6 Reflective Measurement Model Analysis Aspects

No.	Analysis method	Definition	Recommended criteria and threshold values
1	Individual indicator reliability	Squared standardized outer loadings (Joe F Hair et al., 2012)	Indicator loadings > 0.707 to ensure reliability (Joseph F Hair et al., 2018)
2	Internal consistency reliability via…	Split-half approach to test-retest reliability through the measurement of related aspects of the same underlying construct (Sarstedt & Mooi, 2014)	
2a	… Cronbach's Alpha (CA)	Function representing the interrelatedness of survey items (Schmitt, 1996) assuming that all indicators show equal reliability (Joe F Hair et al., 2012)	CA > 0.7 (Joseph F Hair et al., 2018; Sarstedt & Mooi, 2014)

No.	Analysis method	Definition	Recommended criteria and threshold values
2b	… Composite Reliability (CR)	Reliability measure prioritizing indicators according to their individual reliability (Joe F Hair et al., 2012)	0.70 ≤ composite reliability value ≤ 0.95 (Joseph F Hair et al., 2018)
3	Convergent validity	Level of positive correlation of a measure with alternative measures in a construct (Hair Jr et al., 2017)	Average variance extracted (AVE) > 0.5 (Joseph F Hair et al., 2018)
4	Discriminant validity via…	Level of distinction of the construct to others in terms of uniqueness (Hair Jr et al., 2017); "correlations among latent variable and other latent variables in a model are lower than a measure of communality among the latent variable indicators" (Kock, 2015, p. 5)	
4a	… Indicator item cross loadings	Each indicator should load highest on the construct it is intended to measure and have lower cross-loadings in the form of correlation on other constructs	Highest load on the construct the items belong to (Hair Jr et al., 2017)
4b	… Fornell and Larcker criterion	Comparison of the construct's AVEs with the inter-construct correlations (Hair et al. 2012) to assess the empirical distinction between the constructs of the model (Joseph F Hair et al., 2018)	Each construct's AVE needs to be higher than its squared correlation with any other construct (Hair Jr et al., 2017)
4c	… Heterotrait-Monotrait (HTMT)	"Ratio of the between-trait correlations to the within-trait correlations" (Hair Jr et al., 2017, p. 118)	Conceptually similar constructs: HTMT < 0.90; Conceptually different constructs: HTMT < 0.85 (Joseph F Hair et al., 2018)

There are two types of internal consistency reliability measurement: (1) Cronbach's Alpha, which represents the lower bound, and (2) composite reliability, which represents the upper bound. Cronbach's alpha coefficient "provides an estimate of the reliability based on the intercorrelations of the observed indicator variables." (Hair Jr et al., 2017, p. 111) It is the most popular method to assess the internal consistency reliability (Joe F Hair et al., 2012). Composite reliability was introduced to cope with the limitations of Cronbach's Alpha in the form of an equal reliability assumption for all indicators and its sensitivity to the number of items in the scale (Hair Jr et al., 2017). The construct's true reliability however lies between the two values of Cronbach's Alpha as lower bound and composite reliability as upper bound (Joseph F Hair et al., 2018).

For formative models, internal consistency reliability statistics are not appropriate (Joseph F Hair et al., 2018). In case of formative variables and constructs, the internal consistency perspective is inappropriate as reliability is an irrelevant criterion for the assessment of measurement quality as the items are not interchangeable. Generally, convergent and discriminant validities cannot be assessed the way it is done for reflective measures. However, a formative construct's convergent validity can be assessed by examining its correlation with alternative measures of the construct: Utilizing a blindfolding redundancy analysis, the correlation between the constructs are uncovered, which should be ≥ 0.80 (Hair Jr et al., 2017). One requirement for redundancy analyses are unidimensional constructs (Ringle, 2017), which the higher-order variables of inertia and switching efforts are not and is thus not applicable for the study at hand. As overlapping between the indicators is not desired for formative models, the VIF values should be low to avoid multicollinearity (Joe F Hair et al., 2012). According to Hair Jr et al. (2017), $0.2 < VIF < 5$ is necessary to avoid pathological collinearity; Joseph F Hair et al. (2018) even suggest VIF levels < 3. The tolerance level is supposed to be > 0.2 with a condition index of < 30 and at most one value > 0.9 in the variance proportion section (Joe F Hair et al., 2012). The indicators' outer weight yields the relative importance in the form of those indicators' absolute contribution to the constructs and loadings via bootstrapping to assess their respective significance requiring $t > 1.96$ and $p < 0.05$ to reject H_0 (path coefficient = 0 indicating insignificance) at a five percent significance level (Hair Jr et al., 2017). In this study, 5,000 bootstrap samples are applied.

5.4.5 Structural Model Assessment Method

In accordance with Joe F Hair et al. (2012), inner model examination is conducted after reliability and validity consideration of the outer model. In the structural model, the theoretically established relations between the independent and dependent variables are specified (Christian Maier, 2014). For model prediction, path analysis is conducted for the structural model. Via Smart PLS 3, the model is estimated utilizing PLS algorithm with path weight. In order to examine the higher-order endogenous construct of INA, the latent variable scores of the PLS algorithm calculated for the measurement model evaluation are utilized again. The data is analyzed in Smart

PLS with 5,000 iterations for each bootstrapping and PLS algorithm analysis round. All utilized structural model analysis aspects are summarized in Table 5.7.

Table 5.7 Structural Model Analysis Aspects

No.	Aspect of analysis	Definition	Recommended criteria and threshold values
1	Collinearity	Full VIF and tolerance assessment to uncover collinearity issues among the path coefficients (Hair Jr et al., 2017)	VIF < 5 (Joe F Hair et al., 2012); Tolerance > 0.2 (Joe F Hair et al., 2012)
2	Path coefficient	Estimations of the structural model relationships (Hair Jr et al., 2017)	$-1 \leq$ path coefficient ≤ 1, with $\|1\|$ as strongest and $\|0\|$ as weakest level of relationship (Hair Jr et al., 2017)
3	T-statistics/ significance	T-statistics and significance assessment to see whether the path coefficients significantly differ from zero (Hair Jr et al., 2017)	T > 1.96 for the 5% significance level; $p < 0.05$ (Hair Jr et al., 2017)
4	R^2	Coefficient of determination to assess the model's predictive power in the form of the "[…] amount of variance in the endogenous constructs explained by all the exogenous constructs linked to it." (Hair Jr et al., 2017, p. 198)	$0 \leq R^2 \leq 1$, range of acceptable R^2 value ranges vary according to the research discipline and complexity of the model ((Hair Jr et al., 2017, pp. author-year); general compilation by Christian Maier (2014)): R^2 > 67% = substantial R^2 > 33% = moderate R^2 > 19% = weak
5	f^2	Effect size concerning exogenous variable effects (Joe F Hair et al., 2012)	$f^2 > 0.35$ strong effects $f^2 > 0.15$ moderate effects $f^2 > 0.02$ weak effects
6	Q^2	Indicator of cross-validated predictive relevance of the PLS path model (Joe F Hair et al., 2012; Smart PLS, 2021)	$Q^2 > 0$ indicates predictive relevance (Henseler et al. 2009)
7	q^2	Relative impact of the predictive relevance Q^2 (Henseler et al., 2009); $q^2 = (Q^2_{included} - Q^2_{excluded})/(1- Q^2_{included})$ (Hair Jr et al., 2017)	$q^2 > 0.35$ large predictive relevance $q^2 > 0.15$ medium predictive relevance $q^2 > 0.02$ small predictive relevance (Henseler et al., 2009)

No.	Aspect of analysis	Definition	Recommended criteria and threshold values
8	Model fit	Standardized Root Mean Square Residuals (SRMR), defined as "the root mean square discrepancy between the observed correlations and the model-implied correlations" (Hair Jr et al., 2017, p. 193) are calculated (Hair Jr et al., 2017); the Normed fit index (NFI) calculates the Chi^2 value of the regarded model while comparing it to the null model (PLS, 2020)	SRMR < 0.08 for good fit (Hair et al. 2017); $0 \leq NFI \leq 1$, NFI > 0.9 for an acceptable fit (PLS, 2020)

As higher-order constructs inertia and switching efforts (formative) are involved, the regular bootstrapping method is applied (Smart PLS, 2020). The predictive relevance is calculated in a blindfold analysis in Smart PLS3. Plainly Chi-square-based model fit measures originally introduced for covariance bases SEM are not suitable for the assessment of model fit in PLS-SEM analyses (Joseph F Hair et al., 2018). Thus, bootstrap-based model fit assessments such as SRMR have to be examined cautiously and reliance should be on the PLS-SEM evaluation methods introduced for the measurement model and structural model (Joseph F Hair et al., 2018). As recommended by Hair Jr et al. (2017), the goodness-of-fit (GoF) criterion is not examined as it is not capable of separating valid from invalid models and formative as well as single indicator constructs are included so that GoF cannot be applied. Furthermore, GoF metrics are suited rather for covariance-based SEM than for PLS-SEM (Hair Jr et al., 2017).

Full and partial mediation effects are observed during structural model analysis to uncover significant effects not originally conceptualized in the HCCAM model. Mediation effects can further explain relationships between exogenous and endogenous constructs by identifying intervening variables between them (Hair Jr et al., 2017). Regarding the control variables, this research follows the approach of Iconaru (2012): SEM analysis is conducted and completed without the control variables before it is redone while including each control variable individually to compare the resulting R^2 and p-values. As suggested by De Battisti and Siletti (2019), the control variables as derived from theory are included and compared to the model without control variable application to gauge the effects of implementation regarding the intensity and significance.

5.5 Pilot Study

A pilot (pre-)study is conducted to control for issues during scale development such as item discrimination or undesired consistencies (e.g., Johanson & Brooks, 2010). The applicability of the instruments is analyzed in order to ensure data reliability and validity by correcting ambiguous wording or recession of unnecessary, model deteriorating items for example. Prior to the actual pre-study survey handout, the questionnaire was given to ten industry and academical experts (cf. section 5.3.2). As suggested by Schmaltz (2009), they evaluated the questionnaire for comprehensibility and appropriateness. Within this first logic and answerability check, notable errors and understandability as well as ambiguity and accuracy issues were eradicated by wording adjustments.

In a second step, a substantial number of members of the target group was acquired and asked to answer the questionnaire allowing for a detailed examination. The resulting primary data set is checked for respondent suitability yielded from the presented methods of survey distribution in terms of answer quality. As suggested by Johanson and Brooks (2010), a pilot study needs to be conducted with a minimum of 30 respondents. Out of 131 potential participants in an access panel being exposed to the questionnaire, 31 were screened out because of quality issues (answer time < 10 minutes or > 10 unanswered items). Of the remaining 100 keen participants, none needed to be deleted because of missing values but 40 were screened out because of lacking affiliation with HR-related work tasks (screen out question to ensure target group membership). Hence, 60 first respondents were acquired for the pilot study, resulting in a first response rate of 45.8 percent[46] surpassing the average response rate for e-mail surveys of 33 percent as found by T.-H. Shih and Fan (2009) by 12.8 percent point. The results are utilized to validate the envisioned constructs and variables for

[46] The response rate is calculated via division of the number of returned questionnaires by the actual sample size of potential participants who received the survey as suggested by Mitchell and Carson (1989).

measurement. This is in accordance with Connelly (2008), who suggests a rule of thumb for pilot study conduct of at least 10 percent of the targeted sample – between 400 and 450 respondents for the survey at hand requiring at least 40 to 45 participants for the pilot study.

The seven items PI03, TU02, RES04, PEC04, RCANX01, PST04, and LIMP01 are recoded to fit the overall polarization of the respective variable like discussed in section 5.2.2. As a preparatory step for data analysis, the data is screened for anomalies and outliers. Standard deviations for each item answer of each case in the data set is performed to detect unengaged response patterns. The pre-study data set shows one case of unengaged response behavior with SD = 0 across all items of the HCCAM part of the questionnaire with variations for no more than two of the 68 specific items, which was deleted from the data set reducing it to n = 59.

5.5.1 Sample Description

Prior to statistical data analysis of the pre-study, the sample characteristics are examined to ensure that respondents with different demographical backgrounds and specifications are being considered in the participant acquisition strategy and thus represented in the sample.

Focusing on the situation in the three German-speaking DACH countries,[47] the pilot study includes participants from Germany (DE; n = 35), Austria (AT; n = 14) and Switzerland (CH; n = 10). An examination of the demographical background and the work-affiliated characteristics is shown in Table 5.8. The study respondents are mainly female (64.4 percent), 30-59 of age (77.9 percent) and they primarily work in the positions of HR administrators or HR managers (30.5/22.0 percent) for companies of all different sizes. The gender ratio reflects the general predominance of women in HR in Germany (Human Resources Manager, 2015). With human resource administrators and managers as prevalent job titles, both positions with and without decision-making responsibility in terms of strategic recruiting decisions are represented in the sample. Most prominently selected industry affiliations are public and other private service providers and the manufacturing industry (40.7/24.7 percent). As found for the

[47] Main focus is Germany, also considered are the German-speaking nationalities Austria and Switzerland to ensure sufficient participant acquisition as discussed in section 5.3.2.

company size, the number of conducted interviews per year is distributed across all options from 1-10 up to more than 1,000 interviews within the pre-study data set.

Table 5.8 Demographic and Work-Related Characteristics

Age	Under 20 years old: 0 (0.0%) 20-29 years old: 2 (3.4%) 30-39 years old: 20 (33.9%) 40-49 years old: 15 (25.4%) 50-59 years old: 11 (18.6%) 60-69 years old: 2 (3.4%) 70 years or older: 0 (0.0%) Missing: 9 (15.3%)
Gender	Male: 21 (35.6%) Female: 38 (64.4%) Diverse: 0 (0.0%)
No. of Employees in the Company	Under 50 employees: 11 (18.6%) 50-100 employees: 4 (6.8%) 101-250 employees: 2 (3.4%) 251-500 employees: 12 (20.3%) 501-1,000 employees: 11 (18.6%) 1,001-3,000 employees: 1 (1.7%) 3,001 and more employees: 17 (28.8%) Missing: 1 (1.7%)
Industry Affiliation	Agriculture, forestry and fishing: 0 (0.0%) Manufacturing industry: 14 (24.7%) Construction: 2 (3.4%) Trade, transport and hospitality: 7 (11.9%) Information and communication: 4 (6.8%) Financial and insurance service providers: 0 (0.0%) Real estate and housing activities: 0 (0.0%) Professional, scientific and technical services: 0 (0.0%) Business services: 6 (10.2%) Public and other private service providers: 24 (40.7%) Creative, artistic and entertainment activities: 0 (0.0%) Missing: 2 (3.4%)
Position in the Company	Recruiter: 4 (6.8%) Recruiting manager: 4 (6.8%) Human Resources (HR) administrator: 18 (30.5%) HR officer: 8 (13.6%) HR manager: 13 (22.0%) General manager in charge of HR (e.g., CHRO): 5 (8.5%) My tasks are unrelated to HR: Screen out question (participants answering this question are not regarded for this study) Other: 7 (11.9%)

Number of Interviews	1-10 Interviews: 4 (6.8%) 11-25 Interviews: 6 (10.2%) 26-50 Interviews: 9 (15.3%) 51-100 Interviews: 7 (11.9%) 101-200 Interviews: 10 (16.9%) 201-500 Interviews: 9 (15.3%) 501-1,000 Interviews: 4 (6.8%) More than 1,000 Interviews: 8 (13.6%) I don't know: 2 (3.4%)

n = 59 DACH recruiters

As for the standard interview conduct, most of the respondents (61.7 percent) state that in-person interviews in physical form are performed with the candidates of their company (cf. Table 5.9).

Table 5.9 Technological Recruiting and Chatbot-Related Characteristics

Modus Operandi for Candidate Interviewing	In-person interview(s) (physical meeting(s)): 37 (62.7%) In-person interview (digital meeting(s)): 9 (15.3%) Technology-led interview(s) (= software-based, automated interview process such as time-delayed video interviews): 0 (0.0%) Chatbot interview(s): 0 (0.0%) Mixture of technology-led and in-person interviews: 8 (13.6%) I am not involved in the candidate interview conduct in my company: 5 (8.5%)
ATS Deployment	Yes: 30 (50.8%) No: 22 (37.3%) I don't know: 6 (10.2%) Missing: 1 (1.7%)
Chatbot Experience	I do not have any chatbot experience: 22 (37.3%) I have heard about chatbots prior to this questionnaire: 16 (27.1%) I have already used one chatbot before: 8 (13.6%) I have already used more than one chatbot before: 12 (20.3%) I am/was part of a chatbot development project 1 (1.7%)
Chatbot Knowledge	Yes: 40 (67.8%) No: 15 (25.4%) I don't know 4 (6.8%)
(Recruiting) Chatbot in Deployment	Yes: 7 (11.9%); 5 (8.5%) No: 46 (78.0%); 45 (76.3%) I don't know: 6 (10.2%); 9 (15.3%)
Recruiting Chatbot ATS Linkage	Yes: 5 (8.5%) = 100.0% of the ones with a deployed recruiting chatbot No: 0 (0.0%)
(Recruiting) Chatbot in Development	Yes: 1 (1.7%); 2 (3.4%) No: 35 (59.3%); 34 (57.6%)

	I don’t know: 10 (16.9%); 9 (15.3%) Not applicable: 13 (22.0%); 14 (23.7%)
(Recruiting) Chatbot in Planning	Yes: 4 (6.8%); 2 (3.4%) No: 18 (30.5%); 21 (35.6%) I don’t know: 18 (30.5%); 20 (33.9%) Not applicable: 19 (32.2%); 16 (27.1%)

n = 59 DACH recruiters; grey font indicates an affiliation with recruiting

None of their companies deploys technology-led interviews, so no company has implemented a chatbot-based first interview. Notable other characteristics concerning the recruiter and his company are the technological infrastructure in the form of ATS deployment (deployed by half of the respondents’ companies), their levels of chatbot experience (33.9 percent utilized a chatbot at least once) and knowledge about the technology prior to study participation (67.8 percent bring knowledge), and the level of chatbot deployment in their companies: While 11.9 percent of the recruiters report having a chatbot in their company, 8.5 percent state that they have a chatbot implemented in their recruiting process. All of them are linked to the ATS system, which serves as database for the operation. While four recruiters (6.8 percent) not equipped with a (recruiting) chatbot yet have one planned in their company, only one recruiter states that a chatbot is in development at the moment. For recruiting-specific chatbots, there are two in the planning (3.4 percent) and two in current development (3.3 percent).

In sum, the sample reflects a wide spectrum of different kinds of companies regarding industry affiliation, size and approach to interview conduct, different levels of chatbot knowledge and experience as well as different technological infrastructure scenarios regarding ATS deployment and chatbot implementation into their company’s processes.

5.5.2 Pilot Data Assessment

Prior to statistical analysis, the data set of this pre-study is examined to (1) ensure adequacy, (2) report the distribution details, and 3) control for common method bias.

The sampling adequacy results are shown in Table 5.10. The KMO value of 0.566 > 0.500 indicates sample adequacy (Sarstedt & Mooi, 2014); the significance value of the Bartlett's Test with $p < 0.05$ shows that the data is appropriate.

Table 5.10 Pilot Study KMO Index and Bartlett's Test for Sphericity (n = 59)

Test	**Kind of Value**	**Value**
KMO Measure of Sampling Adequacy	-	0.566
Bartlett's Test of Sphericity	Approx. Chi-Square	3,049.401
	df	1225
	Sig.	0.000

For an examination of the data distribution and the manifestation of normality in the data, Kolmogorov-Smirnov and Shapiro-Wilk tests of normality are conducted. As seen in Appendix E, both tests yield significances < 0.05 indicating that the null hypothesis of normal distribution needs to be rejected and that the data is indeed non-normally distributed. Additionally, skewness and kurtosis values are assessed: while only one item, EIMP01 of the construct ethical implications, is slightly skewed with a skewness level of 1.153 > |1.000|, five items show signs of kurtosis with values > |1.000| (PEC = 1.096, PST01 = 1.027, PST05 = 1.015, PEOU01 = 1.374, and PEOU02 = 1.033. However, the values are well below |2.0| and thus deemed acceptable (George & Mallery, 2010).

Astonishingly, this does not match the expectation regarding the negative behaviors of inertia and recruiting chatbot anxiety, that were hypothesized to show a skewed distribution (cf. section 5.4.2). Nevertheless, the two skewed items are closely monitored within the following measurement and structural model analyses and deleted if necessary but not deleted for now as they had been identified as relevant for variable operationalization and are in an acceptable range according to George and Mallery (2010). For the examination of potential common method bias, the full VIF values are calculated: All latent variables have inner VIF values < 3.3 (cf. Table 5.11).

Table 5.11 Pilot Study Inner VIF Values (n = 59)

	BI	INA	PEOU	PST	PU	SWE
BI						
EIMP					1.674	
INA	1.210				1.327	
INA AB		1.407				
INA BB		1.572				
INA CB		1.280				
LIMP					1.465	
OUT					3.056	
PEC			1.518			
PEOU	1.492				1.616	
PST	1.779		1.492			
PU	2.041					
RCANX			1.119			
RCSE			1.411			
REL					2.797	
RES					2.529	
SIMP					1.557	
SN	1.752				2.691	
SWE		1.784				
SWESE						1.107
SWETE						1.175
SWEUE						1.160

Based on the inner VIF values of VIF < 3.3, no signs of pathological collinearity and thus common method bias are found.

5.5.3 Pilot Measurement Model Assessment

The data set is statistically analyzed to ensure validity and reliability of the data. The relatively small sample of n = 59 recruiters does not pose a problem for measurement model assessment, since PLS-SEM is particularly utilizable for statistical hypotheses testing with small sample sizes (Joe F Hair et al., 2012).

CFA

Reliability and validity analyses were conducted along the different analysis process steps drawn from theory (cf. section 5.5.3).

Individual indicator reliability: The outer loadings of the indicators are all > 0.707 and thus satisfactory (Joseph F Hair et al., 2018) except EIMP01 (0.476), PEOU01 (0.654), PST02 (0.693), PST07 (0.643), PEC02 (0.665), RCANX02 (0.455) and SWETE01 (0.635). However, all values are > 0.400 and thus do not need to be eliminated from the data set (Henseler et al., 2009). They are closely monitored within the main study analysis.

Internal consistency reliability**:** The Cronbach's Alpha values for the variables in the pilot study with n = 59 can be seen in Table 5.12.

Table 5.12 Pilot Study Reliability Analysis (n = 59)

Variable	**Cronbach's Alpha α**	**Variable**	**Cronbach's Alpha α**
Job-Related Automation Concerns		Other HCCAM Variables	
SN	0.877	RES	0.676
REL	0.944	RES without RES04	0.891[a]
OUT	0.916	PU	0.957
RCSE	0.860	PEOU	0.850
RCSE without RCSE01	0.877[a]	BI	0.887
PEC	0.620	Control Variables	
PEC without PEC04	0.772[a]		
RCANX	0.870	PI	0.868
EIMP	0.708	TA	0.915
LIMP	0.603[b]	TU	0.769
LIMP without LIMP02	1.000[a]		
SIMP (Single-Item Construct)	1.000	TU without TU02	0.806[a]
PST	0.871		
PST without PST04	0.910[a]		
INAAB	0.702		
INAAB without INAAB01	0.876[a]		

Variable	Cronbach's Alpha α
INABB	0.933
INACB	0.908
SWETE	0.646
SWETE without SWETE01/02	1.000[a]
SWESE	0.768
SWEUE	0.857

[a] Corrected α-value after model adaptation based on the joint results of (1) an indicator cross loading validity analysis via Smart PLS, and (2) a scale reliability analysis regarding each scale's Cronbach Alpha values based on all queried items in the survey examining the change of α-value when leaving out one of the items via SPSS and opting for the maximum α-value.[48]

Perceptions of external control, result demonstrability and transition efforts yield non-satisfactory CA values < 0.7; recruiting chatbot self-efficacy, perceived system transparency, affective-based inertia, and technological understanding are satisfactory but show room for improvement after comparing the item's values to the indicator cross loadings: It became apparent that one of the items respectively was deteriorating the figures. The items are removed from the model, resulting in increased CA values. The legal implications however are modelled into a formative variable calling for formative factor analysis steps: The VIF is inadequate with $VIF_{LIMP02} = 17.79 > 5$ and also non-satisfactory tolerance of $0.056 < 0.20$ indicates signs of collinearity. The outer weight of the indicator LIMP02 shows $T = 1.842 < 1.96$ and $p = .066 > 0.05$. Hence, the newly introduced item LIMP02 is omitted from further examination in the analysis alongside the CA-worsening items RCSE01, PEC04, RES04, PST04, INAAB01, SWETE01 (lower cross loadings of the two items), and TU02. However, these changes are considered to be tentative and will be re-evaluated in the main study. The removal of the beforementioned six items improve the composite reliability for all affected latent variables from values < 0.7 to values > 0.7.

Convergent validity: The AVE values for the latent variables are > 0.5 and thus satisfactory (Joseph F Hair et al., 2018) except for $AVE_{EIMP} = 0.463$.

[48] See Gliem and Gliem (2003) for details on the Cronbach's Alpha value if a certain item is deleted.

Discriminant validity: An indicator item cross loading analysis shows an overall valid survey concept with all item loads highest on the respective constructs (Hair Jr et al., 2017) except for recruiting chatbot anxiety (RCANX02 = 0.453 < actual fourth biggest loading; cf. Appendix F and Appendix G). The item of RCANX02 will be closely monitored in the main study examination. Regarding the Fornell and Larcker criterion, each construct's AVE is higher than the squared correlations with other constructs (Hair Jr et al. (2017); cf. Appendix H and Appendix I). The HTMT values are all < 0.9 as desired (Joseph F Hair et al., 2018).

5.5.4 Pilot Study Discussion and Implications for Hypotheses

The statistical analysis of the HCCAM with a pilot study sample yields several implications on the further process and the main study regarding the research questions and underlying hypotheses.

Several items have been identified in the pilot study assessment that did not perform according to the requirements and were not held by the thresholds stipulated in academic literature: Certain items show unsatisfactory outer loadings (EIMP01 (0.476), PEOU01 (0.654), PST02 (0.693), PST07 (0.643), PEC02 (0.665), RCANX02 (0.455), and SWETE01 (0.635)), indicating that there are reliability issues; they will be closely examined during main study conduct. Several items (RCSE01, PEC04, RES04, LIMP02, PST04, INAAB01, SWETE01, and TU02) worsen the CA-values and have been omitted from pilot study analysis; they might need to be removed from the main study data set as well. Regarding the validity assessment, one item (RCANX02) does not load highest on its construct, all others do and thus indicate that the survey concept is valid. All questionable items will be closely monitored in the main study analysis. Because of two low loading values, the items for the latent variable of perceived system transparency were slightly altered in the form of an additional explanation: The term "job" is explained now to avoid confusion or misunderstandings (PST04: "I do not understand how a recruiting chatbot performs its job (conducting interviews)."). In literature, the items for several variables such as recruiting chatbot anxiety, perceived system transparency, inertia, switching efforts, and ethical implications were only available in English language not validated for German questionnaires yet so the author applied an own translation, which might have caused confusion prior to wording adaptation based on remarks by the pilot study participants via input boxes that were offered alongside the questions of the survey. The final set of constructs and according items of the questionnaire is summarized in Appendix D.

CHAPTER 6

EMPIRICAL STUDY RESULTS

1,501 potential participants were being offered the questionnaire via e-mail through an access panel operating in the DACH region and an indeterminable number of potential respondents were exposed to the survey in online business networks and addressed in thirteen particular German HR and recruiting business forums (cf. section 5.3.2). The thirteen approached business network and forum groups vary between 170 and 7,504 members. A post was submitted to these forums by the author of the study containing a short description of the study, a link leading to the questionnaire and an invitation to participate. In total, 1,074 participants submitted answered questionnaires. Of these initially acquired participants, 326 were screened out because of missing HR relation in their work tasks, which represents the main screen out question for the survey at hand. Of the remaining keen participants, 138 (> 10 missing values) and additional 177 (answer time < 10 minutes) quality screen outs were removed from the data set. In total, 433 respondents delivering valid and complete data sets with no further missing values were acquired, resulting in a response rate of 28.84 percent for the e-mail acquisition regarding the valid and complete data sets for the scientific study at hand.

As a preparation for data analysis, the data was screened to identify anomalies and multivariate outliers. Standard deviations are calculated for all item answers in the cases of the data set to uncover unengaged response patterns. Eight cases showing non-differentiated response behavior with SD = 0 across the HCCAM items with no more than 2 of the 68 items varying from the standard answer were identified among the 433 participants, which were omitted and thus disregarded for further analyses resulting in a final set of 425 responses. As already conducted for the pilot study sample, the seven originally reversely coded items PI03, TU02, RES04, PEC04, RCANX01, PST04 and LIMP01 (cf. Appendix D for details concerning the affected items) were recoded for equal assertion and orientation to suit the subsequent analyses.

6.1 Sample Description

In the following, the screened and cleansed data set of 425 records is presented concerning the descriptive sample characteristics and the technological background of the acquired respondents.

6.1.1 Demographic Traits of the Sample

This recruiting chatbot study consists of data sets from 283 participants from Germany, 71 respondents from Austria and another 71 participants from Switzerland.

Table 6.1 Demographic and Work-Related Characteristics

Age	Under 20 years old: 3 (0.7%) 20-29 years old: 49 (11.5%) 30-39 years old: 127 (29.9%) 40-49 years old: 94 (22.1%) 50-59 years old: 68 (16.0%) 60-69 years old: 19 (4.5%) 70 years or older: 0 (0.0%) Missing: 65 (15.3%)
Gender	Male: 128 (30.1%) Female: 286 (67.3%) Diverse: 1 (0.2%) Missing: 5 (1.2%)
No. of Employees in the Company	Under 50 employees: 59 (13.9%) 50-100 employees: 36 (8.5%) 101-250 employees: 54 (12.7%) 251-500 employees: 56 (13.2%) 501-1,000 employees: 54 (12.7%) 1,001-3,000 employees: 41 (9.6%) 3,001 and more employees: 117 (27.5%) Missing: 8 (1.8%)
Industry Affiliation	Agriculture, forestry and fishing: 2 (0.5%) Manufacturing industry: 62 (15.1%) Construction: 19 (4.5%) Trade, transport and hospitality: 74 (17.4%) Information and communication: 16 (3.8%) Financial and insurance service providers: 8 (1.9%) Real estate and housing activities: 5 (1.1%) Professional, scientific and technical services: 15 (3.5%) Business services: 36 (8.5%) Public and other private service providers: 168 (39.5%) Creative, artistic and entertainment activities: 10 (2.4%)

	Missing: 10 (2.4%)
Position in the Company	Recruiter: 39 (9.2%) Recruiting manager: 31 (7.3%) Human Resources (HR) administrator: 127 (29.9%) HR officer: 56 (13.2%) HR manager: 87 (20.5%) General manager in charge of HR (e.g., CHRO): 17 (4.0%) My tasks are unrelated to HR: Screen out question (participants answering this question are not regarded for this study) Other: 66 (15.5%)
Number of Interviews	1-10 Interviews: 43 (10.1%) 11-25 Interviews: 38 (8.9%) 26-50 Interviews: 52 (13.2%) 51-100 Interviews: 56 (13.2%) 101-200 Interviews: 45 (10.6%) 201-500 Interviews: 62 (14.6%) 501-1,000 Interviews: 34 (8.0%) More than 1,000 Interviews: 72 (16.9%) I don’t know: 22 (5.2%) Missing: 1 (0.2%)

n = 425 DACH recruiters

Table 6.1 gives an overview of the recruiters’ demographic traits. The age distribution is diverse, depicting the actual age range within recruiting departments in companies, with the relatively largest group being 30 to 39 years old (29.9 percent). With the majority of recruiters being female (67.3 percent), the findings from the pre-study as well as from Human Resources Manager (2015) are confirmed stating that there is a general predominance of women in HR departments in German-speaking countries.

All ranges of company sizes and types of industry are represented with a slight tendency towards large enterprise affiliation (27.5 percent of the respondents) processing more than 1,000 interviews per year (16.9 percent of the respondents) and public and other private service providers – comprising public administration, education, teaching, health care and social services – as best represented industry sector (39.5 percent of the respondents, corresponding with the statistical industry sector affiliation distribution in Germany concerning public and other private service providers (Destatis, 2022)[49]). Regarding the participants’ specific position in the

[49] Public and private services accounted for 14,684,000 (= 32.7 percent of the) employed persons in Germany in 2021, which represents the employment largest part in this sector comparison; the next

recruiting department, all types of job roles are represented with the largest group being employed as HR administrators (29.9 percent) followed by HR managers (20.5 percent). Hence, both the perspective of the managers potentially deciding on new technology for the recruiting process as well as the opinion of operational staff working with such technology are included in the study at hand. The 15.5 percent of the participants stating "other" as HR-related position hold positions such as commercial manager, personnel controller, HR developer, personnel consultant, HR IT project manager or HR lawyer.

6.1.2 Technological Background Examination

Regarding the technological recruiting and chatbot-related background of the participating recruiters, a similar depiction as in the pilot study forms (cf. Table 6.2): Most recruiters (64.5 percent) conduct physical in-person interviews as modus operandi for candidate interviewing. Hence, they answer the survey from a perspective of unawareness and inexperience. Astonishingly, one respondent (0.2 percent of the sample) stated that chatbot interviews are implemented into his company's recruiting process. Overall, they are interview-savy: Only 27 (= 6.4 percent) of the participants are not at all involved in the interviewing process of their company.

The figures for ATS deployment, chatbot experience and chatbot knowledge are analogous to the ones in the pilot study as well (cf. Table 6.2): The majority of the companies (51.3 percent) deploys an ATS for candidate data management. Almost half of the respondents do not have personal chatbot experience (41.6 percent) while 31 percent of the recruiters have already used a chatbot before at least once. This is well below the percentage of 63 percent that was found in a study across industries (aiaibot, 2021). After all, 67.1 percent of the participants bring knowledge concerning this technology. Hence, the technology is known but not yet tried by the majority of the participants.

largest part is trade, transport and hospitality with 9,836,000 employed persons in Germany (Destatis, 2022).

Table 6.2 Technological Recruiting and Chatbot-Related Characteristics

Modus Operandi for Candidate Interviewing	In-person interview(s) (physical meeting(s)): 274 (64.5%) In-person interview (digital meeting(s)): 64 (15.1%) Technology-led interview(s) (= software-based, automated interview process such as time-delayed video interviews): 4 (0.9%) Chatbot interview(s): 1 (0.2%) Mixture of technology-led and in-person interviews: 55 (12.9%) I am not involved in the candidate interview conduct in my company: 27 (6.4%)
ATS Deployment	Yes: 218 (51.3%) No: 151 (35.5%) I don’t know: 41 (9.6%) Missing: 15 (3.5%)
Chatbot Experience	I do not have any chatbot experience: 177 (41.6%) I have heard about chatbots prior to this questionnaire: 113 (26.6%) I have already used one chatbot before: 75 (17.6%) I have already used more than one chatbot before: 57 (13.4%) I am/was part of a chatbot development project 3 (0.7%)
Chatbot Knowledge	Yes: 285 (67.1%) No: 108 (25.4%) I don’t know 32 (7.5%)
(Recruiting) Chatbot in Deployment	Yes: 51 (12.0%); 49 (11.6%) No: 313 (73.6%); 307 (72.2%) I don’t know: 61 (14.4%); 67 (15.8%) Missing: 2 (0.5%)
Recruiting Chatbot ATS Linkage	Yes: 29 (6.8%) = 59.18% of the ones with a deployed recruiting chatbot No: 8 (1.9%) = 16.33% of the ones with a deployed recruiting chatbot I don’t know: 12 (2.8%) = 24.49% of the ones with a deployed recruiting chatbot
(Recruiting) Chatbot in Development	Yes: 17 (4.0%); 15 (3.5%) No: 237 (55.8%); 215 (59.6%) I don’t know: 60 (14.1%); 72 (16.9%) Not applicable: 111 (26.1%); 123 (28.9%)
(Recruiting) Chatbot in Planning	Yes: 30 (7.1%); 25 (5.9%) No: 113 (26.5%); 125 (29.4%) I don’t know: 154 (36.2%); 143 (33.6%) Not applicable: 128 (30.1%); 132 (31.1%)

n = 425 DACH recruiters; grey font indicates an affiliation with recruiting.

As expected, most recruiters (313, almost three quarters), state that there is no chatbot and especially no recruiting chatbot deployed their companies’ processes yet. Only 12 percent report having a chatbot implemented in their companies’ digital processes with 49 of the 51 projects in recruiting. However, more than 11 percent of the remaining respondents state that their company either develops a chatbot at the moment (4 percent of the respondents, 17 chatbot projects) or plans on integrating one into their strategy within the next two years (7.1 percent of the respondents, 30 chatbot deployment plans). The striking similarity of pilot study and main study findings regarding the percentage distribution of the answers allows for the assumption that the findings of the study are at least tentatively generalizable to the examined population of recruiters in Germany. However, the similar survey distribution methods were used in both cases (access panel, business network postings), so that this argument of generalizability is to be treated prudently.

The other control variables apart from age and chatbot experience are perceived innovativeness, technology affinity, and technological understanding (TU). Table 6.3 shows the mean values of these characteristics. Remarkably, all mean values lay above the center point of the 7-point Likert scaled items indicating general consent with the statement with TU01 (self-attributed knowledge of a technological system's functions) and TU03 (self-attributed easiness of learning how to handle new technological systems) showing highest mean values and thus highest approval scores.

Table 6.3 Mean Values of PI, TA and TU

PI01	**PI02**	**PI03**	**PI04**	**TA01**	**TA02**	**TA03**
5.07	4.36	4.56	5.36	4.35	4.52	4.17
TA04	**TA05**	**TU01**	**TU02**	**TU03**	**TU04**	
4.22	4.88	5.63	4.61	5.49	4.98	

Certain demographical variables show strong associations with the chatbot-related control variables of chatbot experience and chatbot knowledge. Furthermore, strong correlations exist between certain demographics and the main HCCAM variables, which are hypothesized to influence recruiting chatbot acceptance, particularly perceived system transparency, inertia, and recruiting chatbot anxiety for example. These relationships are regarded within cross tabulations. Such considerations allow for an examination of the importance of the surveyed demographics, a more comprehensive analysis of the HCCAM, and an illustration of potential future focus studies. Cross tabulations are used as a common approach to test associations between categorical variables (Momeni, Pincus, & Libien, 2018). The values Chi^2 (χ^2) and Cramer's V are reported for the assessment of probability and association between two variables with Cramer's V ranging from 0 (no association) to 1 (perfect association) (Saunders et al., 2009). Cramer's V is one of the most common coefficients based on Chi^2, which is mainly used for nominal-scaled variables (Kuckartz, Rädiker, Ebert, & Schehl, 2010). However, it is also utilized for ordinal data or grouped interval as well as ration data in research (McHugh, 2018). While for 2 x 2 tabulation, also phi can be reported to assess the strength of associations between variables (Akoglu, 2018), Cramer's V is the more suitable criterion for non-dichotomous variables (Saunders et al., 2009) and thus chosen for this research. Cramer's V values > 0.05 are considered weak, > 0.10 moderate, > 0.15 strong, and > 0.25 very strong (Akoglu, 2018).

Table 6.4 Cross Tabulations Regarding the Demographics and Technological Background

Cross tabulation variables	**Chi-square**	**Cramer's V**	**P-value**
AGE x CKNOW	20.158	0.167	0.028
AGE x SN	171.139	0.308	0.001
AGE x PST	283.637	0.397	0.000
AGE x INA BB	126.921	0.266	0.006
AGE x SWEUE	117.316	0.255	0.028
AGE x PEOU	147.740	0.286	0.004
SEX x RCANX	91.452	0.269	0.021
SEX x PST	217.215	0.415	0.000
NOE x CKNOW	26.588	0.177	0.022
NOE x CEXP	45.579	0.164	0.019
NOE x SN	216.684	0.270	0.007
NOE x RCSE	191.294	0.254	0.022
NOE x PEC	186.775	0.251	0.000
NOE x RCANX	241.545	0.285	0.000
NOE x EIMP	155.299	0.229	0.039
NOE x INA AB	140.451	0.218	0.036

Cross tabulation variables	Chi-square	Cramer's V	P-value
NOE x SWESE	133.322	0.195	0.018
NOE x SWEUE	157.924	0.231	0.028
NOE x PEOU	228.460	0.277	0.000
NOE x TA	247.382	0.289	0.039
NOE x IA	475.170	0.405	0.000
NOE x CP	463.589	0.395	0.007
NOE x ATSD	106.682	0.361	0.000
NOE x CDEP	28.054	0.182	0.014
NOE x CDEV	24.996	0.200	0.035
NOE x CPLAN	29.122	0.222	0.010
NOE x RCPLAN	33.457	0.239	0.002
NOE x NI	368.805	0.353	0.000
GSR[1] x CEXP	358.196	0.459	0.001
GSR x SN	1,990.296	0.442	0.000
GSR x REL	1,366.166	0.423	0.008
GSR x RES	1,332.793	0.417	0.037
GSR x RCSE	1,685.160	0.425	0.002
GSR x PEC	1,866.112	0.494	0.000
GSR x RCANX	1,805.715	0.439	0.000
GSR x EIMP	1,526.841	0.447	0.000
GSR x PST	2,987.232	0.425	0.000
GSR x INA BB	1,534.142	0.448	0.000
GSR x INA CB	1,436.414	0.446	0.000
GSR x SWESE	1,020.186	0.447	0.000
GSR x PU	1,796.717	0.420	0.008
GSR x PEOU	1,826.777	0.452	0.000
GSR x BI	1,443.637	0.434	0.000

[1] GSR = German-speaking region (DACH, divided into DE, AT, CH).

Looking at demographic links, there are many significantly strong to very strong associations between certain demographic variables and the other latent variables (cf. Table 6.4). The level of chatbot knowledge the participants hold is (very) strongly associated with their age, and the size of the company they work for according to the number of employees. Perceived system transparency as one of the two newly introduced latent variables is very strongly associated with the demographic variables age, sex, and German-speaking region. While German recruiters seemingly show the lowest level of inertia according to the lowest level of consent ($\mu_{INAAB} = 4.542$, $\mu_{INABB} = 4.027$, $\mu_{INACB} = 3.451$), it is highest for recruiters from Austria ($\mu_{INAAB} = 4.737$, $\mu_{INABB} = 4.230$, $\mu_{INACB} = 3.577$) with an exception of the cognitive aspects that is highest for the Swiss ones ($\mu_{INAAB} = 4.704$, $\mu_{INABB} = 4.202$, $\mu_{INACB} = 3.667$). Hence, inertia is a potential obstacle in companies in Germany but seems to be below the levels of inertia prevailing in the neighboring countries Austria and Switzerland. However, as the sample sizes regarding AT and CH are relatively low (n = 71 each), the findings have to be treated cautiously. While the affective-based part of the second newly suggested indicator inertia is strongly associated with the number of employees, the behavioral-based aspect of inertia is very strongly associated with age and the respective German-speaking region. A very strong association lies between the cognitive-based part of inertia and the German-speaking region. Age is also very strongly associated with subjective, uncertainty effort as indicator of inertia, and perceived ease of use.

6.1.3 Relevant Use Cases

The participants are asked to assess the ascribed relevance for 13 use cases (“In your personal opinion, how relevant is a recruiting chatbot for the following areas within the recruiting processes of your company?”; 7-point Likert-scale items). The general mean rank across all use cases is 4.92, which already shows a positive tendency regarding the seen relevancy of recruiting chatbots for various scenarios along the recruiting process. The ranking distribution concerning the five highest relevancy ranks (mean values of $\mu > 5$) shown in Figure 6.1 illustrates this positive trend.

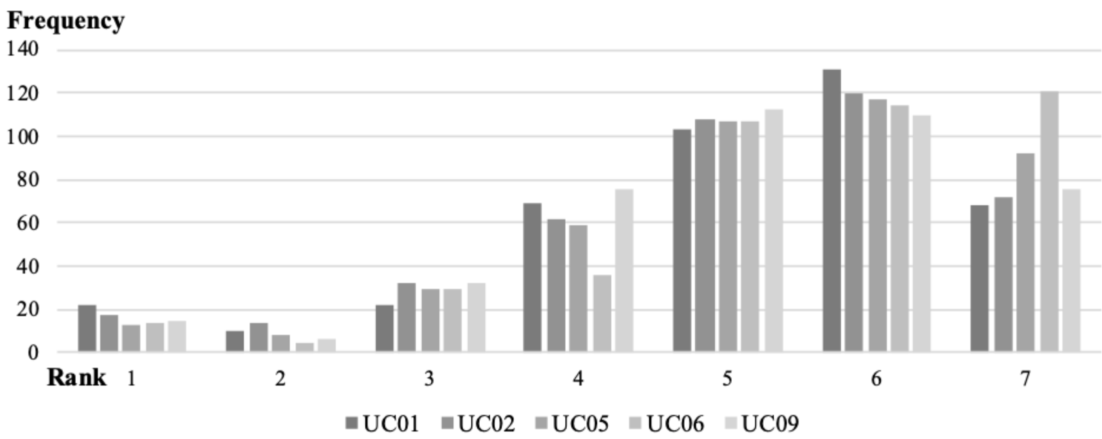

Figure 6.1 Mean Distribution of the Ranked Recruiting Chatbot Use Cases
Source: Own illustration.

According to the mean ranks (Sarstedt & Mooi, 2014), UC06, UC05, UC09, UC01, and UC02 are the most relevant ones for recruiting chatbot deployment as they show a mean rank of $\mu > 5$ as most meaningful cut-off point with highest upward and downward deviations:

1) UC06 ($\mu = 5.46$): Query of missing applicant data from the candidate
2) UC05 ($\mu = 5.25$): Partial applicant guidance through application process
3) UC09 ($\mu = 5.10$): Clarification of post-submission application-related questions of the candidate (e.g., application status)
4) UC01 ($\mu = 5.08$): Clarification of application-related questions of the candidate (e.g., concerning the application process)
5) UC02 ($\mu = 5.07$): Supporting the candidate in his search for job offers

Hence, the recruiters see chatbots most eligible for data collection, practical guidance of the candidates through the job search as well as the application, and information distribution concerning questions prior as well as after application submission.

Furthermore, there were several free-text input answers for relevant use cases: Appointment inquiry and cancellation handling are mentioned as use cases as well as specific information regarding salary expectations or the contract.

6.1.4 Relevant Utilization Drivers and Barriers

Regarding new technologies such as recruiting chatbots uncovers various potential drivers and barriers that may push or limit utilization.

Table 6.5 Mean Ranks of Recruiting Chatbot Utilization Drivers and Barriers

Rank	Item	Mean (μ)	Frequency scale ≥ 5[1]	Rank	Item	Mean (μ)	Frequency scale ≥ 5[1]
Utilization Drivers				**Utilization Barriers**			
1	DU05: Permanent accessibility	5.42	330	1	BU04: Expected lack of understanding complex contexts	4.93	271
2	DU02: Faster recruiting process step conduct	5.35	336	2	BU09: Deterioration of candidate-recruiter relations	4.87	267
3	DU03: Facilitation of data management	5.32	331	3	BU02: Data security issues	4.84	269
4	DU08: Standardization of data quality	5.14	314	4	BU03: Complexity due to fragmented IT infrastructure	4.75	245
5	DU11: Low inhibition threshold to ask questions	5.01	291	5	BU01: Cyberattacks	4.63	234
6	DU01: Cost reduction	4.91	288	6	BU10: Slow transformation of necessary techno-logical competencies in the HR team	4.55	210
7	DU09: Reduction of human bias	4.88	272	7	BU08: Job replacement by automation	4.51	216
8	DU04: Improvement of decision-making process	4.41	199	8	BU06: Lack of investment in training	4.41	207
9	DU12: Chatbot as value driver for innovation and image	4.51	218	9	BU07: Recruiters' resistance to change established processes	4.34	196

Rank	Item	Mean (μ)	Frequency scale ≥ 5[1]	Rank	Item	Mean (μ)	Frequency scale ≥ 5[1]
Utilization Drivers				**Utilization Barriers**			
10	DU07: Reduction of human errors	4.32	201	10	BU05: Changing business and organizational structure for the worse	4.01	137
11	DU10: Improvement of the candidate experience	4.20	186				
12	DU06: Better output quality than via human task completion	4.04	182				

[1]Relevant driver or barrier according to the Likert-scale definition: 5 = Somewhat relevant, 6 = moderately relevant, 7 = very relevant; n = 425 DACH recruiters.

The respondents were asked to gauge the relevance of twelve potential drivers and ten possible barriers of recruiting chatbot utilization as compiled from literature (7-point Likert-scale items). As suggested by Sarstedt and Mooi (2014), means were computed for all items and ranked in descending order (cf. Table 6.5). The mean ranks and the frequencies of relevancy ratings showing values ≥ 300 as conclusive cut-off point with high upward and downward deviations result in the following four drivers as the most relevant ones from the recruiters' perspective:

1) DU05: Permanent accessibility (detached from time and location restrictions)
2) DU02: Faster recruiting process step(s) conduct
3) DU03: Facilitation of data management
4) DU08: Standardization of data quality

Thus, two efficiency-related items are chosen highlighting the chatbots' ubiquitous accessibility and potential to facilitate data management, for example in terms of information retrieval, processing and storage, as well as the time-based reasoning of faster recruiting process conduct. Furthermore, the quality-related aspect of data quality standardization, for instance through the constant level of performance, is seen as a recruiting chatbot utilization driver in many cases. The potential driver to use ranked least relevant is a better output quality than human task completion.

As barriers to use, the ones with the highest mean ranks as well as a relevancy rating value ≥ 250 as informative cut-off point with high upward and downward deviations are deemed most relevant. Two technological aspects and one social characteristic emerge as most relevant ones:

1) BU04: Recruiting chatbot's expected lack of understanding complex contexts
2) BU09: Deterioration of candidate-recruiter relations
3) BU02: Data security issues (e.g., leakage of candidates' personal information)

Remarkably, the technical progressiveness in terms of complex inquiry handling is doubted more strongly than there is a potential fear of loss of contact to the candidates. Data security issues are mentioned as important utilization barrier as well with special focus on the loss of the candidates' personal information.

6.1.5 Relevant Aspects and Skills for Recruiters

Alongside relevant use cases as well as drivers and barriers for utilization, the respondents had to rank relevant aspects of the recruiting process which might be supported by chatbots as well as relevant recruiter skills that are necessary for meaningful candidate interview conduct. As the respondents had to rank from 1 (most relevant aspect) to 8 (least relevant aspect), not the means are considered but the mode instead.

Table 6.6 Mode Ranks of Relevant Candidate Interview Aspects and Required Recruiter Skills

Rank	**Item**	**Mode (Frequency)**	**Rank**	**Item**	**Mode (Frequency)**
Relevant Aspects			**Relevant Skills**		
1	RASP01: Efficient candidate handling	1 (168)	1	RSKILL02: Application of expert knowledge and skills during selection	1 (199)
2	RASP03: Soft skill assessment	2 (99)	1	RSKILL01: Ethical practice	1 (72)

Rank	Item	Mode (Frequency)	Rank	Item	Mode (Frequency)
	Relevant Aspects			**Relevant Skills**	
2	RASP02: Hard skill assessment	2 (88)	2	RSKILL03: Diversity management/ cultural awareness	2 (76)
3	RASP04: Social cue/ cultural fit assessment	3 (73)	3	RSKILL04: Critical thinking	5 (70)
4	RASP05: Relationship management	5 (81)	3	RSKILL05: Transparency	5 (67)
5	RASP06: Digital communication possibility	6 (112)	4	RSKILL08: Problem-solving	6 (79)
6	RASP07: Data analytics	8 (118)	5	RSKILL07: Working in an agile way, creativity	7 (70)
6	RASP08: Offering diverse communication channels	8 (133)	6	RSKILL06: Multitasking	8 (137)

n = 425 DACH recruiters.

Table 6.6 shows the ranking as produced by the participants of the study according to the respective mode values. As most relevant aspects sorted mainly into the top three ranks (mode ≤ 3), ways of candidate handling and skill assessment skills are mentioned:

1) RASP01: Efficient candidate handling
2) RASP03: Soft skill assessment
3) RASP02: Hard skill assessment

The goal of recruiting chatbot deployment should be some sort of process facilitation and support of the recruiter in his routines. Hence, an increase in candidate handling efficiency is expected in order to render the technology relevant for the recruiting process. Recruiting is about identifying and employing the right candidate for the job position in focus (Chhabra & Ahuja, 2018). A deployed chatbots would need to help reaching this aim by supporting the soft skill and hard skill evaluation of the applicants.

According to the respondents, the following three skills (mode ≤ 3) are necessary for successful candidate interview conduct according to the relevancy ranking:

1) RSKILL02: Application of expert knowledge and skills during selection
2) RSKILL01: Ethical practice
3) RSKILL03: Diversity management/cultural awareness

During interview conduct, the recruiters want to be supported and the interview facilitated so that they themselves can work to their best abilities. The two other relevant skills, ethical practice and diversity management together with cultural awareness, should be reinforced by chatbot deployment as well. A recruiting chatbot needs to comply with the associated specifications and support the recruiter to comply with ethical standards and diversity specifications, which can be implemented as rules and will be reliably and consistently adhered to by the chatbot.

6.2 Data Assessment

The sampling adequacy is examined regarding the KMO measure as well was the Bartlett's test of sphericity for the main items of the questionnaire subsequently regarded in the factor analysis for measurement model assessment. The calculated KMO value of 0.895 is deemed appropriate (Sarstedt & Mooi, 2014), indicating a good adequacy of the correlations; the significance value of the Bartlett's Test indicates appropriateness of the data (cf. Table 6.7).

Table 6.7 KMO Index and Bartlett's Test for Sphericity

Test	**Kind of Value**	**Value**
KMO Measure of Sampling Adequacy	-	0.895
Bartlett's Test of Sphericity	Approx. Chi-Square	16,160.866
	df	1,326
	Sig.	0.000

Concerning the data distribution and the manifestation of normality in the data, Kolmogorov-Smirnov and Shapiro-Wilk tests of normality are conducted. The results can be seen in *Appendix J*: Both tests show significances < 0.05 for all observed items, indicating that they do not follow a normal distribution. The skewness and kurtosis values are all well below the cut off value of > |1.0| except for the slightly peaked item PEOU01 (kurtosis = 1.044). As all values are well below |2.0|, the level of kurtosis is still considered to be acceptable (George & Mallery, 2010). Surprisingly, the variables inertia and recruiting chatbot anxiety are not skewed as normally expected because of their generally negative assertion (Turel et al., 2011). The inner VIF values of all latent variables are computed to control for common method bias occurrence: With full VIF < 3.3 for all variables, the model does not give reason to assume that common method bias distorts the results. An independent sample t-test, conducted with SPSS27, showed no significant differences between the respondents who are and who are not involved with interviewing within their companies' recruiting processes. Hence, an additional analysis of the two split groups of those involved and those not involved in the interviewing process was not deemed necessary and thus not carried out.

6.3 Measurement Model Assessment

The measurement model (cf. Figure 5.2) is analyzed via a confirmatory factor analysis to ensure overall model fitness for the statistical analysis.

Confirmatory Factor Analysis

Within CFA, reliability and validity analyses are run for the reflective measurement model to evaluate the indicator reliability, internal consistency and convergent validity with the software package Smart PLS 3 (factor weight, 5,000 max. iterations). For individual indicator reliability, the squared standardized outer loadings are examined with all main variable loadings > 0.707 except for the items EIMP01 (0.493), LIMP02 (0.624), PST01 (0.634), PST04 (0.401), and RES04 (0.353). Astonishingly, only the item EIMP01 was also identified as potentially problematic in the pilot study. In accordance with Henseler et al. (2009), only RES04 is deleted at this stage because of its outer value < 0.400. Henseler et al. (2009) argue that item elimination is a delicate matter in need of careful consideration; outer loadings > 0.400

but < 0.707 do only need to be eliminated if this elimination yields substantially higher composite reliability values. Schmitt (1996) reinforces this idea stating that meaningful content treatise renders low reliability values negligible.

Hence, in a second step, the internal consistency reliability values in the form of Cronbach's Alpha and composite reliability are computed. Cronbach's Alpha (α) analysis showed room for improvement for perceptions of external control, legal implications, and perceived system transparency (cf. Table 6.8): Apparently, one item per variable deteriorates the figure. The respective problematic items are removed from the model, not only resulting in higher α values, but also showing substantial improvement of the composite reliability values. Hence, PEC04, LIMP02, and PST04 need to be deleted from the data set. Legal implications however, adapted from Bröhl et al. (2019), complemented by another item from literature, is configured as a formative variable. Consequently, formative factor analysis steps are taken: Although the VIF is adequate with $VIF_{LIMP02} = 1.999 < 5$ and a tolerance of $0.50 > 0.20$ thus showing no signs of collinearity, the outer weight of the indicator LIMP02 shows $T = 1.48 < 1.96$ and $p = 0.140 > 0.05$. Subsequent to non-satisfactory outer weight and VIF for the formative perspective as well as Cronbach's Alpha (examining a reflective approach) analyses, the additional item was taken out again. Hence, LIMP02 is omitted from further consideration in the analysis alongside PEC04 and PST04.

After eliminating those critical items, only two questionable outer loadings remain after model rerun: EIMP01 (0.493), and PST01 (0.645). The omittance of PST01 from the model improves the composite reliability of the respective factor from a value of 0.940 to 0.952; a deletion of EIMP01 increases the composite reliability value from 0.841 to 0.923. However, all composite reliability values are > 0.70, which complies with the threshold value as suggested by Joseph F Hair et al. (2018). Furthermore, indicator cross loading analysis showed highest indicator loading values regarding their associated constructs without cross loadings. Since the concepts of ethical implications and perceived system transparency are newly introduced to TAM research, it can be argued that the compliance with this threshold is deemed sufficient and does not justify deletion from the data set. They are carefully retained in the set. The CA value of the variable transition efforts is below the threshold of 0.70 but above 0.60 as lower limit for exploratory research (Joseph F Hair et al., 2018). As a questionable case, the indicator loading values were inspected thoroughly, which are highest in row and column thus showing no sign of cross loadings. Furthermore, the mistake of overreliance on CA and thus misguided correction for decreasing attenuation is to be avoided (Schmitt, 1996; Sijtsma, 2009). The author decided to leave both items for transition efforts in the data set because of the good cross loading values and the fact that only two items are in the set.

The convergent validity is examined via the average variance extracted: In accordance with Joseph F Hair et al. (2018), the variables are required to have AVE values > 0.5. In the study at hand, the AVE values of all variables comply with this prerequisite.

The outer loadings, Cronbach’s alpha, composite reliability and AVE values for the variables in the pilot study with n = 425 can be seen in Table 6.8.

Table 6.8 Main Study CFA Reliability and Convergent Validity Analysis (n = 425)

		Indicator Reliability	**Internal Consistency Reliability**		**Convergent Validity**
Constructs	**Items**	Outer Loadings	Cronbach’s Alpha α	Composite Reliability	AVE
Threshold		> 0.707	> 0.7	0.7 ≤ value ≤ 0.95	> 0.5
Job-Related Automation Concerns					
Subjective Norm	SN01	0.811			
	SN02	0.834	0.854	0.901	0.695
	SN03	0.842			
	SN04	0.847			
Job Relevance	REL01	0.938			
	REL02	0.942	0.924	0.952	0.868
	REL03	0.915			
Output Quality	OUT01	0.923			
	OUT02	0.850	0.878	0.925	0.804
	OUT03	0.915			
Recruiting Chatbot Self-Efficacy	RCSE01	0.746			
	RCSE02	0.837	0.808	0.874	0.635
	RCSE03	0.800			
	RCSE04	0.801			
Perceptions of External Control	PEC01	0.849			
	PEC02	0.852	0.619	0.778	0.516
	PEC03	0.899			
	PEC04	0.712			
Perceptions of External Control without PEC04	PEC01	0.881			
	PEC02	0.760	0.777[1]	0.867	0.686
	PEC03	0.840			

		Indicator Reliability	Internal Consistency Reliability		Convergent Validity
Constructs	**Items**	Outer Loadings	Cronbach's Alpha α	Composite Reliability	AVE
Threshold		> 0.707	> 0.7	0.7 ≤ value ≤ 0.95	> 0.5
Recruiting Chatbot Anxiety	RCANX01	0.768	0.870	0.909	0.716
	RCANX02	0.835			
	RCANX03	0.880			
	RCANX04	0.895			
Ethical Implications	EIMP01	0.493	0.776	0.841	0.653
	EIMP02	0.917			
	EIMP03	0.935			
Legal Implications	LIMP01	0.924	0.434	0.760	0.621
	LIMP02	0.624			
Legal Implicat. without LIMP02	LIMP01	1	1.000[1]	1	1
Social Implications (Single-Item Construct)	SIMP01	1	1.000	1	1
Perceived System Transparency	PST01	0.634	0.909	0.928	0.627
	PST02	0.841			
	PST03	0.086			
	PST04	0.401			
	PST05	0.837			
	PST06	0.874			
	PST07	0.841			
	PST08	0.880			
Perceived System Transparency without PST04	PST01	0.645	0.925[1]	0.940	0.694
	PST02	0.839			
	PST03	0.855			
	PST05	0.874			
	PST06	0.874			
	PST07	0.841			
	PST08	0.879			
Affective-Based Inertia	INAAB01	0.756	0.731	0.847	0.649
	INAAB02	0.859			
	INAAB03	0.798			
Behavioral-Based Inertia	INABB01	0.928	0.931	0.956	0.878
	INABB02	0.938			
	INABB03	0.945			
Cognitive-Based Inertia	INACB01	0.920	0.925	0.952	0.869
	INACB02	0.941			
	INACB03	0.936			
Transition Efforts	SWETE01	0.864	0.677	0.861	0.756
	SWETE02	0.875			
Sunk Efforts	SWESE01	0.904	0.791	0.905	0.827
	SWESE02	0.915			
Uncertainty Efforts	SWEUE01	0.840	0.832	0.899	0.748
	SWEUE02	0.887			
	SWEUE03	0.867			

		Indicator Reliability	Internal Consistency Reliability		Convergent Validity
Constructs	**Items**	Outer Loadings	Cronbach's Alpha α	Composite Reliability	AVE
Threshold		> 0.707	> 0.7	0.7 ≤ value ≤ 0.95	> 0.5
Other HCCAM Variables					
Result Demonstrability	RES01	0.879	0.794	0.862	0.631
	RES02	0.918			
	RES03	0.886			
	RES04	0.353			
Result Demonstrability without RES04	RES01	0.883	0.876[1]	0.924	0.802
	RES02	0.919			
	RES03	0.884			
Perceived Usefulness	PU01	0.941	0.956	0.968	0.884
	PU02	0.944			
	PU03	0.960			
	PU04	0.916			
Perceived Ease of Use	PEOU01	0.849	0.848	0.899	0.690
	PEOU02	0.852			
	PEOU03	0.898			
	PEOU04	0.713			
Behavioral Intention to Use	BI01	0.939	0.877	0.925	0.805
	BI02	0.918			
	BI03	0.831			

[1] Corrected α-value after model adaptation based on the joint results of (1) an indicator cross loading validity analysis via Smart PLS, and (2) a scale reliability analysis regarding each scale's Cronbach Alpha values based on all queried items in the survey examining the change of α-value when leaving out one of the items via SPSS and Smart PLS while opting for the maximum α-value.[50]

While originally no part of the measurement model analysis, a reliability analysis of the control variable PI showed poor reliability statistics although PI03 has been recoded with α = 0.139 for the four items. PI03 was identified as unfit for the variable as it lowered the α-value dramatically. A removal of PI03 enhanced Cronbach's Alpha to α = 0.887.

For discriminant validity, the indicator item cross loadings are examined: all indicators load highest on the respective construct it is intended to measure with no higher cross-loadings on other constructs (cf. grey areas in Appendix K and Appendix L). In a second step, the Fornell-Larcker criterion is examined to assess the empirical

[50] See Gliem and Gliem (2003) for details on the Cronbach's Alpha value if a certain item is deleted.

distinction between the constructs of the model (Hair Jr et al. (2017); cf. values highlighted in bold font in Appendix M and Appendix N): The constructs' AVEs all load highest on themselves; there is no apparent cross-loading problem. Regarding the Heterotrait-Monotrait Ratio regarding the relationship strengths of the constructs and their indicators (Smart PLS, 2022), all values are < 0.90 (cf. Appendix O and Appendix P) as suggested by Joseph F Hair et al. (2018).

For the higher-order endogenous latent variable of inertia as part of the reflective-formative HCM construct of inertia, influenced by switching efforts, latent variables scores are calculated via PLS algorithm computation. A descriptive analysis of the data showed no signs of skewness or kurtosis with values of < |1.0| for all latent variable scores. With outer weights of T = 10.50 > 1.96 and $p < 0.05$, switching efforts does significantly predict inertia.

6.4 Structural Model Assessment and Hypotheses Test

After measurement model evaluation, the structural model is analyzed for hypothesis testing purposes regarding all relevant assessment criteria and values. Prior to hypothesis testing, the structure model is examined for potential multicollinearity issues. No such issues are found with all inner VIF values < 5 and tolerances of > 0.20 (cf. Appendix Q and Appendix Q). The general multicollinearity analysis shows 42 condition indices > 30, presenting potential collinearity problems (Joseph F Hair, Black, Babin, & Anderson, 2013; Joe F Hair et al., 2012). However, an examination of the variance proportions of these condition indices > 30 shows no cases of two or more coefficients with variance proportions > 0.90 (threshold values by Joseph F Hair et al. (2013)). Furthermore, all tolerance levels are > 0.20 (Joe F Hair et al., 2012). Hence, no collinearity problem is found.

Means and Standard Deviation

Table 6.9 gives an overview of the means and standard deviations (SD) of all endogenous, exogenous, and control variables belonging to the proposed HCCAM model; classified into job-related automation concerns and the other HCCAM variables.

Table 6.9 Main Study Mean and Standard Deviation Overview

Job-Related Automation Concerns	**Mean (μ)**	**SD**
ELSI		
Ethical Implications (EIMP)	3.033	1.381
Legal Implications (LIMP)	3.960	1.639
Social Implications (SIMP)	4.840	1.685
Inertia		
Affective-Based Inertia (INAAB)	4.602	1.127
Behavioral-Based Inertia (INABB)	4.090	1.438
Cognitive-Based Inertia (INACB)	3.508	1.437
Output Quality (OUT)	4.379	1.223
Perceptions of External Control (PEC)	4.729	1.149
Perceived System Transparency (PST)	4.377	1.171
Job Relevance (REL)	3.581	1.597
Recruiting Chatbot Anxiety (RCANX)	3.079	1.321
Recruiting Chatbot Self-Efficacy (RCSE)	4.931	1.155
Subjective Norm (SN)	3.783	1.309
Switching Efforts (SWE)		
Sunk Efforts (SWESE)	4.161	1.354
Transition Efforts (SWETE)	4.527	1.158
Uncertainty Efforts (SWEUE)	4.167	1.272

Other HCCAM variables	**Mean (μ)**	**SD**
Age (AGE)[1]	3.640	1.118
Behavioral Intention to Use (BI)	3.802	1.471
Chatbot Experience (CEXP)[1]	2.050	1.092
Personal Innovativeness (PI)	4.837	1.263
Perceived Ease of Use (PEOU)	4.748	1.036
Perceived Usefulness (PU)	4.185	1.440
Result Demonstrability (RES)	4.656	1.241
Technology Affinity (TA)	4.429	1.388
Technological Understanding (TU)	5.177	0.994

[1] Exception from 7-point Likert scale: Age: ratio scale; chatbot experience: nominal scale.

Regarding the means of the job-related automation concerns as central aspect of the study, a general consent with the proposed statements can be derived: Except for the two variables ethical implications and recruiting chatbot anxiety, all mean values are μ > 3.5 and above expressing at least minor consent with the statements offered in the questionnaire.

Those statements have to be separated into two opposing streams: There are

1) a positive one comprising advantageous aspects of the proposed recruiting chatbot implementation (legal implications, output quality, perceptions of external control, perceived system transparency, job relevance, recruiting chatbot self-efficacy, and subjective norm), and
2) a negative one with all potentially concerning aspects affiliated with recruiting chatbots belonging to the group of job-related automation concerns (ethical implications, social implications, affective-based inertia, behavioral-based inertia, cognitive-based inertia, recruiting chatbot anxiety, sunk efforts, transition efforts, uncertainty efforts).

For the positive aspects, all associated variables and items were approved by the participants with $\mu > 3.5$ – especially the perceptions of external control, the perceived system transparency, and the recruiting chatbot self-efficacy (highest approval value of $\mu_{RCSE} = 4.931$) with an overall $\mu > 4.3$. Agreeing with the legal implications means that the recruiters do not mind if the recruiting chatbot records personal information of the applicant. Thus, there is no perceived data protection issue here. This corresponds with the detected consent of the participants with the statements regarding their personal technological understanding, especially regarding their self-attributed knowledge of a technological system's functions and easiness of learning how to handle new technological systems.

Concerning the negative perspective reflecting the actual concerns, they are mainly agreed upon as well. The most striking issue is seen in the social implication regarding the loss of contact with the applicants ($\mu_{SIMP} = 4.840$) followed by affective-based inertia (continuance of the existing recruiting method is preferred because change would be stressful and the participant is comfortable with the traditional ways and enjoying conducting the current method; $\mu_{INAAB} = 4.602$). However, the aspects theoretically seen as most critical in the form of ethical implications (potential job loss, higher productivity or quality level in chatbot labor) and recruiting chatbot anxiety (feelings of scare, nervousness, discomfort or uneasiness) are not seen by the participants with low agreement levels of $\mu < 3.1$. This surprising finding, at least validating the finding by Haufe (2020) stating that 97 percent of the HR employees do not think that chatbots will render them redundant, will be kept in mind and further regarded in the following analyses regarding the structural model of the study and the discussion of the results.

Looking at the other HCCAM variables, all show $\mu > 3.5$ except for chatbot experience, which is one of the scarce items not following the 7-point Likert scale. The mean value $\mu_{CEXP} = 2.050$ indicates that in general, the participants have some sort of experience with a chatbot. This goes along with the actual answer distribution stating that 58.4 percent of the participants have a form of personal experience with the technology by having at least heard of it or having used one or more solutions at least once. The other item not measured via the 7-point Likert scale is age; $\mu_{AGE} = 3.640$ would indicate a general age of the participants of 30 to 49 years while here, the percentage distribution is the more informative value confirming this finding (cf. section 6.1.1). The highest consent value with $\mu_{TU} = 5.177$ is attributed to the technological understanding, which is exceptionally strongly pronounced among the participants according to their self-evaluation. With a mean value of $\mu_{PI} = 4.837$, the level of personal innovativeness is also high according to the self-assessment of the recruiters. Thus, the participants describe themselves as technology savvy and innovative. In generalized terms, recruiting chatbots are perceived as easy to use ($\mu_{PEOU} = 4.748$) and useful ($\mu_{PU} = 4.185$) offering a high level of result demonstrability ($\mu_{RES} = 4.656$), which is in line with the result for perceived system transparency ($\mu_{PST} = 4.377$).

Path Coefficients of the Structural Model

The path coefficients and their respective significance values are analyzed to identify the statistically significant impactors of the behavioral intention to use recruiting chatbots. Table 6.10 shows the path coefficients and information regarding the significance of the HCCAM variables in the model.

Table 6.10 Main Study PLS-SEM T-Statistics and Significance

	Path Coefficient (β) (Original Sample)	Sample Mean	Standard Deviation (SD)	T Statistics (|O/SD|)	P Values
EIMP → PU	0.174	0.176	0.034	5.109	0.000
INA → BI	-0.045	-0.045	0.037	1.194	0.233
INA → PU	-0.113	-0.113	0.035	3.214	0.001
INAAB → INA	0.253	0.252	0.016	15.644	0.000
INABB → INA	0.491	0.491	0.016	31.450	0.000
INACB → INA	0.446	0.446	0.015	29.239	0.000
LIMP → PU	-0.114	-0.114	0.039	2.945	0.003
OUT → PU	0.213	0.211	0.057	3.752	0.000
PEC → PEOU	0.035	0.040	0.059	0.601	0.548
PEOU → BI	0.139	0.139	0.042	3.337	0.001
PEOU → PU	0.179	0.180	0.048	3.757	0.000
PST → BI	0.088	0.090	0.042	2.091	0.037
PST → PEOU	0.324	0.321	0.051	6.398	0.000
PU → BI	0.350	0.350	0.049	7.206	0.000
RCANX → PEOU	-0.219	-0.221	0.045	4.888	0.000
RCSE → PEOU	0.199	0.200	0.059	3.376	0.001
REL → PU	0.233	0.233	0.052	4.491	0.000
RES → PU	0.021	0.022	0.047	0.437	0.662
SIMP → PU	-0.054	-0.053	0.036	1.506	0.132
SN → BI	0.353	0.353	0.041	8.537	0.000
SN → PU	0.157	0.153	0.051	3.100	0.002
SWESE → INA	0.487	0.474	0.036	13.433	0.000
SWETE → INA	0.122	0.124	0.097	1.252	0.211
SWEUE → INA	0.755	0.749	0.055	13.847	0.000

95 percent confidence interval requiring $T > 1.96$ significant at $p < 0.05$; the values are shown as regular structural model calculations to be able to analyze the aspects of inertia and switching efforts, which are not considered in the calculations at the latent variable score (LVS) level; the LVS values (all similar values, with same directions for all path coefficients and the same specifications of p-values concerning the significance) are noted in Appendix S.

The values are taken from the standard structural model analysis observing the consistent PLS algorithm and bootstrapping results. However, an additional structural model analysis concerning the path coefficients and significances regarding the latent variable scores was run to control for the HCM effect regarding the variable of inertia. The results are highly similar to the standard ones so that for reasons of legibility, the result discussion is limited to those figures except for the R^2-values, which need to be drawn from the latent variable score structural model analysis as R^2-values > 1 are non-interpretable for this analysis. The values of the latent variable score analysis can be seen in Appendix S. All values with T-statistics > 1.96 are significant at the 0.05 level, which is the desired level for the study at hand. The results show significant path coefficients for all paths except for the relationships between inertia and the behavioral intention to use, between perceptions of external control and perceived ease of use, between result demonstrability and perceived usefulness, and between social implications and perceived usefulness. The insignificant influence of social implications is also negative and not positive as specified by other acceptance research.

Unexpectedly, the newly introduced concern of inertia seems to only influence the perceived usefulness while not having a significant impact on the behavioral intention of recruiting chatbot utilization. However, most variables have a significant impact on the behavioral intention to utilize a recruiting chatbot; also recruiting chatbot anxiety which was earlier found to yield a low level of consent regarding the mean values. A detailed discussion of these results will follow after analyzing the further PLS-SEM parameters R^2, f^2, Q^2, q^2, the model fit, a mediator analysis and a detailed examination of the control variables.

PLS-SEM parameters R^2, f^2, Q^2, and q^2

In the following, the strength of the impact of the identified predictors is analyzed. For the predictive power of the HCCAM in the form of R^2, the structural model with its latent variables is observed as well as the calculated latent variable scores. As apparent in Table 6.11, the R^2 value of inertia exceeds the maximum value of 1 with R^2 = 1.173.

Table 6.11 Main Study Amount of Explainable Variance (R^2)

	Standard Structural Model		**Latent Variable Scores**	
	R Square	**R Square Adjusted**	**R Square**	**R Square Adjusted**
BI	0.674	0.670	0.567	0.562
INA	1.173	1.174	0.228	0.226
PEOU	0.404	0.398	0.328	0.321
PU	0.667	0.659	0.620	0.603

R^2 values based on the threefold ranking 19-32% = weak; 33-67% moderate; > 67% substantial (Hair Jr et al., 2017; Christian Maier, 2014).

Reason for that is the nature of the variable as part of a reflective-formative hierarchical component model: Inertia is impacted by affective-, behavioral-, and cognitive-based reflective items and hypothetically completely explained by those three aspects. With the high R^2 value resulting from this constellation, the addition of any other impacting variable incorrectly further increases the R^2 value. As inertia is hypothesized to also be influenced by the formative items of the three types of switching efforts (sunk, transition, and uncertainty efforts), a prohibitively high R^2 is computed. Hence, the latent variable score values need to be considered thus calculating with the aggregated scores for this statistical analysis. Regarding the amount of explainable variance of the endogenous constructs, especially the behavioral intention to use, moderate to substantial values form: R^2 is 0.674 ($R^2_{adjusted}$ = 0.670) for the standard structural model; regarding the latent variable scores considering the HCM construct of inertia, R^2 is slightly lower with 0.567 ($R^2_{adjusted}$ = 0.562).

The effect sizes, measuring the meaningfulness of the significant effects based on T-values and p-values via the evaluation criterion f^2, are displayed in

Table 6.12. The path coefficients already deemed insignificant (INA → BI, PEC → PEOU, RES → PU, SIMP → PU) are shown as insignificant values < 0.02 here as well. However, switching efforts shows a moderate effect on inertia with f^2 = 0.295. The effects of perceived usefulness and subjective norm on the behavioral intention to use (PU → BI, SN → BI) are also moderate with f^2 > 0.15. All other effect sizes, including the newly introduced variables inertia and perceived system transparency, are existent but weak.

Table 6.12: Main Study Effect Size (f^2)

	BI	INA	PEOU	PST	PU
BI					
EIMP					0.057
INA	0.005				0.033
LIMP					0.037
OUT					0.067
PEC			0.001		
PEOU	0.030				
PST	0.012		0.118		
PU	0.152				
RCANX			0.061		
RCSE			0.037		
REL					0.063
RES					0.008
SIMP					0.004
SN	0.174				0.028
SWE		0.295			

Joe F Hair et al. (2012): > 0.02 weak effects, > 0.15 moderate effects; >0.35 strong effects.

The criterion of Q^2, indicating the predictive relevance of the path model, is calculated in Smart PLS 3 and shown in Table 6.13. While the relevance is strong with $Q^2 > 0.35$ for the behavioral intention to use and perceived usefulness, the relevance is moderate for inertia and perceived ease of use with $Q^2 > 0.15$. Overall, the model has predictive value as $Q^2_{BI} = 0.545 > 0$.

Table 6.13 Main Study Predictive Relevance Analysis (Q^2)

	SSO	SSE	Q^2 (=1-SSE/SSO)
BI	425.000	193.203	0.545
EIMP	425.000	425.000	
INA	425.000	331.534	0.220
LIMP	425.000	425.000	
OUT	425.000	425.000	
PEC	425.000	425.000	
PEOU	425.000	294.132	0.308
PST	425.000	425.000	
PU	425.000	186.863	0.570
RCANX	425.000	425.000	
RCSE	425.000	425.000	
REL	425.000	425.000	
RES	425.000	425.000	
SIMP	425.000	425.000	
SN	425.000	425.000	
SWE	425.000	425.000	

Predictive relevance categories: > 0.02 weak effects, > 0.15 moderate effects; >0.35 strong effects (Henseler et al., 2009).

Subsequent to the predictive relevance analysis is the observation of the relative impact of this relevance, which is calculated via $q^2 = (Q^2_{included} - Q^2_{excluded})/(1 - Q^2_{included})$ based on the Q^2 values (Hair Jr et al., 2017). Table 6.14 gives an overview of the generally present relative impact of the respective relevance. While some paths seem to have no predictive relevance (LIMP → PU, RES → PU, SIMP → PU, SN → PU, PEOU → BI, INA → BI, PST → BI), most show small relative influence values with the effect of subjective norm on the behavioral intention to use (SN → BI) even showing medium predictive relevance.

Table 6.14 Main Study Relative Impact of the Predictive Relevance (q^2)

	Q^2 (Var. included)	Q^2 (Var. excluded)	q^2
EIMP → PU	0.570	0.546	0.0558
INA → PU	0.570	0.548	0.0511
LIMP → PU	0.570	0.562	0.0186
OUT → PU	0.570	0.553	0.0395
PEOU → PU	0.570	0.535	0.0814
REL → PU	0.570	0.545	0.0581
RES → PU	0.570	0.572	-0.0047
SIMP → PU	0.570	0.574	-0.0093
SN → PU	0.570	0.562	0.0186
PEC → PEOU	0.308	0.311	-0.0043
PST → PEOU	0.308	0.231	0.1113
RCANX → PEOU	0.308	0.270	0.0549
RCSE → PEOU	0.308	0.292	0.0231
PEOU → BI	0.545	0.537	0.0175
INA → BI	0.545	0.545	0.0000
PST → BI	0.545	0.545	0.0000
PU → BI	0.545	0.484	0.1341
SN → BI	0.545	0.469	0.1670

Relative impact values: > 0.02 small, > 0.15 medium; >0.35 large predictive relevance (Henseler et al., 2009).

As a last structural model analysis aspect, the model fit of the HCCAM is evaluated. With SRMR = 0.044 <0.080 and NFI = 0.944 >0.900 and < 1.000, the results correspond to the recommended values indicating a good model fit (Hair Jr et al., 2017; PLS, 2020). Analyzing the Chi-Square value, χ^2 = 176.950 < 2df (2df = 850) is an indication for a good fit (Schermelleh-Engel, Moosbrugger, & Müller, 2003).

Control Variable Analysis

The influence of the control variables is examined via comparative tests to observe the differences in path intensity and significance made by including control variables as suggested by De Battisti and Siletti (2019).

The according indices regarding the emerging path coefficients, t-statistics, R^2 values and significance of the five control variables are summarized in Table 6.15.

Table 6.15 Main Study Control Variable Analysis

	AGE Age	**PI** Personal Innovativeness	**TA** Technology Affinity	**TU** Technological Understanding	**CEXP** Chatbot Experience
Path coefficient	-0.014	0.130	0.063	0.043	0.073
T-Statistics	0.422	3.445	1.800	1.126	2.159
R^2_{new}	0.674	0.684	0.677	0.675	0.679
Absolute change in R^2	0.000	0.010	0.003	0.001	0.005
Significance (p)	0.673	0.001	0.072	0.260	0.031

The two control variables personal innovativeness and chatbot experience have a significant influence on the behavioral intention to use with personal innovativeness showing the highest increase in R^2. Including both the significant control variables personal innovativeness and chatbot experience, R^2 increases to 0.687 ($R^2_{adjusted} = 0.681$) – however, only the influence of personal innovativeness remains significant ($p = 0.002 < 0.05$) and the impact of chatbot experience becomes insignificant ($p = 0.134 > 0.05$). Hence, only personal innovativeness remains as meaningful control variable. The insignificance of age confirms the findings of Bastam et al. (2020), who found no differences between age groups below 30 and above 50 concerning the intensity of wish for digitalization. Age, initially expected to also influence the ethical implications and recruiting chatbot anxiety (cf. *section 4.1.3*) alongside the behavioral intention to use, was not found to significantly impact any of these variables ($p_{BI} = 0.673$, $p_{EIMP} = 0.797$, $p_{RCANX} = 0.459$). Regarding the experience with chatbots, the found insignificance is in line with the findings of Oturakci and Oturakci (2018), who also found that experience does not significantly influence the behavioral intention to use a technology.

Figure 6.2 illustrates the complete structural model summarizing all discussed path coefficients, significances and R^2-values from the regular PLS algorithm and bootstrapping results.

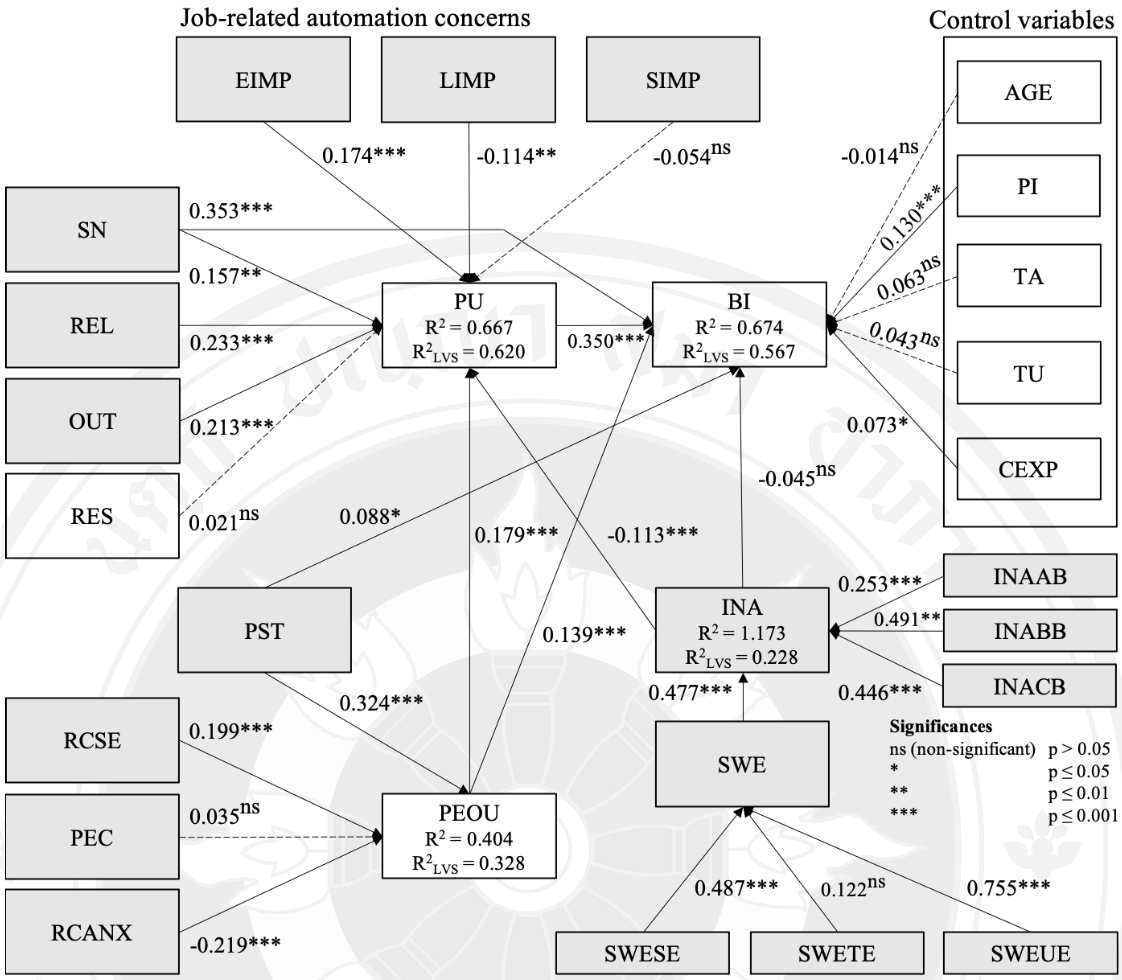

Figure 6.2 Full Structural Model with Path Coefficients, Significance Information, and R^2

Source: Own illustration.

The variables highlighted in grey belong to the group of job-related automation concerns; the dashed lines indicate insignificant paths. The values with T-statistics > 1.96 are considered significant at the 0.05 level. As shown, the proposed HCCAM model is overall significant indicating moderate up to a substantial predictive power (R^2). With the exception of social implications and perceptions of external control, all suggested variables treated as job-related automation concerns (highlighted in grey in Figure 6.2) have a significant influence on the core variables of the HCCAM. The final results of the hypotheses test derived from the structural model analysis and the significances of the path coefficients are summarized in Table 6.16.

Table 6.16 HCCAM Hypothesis Testing Results

Variable	Hypotheses	Result
Subjective Norm	H_{1a}: Subjective norm has a positive influence on the perceived usefulness of recruiting chatbots.	Supported
	H_{1b}: Subjective norm has a positive influence on the behavioral intention to use a recruiting chatbots.	Supported
Job Relevance	H_2: Job relevance has a positive influence on the perceived usefulness of recruiting chatbots.	Supported
Output Quality	H_3: Output quality has a positive influence on the perceived usefulness of recruiting chatbots.	Supported
R. Chatbot Self-Efficacy	H_4: Self-efficacy has a positive influence on the perceived ease of use of recruiting chatbots.	Supported
Perceptions of External Control	H_5: Perceptions of external control have a positive influence on the perceived ease of use of recruiting chatbots.	Not supported
R. Chatbot Anxiety	H_6: Chatbot anxiety has a negative influence on the perceived ease of use of recruiting chatbots.	Supported
Ethical Implications	H_7: (Negative) ethical implications have a positive influence on the perceived usefulness of recruiting chatbots.	Supported
Legal Implications	H_8: (Negative) legal implications have a negative influence on the perceived usefulness of recruiting chatbots.	Supported
Social Implications	H_9: (Negative) social implications have a positive influence on the perceived usefulness of recruiting chatbots.	Not supported
Result Demonstrability	H_{10}: Result demonstrability has a positive influence on the perceived usefulness of recruiting chatbots.	Not supported
Perceived Ease of Use	H_{11a}: Perceived ease of use has a positive influence on the perceived usefulness of recruiting chatbots.	Supported
	H_{11b}: Perceived ease of use has a positive influence on the behavioral intention to use a recruiting chatbot.	Supported
Perceived Usefulness	H_{12}: Perceived usefulness has a positive influence on the behavioral intention to use a recruiting chatbot.	Supported
Perceived System Transparency	H_{13a}: Perceived system transparency has a positive influence on the perceived ease of use of recruiting chatbots.	Supported
	H_{13b}: Perceived system transparency has a positive influence on the behavioral intention to use a recruiting chatbots.	Supported

Variable	Hypotheses	Result
Inertia	H_{14a}: The recruiter’s level of inertia has a negative influence on the perceived usefulness of recruiting chatbots.	Supported
	H_{14b}: The recruiter’s level of inertia has a negative influence on the behavioral intention to use recruiting chatbots.	Not supported
Perceived Switching Efforts	H_{15a}: Perceived switching efforts (transition efforts) have a positive influence on the recruiter’s inertia concerning recruiting chatbots.	Not supported
	H_{15b}: Perceived switching effort (sunk efforts) have a positive influence on the recruiter’s inertia concerning recruiting chatbots.	Supported
	H_{15c}: Perceived switching efforts (uncertainty efforts) have a positive influence on the recruiter’s inertia concerning recruiting chatbots.	Supported

In this study, 16 of the 21 and by that most of the established hypotheses are supported leaving five hypotheses that are not supportable via the data at hand.

Mediator analysis

Furthermore, there are significant ($p < 0.05$) mediation effects from various variables to behavioral intention to use and one to perceived usefulness (switching efforts to perceived usefulness via inertia), with the exceptions of perceptions of external control, result demonstrability, and social implications to behavioral intention to use (cf. Table 6.17).

Table 6.17 Main Study Mediation Analysis Results

	Original Sample (O)	Sample Mean	Standard Deviation (SD)	T Statistics (|O/SD|)	P Values
EIMP → BI	0.059	0.059	0.015	3.954	0.000
INA → BI	-0.042	-0.042	0.013	3.129	0.002
LIMP → BI	-0.047	-0.046	0.014	3.250	0.001
OUT → BI	0.091	0.090	0.023	3.946	0.000
PEC → BI	0.005	0.006	0.009	0.546	0.585
PST → BI	0.045	0.045	0.016	2.856	0.004
RCANX → BI	-0.031	-0.031	0.012	2.640	0.008
RCSE → BI	0.028	0.028	0.012	2.244	0.025

	Original Sample (O)	Sample Mean	Standard Deviation (SD)	T Statistics (|O/SD|)	P Values
REL → BI	0.084	0.085	0.022	3.915	0.000
RES → BI	0.027	0.027	0.016	1.647	0.100
SIMP → BI	-0.016	-0.016	0.014	1.162	0.245
SN → BI	0.054	0.052	0.019	2.798	0.005
SWE → BI	-0.043	-0.043	0.018	2.396	0.017
SWE → PU	-0.057	-0.057	0.018	3.130	0.002

Regarding the newly introduced variables of inertia and perceived system transparency, two findings emerge: While the direct effect from inertia to the behavioral intention to use is non-significant ($p = 0.233$), there is a full mediation effect from inertia to the behavioral intention to use via perceived usefulness ($p = 0.002$). For perceived system transparency, there is a partial mediation effect (perceived system transparency on the behavioral intention to use via perceived ease of use; $p = 0.004$) since a significant relationship from perceived system transparency on the behavioral intention to use on its own is established as well. For perceptions of external control, result demonstrability, and social implications, both the direct relationships suggesting partial mediation as well as the full mediation results show non-significant values. Apart from these variables, the other ones explaining the concept of job-related automation concerns – ethical implications, legal implications, subjective norms, job relevance, output quality, recruiting chatbot self-efficacy, and recruiting chatbot anxiety – are partially mediated either by perceived ease of use or by perceived usefulness stressing the importance of the two aspects for the variance explanation of the dependent variables in the HCCAM and the acceptance of recruiting chatbots in general.

CHAPTER 7

DISCUSSION, RESEARCH IMPLICATIONS, AND OUTLOOK

The overall goal of this study was to identify relevant acceptance determinants for recruiters that need to be taken into consideration when integrating a chatbot into the recruiting processes of a company, specifically for first candidate interviews served as exemplary use case. As a theoretical framework, the Human-Chatbot Collaboration Acceptance Model, was built based on the HRCAM as proposed by Bröhl et al. (2019). Particular focus was laid on the job-related automation concerns and the impact of the variables perceived system transparency and inertia the model was adapted with. A quantitative study was designed and conducted to validate the HCCAM based on a sample of 425 recruiters in diverse job positions within German-speaking companies of different sizes and industries: Most hypotheses are supported with subjective norms and perceived usefulness as most relevant significant acceptance factors for recruiting chatbots from the recruiters' point of view.

In the following, the essential results are summarized before showing the academic as well as the practical contributions but also the limitations of the study. At the end, an outlook is given on possible future recruiting chatbot research.

7.1 Discussion of the Results

This study regards the influence of certain adapted and developed factors on the acceptance of recruiting chatbots as exemplary automation technology. In the HCCAM, TAM-related acceptance determinants are combined and brought together with the concept of job-related automation concerns comprising inertia and perceived system transparency as novel aspects and special focus of this research. The results from the study provide strong support for the developed HCCAM model explaining 56.7 percent (R^2 = 0.567) of the variance in the behavioral intention to use a recruiting chatbot. In total, 16 of the 21 developed hypotheses, including most of the ones associated with job-related automation concerns, are supported indicating that the proposed HCCAM and its variables are able to depict and estimate recruiter-sided chatbot acceptance. Out of the 21 main and five control variables, 19 significant factors are identified to either positively or negatively influence the behavioral intention to work with a recruiting chatbot. Generally, all found relationships correspond to the drawn hypotheses based on extensive literature with the exception of social implications, which turned out as a negative influencer of perceived usefulness. However, this effect is identified to be insignificant.

Overall, high agreement values are observed towards most of the survey questions, especially the ones regarding the positive impact of recruiting chatbots. These high values elucidate the impression that there is an apparent positive attitude towards recruiting chatbots and their capabilities (cf. Table 6.9). Predictive relevance is ascribed to both newly embedded variables perceived system transparency and inertia. In the following, the effects of the exogenous, the endogenous, and the control variables are discussed in detail as well as the other aspects regarded in the study (use cases, drivers, barriers, interviewing aspects and skills, and cross tabulations).

7.1.1 Influencing Independent Variables

Strongest impact is ascribed to switching efforts on inertia ($f^2_{SWEonINA} = 0.295$; $\beta_{SWE} = 0.477$, $p < 0.001$), confirming the predicting power of switching efforts on inertia as suggested by Lucia-Palacios et al. (2016). The second strongest relationship is the one of subjective norm on the behavioral intention to use ($f^2_{SNonBI} = 0.174$; $\beta_{SN} = 0.353$, $p < 0.001$) based on the recruiters' behavioral intention to work with such a system, which is most strongly influenced by their surrounding subjective norms. Hence, the opinions of their peers, management and overall organization play the most important role for their recruiting chatbot acceptance. There might be different reasons for this outcome, for example the Germans' general sensitivity towards data security issues related to technology (Dogruel & Joeckel, 2019) and the resulting desire to behave in conformity with the societal norms and in accordance with the behavior of their peers. Another reason might be the recruiters' dependence on their superiors regarding technology utilization for their processes: Their managers need to approve of the technology under consideration of the underlying risks and possible consequences. Consequently, it is highly important for the acceptance of recruiting chatbots that the company's management and influencing peers of their work context act as ambassadors for the technology to help recruiters accept this technology in their work process.

Contrary to hypothesis development, result demonstrability is no significant predictor of perceived usefulness. Hence, the ability to grasp and to tell others about the results or consequences of using a recruiting chatbot is not related to the positive impacts of the recruiting chatbot from the recruiters' point of view. This could be an indication for their priority on the chatbot's effect on their own job in the form of job performance improvement for example over the desire to understand and to be able to explain the accomplishments of the technology. In contrast to the generally insignificant effect of result demonstrability, which could be argued to be similar to perceived system transparency but solely regards the results while transparency spans the whole inner workings of the technology, the latter significantly influences the perceived ease of use ($\beta_{PST} = 0.324$, $p < 0.001$; $f^2_{PSTonPEOU} = 0.118$) and the behavioral intention to utilize recruiting chatbots ($\beta_{PST} = 0.088$, $p \leq 0.05$; $f^2_{PSTonBI} = 0.012$). The importance of perceived system transparency for the behavioral intention to utilize a recruiting chatbot is emphasized regarding both a direct relationship and a partial mediation via perceived ease of use. Thus, recruiters are more inclined to develop an intention to utilize a recruiting chatbot when the level of perceived transparency of the specific technological solution is high. They want to understand the rules defined for the technology, the algorithm, the inquiry processing, and the reasoning of the automation system in order to decide whether or not to intend utilizing it. A reason for that may be the requirement for recruiters to justify their procedure for processing applications as well as their (pre-)selection decision: They need to be transparent about their application handling measures and thus expect chatbots as alternative communication interface to be equally transparent in their workings. Ascribing a relationship with perceived ease of use, recruiters also find transparency beneficial for the applicants' interaction with the technology: The higher the level of perceived system transparency, the higher is the recruiter's expectation that applicants will find the chatbot easy, clear, and understandable to interact with. That way, the recruiters establish a connection between the transparency of the automated dialogue system with the simplicity of interaction, perhaps based on the assumption that either transparency offers an understanding of the workings of the technology or that transparency equals predictability during interaction.

Alongside perceived system transparency, further important aspects and central elements of the job-related automation concerns are the variables of job relevance, recruiting chatbot anxiety, ethical implications, and recruiting chatbot self-efficacy (sorted in descending order according to their relevance in the form of effect size based on the f^2-values). Job relevance positively impacts the perceived usefulness with highest significance ($\beta_{REL} = 0.233$, $p < 0.001$; $f^2_{RELonPU} = 0.063$). As a matter of course, recruiters who expect chatbots to improve their job performance, increase their job productivity, and enhance their job effectiveness, base this on the fact that they perceive them as relevant and important for their job. Hence, one of the central measures for the enhancement of recruiter-sided chatbot acceptance beside the manager's chatbot ambassador role is the communication of their advantages and support functions for their respective job tasks so that they can see their pertinence for the process. Recruiting chatbot anxiety negatively influences perceived ease of use with highest significance ($\beta_{RCANX} = -0.219$, $p < 0.001$; $f^2_{RCANXonPEOU} = 0.061$) showing that recruiters who feel uneasy around the technology expect it to be cumbersome to use for applicants. Comprehensibly, a recruiter who is made uncomfortable by chatbots struggles with seeing the intended added value and easiness of interaction the systems are meant to bring into the recruiting process. This circumstance needs to be considered in employee management when implementing such a technological system into work procedures: Managers are required to minimize any feelings of nervousness of recruiters around chatbots so that they can appreciate and embrace them as efficient alternative communication interface for their candidates. The study further shows that ethical implications positively impact perceived usefulness with highest significance ($\beta_{EIMP} = 0.174$, $p < 0.001$; $f^2_{EIMPonPU} = 0.057$). Hence, even if not seen as personal threats by the recruiters who participated in the study (mean values of $\mu_{RCANX} = 3.08$ and $\mu_{EIMP} = 3.03$, thus no overall consent with the relevance of the respective items across all participants), the risk of work force substitution by an automated system on the example of an interview-conducting chatbot and feelings of nervousness or discomfort working with it are identified as actual acceptance determinants. The higher the perceived threat of substitution by the automation technology, the higher is the seen usefulness of the system so that recruiters correlate the helpfulness of a recruiting chatbot with its ability to replace their own work through automation thus defining their worth by their aptitude to take over certain tasks and making room for a focus on other duties. While this outcome may appear to be obvious, it validates the general assumption that automation technology is required to be perceived as a relevant alternative to human labor in order to represent a useful addition to the recruiting process. This finding is reinforced by the significance and relatively high effect size of job relevance as profound acceptance factor in this study. Recruiting chatbot self-efficacy positively impacts the perceived ease of use of the technology ($\beta_{RCSE} = 0.199$, $p < 0.001$; $f^2_{RCSEonPEOU} = 0.037$). It shows that contrary to manuals in the form of material resources as well as generally perceived control, expressed through the insignificant factor of perceptions of external control, the own skills and capabilities do influence the expected easiness of interaction with the chatbot. The recruiters seem to ascribe relevance to the ability to use the system alone or with the help of others rather than to the personally felt control and resource possession when it comes to the easiness of chatbot utilization. Furthermore, ethical implications and recruiting chatbot anxiety as well as legal implications, subjective norm, job relevance, output quality, and recruiting chatbot self-efficacy defined as further job-related automation concerns are partially mediated by either perceived usefulness or perceived ease of use. Hence, this concept is established as relevant in the context of recruiting chatbots further validating the importance of the constructs perceived usefulness and perceived ease of use.

The element of trust is regarded as a compilation of the aspects of output quality and legal implications in this study. Both variables in regard to the individual attitude towards the level of result excellence and data security are found to significantly impact the perceived usefulness ($\beta_{OUT} = 0.213$, $p < 0.001$; $\beta_{LIMP} = -0.114$, $p = 0.003$). The more value they ascribe to the output that a chatbot generates, the more useful they perceive the technology to be in regards to their performance, productivity, and effectiveness. Despite the removal of the item LIMP02 because of bad formative factor analysis results, the legal implication of personal data collection is relevant: The more the recruiters think that chatbots are suitable for collecting personal data of applicants, the more useful they perceive the system to be. A reason for this might be the importance of personal data collection and overall data management within the recruiting process highlighting the potential of automation technology for such process steps. Facilitation of data management and data quality standardization are chatbot utilization drivers ranked high by the recruiters, which reinforces this acceptance factor and underlines its relevance. Hence, trust also plays an important role concerning the acceptance of recruiting chatbots.

The rejection of the hypothesis for transition efforts is in accordance with Samuel and Joy (2018), who also found that transition efforts do not significantly influence inertia. The overall non-significance of the remaining hypotheses concerning the perceptions of external control, result demonstrability, and social implications however come as a surprise. Observing that perceptions of external control do not have a significant impact on perceived ease of use, the recruiters participating in this study seem to not ascribe influence from the facilitating resources and structures within their organization to their individual intention to utilize a recruiting chatbot. They might feel capable of learning chatbot handling without such resources or simply do not associate their decision to intent utilization with them. Another reason could be the inevitability that recruiters see with a new technology like that: It might be implemented based on a management decision and by that presented and explained to them regardless of the kind of technology so that they neither ascribe special importance to the imposed learning resources nor give it the power to influence their utilization intention decision. The peers and managers themselves however have a significant impact (expressed through the variable of subjective norm) so that companies need to be careful in their strategy setup and change management process when conducting a chatbot project. Astonishingly, social implications as the recruiters’ fear to lose the contact to their applicants because of the automated dialogue system does not significantly influence perceived usefulness despite the high overall approval rate towards this concern based on the mean values ($\mu_{SIMP} = 4.84$). Hence, the recruiters` perception of a chatbot’s usefulness for first candidate interviews is not related to their concern of contact reduction through the interposed automated dialogue system.

7.1.2 Influencing Dependent Variables

Alongside the exogenous variable of subjective norm ($f^2_{SNonBI} = 0.174$), perceived usefulness as endogenous variable in the form of performance improvement, productivity increase, and effectiveness enhancement has the largest significant impact on the behavioral intention to use ($f^2_{PUonBI} = 0.152$; $\beta_{PU} = 0.350$, $p < 0.001$), which makes it the second most relevant recruiting chatbot acceptance criterion. Beside the opinion of their peers, recruiters base their level of chatbot acceptance mainly on the pertinence they see in the technology, reinforced through the already presented significant impact of job relevance.

Regarding inertia, the answers of the recruiters confirm the idea that this concept is influenced by the switching efforts connected to a change of candidate interview procedure towards recruiting chatbot implementation: The higher the invested switching efforts, the higher is the recruiters' level of inertia. A negative influence of inertia on perceived usefulness is ascribed ($\beta_{INA} = -0.113$, $p < 0.001$), showing that in their perceptions, recruiters who experience states of inertia would degrade the level of recruiting chatbot usefulness justifying their logic to stay with the current ways of working. A direct relationship of inertia with the behavioral intention to utilize such a system is not supported by the study at hand showing that the intention to use is not directly influenced by the recruiters' tendency to preserve familiar assumptions and existent structures while highlighting the relevance of the other predictors of the behavioral intention to use a recruiting chatbot (i.e., subjective norm, perceived usefulness). However, there is a full mediation effect from inertia to the behavioral intention to use via perceived usefulness, which corresponds with the direct relationship found between inertia and perceived usefulness. Hence, inertia is related to the behavioral intention to use after all through the mediation effect despite the non-significance of their direct relationship.

Strongest predictive relevance values are yielded for the behavioral intention to use ($Q^2_{BI} = 0.545$) and perceived usefulness ($Q^2_{PU} = 0.570$). Encouragingly, inertia as newly introduced predictor shows moderate relevance as well ($Q^2_{INA} = 0.220$) alongside perceived ease of use ($Q^2_{PEOU} = 0.308$). Hence, the existent inertia does significantly negatively influence the behavioral intention to work with an automated dialogue system in recruiting via the perceived usefulness and by that explains the reluctance of those recruiters not intending to utilize it. At the same time, the perceived ease of use, defined by a clear and understandable interaction with the technology that is easy to implement and does not require a lot of the applicant's mental effort, has been identified as a substantial effect.

7.1.3 Influencing Control Variables

Regarding the control variables, only personal innovativeness could be established as robust control variable to be included in the final version of the HCCAM as age, technology affinity, and technological understanding were insignificant. Furthermore, chatbot experience, significant during inclusion of all five control variables, rendered insignificant when only regarding chatbot experience and personal innovativeness were regarded in the model. This is an astonishing finding as the recruiters' previous experience with chatbots could reasonably be anticipated to have an influence on their intention to work with one at their job site. In conclusion, the study at hand showed that the recruiters' personal level of innovativeness, measured via their willingness to try out and experiment with new technology and the earliness of trial compared to their peers, indeed impacts their behavioral intention to utilize a recruiting chatbot. This relationship was expected and validated in this study: Recruiters who are fond of innovative technology trials in their spare time are likely to open-mindedly experiment with novel technology in their work environment as well.

The hypotheses regarding the potential fondness of technology affine people and those possessing technological understanding towards recruiting chatbots could not be approved. Similarly, age, expected to impact the behavioral intention to use, was not identified as a significant determinant. Overall, only the inclusion of the control variable personal innovativeness caused an absolute increase in R^2 of 0.01. This is in line with Atinc et al. (2012), who state that control variables are supposed to account for a minimal part of R^2. However, many of the regarded aspects were found to be related to the company size of the participants' employers, for example the knowledge regarding chatbots, the previous chatbot experience, and the state of chatbot deployment within the recruiting processes. This does not come as a surprise since large enterprises with more voluminous application rounds and recruiting processes in general as well as a stronger work force and resource portfolio might be in a better position to discuss and integrate such an innovation.

7.1.4 Discussion of Use Cases, Drivers, Barriers, and Interviewing Aspects

The most relevant use cases for recruiting chatbot deployment are the query of missing applicant data, partial applicant guidance through the application process, the clarification of application-related as well as post-submission questions, and support during job search. Thus, chatbots are seen eligible for data collection but also information distribution tasks and for navigation in the form of job search and application process guidance. It shows that such systems are perceived as a versatile technology for various recruiting process steps. The majority of the five use cases ranked as most relevant are low involvement tasks showing that generally, recruiters trust chatbots with such simple tasks. In case the automation technology takes over (routine) tasks or partial process steps, the recruiters can parallelize tasks and concentrate on creative work as well as inquiry handling where their workforce cannot be substituted by automated systems. By absorbing standard questions and filtering or re-routing complex inquiries for example, a chatbot can help the recruiters to solve problems. Guidance through the job search however is a rather demanding process including navigation, filtering, and suggestion activities so that recruiters seem to at least partly trust them to accomplish complex tasks. Alongside the ranking of pre-defined use cases, free-text input answers were provided by the participants regarding further relevant use cases: Appointment inquiry and cancellation handling are mentioned as use cases as well as specific information regarding salary expectations or the employment contract. The first two ideas show that recruiters see chatbots as suitable support systems for rather non-critical, low-involving routine tasks without a high potential for job substitution: However, it also suggests that the recruiters trust the technology to be capable of mediating between the involved parties while matching the available slots and also to manage cases of cancellation. Answering questions regarding salary expectations or the content of the specifications of the work contract indicates that the participants see chatbots as a suitable interface for sensitive issues concerning matters potentially preferred to be addressed anonymously by the applicants.

The four drivers deemed as most relevant from the recruiters' perspective are the permanent accessibility, faster recruiting process step conduct, facilitation of data management, and standardization of data quality. Accessibility represents the most essential advantage of chatbots as automated communication interface since it substitutes human labor that is bound to time, sometimes also location restrictions, which is seen as most striking benefit in the area of recruiting as well. It gives candidates the opportunity to conveniently inform themselves about the company and specifically its application process without such limitations. The mentioned driver in the form of faster recruiting process step conduct expresses the recruiters' need for efficiency enhancement and their expectation concerning chatbots to act towards it. The high rankings of facilitation of data management and the standardization of data quality show the recruiters' need for support regarding the applicant data handling and their perception of chatbots as suitable technology to help the data management process and improve data quality through their consistent performance.

Potential barriers to use for the recruiters are an expected lack of understanding complex contexts, a deterioration of the candidate-recruiter relation, and data security issues. Thus, recruiters see a danger of underperformance regarding complex tasks. This is in accordance with the mainly simple, low-involvement tasks chosen as most relevant use cases as discussed before. While the danger of getting out of touch with the candidates is seen as a barrier, this risk is no significant recruiting chatbot acceptance factor as seen by the non-significance of the social implications in this study. Data security issues are expected from Germans as data security sensitive population (e.g., Dogruel & Joeckel, 2019) and was already found to be a reason for resistance concerning chatbots (Völkle & Planing, 2019). Job replacement by automation, a barrier summarizing the main concept of job-related automation concerns, was ranked the 7th most relevant barrier with an overall mean value of $\mu_{BU08} = 4.51$ showing overall consent regarding the relevance of this item. A personal fear of being replaceable by a chatbot however is not seen by the recruiters ($\mu_{EIMP} = 3.033$). Hence, job replacement by the chatbot is not seen as an imminent fear but yet deemed a serious barrier for recruiting chatbot utilization. The level of perceived recruiting chatbot anxiety is also low ($\mu_{RCANX} = 3.079$) meaning that recruiters do not expect to be scared or feeling uncomfortable around chatbots. Hence, the finding by

Haufe (2020) stating that HR employees do not expect chatbots to substitute their work are validated in this study.

Concerning the most relevant interview aspects, efficient candidate handling, soft skill assessment, and hard skill assessment are classified as most relevant. Like the driver of faster recruiting process conduct, this shows the recruiters' need for efficiency enhancement. Chatbots shall support the main goal of recruiting, which is the employment of the right candidate through thorough soft and hard skill evaluation. Systems that can support these tasks is relevant for the recruiters and suitable for deployment in the recruiting process. Automation technology is not yet feasible for soft skill assessment on a level comparable to human task conduct. However, this is a possible future scenario.

The skills deemed most important for candidate interviewing are the application of expert knowledge and skills during selection, an overall ethical practice, and diversity management or cultural awareness. For best recruiter support and interview facilitation, a chatbot would need to support recruiters in applying expert knowledge and skills, for example through taking over repetitive parts of the interviewing process to leave them to the more challenging tasks demanding their expertise. Furthermore, they should provide expert knowledge themselves, for instance through well-kept databases and capabilities to process complex inquiries. The two other relevant skills are ethical practice and diversity management together with cultural awareness. These tasks require subtlety, sensitivity and delicate handling generally not inherent to automation technology. A recruiting chatbot would then expected to support the recruiter complying with ethical standards and diversity specifications himself, for example through a well-maintained database and impeccable behavior towards the candidates.

7.1.5 Discussion of Cross Tabulations

The cross tabulations show that the level of chatbot knowledge the participants hold is strongly associated with their age, and the size of the company. Hence, the interest in and interaction with chatbot is related to the age of the interlocutor as well as the company size calling for an age- and company type-specific chatbot deployment and operation strategy. While the first finding confirms the assumption that openness to chatbots is related to age (e.g., Steinbauer et al., 2019), it is a logical conclusion that recruiters from larger companies hold greater chatbot knowledge as they are the ones predominantly implementing chatbots into their processes because of the expectedly higher financial strength and need for automated process facilitation systems. This is expressed via strong associations between the number of employees and chatbot deployment status, chatbot development status as well as chatbot planning status. The strong associations between perceived system transparency and age, sex, as well as German-speaking region indicates that there might be age-, gender-, and country-related differences in recruiting chatbot transparency perception. In the case of age, this could be related to the different levels of chatbot experience among the age groups. The gender- and country-related dissimilarities can be examined in more detail in further studies to shed light on demographical specifics, which might need to be considered for chatbot acceptance. While affective-based inertia is strongly associated with the company size by number of employees, behavioral-based inertia is very strongly associated with age and the respective German-speaking region. A very strong association lies between cognitive-based inertia and the German-speaking region. Hence, inertia has many relationships with demographical aspects, which need to be considered in the context of recruiting chatbot implementation. The various kinds of or respective reasons for inertia need to be addressed via suitable campaigns and communication strategies in order to successfully implement a recruiting chatbot that represents a meaningful automation and efficiency enhancement tool. Age is also very strongly associated with subjective norm, uncertainty effort as indicator of inertia, and perceived ease of use confirming the findings of Chien et al. (2019), who found relationships between age and perceived ease of use as well as inertia (in the form of a general negative attitude). The number of employees is associated with most latent variables, amongst them the number of interviews held in the respective company. This is obvious as larger companies will automatically initiate and process a higher number of interviews per year. German-speaking region as the respondents' country affiliation (DE, AT, CH) is apparently associated with their level of chatbot experience, which contrary to the author's pre-survey conduct opens up analysis possibilities tentatively regarding country-specifics.

7.2 Research Implications

The question as to why humans accept a new technology is common and vital for decision makers so that the associated factors can be taken into consideration from the beginning of the design process (Taherdoost, 2018). This study observed the recruiters' points of view towards chatbots within the recruiting process in order to create an overview of prerequisites and circumstances under which chatbots represent an efficient, feasible and stakeholder-approved way of handling the recruiting process from the recruiters' perspective. The newly established HCCAM provides insights for theoretical technology acceptance research regarding digital automation technology as new field of interest derived from already established findings analyzing physical robotics. Furthermore, practical contributions are yielded in the form of relevant acceptance determinants, which need to be taken into consideration for successful chatbot implementation accepted by the recruiters. The academic and practical contributions resulting from this research are illustrated in the following sections.

7.2.1 Academic Contribution

Chatbots represent a nascent topic in acceptance research: Manifold studies have emerged in recent years but there are still many aspects that require investigations such as chatbot acceptance determinants. There is a lack of knowledge about chatbot users' reasons for utilization (Følstad & Brandtzæg, 2017). By examining the perceived advantages of the technology, this study improves the understanding of chatbot usage prerequisites and thus avails the closing of this research gap. While some researchers already conducted exploratory chatbot studies of broad nature such as motivations for general utilization and favorable aspects like the naturalness of the system (e.g., Følstad & Brandtzæg, 2017; Morrissey & Kirakowski, 2013; Bayan Abu Shawar & Eric Atwell, 2007; Stoeckli et al., 2018), no focused recruiting chatbot acceptance study is known to the author yet at this point. The study at hand regards novel aspects of automation technology acceptance and thus adds to the collection of chatbot utilization factors and complements the existing findings: The regarded stream of research is enriched through the introduction and validation of job-related automation concerns as not yet regarded but significant and thus relevant influencing aspects of chatbot acceptance in the field of recruiting. At the same time, results of previous research are verified. Especially subjective norm and perceived usefulness as traditional TAM-related constructs could be validated and confirmed in their relevance for technology acceptance research. Regarding the firm-internal perspective during company-internal technology implementation alongside expected end user behavior towards the technology of recruiting chatbots is a new perspective complementing the already existing chatbot research from an end user view and closing the corresponding research gap. This study offers a conceivable, realistic use case example, which has not been offered yet and can serve as a template for future research on this but also for other exemplary use cases.

The quantitative survey findings yield new perceptions of pain points in the recruiting process and specifically relevant aspects of the recruiting process where chatbots can add value and as well as acceptance requirements necessary for deployment. Specifically, the constructs of perceived system transparency and inertia are introduced, embedded in the field of chatbot acceptance research, and validated as relevant technology acceptance determinants on the example of recruiting chatbots. Also, the influence of the ELSI – ethical, legal, and social implication – factors as suggested by Bröhl et al. (2019) in their HRCAM could be confirmed except for the social component, which was found to be insignificant. Many other already established acceptance factors in the form of social norms, job relevance, output quality, self-efficacy, technology anxiety, perceived usefulness, and perceived ease of use all influencing the behavioral intention to work with the system, could be validated as well. Overall, 21 hypotheses were developed in the study at hand. 16 of these hypotheses have been supported indicating that the proposition of the HCCAM is a generally valuable addition to the collection of technology acceptance models and reliably depicts the specific focus topic of recruiter-sided chatbot acceptance. 19 significant relevant factors could be identified, which either positively or negatively impact the behavioral intention to work with a chatbot in the context of recruiting. This makes the established HCCAM a relevant model for recruiting chatbot acceptance research leaving room for further validation, adaptation, and extension regarding other areas of application. Special evidence is provided for the importance of social norms and perceived usefulness for the acceptance of technology. Two constructs however, the result demonstrability and the perceptions of external control, were found to be insignificant.

These findings can be considered in further acceptance research on automation technology and the focus shifted to the significant impacting factors. In terms of control variables, the importance of personal innovativeness and – tentatively – the chatbot experience could be established while age, technology affinity and technological understanding did not show a significant influence.

Several further aspects of the study at hand add value to the academic fields of information system and especially chatbot research. The findings and conclusions from the systematic identification, examination and evaluation of possible chatbot deployment areas, support tasks, utilization drivers and barriers as well as relevant acceptance criteria within the context of recruiting extend the knowledge about requirements for new technologies using the example of recruiting chatbots. By giving a detailed overview of the important automation technology acceptance models in a meta-study and applying the core idea of the HRCAM as well as other relevant acceptance constructs to the new context of digital dialogue automation technology acceptance, new findings arose. The newly developed and validated HCCAM model aggregates these new ideas and represents an extensive model for related automation acceptance research. The results of the study at hand can be utilized and put to use by future chatbot acceptance research studies. A detailed analysis of potential acceptance factors further contributes to the advancement of chatbot research. By advancing the HRCAM and forming the HCCAM, the TAM model was adapted and modified to suit contemporary technology.

7.2.2 Practical Contribution

Alongside the academic benefits, this study also generated implications for recruiters in various types of companies. Dillon and Morris (1996) found predictive acceptance factor determination and measures for increasing the level of acceptance to gain importance since work practices develop away from authoritarian leadership styles towards more encouraging methods and society more and more depends on information technologies. The big four international players in the current complex chatbot technology market, Apple with Siri, Microsoft with Cortana, Amazon with Alexa and Google with the Assistant, have integrated research expertise into their digital assistant creation process (Dale, 2016). This thesis adds to this area of research with a scientific, research model-based study approach bringing profound research findings into the chatbot advancing environment – not from a technological but rather from economic perspectives in terms of efficiency and acceptance of chatbots in the context of recruiting requisite for economic success in the form of high-level recruiting performance.

The findings of this research provide practical recommendations for companies that want to integrate the innovative technology of chatbots into their recruiting processes yielding high levels of acceptance by their employees. More specifically, recruiters and recruiting managers can benefit from the insights into necessary requirements concerning the acceptance of text-based dialogue systems as well as an overview over and classification of possible fields of application for chatbots. This is helpful for companies' own pilot recruiting chatbot solution projects. A distinct advantage of the proposed HCCAM is its applicability to the pre-market maturity stage automated dialogue systems, especially in the field of recruiting, are currently in. No actual system utilization is required to apply the model and investigate the manifestations of the observed acceptance determinants. Social norms, perceived usefulness, perceived system transparency, job relevance and recruiting chatbot anxiety have been identified as most important determinants of the intention to use recruiting chatbots based on their path coefficient values. These are important findings as social norms can be directly influenced by the company's management for example. The importance of transparency can be seen as a result of the increasingly complex technological innovations calling for explanations and a transparent handling of the system's underlying workings in the form of algorithms and processes. In sum, it was found that

1) infrastructural (social norms, recruiting chatbot self-efficacy),
2) technology-related (perceived system transparency, job relevance, perceived ease of use, output quality),
3) personal (inertia, recruiting chatbot anxiety),
4) ethical (ethical implications in terms of potential job loss and fear of better productivity and quality in the work of the system), and

5) legal (legal implications in terms of data protection issues, which are not associated with recruiting chatbots as seen by the participants of the study)

aspects are significant influencers of recruiting chatbot acceptance. Hence, this research does not only introduce the variables perceived system transparency and inertia as relevant acceptance factors for chatbots in recruiting, but also identifies different job-related automation concerns that significantly impact the recruiter's behavioral intention to work with such a system. Contrary to previous acceptance research, the result demonstrability, the perceptions of external control, social implications as well as the transition efforts do not significantly influence technology acceptance in this study. This can serve as first indication or rather sign of caution for future acceptance studies dealing with automated dialogue systems in different contexts to also rethink and adapt the traditional and sometimes no longer up-to-date acceptance models.

Regarding the use cases, obtaining missing candidate information, applicant guidance though the application and post-application process, FAQ scenarios in general and specifically clarification of post-submission application-related questions, and job selection facilitation emerged as most relevant ones. Considering this list of relevant scenarios, companies can decide which step in their recruiting process they would like to improve and have supported by chatbot technology. Furthermore, the system needs to complement the skills and process elements recruiters see relevant for their work processes: As a digital communication alternative for candidates, the automated dialogue systems need to support efficient candidate handling, soft skill assessment and also hard skill assessment. Recruiters want to be supported concerning the execution of expert knowledge and skills during selection, conducting ethical practice, and diversity management or rather cultural awareness. The findings about important characteristics for chatbots in the recruiting process, categorized as utilization drivers, can be applied by companies as a way to manage more efficiently and to prioritize which aspects to focus on as most important ones for the HR context. The most critical barriers are seen in an expected lack of understanding regarding complex tasks, potentially deteriorating candidate-recruiter relations – however, this is not significantly related to the behavioral intention to utilize the technology –, and expected data security issues. Companies can align their automation strategy to these findings by addressing the underlying concerns and supporting as well as reinforcing the driving forces.

As this study is set out from the recruiter's point of view, the theoretical findings from the quantitative survey are now put to practical use by transferring them to the actual implementation and collaboration situation in companies. The implications are sought to give practical advice on the actions to take for enhancing the acceptance of chatbots in the context of recruiting to ultimately successfully realize a chatbot project in the HR department of a company. Based on the identified acceptance determinants, possible measures are proposed to support recruiter-sided recruiting chatbot acceptance in companies in Germany.

7.2.2.1 Handling of Recruiting Chatbot Acceptance Factors

As a first practical recommendation, general precaution is advised for companies seeking to deploy a recruiting chatbot as most included recruiting departments (366 or 88.4 percent of the 425 asked recruiters) have no chatbot installed in their processes yet and thus need to be carefully introduced and accustomed to the technology. The newness of sophisticated dialogue system solutions in this setting needs to be considered and the recruiters whose processes will be affected by the technology need to be scouted accordingly. More specifically, this study examined the variables of the HCCAM as theoretical proposition for acceptance factor analysis. Validating many other acceptance studies, the main variables of TAM, perceived usefulness and perceived ease of use, significantly influence the behavioral intention to use the observed technology. Derived from the items of perceived ease of use, the queried recruiters request an easy, clear and understandable interaction with the chatbot for the applicants in order to accept this technology. This is in line with the findings by aiaibot (2021), who saw that chatbot users highly value the easiness, practicability, effectiveness and helpfulness of the system ranking easiness as highest demand. Managers need to carefully plan and realize a chatbot project that helps their recruiters to thrive in their jobs by designing the chatbot to enhance their performance, productivity, and effectiveness via precise process step automation. All procedures need to be sensibly analyzed to find the best approaches. This study gives hints regarding possible points of interest: As most fitting use cases for recruiting chatbot deployment from the recruiters' point of view, the five scenarios (1) query of missing applicant data from the candidate, (2) partial applicant guidance through application process, (3) clarification of post-submission application-related questions of the candidate, (4) clarification of application-related questions of the candidate, and (5) supporting the candidate in his search for job offers emerged. More than half of the participants stated that they currently utilize an ATS system for data management indicating that the query of missing applicant information of a chatbot in this environment represents a relevant facilitation of work for them. Managers are encouraged to consider this circumstance when contemplating chatbot introduction in the department. Chatbot solutions are diverse and allow for recruiter support prior, during and also after application submission thus offering different deployment points for first trial cases. In these scenarios, a chatbot can help to collect information, navigate the applicant combining the two lines of questioning (1) technically or (2) content-wise and also act as a single point of contact for FAQ scenarios. The participants of the quantitative study at hand also suggested dialogues regarding sensitive topics such as salary expectations or contents of the work contract as fitting scenarios for chatbot communication so that companies might think about offering this line of communication automation as well.

The following most important drivers and barriers for recruiting chatbot utilization have been compiled in this study: Permanent, ubiquitous accessibility is most vital followed by faster recruiting process completion thus efficiency enhancement, simplification of data management, and standardization of data quality as essential drivers seen by the study participants. This goes well together with the most favored use case of applicant data generation. Hence, the chatbot solution needs to perform in a robust and standardized fashion allowing for non-stop accessibility. Furthermore, it must be of true value for the recruiters bringing efficiency advantages compared to the traditional recruiting process step in terms of faster task accomplishment. Data quality standardization is apparently seen as an advantage of chatbots over human recruiters by the participants and at the same time as a requirement upon development regarding constant high-quality task execution. Technically, a database has to be integrated with a well running interface towards the dialogue system for peak data management performance. Another important driver is the low inhibition threshold for candidates to ask questions. The latter is in line with other research finding that automated interfaces encourage candidates to ask questions (Nikhila et al. (2019) in Nawaz and Gomes (2019)). It also matches the participant suggestion to offer information about the salary expectations or the contract. Astonishingly, better output quality than task completion by humans is seen as the least relevant driver for utilization. However, this is congruent with the relatively low agreement level regarding recruiting chatbot anxiety as well as ethical implications showing that recruiters generally do not fear recruiting chatbots and do not think that they will substitute their human labor force. Major barriers to chatbot utilization are a lack of understanding complex contexts, a potential deterioration of the relationship between recruiter and candidate from the recruiters' perspective and data security issues. These findings show that the participants mostly have technological concerns regarding automated dialogue systems and the handling of complex, individual matters indicating a general suitability for standard issues, which is reflected in the preferred use cases as well. It also mirrors the findings by aiaibot (2021), who identified comprehension problems as second worst experience when interacting with a chatbot following bad answer quality and shows that the recruiters can empathize with the applicants. Companies need to analyze their processes and choose those containing – ideally redundant – steps that are transferrable into dialogue strings. The data security issue can be converted into a prerequisite for chatbot implementation: A secure environment in the form of the interface and database needs to be ensured to avoid any leakages of the candidates' personal information. Another issue is seen with the social aspect of personal contact as recruiters fear losing the individual relation to the applicants even if it does not represent a significant acceptance determinant. Swapna and Arpana (2021) offer a counterargument by saying that implementing recruiting chatbots in early stages of the recruiting process saves the recruiters valuable time they would normally spend on narrowing down the candidate pool. This time can instead be spent on focused, personal applicant relationship building later on in the recruiting process. Hence, the recruiters need to be sensitized regarding the efficiency advantages such technology leverages instead of leaving them to hypothetical social apprehensions. As this social aspect is no significant factor in the HCCAM, it is no central concern regarding chatbot implementation and should be treated accordingly. The least important barrier for the participants based on the mean value is a fear of changes in the business and organizational structure for the worse rendering this concern negligible in the context of dialogue automation within the recruiting process. Contra-intuitively, the recruiters' resistance to change established processes is also ranked low denoting a low relevancy while the overall mean values for the items of inertia ($\mu > 3.5$) indicate that a general level of inertia exists among recruiters and a significant negative relationship with the perceived usefulness of recruiting chatbots was identified.

While the recruiters self-attribute high levels of knowledge concerning technological system's functions and perceived easiness to learn how to handle those, this self-assessment of their technological understanding could not be validated as significant acceptance determinant. Hence, companies must not rely on this potential trait during implementation projects. The same attentiveness is required for recruiters striking as technology affine regarding their enjoyment to inform themselves about new systems or try them for example – their level of acceptance is not significantly influenced by this affinity as well as by their age segment. Hence, recruiters exhibiting traits such as innovation affinity or understanding must not be expected to automatically accept recruiting chatbots in their processes. They might still need to be shown the advantages of the system to appreciate such support in their processes and embrace it without preponderant reservations. Their individual level of personal innovativeness however, expressed via the speed of system trial compared to peers or the willingness to try out such technological advancements in general, is significantly positively related to their intention to utilize a chatbot. A company's management shall assess this characteristic amongst their recruiters to estimate the level of acceptance and draft a concept for high-acceptance chatbot implementation. Training measures and information material as well as the whole approach towards chatbot introduction and advantage communication should be adjusted to the level of innovativeness the recruiters in the companies possess. A weak significance is associated with the recruiters' previous chatbot experience, which in turn is significantly positively related to company size. Hence, more accustomed recruiters seem to get along better with automated dialogue systems that are introduced to their business processes. However, as this significance diminished when disregarding the other insignificant control variables, it needs to be regarded with caution. As a general rule, managers shall adapt their approach to the size of their company and the potentially prevailing differences in these respects.

As a conclusion, managers responsible for new technology implementation need to pay attention especially to the perceived usefulness of the recruiting chatbot. Furthermore, they need to choose the right use cases. The recruiters need to be supported differently according to their level of personal innovativeness as to increase their level of acceptance for the newly introduced technology. It is vital to let them unfold their advantages by ensuring technical flawlessness since all relevant drivers and barriers assessed as relevant regard technical matters of the system, for example concerning its availability, efficiency, performance regarding complex matters and data security.

7.2.2.2 Assessing and Preventing Job-Related Automation Concerns

In this study, twelve potential job-related automation concerns have been compiled, ten of which significantly influence either the perceived usefulness, the perceived ease of use or the behavioral intention to work with a recruiting chatbot directly. The two newly introduced variables of perceived system transparency and inertia both have a significant effect: While the level of inertia significantly negatively impacts the perceived usefulness, rising levels of perceived system transparency positively influence both the perceived ease of use and the behavioral intention to utilize the chatbot. As a consequence, managers need to pay attention to the levels of inertia their recruiting employees' potentially bear while implementing and communicating the technology as transparently as possible. Managers need to be cautious regarding the potentially predominating inertia amongst their employees as it does not show direct effects on the behavioral intention to work with a recruiting chatbot, but it influences their perceptions on the perceived usefulness of the system. Cross tabulations show that aspects of inertia are strongly associated with the size of the company based on the number of employees, age, and the country the recruiter works in. These differences need to be considered and addressed since it is taking a direct negative effect on the level of acceptance of recruiters.

As expected, the perceived transparency of a recruiting chatbot plays an important role both impacting the perceived ease of use and the behavioral intention to utilize such a system. This finding is in line with the theoretical information on its vital part in the acceptance process – especially for complex automated systems involving algorithms for example, transparency is required (J. D. Lee & See, 2004; Ochmann & Laumer, 2019). Managers need to make sure that the system and its workings are understood by the recruiting employees and that no “black box” perception arises in the HR department. The perceived system transparency is significantly related to the age, gender and most remarkably, the location of the participant. While the mean for perceived system transparency is $\mu = 4.36$ in DE; it is $\mu = 4.27$ in AT and $\mu = 4.53$ in CH. Thus, recruiting chatbots seem to be most transparent to Swiss recruiters followed by German ones while Austrian recruiters ascribe least transparency to the technology in this study. As a consequence, HR departments in Austria and in Germany need more information on the functionality of automated dialogue system for the recruiting process than in Swiss companies. The participants’ origin is also associated with their level of chatbot experience: While the Austrian recruiters generally have at least heard about recruiting chatbots ($\mu = 1.93$), the German ($\mu = 2.07$) and Swiss ($\mu = 2.08$) ones have also partially used a chatbot before. This finding might be utilized to adapt the amount and depth of explanatory information regarding the technology while implementing it in the company. Astonishingly, the result demonstrability is found to be no significant acceptance factor. Consequently, managers have to make sure that transparency in the form of an individual, internal understanding of the chatbot’s inner working, which seems to be important for the recruiters, is granted rather than conveying explainable knowledge. As no importance is attached to the explainability towards other people, the level of required transparency regarding the technical mode of operation seems to be moderate. Hence, managers seeking to maximize the level of recruiting chatbot acceptance should be careful to not overwhelm their employees with systemic details.

Social norms represent the main recruiting chatbot acceptance factor. The attitude of peers as well as the support behavior of both the organization in general and senior management plays a vital role for the perceived usefulness as well as their behavioral intention to work with the chatbot. Naturally, they want to feel safe by knowing that the company will assist them during chatbot implementation and utilization. With low levels of support, the system is perceived to be significantly less useful as the lack in maintenance infrastructure causes potential additional efforts and stress rather than the desired facilitation and increase in efficiency. Problems that may occur cannot be solved satisfactorily without organizational support. Companies need to provide productive care structures to push the level of acceptance at their end. At the same time, the recruiters' personal environment, which lays outside the sphere of influence the management has, impacts their view on such technology's usefulness. This aspect cannot be estimated as it is an unknown variable to the company so that managers have to expect the worst, anticipate resistance their recruiters bring along from their peers and consider the possibly negative mentality in their recruiting chatbot implementation strategy.

Two other important job-related automation concern influencers of perceived usefulness are the perceived job relevance and output quality: The more value the recruiters ascribe to the chatbot in terms of importance, pertinence, performance quality and excellency, the more useful the technology is for them. With mean values of $\mu > 3.50$, the participants generally see a relevance for the tasks of their jobs and associate a high output quality with the system. This suggests that an overall apprehension of the advantages automated dialogue systems can bring exists amongst recruiters. This mindset has to be reinforced and nurtured by their supervisors to foster acceptance for the technology.

Recruiting chatbot self-efficacy strongly and significantly influences its perceived ease of use. Companies enabling their HR employees to work with the system motivate them to plan on and actually utilize it. Showing a mean value of $\mu = 4.93$, the participants generally state that they would be cognitively able to use a recruiting chatbot for interviewing candidates either by themselves, with an enclosed manual, with an example or based on past experiences with a similar system. This is a positive sign and motivator for companies to implement a chatbot for this use case and to provide sufficient instruction material.

The environmental factors (ELSI) have to be considered as well since the ethical and legal implications significantly influence the perceived ease of use of recruiting chatbots. While the social aspect regarding a supposed fear of contact loss towards the candidates has proven to be insignificant, the two others indeed affect the acceptance of recruiting chatbots. Ascribing higher productivity and quality levels to recruiting chatbots and fearing that they might be a substitution for the own job is significantly positively related to the perceived usefulness. This is a comprehensible train of thought: Recruiters who expect or, in case of fearing substitution by the system, worry that the system to perform on higher efficiency levels than themselves will find it useful for the task. Companies need to take preventive actions to minimize any recruiter-sided anxiety of substitution by automated dialogue systems and at the same time foster the perceptions of high productivity and quality outcome by the system to increase the level of acceptance for the technology. This aspect leads to the variable of recruiting chatbot anxiety, which has also been found to be a significant acceptance or rather rejection factor because of its negative relation with perceived ease of use. Knowing that higher levels of anxiety, expressed through nervousness, an uneasy or an uncomfortable feeling towards the chatbot, reduce the level of perceived ease of use of the system, companies have to raise awareness for new and innovative technologies and provide a pleasant, relaxing and supportive system acquaintance atmosphere. After dispelling the potentially negative preconceptions, specific manuals and instructions regarding the particular chatbot can be distributed to show its handling simplicity.

The potential loss of contact towards the candidates, the perceptions of external control regarding the control over the chatbot and the resources for that as well as the result demonstrability of the system are no significant acceptance factors within the HCCAM. While this does not automatically render these aspects irrelevant for recruiting chatbot implementation projects, it suggests that these aspects do not need to be the central parts of the venture and not the managers' first priority.

7.3 Conclusion

The objectives of this study are the identification of imperative acceptance factors for recruiters regarding chatbots as exemplary automation technology with special focus on job-related automation concerns and especially the two concepts of inertia and perceived system transparency. The HCCAM was validated as a well-founded, significant model explaining recruiter-sided chatbot acceptance. With $R^2 = 0.567$, the variables of HCCAM are able to explain almost 57 percent of the variance in the behavioral intention to utilize a recruiting chatbot with 16 supported hypotheses out of 21 developed ones (the influences of perceptions of external control, social norms, result demonstrability, inertia on the behavioral intention to use, and transition efforts are not significant). The hypotheses for both newly introduced variables perceived system transparency and inertia are supported suggesting that they indeed have a relevant effect and thus enrich the TAM-based HRCAM model. While system transparency significantly positively influences the perceived ease of use and the behavioral intention to work with a recruiting chatbot, inertia significantly negatively impacts the perceived usefulness of such a system. Strongest impacts have been found for subjective norm and perceived usefulness so that these aspects are most relevant for recruiting chatbot acceptance. Overall, all potential job-related automation concerns[51] were found to significantly directly or indirectly influence the behavioral intention to use a recruiting chatbot except for perceptions of external control and social implications.

Apart from the validation of the HCCAM model, several recruiting chatbot use cases alongside interviewing were identified, relevant interviewing aspects and skills uncovered, that need to be supported or reinforced by automation technology, and utilization drivers and barriers for such a technology classified. The participating recruiters found chatbots to be useful for missing data acquisition, guidance through the application process, FAQs for application-related and post-submission questions as well as for job search scenarios. Within the interviewing process, chatbots are expected to support efficient candidate handling as well as to provide help in the assessment hard and soft skills. They are demanded to reinforce the recruiters' skills of expert knowledge and proficiency execution, ethical practice and diversity management as well as cultural awareness. Utilization drivers are the permanent accessibility, faster recruiting process step conduct, facilitation of data management, and standardization of data quality the technology can offer. Most relevant utilization barriers are an expected lack of understanding complex contexts, a potential deterioration of candidate-recruiter relations, and data security issues. However, the underlying social implication of

[51] The job-related automation concerns regard perceived system transparency, inertia – influenced by switching efforts –, recruiting chatbot anxiety, ethical/legal/social implications, subjective norm, job relevance, output quality, recruiting chatbot self-efficacy, and perceptions of external control.

contact loss fear from the recruiter to the applicants was not found to be significant in this study.

Overall, chatbots were found to be perceived as advantageous automated communication alternatives in the context of recruiting and specifically for first candidate interviews in case the yielded acceptance criteria are considered during implementation and while deploying the technology in the work processes. Thus, the idea of a chatbot as a collaborator as theoretically taken over from the HRCAM research of Bröhl et al. (2019) and adapted to digital process step conduct has been validated and proven feasible for the research at hand.

7.4 Limitations of the Study

The research at hand followed a rigorous and thorough study conduct. Nevertheless, there are certain limitations that need to be addressed. First of all, this study differs from regular acceptance research in so far as it regards technology usage but not from an end-user perspective: The recruiters are asked about their implementation usage (e.g., utilization of the chatbot's outcome) and opinion instead of actual end-user behavior in the form of prospective applicants that would normally be considered. Instead, the opinion of recruiters currently conducting physical in-person interviews thus evaluating the concept of chatbots for first candidate interviews from a perspective of potential inexperience and unawareness is considered. This is reflected by the demographic structure of the sample: Only one respondent works in a company conducting chatbot-based candidate interviews while almost 65 percent of the recruiters have physical in-person interviews as modus operandi for interviewing. Hence, the study sample does not include many recruiters with first-hand experience of chatbot utilization for candidate interviews. While this prevents the inclusion of the utilization aspect, which is generally regarded in TAM-related research, such a perspective allows for acceptance analyses in the pre-market maturity stage of the technology. Recruiters can participate regardless whether they used a chatbot prior to questionnaire participation or not; the questions do not rely on past experiences of the respondents. Surveys represent a common way of acceptance factor identification for subjects with only little coverage by previous research (e.g., Quiring, 2006). In such circumstances, the so-called newness problem occurring for innovations that have not been utilized prior to research may occur (cf. Følstad & Brandtzæg, 2017 for details), which might pose a problem for the data analysis. According to Wilde, Hess, and Hilbers (2008) however, distortions because of topic novelty occur neither regarding the internal validity nor the theoretical foundation (i.e., if a participant's understanding of the research subject differs from the definition considered for the study in any respect). Against this background, the standard item sets as commonly utilized within acceptance studies for actual users of the system needed to be adapted not only to the technology of chatbots but also to the recruiters' point of view. All changes have been substantiated by suitable literature and adaptation practices. The particular perspective change from the recruiters' to the applicants' perspective was only necessary for the construct of perceived ease of use and the respective three items.

The scope of this research is limited to the context of German language-based recruiting and the technology of text-based conversational agents, which represents a narrow thematic focus. While job-related characteristics are being part of the study, market forces as another socio-economic impact (B. Pérez, 2010) may have an influence on the success of chatbot implementation into the recruiting process as well but they are no part of the examination, which only considers Germany and the neighboring, similar German-speaking rest of the DACH region. Furthermore, the study at hand dispenses with the examination of psychometric measures such as personality traits. However, this feature-based approach enables a high level of objectivity as suggested by B. Pérez (2010).

Concerning the use case, the conduct of first (hard skill) candidate interviews was chosen as an example for this study because of its realistic content easily conceivable, the high level of involvement it implicates from the recruiters, the component of voluntariness in deployment choice for each conducted interview, and its appropriateness for dialogue depiction thus high level of automatability. It represents one of the core tasks of the recruiting process and by that bears potential job-related automation concern tendencies because it holds the potential for full automation of previously recruiter-led task conduct. Unexpectedly, the use case was not ranked among the five most relevant ones by the participating recruiters with no significant difference between the ones accustomed to chatbots and the ones without previous chatbot experience. Sophisticated chatbot solutions for automated candidate interviewing are not yet common on the German market (cf. section 2.4.5.3), which might be a possible reason for this. As a result, there may be a lack of imaginative power the recruiters have concerning a chatbot-based interview conduct contrary to the assumption of this study because they do not personally know any solutions incorporating an interviewing module or they did dot encounter chatbots before at all.

Other limitations are related to the methodology such as generalizability issues and the neglect of longitudinal effects. Focusing on the exemplary field of interviewing within the recruiting process, the area of research is set narrowly and the results cannot be generalized for use cases outside the recruiting context. Regarding this recruiter-sided examination, the quantitative survey yielded 425 data sets. This sample size is arguably sufficient to ensure generalizability but it is questionable whether it is exhaustive enough concerning generalizability to recruiting external use cases. Especially the generalization of control variables needs to be treated with caution (De Battisti & Siletti, 2019). However, regarding the resemblance of the main study findings with the pilot study results permits the assumption that at least tentative generalizability has been achieved for the context at hand. Since this study is designed as a cross-sectional examination, longitudinal effects are left out of scope. Further research could implement a longitudinal design to determine the replicability and generalizability of the one at hand (e.g., Liew, Tan, & Ismail, 2017).

Regarding the questionnaire, the utilization of reversely-coded items might be problematic: According to Suárez Álvarez et al. (2018), such items may cause reliability as well as internal consistency flaws because of inconsistent response behavior and, if not developed carefully, interpretation problems because phrases with opposite polarity do not necessarily mean the same as the opposite of the initial phrase (e.g., “I am not a good person” vs. “I am a bad person”). In the study at hand, these concerns are negligible as no reliability and internal consistency problems were detected in the analysis. All items were taken from the original questionnaires. The necessary polarization changes were conducted with utmost caution. In the sampling phase, a systematic error might have occurred resulting from non-sampling factors lying in the nature of the study’s design and depending on the correctness of access panel participant recruitment execution. During the completion phase of the survey, there might have been a self-selection bias where recruiters feeling strongly about the research subject at hand might have been considered disproportionately in comparison to those rather feeling indifferent about it. The participant acquisition strategy via an access panel offering the participants a compensation and the fact that the participating recruiters ascribed high levels of technological understanding and personal innovativeness to themselves make this bias a substantial limitation of this study. As a result, a nonresponse bias in the form of a statistical difference between a survey including the cleansed data set and one including those who failed to respond might have occurred here. Both an extremity and an acquiescence bias could not be detected in the study during the assessment of the data while social desirability bias might have played a role or at least cannot be ruled out in this study.

7.5 Outlook on Further Research

This study serves as a first research contribution regarding instantaneous acceptance factors for chatbots in the field of HR and the job-related automation concerns of recruiters that need to be considered when implementing such an automated dialogue system into the recruiting process. A longitudinal observation could be a meaningful expansion and yield a deeper understanding of the acceptance structure amongst recruiters and its potential variations overtime. Future research may also adapt the HCCAM founded in this investigation to other contexts and industries and include other aspects of conversational agents in the form of voice-based assistants in order to enrich and broaden the findings. Especially the scenario for system implementation – within the area of recruiting but regarding another scenario or regarding a different department of a company altogether – should be varied to other domains as there might be dissimilarities regarding the openness towards them and thus to the perceived job-related automation concerns relevant for acceptance and other acceptance factors regarding chatbots. In a future research project, the results of this study may be enriched with survey data examining the candidates' point of view to validate the assumptions the recruiters had about their candidates who potentially utilize the recruiting chatbot within their processes.

Over time, chatbots might diffuse into various processes and become a standard tool generating high levels of practical experience within companies. This allows for a repetition of the study measuring actual chatbot implementation performance. Such a study could profit from a measurement model as introduced by Son et al. (2012), which might be an insightful option as it also regards user satisfaction and perceived performance within the business process it has been implemented in. Aspects such as chatbot experience, the relevancy of which was not clear-cut in this study, then need to be closely researched on as a potentially significant influencer in different and future contexts. Other job-related automation concerns could be considered to yield an even more exhaustive overview. Furthermore, the implications of other demographic variables could be examined more closely to discover relevant gender-, skill-, company-, or country-related differences in (recruiting) chatbot acceptance for example. Overall, this study laid a profound foundation for acceptance research on chatbots as automation technology, which can be adapted to other contexts, expanded to include further constructs, and changed for example concerning the examined point of view.

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APPENDICES

Appendix A: Examination of the Chatbot Status in the 100 largest companies in Germany

Structured search via (1) Facebook Messenger, (2) the companies' websites and (3) a search engine search via Google based on the keywords "chatbot and [company name] based on the 100 largest DE companies in 2018

	Company (*name change)	**Revenue** in EUR Bn.	**Chatbot**	**HR**	**Recruiting**	**Active**	**NLP** (*assumption)	**Platform/ Builder**	**Founding Date**	**Features**
1	Volkswagen	230.7	●	○	○	○	○*	Inbenta	2017, March	Instructions, Avatar
2	Daimler	164.3	●	○	○	●	● (IBM Watson)	adesso; IBM	2018, April	FAQ, Assistance, AR
3	BMW	98.7	●	○	○	●	○*	Oracle	2017, May	FAQ, Entertainment
4	Schwarz Dienst-leistungen	96.9	○	○	○	○	N/A	N/A	N/A	N/A
5	Siemens	83.0	●	●	○	●	● (IBM Watson)	Siemens; IBM	2017, October	Employee Management, Administration, FAQ, Counselling
6	Robert Bosch	78.1	●	○	○	●	●	assono, CAMELOT	2018, April	Knowledge Management, i.e., Tool Suggestions
7	Deutsche Telekom	74.9	●	●	●	●	●	N/A	2018, January	FAQ, Assistance Job Search
8	Lidl Stiftung	74.6	●	○	○	○	●	Aspect-Software	2018, January	Wine Counselling
9	Uniper*	72.2	○	○	○	○	N/A	N/A	N/A	N/A
10	BASF	64.5	●	○	○	○	○*	N/A	2000, January	Investor Assistance
11	Deutsche Post	60.4	●	○	○	●	●	Artificial Solutions (Teneo)	2013, Decembe r	Knowledge Management, Customer Service
12	Audi	60.1	●	○	○	○	○*	Mike Thurman	2017	Customer Service
13	Rewe Group	57.7	●	○	○	●	●*	N/A	2018	Voice-based Assistance, Google Assistant Skill
14	Edeka Zentrale	51.9	●	○	○	○	○*	N/A	2016, Novemb er	Recipes
15	Aldi Süd	49.0	○	○	○	○	N/A	N/A	N/A	N/A
16	RWE	44.6	○	○	○	○	N/A	N/A	N/A	N/A
17	Continental	44.0	●	●	●	○	N/A	Feedyou	2018	Recruit Trainees for a special program
18	Innogy	43.1	●	○	○	●	●	N/A	N/A	Customer Service
19	Deutsche Bahn	42.7	○	○	○	○	N/A	N/A	N/A	N/A

	Company (*name change)	Revenue in EUR Bn.	Chatbot	HR	Recruiting	Active	NLP (*assumption)	Platform/ Builder	Founding Date	Features
20	Thyssen-Krupp	41.4	●	●	●	○	●	Beyond Conventions Pitch	2018, February	Job Offerings, Information Collection, Screening Questions, Ranking, Data Management/ Referral, Employer Branding
21	E.ON*	39.0	●	○	○	?	○*	N/A	2017, April	Assistance during moving, Account Management
22	Metro	37.1	●	○	○	○	●	IamBot	2017, June	Product Recognition, Photo chat, e-Commerce
23	ZF Friedrichs-hafen	36.4	●	○	○	●	○*	N/A	N/A	FAQ
24	Deutsche Lufthansa	35.6	●	○	○	●	● (Wit.ai)	Wit.ai	2016, Novemb er	Avatar, Flight Price Search and Information
25	Bayer	35.0	●	●	●	●	○*	Microsoft	N/A	FAQ
26	Fresenius	33.9	○	○	○	○	N/A	N/A	N/A	N/A
27	Aldi Nord	33.0	○	○	○	○	N/A	N/A	N/A	N/A
28	Metro Cash & Carry	29.9	○	○	○	○	N/A	N/A	N/A	N/A
29	BP Europa	25.3	○	○	○	○	N/A	N/A	N/A	N/A
30	Phoenix Pharma	24.9	○	○	○	○	N/A	N/A	N/A	N/A
31	Daimler Financial	23.8	●	○	○	○	● (Emotional Intelligenc e)	Daimler Financial Services	2018, February	Avatar, customer service
32	Porsche	23.5	●	●	●	●	○*	Porsche	2017	Job Search
33	SAP	23.5	●	○	○	○	●	SAP, Recast.AI, SAP Leonardo Machine Learning	2018, June	Bot Platform, Bot Building
34	Hochtief	22.6	○	○	○	○	N/A	N/A	N/A	N/A
35	Ford-Werke	22.5	●	○	○	○	○*	Verity Response (Natvive Minds)	2001, July	FAQ
36	Ceconomy (ehem. Media Markt Saturn)	22.2	○	○	○	○	N/A	N/A	N/A	N/A
37	EnBW	21.9	●	●	●	●	○*	Yello	2017, April	Application Process
38	Heraeus	21.8	○	○	○	○	N/A	N/A	N/A	N/A
39	Kaufland	21.6	○	○	○	○	N/A	N/A	N/A	N/A
40	Telekom Deutschland	21.6	●	○	○	○	●	Telekom Deutschland	2017, April	Counselling

	Company (*name change)	**Revenue** in EUR Bn.	**Chatbot**	**HR**	**Recruiting**	**Active**	**NLP** (*assumption)	**Platform/ Builder**	**Founding Date**	**Features**
41	Adidas	21.2	●	○	○	●	●	Adidas; Salesforce	N/A	Customer Service
42	McKesson Europe (ehem. Celesio)	20.7	X	○	○	○	N/A	N/A	N/A	N/A
43	Henkel	20.0	●	○	○	●	○*	Codeflügel	N/A	FAQ
44	Shell Deutschland	19.2	●	○	○	●	●		2017, March	FAQ, Technical Support
45	TUI	18.5	●	○	○	●	○*	Thomson; TUI	2017	FAQ
46	Tennet	18.3	○	○	○	○	N/A	N/A	N/A	N/A
47	Boehringer Ingelheim	18.1	○	○	○	○	●	Cohn & Wolfe	2017	FAQ, Patient Education (Asthma)
48	Fresenius Medical Care	17.8	○	○	○	○	N/A	N/A	N/A	N/A
49	Heidelberg-Cement	17.3	○	○	○	○	N/A	N/A	N/A	N/A
50	Bertelsmann	17.2	●	○	○	○	●	Arvato	N/A	Bot Platform, Bot Building, Customer Relationship Management
51	Linde	17.1	○	○	○	○	N/A	N/A	N/A	N/A
52	Adam Opel	17.0	●	○	○	●	○*	MRM/McCann	2017, February	Scheduling
53	Schenker	16.4	●	○	○	●	○*	DB Schenker	2017, July	FAQ
54	Baywa	16.1	○	○	○	○	N/A	N/A	N/A	N/A
55	Merck	15.3	●	●	○	●	○*	Merck	N/A	FAQ, Meeting Room Scheduling, Voice-based (Alexa)
56	Lufthansa Air Plus Servicekarten	15.3	○	○	○	○	N/A	N/A	N/A	N/A
57	Evonik Industries	14.4	●	●	●	●	○*	Evonik	N/A	FAQ
58	MAN	14.3	○	○	○	○	N/A	N/A	N/A	N/A
59	Covestro	14.1	○	○	○	○	N/A	N/A	N/A	N/A
60	Schaeffler	14.0	○	○	○	○	N/A	N/A	N/A	N/A
61	BSH Hausgeräte	13.8	○	○	○	○	N/A	N/A	N/A	N/A
62	Otto	13.6	●	○	○	●	○	novoMind	2012, December	FAQ, Customer Service
63	Marquard & Bahls	13.5	○	○	○	○	N/A	N/A	N/A	N/A
64	Netto	13.1	○	○	○	○	N/A	N/A	N/A	N/A
65	Amprion	13.0	●	○	○	○	○*	BTC Business Technology Consulting AG	2018, June	Customer Service, Account Management

	Company (*name change)	**Revenue** in EUR Bn.	**Chatbot**	**HR**	**Recruiting**	**Active**	**NLP** (*assumption)	**Platform/ Builder**	**Founding Date**	**Features**
66	Vattenfall	12.9	○	○	○	○	N/A	N/A	N/A	N/A
67	Mahle	12.8	○	○	○	○	N/A	N/A	N/A	N/A
68	Lekkerland	12.8	○	○	○	○	N/A	N/A	N/A	N/A
69	Adolf Würth	12.7	○	○	○	○	N/A	N/A	N/A	N/A
70	Penny-Markt	11.9	○	○	○	○	N/A	N/A	N/A	N/A
71	Brenntag	11.7	○	○	○	○	N/A	N/A	N/A	N/A
72	Airbus Operations	11.6	●	●	○	●	○*	Airbus, LivingActor	2005	Avatar, Instructions, FAQ
73	Dr. August Oetker	11.6	●	○	○	●	●	Cognigy	2017, November	Product Search
74	Droege	11.1	●	●	●	●	●	Trenkwalder, LINKS DER ISAR	2017, March	Recruiting (Job Offerings, Information Collection, Application)
75	Aurubis	11.0	○	○	○	○	N/A	N/A	N/A	N/A
76	Total	10.3	○	○	○	○	N/A	N/A	N/A	N/A
77	Vodafone Kabel Deutschland	10.3	●	○	○	●	●	IBM Watson	2018, July	FAQ, Customer Service
78	dm-drogerie markt	10.3	●	○	○	○	●	allcop	2017	Navigation through ordering process
79	50Hertz Transmission	10.1	○	○	○	○	N/A	N/A	N/A	N/A
80	maxingvest	10.1	○	○	○	○	N/A	N/A	N/A	N/A
81	MAN Truck & Bus	10.0	○	○	○	○	N/A	N/A	N/A	N/A
82	Hapag-Lloyd	10.0	○	○	○	○	N/A	N/A	N/A	N/A
83	Freudenberg & Co.	9.3	○	○	○	○	N/A	N/A	N/A	N/A
84	Lanxess	9.1	○	○	○	○	N/A	N/A	N/A	N/A
85	Salzgitter	9.0	○	○	○	○	N/A	N/A	N/A	N/A
86	DB Regio	8.7	○	○	○	○	N/A	N/A	N/A	N/A
87	Sandoz International	8.6	●	○	○	○	●	MedMee	2017, April	Instructions, FAQ
88	Edeka	8.4	●	○	○	○	○*	N/A	2016, November	Recipes
89	EWE	8.3	○	○	○	○	N/A	N/A	N/A	N/A
90	Dirk Rossmann	7.8	○	○	○	○	N/A	N/A	N/A	N/A
91	Kion Group	7.7	○	○	○	○	N/A	N/A	N/A	N/A
92	Globus Handelshof Gruppe	7.5	○	○	○	○	N/A	N/A	N/A	N/A
93	Helm	7.4	○	○	○	○	N/A	N/A	N/A	N/A

	Company (*name change)	Revenue in EUR Bn.	Chatbot	HR	Recruiting	Active	NLP (*assumption)	Platform/ Builder	Founding Date	Features
94	Obi	7.4	○	○	○	○	N/A	N/A	N/A	N/A
95	Remondis	7.3	○	○	○	○	N/A	N/A	N/A	N/A
96	Telefónica Deutschland	7.3	●	○	○	●	●	Telefónica Deutschland	2018	FAQ
97	Real-SB Warenhaus	7.2	●	○	○	○	●	IamBot	2017, June	Product Recognition, Photo chat, e-Commerce
98	Stadtwerke München	7.2	○	○	○	○	N/A	N/A	N/A	N/A
99	VNG-Verbundsnetz Gas	7.2	○	○	○	○	N/A	N/A	N/A	N/A
100	DKV Mobility-Services Group	7.2	●	○	○	○	○*	DKV Seguros, Artificial Solutions	2003	FAQ, Instructions

Source: Boerse (2018) for the company ranking and revenues.

Appendix B: Sources Chatbot Information of 100 largest companies in Germany

	Company (*change of name)	**Source**
1	Volkswagen	https://www.chatbots.org/chat_bot/volkswagen_chatbot/; https://www.chatbotguide.org/volkswagen-bot/; Volky
2	Daimler	https://www.adesso.de/de/news/presse/adesso-realisiert-chatbot-plattform-ask-mercedes.jsp; https://www.ibm.com/de-de/blogs/think/2017/11/30/ask-mercedes-chatbot-statt-betriebsanleitung/
3	BMW	https://www.autoevolution.com/news/bmw-introduces-whatsapp-chatbot-for-dtm-activity-and-results-it-s-easy-to-use-117424.html; https://chatbottle.co/bots/bmw-skippr-for-messenger
5	Siemens	https://www.bigdata-insider.de/digitalisierung-schlau-umgesetzt-a-654757/
6	Robert Bosch	https://www.assono.de/blog/chatbots-machen-den-kundenservice-besser-und-preiswerter; https://www.industry-of-things.de/chatbot-hilft-bei-der-stammdaten-pflege-a-704961/
7	Deutsche Telekom	https://www.telekom.com/de/blog/karriere/karriere/katy-unser-karriere-chatbot-ist-geboren--512376
8	Lidl Stiftung	https://www.lidl.co.uk/en/How-to-use-Margot-the-Winebot-11782.htm; https://chatbotsmagazine.com/how-we-built-the-wine-bot-margot-for-lidl-b54f42cda4dd
10	BASF	https://www.chatbots.org/virtual_assistant/sophia/
11	Deutsche Post	https://www.artificial-solutions.com/blog/artificial-solutions-delivers-intelligent-virtual-assistant-to-deutsche-post; https://www.chatbots.org/virtual_assistant/jana/
12	Audi	http://www.mikethurman.io/audi-chatbot/
13	Rewe Group	https://www.rewe.de/deine-kueche/voice-assistent-caro/
14	Edeka Zentrale	http://www.edeka-verbund.de/Unternehmen/de/presse/pressekontakte_2/presse_2/presse_detail_gruppe_961488.jsp
17	Continental	https://feedyou.agency/en/portfolio/continental/
18	Innogy	https://www.eprimo.de/
20	ThyssenKrupp	https://www.beyondconventions.de/recruiting-chatbot-challenge/; https://botfriends.de/1-chatbots-in-hr-how-set-up-an-application-process-in-a-chatbot
21	E.ON*	https://article.wn.com/view/2017/04/06/Meet_Sam_EOns_new_chatbot/
22	Metro	https://archiv.metrogroup.de/pressemitteilungen/2017/06/16/delivery-robot-or-the-internet-of-things
23	ZF Friedrichshafen	https://www.zf.com/corporate/de_de/homepage/homepage.html
24	Deutsche Lufthansa	https://www.lufthansagroup.com/fileadmin/data/artikel/2016/q4/20161109_PM_Mildred_DE.pdf
25	Bayer	https://www.microsoft.com/germany/techwiese/know-how/case-study-bayer-ein-chatbot-zur-unterstuetzung-der-personalabteilung.aspx
31	Daimler Financial	https://www.mercedes-benz.com/de/mercedes-benz/messen/mwc/highlights/digital-human-sarah/; https://www.heise.de/newsticker/meldung/Mercedes-Avatar-Laecheln-und-Grummeln-mit-Sarah-3981752.html
32	Porsche	https://www.hr-excellence-awards.de/gewinner-2017/
33	SAP	https://news.sap.com/2018/06/sapphire-now-intelligent-enterprise-chatbots/
35	Ford-Werke	https://www.chatbots.org/virtual_agent/kate_ford/
37	EnBW	https://www2.yello.de/unternehmen/neues-von-yello/presse/pressemitteilungen/5861/yello-chatbot-eve-feiert-comeback
40	Telekom Deutschland	https://www.telekom.com/de/konzern/digitale-verantwortung/digitale-verantwortung-kuenstliche-intelligenz/kuenstliche-intelligenz/artikel-mit-telekom-bezug-490598
41	Adidas	https://www.salesforce.com/video/1758484/
43	Henkel	https://codefluegel.com/de/reference/persil-germany/
44	Shell Deutschland	https://www.shell.com/business-customers/lubricants-for-business/news-and-media-releases/2018/shell-launches-ai-chatbot.html
45	TUI	https://chatbot.neocities.org/; https://www.messenger.com/t/MeinSchiff
47	Boehringer Ingelheim	http://www.pmlive.com/awards/communique/previous_winners/communique_awards_2018_results/healthcare_communications_awards/excellence_in_social_media_strategy/tabatha_the_think.act.breathe_asthma_chatbot
50	Bertelsmann	https://crm.arvato.com/de/services/chatbots.html

	Company (*change of name)	**Source**
52	Adam Opel AG	https://www.horizont.net/marketing/nachrichten/Chad---der-Probefahrt-Assistent-Opel-startet-Chatbot-Pilotprojekt-auf-Facebook-145767
53	Schenker	https://www.messenger.com/t/dbschenkerAskViki
55	Merck	https://pro.merckgroup.com/de/smart-data/routine-uebernimmt-der-chatbot-gern/
57	Evonik Industries	https://corporate.evonik.com/de/pages/article.aspx?articleId=1748
62	Otto	https://www.chatbots.org/virtual_agent/clara1/
65	Amprion	https://www.pressebox.de/pressemitteilung/btc-business-technology-consulting-ag/Chatbot-BIBI-uebernimmt-optimierter-Kundenservice/boxid/910963
72	Airbus Operations	http://blog.livingactor.com/a-3d-talking-avatar-for-airbus-helicopters-online-faq/
73	Dr. August Oetker	https://www.horizont.net/tech/nachrichten/Chatbot-Dr.-Oetker-startet-Produktfinder-fuer-den-Facebook-Messenger-162531
74	Droege	https://www.droege-group.com/de/news-views/aus-der-gruppe/nachricht/article/trenkwalder-launcht-facebook-chatbot/
77	Vodafone Kabel Deutschland	https://www.vodafone.de/featured/inside-vodafone/alexa-und-tobi-beraten-dich-jetzt-im-vodafone-kundenservice_cv/
78	dm-drogerie markt	https://de.slideshare.net/fbmarket/facebook-chatbotentwicklung-in-der-praxis-einblicke-in-den-chatbot-von-dmdrogerie-market
87	Sandoz International	https://www.sandoz.com/stories/access-healthcare/better-access-healthcare-through-mobile-technology-winning-ideas-sandoz; https://www.wired.co.uk/article/wired-health-sandoz-hack
88	Edeka	http://www.edeka-verbund.de/Unternehmen/de/presse/pressekontakte_2/presse_2/presse_detail_gruppe_961488.jsp
96	Telefónica Deutschland	https://blog.telefonica.de/2018/05/chatbots-datenanalyse-und-ki-bei-telefonica-deutschland-hallo-maschine-wie-mensch-und-technik-hand-in-hand-gehen/; https://blog.telefonica.de/2018/03/cat-award-fuer-telefonica-manager-virtuelle-online-hilfe-im-o2-kundenservice-ueberzeugt-fachjury/
97	Real-SB Warenhaus	https://handelsjournal.de/2017/06/13/markt/mirkohackmann/metro-und-der-handel-von-morgen/; https://archiv.metrogroup.de/pressemitteilungen/2017/06/16/delivery-robot-or-the-internet-of-things

Appendix C: Overview Models from Acceptance Research Literature 1962-2020

No.	Model Acronym	Model Short Description	Approach	Source	POV
1	**IDT/DOI**	Innovation Diffusion Theory/ Diffusion of Innovations	SP	Rogers (1962)	O
2	**UGT**	Uses and gratifications theory	SP, H	Katz, Blumler, and Gurevitch (1973)	I
3	**TRA**	Theory of Reasoned Action	SP	Fishbein and Ajzen (1975)	I
4	**MPCU**	Model of PC Utilization	SP, PO	Triandis (1977)	I
5	**TAM0**	Technology Acceptance Model	PO	Davis (1985)	I
6	**DAM**	Degenhardt Acceptance Model	TC, UX	Degenhardt (1986)	I
7	**MIR**	Model of innovation resistance	PO, H	Ram (1987)	I
8	**PVM**	Perceived value model	H	Zeithaml (1988)	I
9	**TAM1**	Technology Acceptance Model	PO	Davis et al. (1989)	I
10	**TOE Framework**	Technology, organization, and environment	TC	Tornatzky and Fleischer (1990)	O
11	**TPB**	Theory of Planned Behavior	SP	Ajzen (1991)	I
12	**Moore/ Benbasat Model**	Adapted Innovation Diffusion Theory/ Diffusion of Innovations (Perceived Characteristics of Innovating)	SP	Moore and Benbasat (1991)	O
13	**Adapted MPCU**	Adapted Model of PC Utilization	SP, PO	Thompson et al. (1991)	I
14	**DSS IRF**	Decision support systems Implementation Research Framework	SP	Alavi and Joachimsthaler (1992)	I
15	**ISS(M)**	Information System Success Model	H	DeLone and McLean (1992)	O/I
16	**Nielsen Model**	Model of the attributes of system acceptability	TC, UX	Nielsen (1993)	I
17	**DTPB (TAM-TPB)**	Decomposed Theory of Planned Behavior	SP	S. Taylor and P. A. Todd (1995)	I
18	**TTF**	Task Technology Fit Model	TC	Goodhue and Thompson (1995)	I
19	**PEO model**	Perceived Benefits, Organizational readiness, External pressure	PO	Iacovou, Benbasat, and Dexter (1995)	O
20	**CSE**	Computer Self-Efficacy Model	SP	Compeau and Higgins (1995)	I

No.	Model Acronym	Model Short Description	Approach	Source	POV
21	**TM**	Trust Model	H	Kipnis (1996)	O
22	**KM**	Kollmann model	SP	Kollmann (1998)	I
23	**P3M**	Power, Perception and Performance (based on usability engineering approach and TAM)	PO, UX	Dillon and Morris (1999)	I
24	**HM**	Herrmann model	SP	Herrmann (1999)	I
25	**ITAM**	Information Technology Acceptance Model	SP, PO	Dixon (1999)	I
26	**TAM2**	Technology Acceptance Model	PO	Venkatesh and Davis (2000)	I
27	**TRI**	Technology Readiness Index	SP	A. Parasuraman (2000)	O/I
28	**ELSI**	Ethical, legal, social implications	TC, SP	Biller-Andorno (2001)	O
29	**FAU**	Framework of Automation Use	SP, PO	Dzindolet et al. (2001)	I
30	**GFTAIP**	Generic Framework for Technology Acceptance by Individual Professionals	SP, PO	Chau and Hu (2002)	I
31	**ICTAM**	Interactive Communication Technology Acceptance Model	SP, PO	C. A. Lin (2003)	I
32	**RISS(M)**	Reformulated Information System Success Model	H	DeLone and McLean (2003)	O/I
33	**UTAUT**	Unified Theory of Acceptance and Use of Technology	PO	Venkatesh et al. (2003)	I
34	**IDT/DOI**	Innovation Diffusion Theory/ Diffusion of Innovations	SP	Rogers (2003)	O
35	**IMUT**	Integrated Model of User Satisfaction and Technology Acceptance	PO, H	Wixom and Todd (2005)	I
36	**DFM**	Dadayan/Ferro Model	SP, PO	Dadayan and Ferro (2005)	I
37	**EPPTML**	Emergent perspective - process theories - mixed level of analysis	PO	H. Sun and Zhang (2006)	O/I
38	**CAT**	Consumer Acceptance of Technology Model	PO	Kulviwat, Bruner II, Kumar, Nasco, and Clark (2007)	I
39	**TRAM**	Technology Readiness and Acceptance Model	SP, PO	C. H. Lin, Shih, and Sher (2007)	I
40	**TAM3**	Technology Acceptance Model	PO	Venkatesh and Bala (2008)	I
41	**TPE**	Technological-Personal-Environmental Framework	SP	Jiang, Chen, and Lai (2010)	I

No.	Model Acronym	Model Short Description	Approach	Source	POV
42	**AAM**	Automation Acceptance Model	PO	Ghazizadeh et al. (2012)	I
43	**UTAUT2**	Unified Theory of Acceptance and Use of Technology	PO	Venkatesh et al. (2012)	I
44	**Adjusted AAM**	Adjusted Automation Acceptance Model	PO	Bekier (2013)	I
45	**UTAUT3**	Revised UTAUT2	PO	Dwivedi et al. (2019)	I
46	**FTAM**	Firm Technology Adoption Model	PO	Doe et al. (2019)	O/I
47	**HRCAM**	Human-Robot Collaboration Acceptance Model	SP, PO	Bröhl et al. (2019)	O/I
48	**CRAM**	Collaborative-Robot Acceptance Model	PO	Lotz et al. (2019)	I
49	**KIAM**	Artificial Intelligence Acceptance Model (Künstliche Intelligenz Akzeptanzmodell)	PO	Scheuer (2020)	I

Abbreviations: **Approach** according to Alexandre et al. (2018): H = Hedonic, PO = Productivity-oriented, SP = Social psychologic, TC = Tool-centered, UX = User experience focused; **POV** (Point of view): I = Individual level, O = Organizational level.

Appendix D: Questionnaire Setup Including All Measurement Items

Construct/ Variable	Details	Item code	Item Formulation	Scales	Source
AGE	Age	AGE01	Please state your age:	Under 20 years old 20-29 years old 30-39 years old 40-49 years old 50-59 years old 60-69 years old 70 years or older	Bundeszentrale für politische Bildung (2020); Eißer et al. (2020)
SEX	Gender	SEX01	Please state your gender:	Male Female Diverse No specification	Eißer et al. (2020)
NOE	Number of employees in the company	NOE01	Please indicate the size of the company that you currently work for:	Under 50 employees 51-100 employees 101-250 employees 251-500 employees 501-1,000 employees 1,001-3,000 employees 3,001 and more employees No specification	Loosely based on Eißer et al. (2020)
IA	Industry affiliation	IA01	Please state the industry of the company that you currently work for:	Agriculture, forestry and fishing, Manufacturing industry, Construction, Trade, transport and hospitality, Information and communication, Financial and insurance service providers, Real estate and housing activities Professional, scientific and technical services, Business services, Public and other private service providers, Creative, artistic and entertainment activities	Destatis (2022); Statistisches Bundesamt (2008)
CP	Position in the company	CP01	Please state the role that you have within the company you currently work for:	Recruiter Recruiting manager Human Resources (HR) administrator HR officer HR manager General manager in charge of HR (e.g., CHRO) My tasks are unrelated to HR	Author of the study

				Other HR-specific position (please specify): _________	
PI	Personal innovativeness	PI01	If I heard about a new information technology, I would look for ways to experiment with it.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Agarwal and Prasad (1998); translation according to Prein (2011)
PI	Personal innovativeness	PI02	Among my peers, I am usually the first to try out new information technologies.		Agarwal and Prasad (1998); translation according to Prein (2011), Dahm and Dregger (2019)
PI	Personal innovativeness	PI03	In general, I am hesitant to try out new information technologies.		Agarwal and Prasad (1998); own translation
PI	Personal innovativeness	PI04	I like to experiment with new information technologies.		Agarwal and Prasad (1998); translation according to Prein (2011)
TA	Technology Affinity	TA01	I inform myself about technological systems, even if I have no intention to buy it.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Bröhl et al. (2019) (based on excitement by Karrer et al. (2009)); translation according to Brauer (2017)
TA	Technology Affinity	TA02	I love to own new technological systems.		Bröhl et al. (2019) (based on excitement by Karrer et al. (2009)); translation according to Brauer (2017)
TA	Technology Affinity	TA03	I am excited when a new technological system is introduced to the market.		Bröhl et al. (2019) (based on excitement by Karrer et al. (2009)); translation according to Brauer (2017)
TA	Technology Affinity	TA04	I like to go to specialist (online) shops for technological systems.		Bröhl et al. (2019) (based on excitement by Karrer et al. (2009)); translation according to Brauer (2017)
TA	Technology Affinity	TA05	I enjoy trying out a technological system.		Bröhl et al. (2019) (based on excitement by Karrer et al. (2009)); translation according to Brauer (2017); Hesse, Walter, and Tietze (2020)
TU	Technolo-gical Under-standing	TU01	I know most of the functions of the	Strongly disagree Moderately disagree Somewhat disagree	Competence acc. to Karrer et al. (2009); translation according to Brauer (2017)

			technological systems I own.	Neutral Somewhat agree Moderately agree Strongly agree	
TU	Technolo-gical Under-standing	TU02	I have or would have problems understanding when reading technological magazines.		Competence acc. to Karrer et al. (2009); translation according to Brauer (2017)
TU	Technolo-gical Under-standing	TU03	It is easy for me to learn the handling of a new technological system.		Competence acc. to Karrer et al. (2009); translation according to Brauer (2017)
TU	Technolo-gical Under-standing	TU04	I know my way around technological systems.		Competence acc. to Karrer et al. (2009); translation according to Brauer (2017)
NI	Number of Interviews	NI01	Please estimate the number of interviews that are being conducted with candidates in your company per year.	1-10 Interviews 11-25 Interviews 26-50 Interviews 51-100 Interviews 101- 200 Interviews 201- 500 Interviews 501- 1,000 Interviews More than 1,000 Interviews I don't know	Author of the study
MOCI	Modus operandi for candidate interviewing	MOCI01	What is your current process for candidate interviewing?	In-person interview(s) (physical meeting(s)) In-person interview (digital meeting(s)) Technology-led interview(s) (= software-based, automated interview process such as time-delayed video interviews) Chatbot interview(s) Mixture of technology-led and in-person interviews I am not involved in the candidate interview conduct in my company	Author of the study
ATSD	ATS deployment in the company	ATSD01	Is there an Applicant Tracking System (ATS) within your company's HR processed?	Yes No I don't know	Author of the study
CEXP	Chatbot experience	CEXP01	Please state the degree of your chatbot experience regarding the past three years	I do not have any chatbot experience I have heard about chatbots prior to this questionnaire I have already used one chatbot before	Author of the study

				I have already used more than one chatbot before□ I am/was part of a chatbot development project	
CKNOW	Chatbot knowledge	CKNOW 01	Prior to this questionnaire, did you know what a chatbot is?	Yes No I don't know	Eißer et al. (2020)
CDEP	Chatbot deployment in the company	CDEP01	Is there a chatbot implemented within any process of your company?	Yes No I don't know	Author of the study
CDEV	In case 13_1 no: 13_2 Chatbot currently in development ?	CDEV01	Is a chatbot currently being developed for the company?		Author of the study
CPLAN	In case 13_2 no: Chatbot being planned?	CPLAN 01	Is there a plan to implement a chatbot within the company in the next two years?		Author of the study
RCDEP	Recruiting chatbot deployment in the company	RC DEP01	Is there a recruiting chatbot implemented within the recruiting processes of your company?	Yes No I don't know	Author of the study
RCATS	In case 14_1 yes: Recruiting chatbot linked to ATS?	RC ATS01	Is the recruiting chatbot linked to the company's ATS (if any)?		Author of the study
RCDEV	In case 14_1 no: Recruiting chatbot currently in development ?	RC DEV01	Is a chatbot currently being developed for the recruiting processes of your company?		Author of the study
RCPLAN	In case 14_2 no: Recruiting chatbot being planned?	RC PLAN01	Is there a plan to implement a chatbot within the recruiting processes of your company in the next two years?	Yes No I don't know	Author of the study
UC	Use cases for recruiting chatbots within the recruiting process: In	UC01	Clarification of application-related questions of the candidate (e.g., concerning the application process)	Very irrelevant Moderately irrelevant Somewhat irrelevant Neutral Somewhat relevant Moderately relevant	Meurer et al. (2019)

UC	your personal opinion, how relevant is a recruiting chatbot for the following areas within the recruiting processes of your company?	UC02	Supporting the candidate in his search for job offers	Very relevant	Meurer et al. (2019)
UC		UC03	Clarification of job-related questions the candidate has (e.g., concerning possible modes of work)		Meurer et al. (2019)
UC		UC04	Candidate support regarding the application process		Meurer et al. (2019)
UC		UC05	Partial applicant guidance through application process		Meurer et al. (2019)
UC		UC06	Query of missing applicant data from the candidate		Meurer et al. (2019)
UC		UC07	Recruiter-sided retrieval of applicant statistics from the database		Meurer et al. (2019)
UC		UC08	Guidance of the candidate through the further process after submission of the application		Meurer et al. (2019)
UC		UC09	Clarification of post-submission application-related questions of the candidate (e.g., application status)		Meurer et al. (2019)
UC		UC10	Conduct of first candidate interviews with the applicant		Meurer et al. (2019)
UC		UC11	Guidance of the candidate through the onboarding process (workflow)		Meurer et al. (2019)
UC		UC12	Guidance of the candidate through the onboarding process (FAQ)		Meurer et al. (2019)
UC		UC13	Guidance of the candidate through the onboarding process (documentation/ issuance of material)		Meurer et al. (2019)
UC		UC14	Other (please specify): ____________________		Meurer et al. (2019)
DU	Please indicate in how far you agree with the following potential	DU01	Costs: Cost reduction along the recruiting process	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree	Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)

DU	drivers for recruiting chatbot implementation	DU02	Time: Faster recruiting process step(s) conduct	Strongly agree	Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)
DU		DU03	Efficiency: Facilitation of data management		Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)
DU		DU04	Efficiency: Improvement of the decision-making process		Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)
DU	Please indicate in how far you agree with the following potential drivers for recruiting chatbot implementation	DU05	Efficiency: Permanent accessibility (detached from time and location restrictions)	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)
DU		DU06	Quality: Better output quality than via human task completion		Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)
DU		DU07	Quality: Reduction of human errors		Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)
DU		DU08	Quality: Standardization of data quality		Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)
DU		DU09	Quality: Reduction of human bias (lower influence of prejudices and discrimination)		Adapted from Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)

DU		DU10	Interaction: Improvement of the candidate experience		Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)
DU		DU11	Interaction: Low inhibition threshold for candidates to ask questions		Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)
DU		DU12	Image: Chatbot as value driver for innovation and image		Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)
DU		DU13	Other driver (If you see another, not yet mentioned driver, please specify): ____________________		Adapted from Mazurchenko and Maršíková (2019), loosely based on Regber et al. (2019), loosely based on Schildknecht et al. (2018)
BU	Please indicate in how far you agree with the following potential barriers for recruiting chatbot implementation	BU01	Technology: Cyberattacks	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Adapted from Mazurchenko and Maršíková (2019), loosely based on Schildknecht et al. (2018)
BU		BU02	Technology: Data security issues (e.g., leakage of candidates' personal information)		Adapted from Mazurchenko and Maršíková (2019), loosely based on Schildknecht et al. (2018)
BU		BU03	Technology: Complexity due to fragmented IT infrastructure		Adapted from Mazurchenko and Maršíková (2019), loosely based on Schildknecht et al. (2018)
BU		BU04	Technology: Recruiting chatbot's expected lack of understanding complex contexts		Adapted from Mazurchenko and Maršíková (2019), loosely based on Schildknecht et al. (2018)
BU		BU05	Company: Changing business and organizational structure for the worse		Adapted from Mazurchenko and Maršíková (2019), loosely based on Schildknecht et al. (2018)
BU	Please indicate in how far you	BU06	Company: Lack of investment in training to support the necessary	Strongly disagree Moderately disagree Somewhat disagree	Adapted from Mazurchenko and Maršíková (2019), loosely based on

	agree with the following potential barriers for recruiting chatbot implementation		technological competencies in the HR team	Neutral Somewhat agree Moderately agree Strongly agree	Schildknecht et al. (2018)
BU		BU07	Recruiter: Recruiters' resistance to change established processes		Adapted from Mazurchenko and Maršíková (2019), loosely based on Schildknecht et al. (2018)
BU		BU08	Recruiter: Job) replacement by automation		Adapted from Mazurchenko and Maršíková (2019), loosely based on Schildknecht et al. (2018)
BU		BU09	Recruiter: Deterioration of candidate-recruiter relations		Adapted from Mazurchenko and Maršíková (2019), loosely based on Schildknecht et al. (2018)
BU		BU10	Recruiter: Slow transformation of necessary technological competencies in the HR team		Adapted from Mazurchenko and Maršíková (2019), loosely based on Schildknecht et al. (2018)
BU		BU11	Other barrier (If you see another, not yet mentioned barrier, please specify): ___________________		Adapted from Mazurchenko and Maršíková (2019), loosely based on Schildknecht et al. (2018)
RASP	In your personal opinion, what are the most relevant aspects during the recruiting process from the company's HR department's point of view? Please rank the following aspects:	RASP01	Efficient candidate handling	Ranking from 1st to 8th	Partly adapted from Mazurchenko and Maršíková (2019)
RASP		RASP02	Hard skill assessment		Partly adapted from Mazurchenko and Maršíková (2019)
RASP		RASP03	Soft skill assessment		Partly adapted from Mazurchenko and Maršíková (2019)
RASP		RASP04	Social cue/cultural fit assessment ("human factor")		Partly adapted from Mazurchenko and Maršíková (2019)
RASP		RASP05	Relationship management		Partly adapted from Mazurchenko and Maršíková (2019)
RASP		RASP06	Digital communication possibility/possibilities		Partly adapted from Mazurchenko and Maršíková (2019)
RASP		RASP07	Data analytics		Partly adapted from Mazurchenko and Maršíková (2019)
RASP		RASP08	Offering diverse communication channels		Partly adapted from Mazurchenko and Maršíková (2019)
RSKILL	In your personal opinion, what are the most relevant	RSKILL 01	Ethical Practice	Ranking from 1st to 8th	Partly adapted from Mazurchenko and Maršíková (2019)
RSKILL		RSKILL 02	Application of expert knowledge and skills during selection		Partly adapted from Mazurchenko and Maršíková (2019)

RSKILL	recruiter skills?	RSKILL 03	Diversity management/cultural awareness		Partly adapted from Mazurchenko and Maršíková (2019)
RSKILL	Please rank the following aspects:	RSKILL 04	Critical thinking		Partly adapted from Mazurchenko and Maršíková (2019)
RSKILL		RSKILL 05	Transparency		Partly adapted from Mazurchenko and Maršíková (2019)
RSKILL		RSKILL 06	Multitasking		Partly adapted from Mazurchenko and Maršíková (2019)
RSKILL		RSKILL 07	Working in an agile way, creativity		Partly adapted from Mazurchenko and Maršíková (2019)
RSKILL		RSKILL 08	Problem-solving		Partly adapted from Mazurchenko and Maršíková (2019)
SN	Subjective Norm	SN01	People who influence my behavior think that I should use a recruiting chatbot for interviewing.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Venkatesh and Bala (2008); translation according to Olbrecht (2010)
SN	Subjective Norm	SN02	People who are important to me think that I should use a recruiting chatbot for interviewing.		Venkatesh and Bala (2008); translation according to Olbrecht (2010)
SN	Subjective Norm	SN03	The senior management of my business is or would be helpful in the use of a recruiting chatbot.		Venkatesh and Bala (2008); translation loosely based on Schmaltz (2009)
SN	Subjective Norm	SN04	In general, the organization has supported or would support the use of the recruiting chatbot.		Venkatesh and Bala (2008); translation according to Bröhl et al. (2017)
REL	Job Relevance	REL01	In my job, usage of a recruiting chatbot is important.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Venkatesh and Bala (2008); translation according to Schmaltz (2009)
REL	Job Relevance	REL02	In my job, usage of a recruiting chatbot is relevant.		Venkatesh and Bala (2008); translation according to Schmaltz (2009)
REL	Job Relevance	REL03	The use of a recruiting chatbot is pertinent to my various job-related tasks.		Venkatesh and Bala (2008); translation according to Bröhl et al. (2017)
RES	Result Demonstrabil ity	RES01	I have no difficulty telling others about the results of a recruiting	Strongly disagree Moderately disagree Somewhat disagree	Venkatesh and Bala (2008); translation

			chatbot for candidate interviews.	Neutral Somewhat agree	according to Schmaltz (2009)
RES	Result Demonstrability	RES02	I believe I could communicate to others the consequences of using a recruiting chatbot for candidate interviews.	Moderately agree Strongly agree	Venkatesh and Bala (2008); translation according to Schmaltz (2009)
RES	Result Demonstrability	RES03	The results of using a recruiting chatbot for candidate interviews are apparent to me.		Venkatesh and Bala (2008); translation according to Schmaltz (2009)
RES	Result Demonstrability	RES04	I would have difficulty explaining why using a recruiting chatbot for candidate interviews may or may not be beneficial.		Venkatesh and Bala (2008); translation according to Schmaltz (2009)
OUT	Output Quality	OUT01	The quality of the output one gets from a recruiting chatbot is high.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree	Venkatesh and Bala (2008); translation according to Schmaltz (2009)
OUT	Output Quality	OUT02	I have no problem with the quality of a recruiting chatbot's output.	Moderately agree Strongly agree	Venkatesh and Bala (2008); translation according to Egger and Pühl (2010)
OUT	Output Quality	OUT03	I assume the results from a recruiting chatbot to be excellent.		Venkatesh and Bala (2008); translation according to Rambusch (2012)
RCSE	Recruiting Chatbot Self-Efficacy	RCSE01	I could use a recruiting chatbot for interviewing if there was no one around to tell me what to do as I go.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Venkatesh and Bala (2008) (modified acc. to Bröhl et al. (2019)); translation according to Schmaltz (2009)
RCSE	Recruiting Chatbot Self-Efficacy	RCSE02	I could use a recruiting chatbot for interviewing if I had just the built-in help facility for assistance.		Venkatesh and Bala (2008) (modified acc. to Bröhl et al. (2019)); translation according to Schmaltz (2009) (examples by Wellmann (2014))
RCSE	Recruiting Chatbot Self-Efficacy	RCSE03	I could use a recruiting chatbot for interviewing if someone showed me how to do it first.		Venkatesh and Bala (2008) (modified acc. to Bröhl et al. (2019)); translation according to Claßen (2012)

RCSE	Recruiting Chatbot Self-Efficacy	RCSE04	I could use a recruiting chatbot for interviewing if I had used similar technology before this one to do the same job.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Venkatesh and Bala (2008) (modified acc. to Bröhl et al. (2019)); translation based on Schmaltz (2009)
PEC	Perceptions of External Control	PEC01	I have control over using the recruiting chatbot for interviewing.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Venkatesh and Bala (2008); translation according to Claßen (2012)
PEC	Perceptions of External Control	PEC02	I have the resources (e.g., training programs, information, assisting material, technical infrastructure, skill expertise, time, money, cooperation by others, staff) necessary to use a recruiting chatbot for interviewing.		Venkatesh and Bala (2008); translation based on Claßen (2012)
PEC	Perceptions of External Control	PEC03	Given the resources (e.g., training programs, information, assisting material, technical infrastructure, money, skill expertise), opportunities (e.g., cooperation by others) and knowledge it takes to use a recruiting chatbot, it would be easy for me to use the recruiting chatbot for interviewing.		Venkatesh and Bala (2008); own translation
PEC	Perceptions of External Control	PEC04	I assume a recruiting chatbot to not be compatible with other systems I use.		Venkatesh and Bala (2008); translation according to Claßen (2012)
RCANX	Recruiting Chatbot Anxiety	RCANX 01	Recruiting chatbots do not scare me at all.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Venkatesh and Bala (2008); own translation
RCANX	Recruiting Chatbot Anxiety	RCANX 02	Working with a recruiting chatbot makes/would make me nervous.		Venkatesh and Bala (2008); own translation
RCANX	Recruiting Chatbot Anxiety	RCANX 03	Recruiting chatbots make me feel uncomfortable.		Venkatesh and Bala (2008); translation according to Claßen (2012)
RCANX	Recruiting Chatbot Anxiety	RCANX 04	Recruiting chatbots make me feel uneasy.		Venkatesh and Bala (2008); translation

					according to Claßen (2012)
PST	Perceived System Transparency	PST01	A recruiting chatbot makes its reasoning process clear to me.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	W. Wang and Benbasat (2016); own translation
PST	Perceived System Transparency	PST02	It is apparent to me how the algorithm of a recruiting chatbot handles the data of incoming inquiries.		W. Wang and Benbasat (2016); own translation
PST	Perceived System Transparency	PST03	It is apparent to me how the algorithm of a recruiting chatbot generates the answers.		W. Wang and Benbasat (2016); translation according to Scheuer (2020)
PST	Perceived System Transparency	PST04	I do not understand how a recruiting chatbot performs its job (conducting interviews).		W. Wang and Benbasat (2016); own translation
PST	Perceived System Transparency	PST05	I easily understand a recruiting chatbot's reasoning process.		W. Wang and Benbasat (2016); own translation
PST	Perceived System Transparency	PST06	It is easy for me to understand the inner workings of a recruiting chatbot.		W. Wang and Benbasat (2016); own translation
PST	Perceived System Transparency	PST07	I understand why and how a recruiting chatbot gives the answers.		W. Wang and Benbasat (2016); own translation
PST	Perceived System Transparency	PST08	The recruiting chatbot's logic in answering inquiries is clear to me.		W. Wang and Benbasat (2016); own translation
INAAB	Inertia (Affective based)	INA AB01	I will continue using my existing recruiting methods for interviewing because it would be stressful to change.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Polites and Karahanna (2012); H.-J. Kim et al. (2017); own translation
INAAB	Inertia (Affective based)	INA AB02	I will continue using my existing recruiting methods for interviewing because I am comfortable doing so.		Polites and Karahanna (2012); H.-J. Kim et al. (2017); own translation
INAAB	Inertia (Affective based)	INA AB03	I will continue using my existing recruiting methods for interviewing because I enjoy doing so.		Polites and Karahanna (2012); H.-J. Kim et al. (2017); own translation
INABB	Inertia (Behavioral based)	INA BB01	I will continue using my existing recruiting methods for interviewing simply because it is what I have always done.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Polites and Karahanna (2012); own translation
INABB	Inertia (Behavioral based)	INA BB02	I will continue using my existing recruiting methods for interviewing		Polites and Karahanna (2012); own translation

			simply because it is part of my normal routine.		
INABB	Inertia (Behavioral based)	INA BB03	I will continue using my existing recruiting methods for interviewing simply because I've done so regularly in the past.		Polites and Karahanna (2012); own translation
INACB	Inertia (Cognitive based)	INA CB01	I will continue using my existing recruiting methods for interviewing even though I know it is not the best way of doing things.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree	Based on Polites and Karahanna (2012); own translation
INACB	Inertia (Cognitive based)	INA CB02	I will continue using my existing recruiting methods for interviewing even though I know it is not the most efficient way of doing things.	Strongly agree	Based on Polites and Karahanna (2012); own translation
INACB	Inertia (Cognitive based)	INA CB03	I will continue using my existing recruiting methods for interviewing even though I know it is not the most effective way to do things.		Based on Polites and Karahanna (2012); own translation
SWETE	Switching Efforts: Transition Efforts	SWE TE01	Learning how to use a recruiting chatbot for interviewing would not take much time.	Strongly disagree Moderately disagree Somewhat disagree Neutral	Moore II (2002); Polites and Karahanna (2012); own translation
SWETE	Switching Efforts: Transition Efforts	SWE TE02	Becoming skilful at using a recruiting chatbot for interviewing would be easy for me.	Somewhat agree Moderately agree Strongly agree	Moore II (2002); Polites and Karahanna (2012); own translation
SWESE	Switching Efforts: Sunk Efforts	SWE SE01	I have already invested a lot of time in learning to use my current method for interviewing.	Strongly disagree Moderately disagree Somewhat disagree Neutral	Moore II (2002); Polites and Karahanna (2012); own translation
SWESE	Switching Efforts: Sunk Efforts	SWE SE02	I have already invested a lot of time in perfecting my skills at using my current method for interviewing.	Somewhat agree Moderately agree Strongly agree	Moore II (2002); Polites and Karahanna (2012); own translation
SWEUE	Switching Efforts: Uncertainty Efforts	SWE UE01	I am concerned about the security of the applicants' personal information when deploying a recruiting chatbot for interviewing.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree	Ghazali et al. (2016); own translation
SWEUE	Switching Efforts: Uncertainty Efforts	SWE UE02	I worry that switching one or more recruiting process steps to recruiting chatbot conduct would result in some unexpected problems.	Strongly agree	Ghazali et al. (2016); H.-W. Kim and Kankanhalli (2009); own translation

SWEUE	Switching Efforts: Uncertainty Efforts	SWE UE03	If I were to implement a recruiting chatbot into my recruiting process, I fear that the task results might worsen.		Ghazali et al. (2016); own translation
EIMP	Ethical Implication (Job Substitution)	EIMP01	I fear that I will lose my job because of a recruiting chatbot.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Bröhl et al. (2019); translation according to Bröhl et al. (2017)
EIMP	Ethical Implication (Job Substitution)	EIMP02	I fear that a recruiting chatbot works with higher productivity than me.		Nelles et al. (2017); own translation
EIMP	Ethical Implication (Job Substitution)	EIMP03	I fear that a recruiting chatbot works at a higher quality level than me.		Nelles et al. (2017); own translation
LIMP	Legal Implication (Data Protection)	LIMP01	I do not mind if a recruiting chatbot records personal information about the applicant.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Bröhl et al. (2019); translation according to Bröhl et al. (2017)
LIMP	Legal Implication	LIMP02	I sense a danger of breach of my duty of care when implementing a recruiting chatbot into the interviewing procedure in my company's recruiting process.		Nelles et al. (2017); own translation
SIMP	Social Implication	SIMP01	I fear that I will lose the contact to the applicants because of a recruiting chatbot.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Bröhl et al. (2019); translation according to Bröhl et al. (2017)
PU	Perceived Usefulness	PU01	Using a recruiting chatbot improves my performance in my job.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Venkatesh and Bala (2008); translation according to Olbrecht (2010)
PU	Perceived Usefulness	PU02	Using a recruiting chatbot in my job increases my productivity.		Venkatesh and Bala (2008); translation according to Olbrecht (2010)
PU	Perceived Usefulness	PU03	Using a recruiting chatbot enhances my effectiveness in my job.		Venkatesh and Bala (2008); translation according to Olbrecht (2010)
PU	Perceived Usefulness	PU04	I find a recruiting chatbot to be useful in my job.		Venkatesh and Bala (2008); translation

					according to Olbrecht (2010)
PEOU	Perceived Ease of Use	PEOU01	The applicants' interaction with the recruiting chatbot will be clear and understandable.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Gefen and Straub (2000), Pavlou (2003), Venkatesh et al. (2003), Venkatesh and Bala (2008), Polites and Karahanna (2012), Samuel and Joy (2018); translation according to Schlohmann (2012)
PEOU	Perceived Ease of Use	PEOU02	Interacting with a recruiting chatbot does not require a lot of an applicant's mental effort.		Venkatesh and Bala (2008); translation according to Olbrecht (2010) and Claßen (2012)
PEOU	Perceived Ease of Use	PEOU03	Applicants will find recruiting chatbots to be easy to use.		Venkatesh and Bala (2008); translation according to Olbrecht (2010)
PEOU	Perceived Ease of Use	PEOU04	Applicants will find it easy to get the recruiting chatbot to do what they want it to do.		Venkatesh and Bala (2008); translation according to Schmaltz (2009)
BI	Behavioral Intention to Use	BI01	Assuming I had access to a recruiting chatbot, I intend to use (use in the sense of implementing it into the interviewing procedure of my recruiting process) it.	Strongly disagree Moderately disagree Somewhat disagree Neutral Somewhat agree Moderately agree Strongly agree	Venkatesh and Bala (2008); translation according to Schlohmann (2012)
BI	Behavioral Intention to Use	BI02	Given that I had access to a recruiting chatbot, I predict that I would use (use in the sense of implementing it into the interviewing procedure of my recruiting process) it.		Venkatesh, 2008 #522@@author-year}; translation according to Diers (2020)
BI	Behavioral Intention to Use	BI03	I plan to use (use in the sense of implementing it into the interviewing procedure of my recruiting process) a recruiting chatbot in the next 12 months.		Venkatesh and Bala (2008); translation based on Schmaltz (2009)

Appendix E: Pilot Study Data Normality Test

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
SN01	0.185	59	0.000	0.913	59	0.000
SN02	0.179	59	0.000	0.909	59	0.000
SN03	0.208	59	0.000	0.932	59	0.003
SN04	0.199	59	0.000	0.936	59	0.004
REL01	0.157	59	0.001	0.925	59	0.001
REL02	0.133	59	0.012	0.936	59	0.004
REL03	0.155	59	0.001	0.936	59	0.004
RES01	0.160	59	0.001	0.937	59	0.004
RES02	0.185	59	0.000	0.913	59	0.000
RES03	0.188	59	0.000	0.929	59	0.002
OUT01	0.233	59	0.000	0.902	59	0.000
OUT02	0.291	59	0.000	0.853	59	0.000
OUT03	0.239	59	0.000	0.904	59	0.000
RCSE02	0.217	59	0.000	0.904	59	0.000
RCSE03	0.167	59	0.000	0.878	59	0.000
RCSE04	0.152	59	0.002	0.908	59	0.000
PEC01	0.197	59	0.000	0.886	59	0.000
PEC02	0.165	59	0.000	0.944	59	0.009
PEC03	0.233	59	0.000	0.887	59	0.000
RCANX01	0.243	59	0.000	0.883	59	0.000
RCANX02	0.187	59	0.000	0.893	59	0.000
RCANX03	0.161	59	0.001	0.921	59	0.001
RCANX04	0.191	59	0.000	0.909	59	0.000
PST01	0.248	59	0.000	0.889	59	0.000
PST02	0.157	59	0.001	0.942	59	0.007
PST03	0.176	59	0.000	0.941	59	0.007
PST05	0.203	59	0.000	0.912	59	0.000
PST06	0.171	59	0.000	0.944	59	0.009
PST07	0.185	59	0.000	0.940	59	0.006
PST08	0.202	59	0.000	0.934	59	0.003

INAAB02	0.153	59	0.001	0.916	59	0.001
INAAB03	0.146	59	0.003	0.907	59	0.000
INABB01	0.171	59	0.000	0.949	59	0.015
INABB02	0.123	59	0.026	0.948	59	0.014
INABB03	0.151	59	0.002	0.942	59	0.008
INACB01	0.163	59	0.000	0.923	59	0.001
INACB02	0.134	59	0.010	0.944	59	0.009
INACB03	0.152	59	0.002	0.943	59	0.008
SWETE01	0.158	59	0.001	0.946	59	0.011
SWETE02	0.166	59	0.000	0.917	59	0.001
SWESE01	0.144	59	0.004	0.949	59	0.015
SWESE02	0.136	59	0.008	0.947	59	0.012
SWEUE01	0.150	59	0.002	0.943	59	0.008
SWEUE02	0.139	59	0.006	0.938	59	0.005
SWEUE03	0.186	59	0.000	0.938	59	0.005
EIMP01	0.241	59	0.000	0.812	59	0.000
EIMP02	0.152	59	0.002	0.915	59	0.001
EIMP03	0.166	59	0.000	0.877	59	0.000
LIMP01	0.148	59	0.003	0.949	59	0.015
SIMP01	0.176	59	0.000	0.912	59	0.000
PU01	0.201	59	0.000	0.902	59	0.000
PU02	0.196	59	0.000	0.919	59	0.001
PU03	0.175	59	0.000	0.931	59	0.003
PU04	0.224	59	0.000	0.898	59	0.000
PEOU01	0.208	59	0.000	0.911	59	0.000
PEOU02	0.211	59	0.000	0.917	59	0.001
PEOU03	0.173	59	0.000	0.925	59	0.001
PEOU04	0.184	59	0.000	0.925	59	0.001
BI01	0.217	59	0.000	0.923	59	0.001
BI02	0.183	59	0.000	0.920	59	0.001
BI03	0.206	59	0.000	0.882	59	0.000
U01	0.211	59	0.000	0.861	59	0.000

a. Lilliefors Significance Correction

Appendix F: Pilot Study Confirmatory Factor Analysis: Discriminant Validity via Cross Loadings (1/2)

	BI	EIMP	INAAB	INABB	INACB	LIMP	OUT	PEC	PEOU	PST	PU	RCANX
BI01	**0.871**	0.311	-0.166	-0.01	0.13	-0.302	0.52	0.42	0.436	0.293	0.643	-0.378
BI02	**0.926**	0.237	-0.144	-0.023	0.06	-0.443	0.561	0.435	0.516	0.261	0.699	-0.466
BI03	**0.77**	0.263	-0.203	0.109	0.164	-0.321	0.414	0.461	0.385	0.226	0.608	-0.117
EIMP 01	0.087	**0.485**	0.149	0.225	0.375	-0.129	0.007	-0.159	-0.094	0.221	0.048	0.321
EIMP 02	0.244	**0.744**	0.281	0.145	0.378	-0.409	0.266	0.118	0.114	0.259	0.35	0.073
EIMP 03	0.275	**0.774**	0.027	0.046	0.322	-0.314	0.404	0.111	0.102	0.403	0.336	-0.031
INAAB 02	-0.204	0.224	**0.84**	0.301	0.225	-0.162	-0.061	0.177	-0.079	0.273	-0.162	0.304
INAAB 03	-0.147	0.165	**0.928**	0.332	0.223	-0.178	0.017	0.226	0.054	0.308	-0.11	0.272
INABB 01	0.089	0.242	0.293	**0.936**	0.549	-0.145	0.163	0.089	0.137	0.173	-0.065	0.481
INABB 02	0.024	0.127	0.346	**0.859**	0.378	-0.066	0.187	0.257	0.095	0.188	-0.064	0.422
INABB 03	-0.046	0.125	0.342	**0.932**	0.384	0.028	0.051	0.222	0.132	0.215	-0.142	0.453
INACB 01	0.217	0.466	0.209	0.424	**0.817**	-0.203	0.153	-0.114	0.058	0.217	0.054	0.407
INACB 02	0.057	0.444	0.297	0.43	**0.991**	-0.099	0.105	0.039	0.123	0.427	0.058	0.535
INACB 03	0.094	0.453	0.149	0.422	**0.821**	-0.212	0.153	-0.113	0.15	0.263	0.104	0.428
LIMP 01	-0.416	-0.44	-0.192	-0.067	-0.188	**1**	-0.444	-0.251	-0.183	0.005	-0.416	0.062
OUT01	0.546	0.295	0.014	0.066	0.129	-0.493	**0.9**	0.587	0.433	0.408	0.656	-0.271
OUT02	0.446	0.369	0.031	0.201	0.156	-0.367	**0.841**	0.503	0.481	0.451	0.528	-0.276
OUT03	0.558	0.325	-0.1	0.125	0.123	-0.321	**0.918**	0.56	0.526	0.418	0.657	-0.323
PEC01	0.317	0.201	0.218	0.019	0.167	-0.243	0.378	**0.746**	0.162	0.549	0.483	-0.196
PEC02	0.365	0.031	0.236	0.314	-0.022	-0.168	0.411	**0.662**	0.121	0.438	0.251	-0.013
PEC03	0.426	-0.079	0.056	0.136	-0.275	-0.136	0.558	**0.766**	0.279	0.3	0.473	-0.287
PEOU 01	0.264	0.034	0.234	0.064	-0.007	-0.043	0.457	0.236	**0.654**	0.318	0.418	-0.22
PEOU 02	0.414	0.014	0.116	0.08	0.026	-0.067	0.412	0.3	**0.815**	0.386	0.502	-0.282
PEOU 03	0.399	0.023	-0.112	0.05	0.106	-0.174	0.404	0.23	**0.819**	0.229	0.495	-0.26
PEOU 04	0.52	0.19	-0.228	0.216	0.249	-0.268	0.414	0.049	**0.792**	0.172	0.449	-0.147
PST01	0.67	0.423	0.03	-0.015	0.103	-0.285	0.667	0.467	0.455	**0.848**	0.614	-0.343
PST02	0.218	0.322	0.129	0.216	0.332	0.055	0.21	0.408	0.203	**0.703**	0.241	0.1
PST03	0.162	0.35	0.269	0.281	0.326	0.082	0.279	0.429	0.267	**0.777**	0.223	0.122
PST05	0.143	0.263	0.361	0.21	0.254	0.08	0.399	0.446	0.303	**0.825**	0.298	0.126

	BI	EIMP	INAAB	INABB	INACB	LIMP	OUT	PEC	PEOU	PST	PU	RCANX
PST06	0.16	0.229	0.315	0.221	0.399	0.119	0.279	0.418	0.291	**0.725**	0.27	0.106
PST07	0.064	0.354	0.283	0.085	0.268	0.053	0.275	0.362	0.128	**0.648**	0.202	0.055
PST08	0.115	0.388	0.372	0.126	0.203	-0.036	0.362	0.564	0.176	**0.726**	0.258	0.01
PU01	0.701	0.36	-0.176	-0.048	0.042	-0.404	0.676	0.55	0.567	0.36	**0.928**	-0.428
PU02	0.615	0.463	-0.146	-0.109	0.15	-0.39	0.626	0.41	0.543	0.377	**0.874**	-0.328
PU03	0.726	0.441	-0.132	-0.099	0.096	-0.421	0.652	0.481	0.551	0.39	**0.943**	-0.358
PU04	0.749	0.187	-0.108	-0.113	0.013	-0.317	0.603	0.623	0.564	0.379	**0.938**	-0.47
RCANX 01	-0.599	-0.057	0.172	0.174	0.261	0.128	-0.48	-0.393	-0.47	-0.281	-0.567	**0.838**
RCANX 02	0.097	0.352	0.187	0.425	0.592	-0.24	0.079	0.108	-0.047	0.2	0.016	**0.453**
RCANX 03	-0.302	0.111	0.364	0.569	0.436	0.049	-0.227	-0.133	-0.119	0.117	-0.341	**0.906**
RCANX 04	-0.26	0.14	0.284	0.442	0.482	0.128	-0.281	-0.216	-0.24	0.115	-0.34	**0.875**

Appendix G: Pilot Study Confirmatory Factor Analysis: Discriminant Validity via Cross Loadings (2/2)

	RCSE	REL	RES	SIMP	SN	SWESE	SWETE	SWEUE	U
RCSE02	**0.752**	0.277	0.505	-0.131	0.427	0.099	0.21	0.02	0.219
RCSE03	**0.884**	0.386	0.633	-0.037	0.417	0.11	0.32	0.017	0.318
RCSE04	**0.892**	0.41	0.604	-0.024	0.353	0.052	0.368	0.078	0.309
REL01	0.377	**0.898**	0.556	-0.3	0.755	0.463	0.152	-0.13	0.447
REL02	0.419	**0.917**	0.577	-0.21	0.637	0.312	0.267	-0.129	0.555
REL03	0.386	**0.951**	0.581	-0.266	0.641	0.454	0.275	-0.181	0.557
RES01	0.526	0.48	**0.78**	-0.236	0.528	0.179	0.367	0	0.235
RES02	0.641	0.551	**0.846**	-0.13	0.546	0.154	0.394	-0.041	0.298
RES03	0.598	0.553	**0.928**	-0.233	0.622	0.247	0.411	-0.178	0.435
SIMP01	-0.072	-0.28	-0.234	**1**	-0.455	0.055	0.19	0.615	-0.403
SN01	0.377	0.549	0.541	-0.391	**0.753**	0.219	0.248	-0.097	0.353
SN02	0.377	0.547	0.492	-0.398	**0.825**	0.289	0.34	-0.146	0.452
SN03	0.295	0.578	0.473	-0.359	**0.75**	0.338	0.099	-0.191	0.36
SN04	0.444	0.669	0.613	-0.313	**0.864**	0.32	0.138	-0.255	0.393
SWESE01	0.07	0.332	0.181	-0.036	0.251	**0.797**	0.122	0.231	0.08
SWESE02	0.09	0.37	0.179	0.125	0.326	**0.782**	0.322	0.239	0.069
SWETE02	0.359	0.252	0.458	0.19	0.259	0.28	**1**	0.382	0.053
SWEUE01	0.201	-0.06	0.014	0.513	-0.035	0.231	0.288	**0.829**	-0.448
SWEUE02	-0.012	-0.134	-0.082	0.456	-0.233	0.271	0.335	**0.773**	-0.4
SWEUE03	-0.075	-0.197	-0.154	0.537	-0.269	0.231	0.316	**0.848**	-0.447
U01	0.337	0.565	0.384	-0.403	0.488	0.094	0.053	-0.529	**1**

Appendix H: Pilot Study Confirmatory Factor Analysis: Discriminant Validity via Fornell and Larcker Criterion (1/2)

	U	BI	EIMP	INA AB	INA BB	INA CB	REL	LIMP	OUT	PEOU	PST
U	1										
BI	0.689	**0.858**									
EIMP	0.163	0.314	**0.68**								
INA AB	-0.252	-0.196	0.218	**0.885**							
INA BB	-0.104	0.024	0.182	0.358	**0.91**						
INA CB	-0.117	0.133	0.513	0.253	0.482	**0.88**					
REL	0.565	0.711	0.287	-0.098	0.075	0.121	**0.922**				
LIMP	-0.476	-0.416	-0.44	-0.192	-0.067	-0.188	-0.23	1			
OUT	0.582	0.584	0.37	-0.023	0.145	0.153	0.758	-0.444	**0.887**		
PEOU	0.383	0.523	0.085	-0.01	0.134	0.126	0.594	-0.183	0.541	**0.773**	
PST	0.207	0.304	0.441	0.329	0.211	0.351	0.454	0.005	0.479	0.355	**0.753**

Appendix I: Pilot Study Confirmatory Factor Analysis: Discriminant Validity via Fornell and Larcker Criterion (2/2)

	PU	PEC	RCANX	RES	SWESE	SWETE	SWEUE	RCSE	SIMP	SN
PU	**0.921**									
PEC	0.562	**0.726**								
RCANX	-0.431	-0.237	**0.79**							
RES	0.682	0.631	-0.377	**0.853**						
SWESE	0.115	0.269	0.088	0.228	**0.79**					
SWETE	0.354	0.53	0.082	0.458	0.28	**1**				
SWEUE	-0.391	-0.062	0.715	-0.091	0.297	0.382	**0.818**			
RCSE	0.508	0.538	-0.049	0.69	0.102	0.359	0.047	**0.845**		
SIMP	-0.326	-0.236	0.472	-0.234	0.055	0.19	0.615	-0.072	**1**	
SN	0.642	0.482	-0.407	0.664	0.365	0.259	-0.218	0.469	-0.455	**0.8**

Appendix J: Main Study Data Normality Test

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
SN01	0.185	425	0.000	0.922	425	0.000
SN02	0.181	425	0.000	0.922	425	0.000
SN03	0.188	425	0.000	0.929	425	0.000
SN04	0.187	425	0.000	0.930	425	0.000
REL01	0.126	425	0.000	0.927	425	0.000
REL02	0.136	425	0.000	0.925	425	0.000
REL03	0.170	425	0.000	0.924	425	0.000
RES01	0.176	425	0.000	0.933	425	0.000
RES02	0.195	425	0.000	0.919	425	0.000
RES03	0.207	425	0.000	0.925	425	0.000
OUT01	0.180	425	0.000	0.926	425	0.000
OUT02	0.185	425	0.000	0.924	425	0.000
OUT03	0.189	425	0.000	0.924	425	0.000
RCSE01	0.178	425	0.000	0.927	425	0.000
RCSE02	0.202	425	0.000	0.917	425	0.000
RCSE03	0.161	425	0.000	0.894	425	0.000
RCSE04	0.163	425	0.000	0.911	425	0.000
PEC01	0.180	425	0.000	0.912	425	0.000
PEC02	0.151	425	0.000	0.945	425	0.000
PEC03	0.215	425	0.000	0.902	425	0.000
RCANX01	0.163	425	0.000	0.921	425	0.000
RCANX02	0.154	425	0.000	0.923	425	0.000
RCANX03	0.139	425	0.000	0.933	425	0.000
RCANX04	0.152	425	0.000	0.921	425	0.000
PST01	0.190	425	0.000	0.921	425	0.000
PST02	0.154	425	0.000	0.943	425	0.000
PST03	0.172	425	0.000	0.945	425	0.000
PST05	0.161	425	0.000	0.943	425	0.000
PST06	0.146	425	0.000	0.947	425	0.000
PST07	0.172	425	0.000	0.942	425	0.000

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
PST08	0.179	425	0.000	0.940	425	0.000
INAAB01	0.129	425	0.000	0.952	425	0.000
INAAB02	0.139	425	0.000	0.933	425	0.000
INAAB03	0.139	425	0.000	0.926	425	0.000
INABB01	0.158	425	0.000	0.947	425	0.000
INABB02	0.174	425	0.000	0.934	425	0.000
INABB03	0.161	425	0.000	0.944	425	0.000
INACB01	0.138	425	0.000	0.945	425	0.000
INACB02	0.132	425	0.000	0.946	425	0.000
INACB03	0.136	425	0.000	0.946	425	0.000
SWETE01	0.180	425	0.000	0.946	425	0.000
SWETE02	0.195	425	0.000	0.929	425	0.000
SWESE01	0.172	425	0.000	0.944	425	0.000
SWESE02	0.146	425	0.000	0.947	425	0.000
SWEUE01	0.127	425	0.000	0.952	425	0.000
SWEUE02	0.149	425	0.000	0.948	425	0.000
SWEUE03	0.155	425	0.000	0.949	425	0.000
EIMP01	0.190	425	0.000	0.861	425	0.000
EIMP02	0.132	425	0.000	0.929	425	0.000
EIMP03	0.141	425	0.000	0.916	425	0.000
LIMP01	0.135	425	0.000	0.946	425	0.000
SIMP01	0.167	425	0.000	0.917	425	0.000
PU01	0.216	425	0.000	0.916	425	0.000
PU02	0.201	425	0.000	0.912	425	0.000
PU03	0.197	425	0.000	0.912	425	0.000
PU04	0.201	425	0.000	0.914	425	0.000
PEOU01	0.204	425	0.000	0.910	425	0.000
PEOU02	0.184	425	0.000	0.930	425	0.000
PEOU03	0.179	425	0.000	0.926	425	0.000
PEOU04	0.181	425	0.000	0.931	425	0.000
BI01	0.195	425	0.000	0.931	425	0.000

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
BI02	0.173	425	0.000	0.928	425	0.000
BI03	0.178	425	0.000	0.905	425	0.000
U01	0.212	425	0.000	0.894	425	0.000

a. Lilliefors Significance Correction.

Appendix K: Main Study Confirmatory Factor Analysis: Discriminant Validity via Cross Loadings (1/2)

	BI	EIMP	INAAB	INABB	INACB	LIMP	OUT	PEC	PEOU	PST
BI01	**0.939**	0.229	-0.101	0.061	-0.082	-0.252	0.602	0.481	0.434	0.416
BI02	**0.918**	0.238	-0.130	-0.016	-0.120	-0.292	0.612	0.439	0.511	0.388
BI03	**0.831**	0.263	-0.091	0.111	0.036	-0.248	0.499	0.363	0.319	0.406
EIMP01	0.021	**0.493**	0.173	0.182	0.276	0.080	-0.085	-0.108	-0.164	-0.015
EIMP02	0.182	**0.917**	0.032	0.119	0.100	-0.143	0.188	0.066	0.105	0.077
EIMP03	0.313	**0.935**	0.065	0.116	0.170	-0.187	0.301	0.085	0.108	0.181
INAAB 01	-0.044	0.169	**0.756**	0.509	0.538	0.031	-0.031	-0.023	-0.060	0.090
INAAB 02	-0.173	-0.013	**0.859**	0.370	0.303	0.020	-0.102	0.040	-0.038	0.021
INAAB 03	-0.083	-0.054	**0.798**	0.378	0.274	-0.041	-0.031	0.194	0.068	0.107
INABB 01	0.052	0.139	0.474	**0.928**	0.590	-0.074	0.079	0.040	-0.023	0.082
INABB 02	0.068	0.114	0.519	**0.938**	0.463	-0.024	0.132	0.079	0.021	0.062
INABB 03	0.034	0.107	0.501	**0.945**	0.517	-0.060	0.097	0.066	0.014	0.085
INACB 01	-0.022	0.160	0.423	0.536	**0.920**	-0.035	0.058	-0.065	-0.053	0.098
INACB 02	-0.076	0.139	0.480	0.505	**0.941**	-0.040	-0.002	-0.041	-0.061	0.113
INACB 03	-0.086	0.123	0.439	0.525	**0.936**	-0.006	-0.030	-0.115	-0.073	0.072
LIMP01	-0.295	-0.177	0.007	-0.057	-0.029	**1.000**	-0.343	-0.277	-0.285	-0.261
OUT01	0.619	0.264	-0.098	0.067	-0.033	-0.332	**0.923**	0.394	0.480	0.471
OUT02	0.485	0.189	0.020	0.133	0.044	-0.249	**0.850**	0.412	0.385	0.419
OUT03	0.599	0.248	-0.083	0.104	0.024	-0.331	**0.915**	0.389	0.463	0.502
PEC01	0.377	0.051	0.081	0.021	-0.071	-0.266	0.345	**0.881**	0.389	0.463
PEC02	0.440	0.082	0.064	0.123	0.009	-0.216	0.407	**0.760**	0.224	0.422
PEC03	0.403	0.076	0.045	0.048	-0.115	-0.201	0.375	**0.840**	0.302	0.293
PEOU01	0.430	0.154	-0.013	-0.001	-0.126	-0.268	0.451	0.375	**0.849**	0.455
PEOU02	0.332	0.032	-0.029	-0.062	-0.090	-0.257	0.328	0.307	**0.852**	0.343

PEOU03	0.417	0.054	-0.040	-0.018	-0.068	-0.231	0.433	0.340	**0.898**	0.398
PEOU04	0.394	0.130	0.028	0.108	0.089	-0.185	0.438	0.229	**0.713**	0.353
PST01	0.534	0.181	0.014	0.065	0.019	-0.236	0.636	0.417	0.388	**0.645**
PST02	0.324	0.104	0.072	0.077	0.117	-0.217	0.340	0.309	0.316	**0.839**
PST03	0.280	0.118	0.045	0.049	0.088	-0.183	0.357	0.314	0.352	**0.855**
PST05	0.418	0.108	0.086	0.124	0.133	-0.196	0.490	0.436	0.440	**0.874**
PST06	0.344	0.077	0.089	0.080	0.113	-0.208	0.364	0.383	0.421	**0.874**
PST07	0.268	0.109	0.136	0.018	0.079	-0.225	0.331	0.404	0.358	**0.841**
PST08	0.338	0.102	0.101	0.042	0.048	-0.237	0.378	0.432	0.403	**0.879**

All values load highest on their own construct as required.

Appendix L: Main Study Confirmatory Factor Analysis: Discriminant Validity via Cross Loadings (2/2)

	PU	**RCANX**	**RCSE**	**REL**	**RES**	**SIMP**	**SN**	**SWESE**	**SWETE**	**SWEUE**	**U**
PU01	**0.941**	-0.310	0.359	0.579	0.453	-0.273	0.558	0.191	0.269	-0.270	0.481
PU02	**0.944**	-0.298	0.332	0.598	0.471	-0.218	0.546	0.130	0.262	-0.227	0.486
PU03	**0.960**	-0.296	0.358	0.627	0.462	-0.254	0.543	0.148	0.254	-0.254	0.504
PU04	**0.916**	-0.372	0.410	0.624	0.525	-0.290	0.564	0.110	0.308	-0.287	0.545
RCANX01	-0.349	**0.768**	-0.315	-0.356	-0.418	0.231	-0.287	-0.064	-0.331	0.232	-0.419
RCANX02	-0.188	**0.835**	-0.133	-0.071	-0.199	0.263	-0.056	0.122	-0.120	0.412	-0.287
RCANX03	-0.292	**0.880**	-0.232	-0.160	-0.273	0.381	-0.149	0.115	-0.164	0.508	-0.374
RCANX04	-0.270	**0.895**	-0.267	-0.135	-0.270	0.312	-0.113	0.126	-0.126	0.467	-0.348
RCSE01	0.335	-0.318	**0.746**	0.349	0.477	-0.167	0.373	0.102	0.350	-0.078	0.323
RCSE02	0.367	-0.242	**0.837**	0.308	0.410	-0.116	0.301	0.116	0.274	-0.121	0.240
RCSE03	0.263	-0.205	**0.800**	0.178	0.309	-0.001	0.157	0.047	0.199	-0.054	0.208
RCSE04	0.264	-0.164	**0.801**	0.216	0.338	0.009	0.125	0.131	0.227	0.020	0.154
REL01	0.605	-0.177	0.274	**0.938**	0.465	-0.222	0.654	0.214	0.290	-0.104	0.417
REL02	0.592	-0.229	0.323	**0.942**	0.463	-0.220	0.607	0.186	0.337	-0.124	0.444
REL03	0.609	-0.263	0.335	**0.915**	0.522	-0.261	0.597	0.209	0.330	-0.144	0.496
RES01	0.491	-0.254	0.399	0.467	**0.883**	-0.190	0.461	0.130	0.387	-0.098	0.335
RES02	0.450	-0.338	0.448	0.479	**0.919**	-0.142	0.448	0.106	0.402	-0.110	0.387
RES03	0.421	-0.398	0.461	0.447	**0.884**	-0.139	0.398	0.125	0.396	-0.157	0.387
SIMP01	-0.276	0.348	-0.091	-0.252	-0.177	**1.000**	-0.271	0.067	-0.126	0.541	-0.374
SN01	0.421	-0.044	0.186	0.485	0.341	-0.235	**0.811**	0.054	0.164	-0.091	0.298
SN02	0.465	-0.072	0.203	0.562	0.377	-0.260	**0.834**	0.094	0.172	-0.111	0.345

SN03	0.508	-0.262	0.284	0.554	0.415	-0.212	**0.842**	0.172	0.245	-0.137	0.407
SN04	0.552	-0.255	0.332	0.603	0.479	-0.203	**0.847**	0.207	0.269	-0.139	0.414
SWESE 01	0.156	0.121	0.095	0.205	0.098	0.016	0.155	**0.904**	0.139	0.179	0.033
SWESE 02	0.124	0.013	0.129	0.192	0.146	0.103	0.145	**0.915**	0.145	0.223	0.013
SWETE 01	0.243	-0.111	0.194	0.313	0.344	-0.125	0.280	0.097	**0.864**	-0.004	0.212
SWETE 02	0.263	-0.302	0.382	0.283	0.422	-0.094	0.173	0.174	**0.875**	-0.032	0.292
SWEUE 01	-0.170	0.363	0.013	-0.040	-0.034	0.401	-0.035	0.205	0.017	**0.840**	-0.198
SWEUE 02	-0.229	0.374	-0.069	-0.127	-0.130	0.488	-0.151	0.182	-0.037	**0.887**	-0.283
SWEUE 03	-0.318	0.464	-0.140	-0.177	-0.185	0.514	-0.190	0.190	-0.035	**0.867**	-0.332
U01	0.537	-0.436	0.295	0.486	0.411	-0.374	0.443	0.025	0.291	-0.314	**1.000**

All values load highest on their own construct as required.

Appendix M: Main Study Confirmatory Factor Analysis: Discriminant Validity via Fornell and Larcker Criterion (1/2)

	U	**BI**	**EIMP**	**INAAB**	**INABB**	**INACB**	**REL**	**LIMP**	**OUT**	**PEOU**	**PST**
U	**1.000**										
BI	0.643	**0.897**									
EIMP	0.072	0.270	**0.808**								
INAAB	-0.197	-0.120	0.056	**0.806**							
INABB	-0.085	0.055	0.128	0.531	**0.937**						
INACB	-0.179	-0.066	0.151	0.480	0.560	**0.932**					
REL	0.486	0.645	0.310	-0.040	0.118	0.000	**0.932**				
LIMP	-0.249	-0.295	-0.177	0.007	-0.057	-0.029	-0.288	**1.000**			
OUT	0.549	0.639	0.264	-0.066	0.109	0.009	0.635	-0.343	**0.897**		
PEOU	0.363	0.475	0.112	-0.018	0.004	-0.067	0.373	-0.285	0.497	**0.831**	
PST	0.395	0.449	0.141	0.091	0.082	0.101	0.485	-0.261	0.519	0.470	**0.833**

All values load highest on their own construct as required (Joe F Hair et al., 2012).

Appendix N: Main Study Confirmatory Factor Analysis: Discriminant Validity via Fornell and Larcker Criterion (2/2)

	PU	PEC	RCANX	RES	SWESE	SWETE	SWEUE	RCSE	SIMP	SN
PU	**0.940**									
PEC	0.412	**0.828**								
RCANX	-0.340	-0.331	**0.846**							
RES	0.509	0.543	-0.364	**0.895**						
SWESE	0.154	0.202	0.072	0.135	**0.909**					
SWETE	0.291	0.496	-0.240	0.441	0.157	**0.869**				
SWEUE	-0.277	-0.081	0.463	-0.134	0.222	-0.021	**0.865**			
RCSE	0.389	0.606	-0.296	0.485	0.124	0.333	-0.076	**0.797**		
SIMP	-0.276	-0.181	0.348	-0.177	0.067	-0.126	0.541	-0.091	**1.000**	
SN	0.588	0.387	-0.199	0.489	0.165	0.259	-0.146	0.307	-0.271	**0.833**

All values load highest on their own construct as required (Joe F Hair et al., 2012).

Appendix O: Main Study Confirmatory Factor Analysis: Discriminant Validity via HTMT (1/2)

	U	BI	EIMP	INAAB	INABB	INACB	REL	LIMP	OUT	PEOU
BI	0.683									
EIMP	0.142	0.279								
INAAB	0.227	0.157	0.181							
INABB	0.088	0.081	0.196	0.630						
INACB	0.186	0.098	0.259	0.560	0.602					
REL	0.505	0.718	0.301	0.111	0.127	0.046				
LIMP	0.249	0.314	0.187	0.045	0.058	0.030	0.300			
OUT	0.581	0.719	0.276	0.096	0.125	0.051	0.698	0.362		
PEOU	0.390	0.545	0.185	0.097	0.071	0.127	0.420	0.308	0.573	
PST	0.397	0.480	0.135	0.123	0.084	0.113	0.507	0.269	0.551	0.517

All values < .90 (Threshold value suggested by Joseph F Hair et al. (2018)).

Appendix P: Main Study Confirmatory Factor Analysis: Discriminant Validity via HTMT (2/2)

	PU	PEC	RCANX	RES	SWESE	SWETE	SWEUE	RCSE	SIMP
PEC	0.475								
RCANX	0.355	0.357							
RES	0.553	0.646	0.396						
SWESE	0.178	0.273	0.155	0.160					
SWETE	0.361	0.671	0.282	0.572	0.213				
SWEUE	0.309	0.098	0.561	0.159	0.273	0.049			
RXSE	0.438	0.743	0.328	0.574	0.155	0.443	0.119		
SIMP	0.281	0.210	0.375	0.187	0.074	0.153	0.593	0.102	
SN	0.645	0.482	0.229	0.556	0.193	0.336	0.170	0.354	0.295

All values < .90 (Threshold value suggested by Joseph F Hair et al. (2018)).

Appendix Q: Main Study Structure Model Analysis: Full VIF Values

	U	BI	EIMP	INA	INAAB	INABB	INACB	REL	LIMP	OUT	PEOU	PST
U												
BI	1.261											
EIMP												
INA		1.045										
INAAB				1.645								
INABB				1.725								
INACB				1.569								
REL												
LIMP												
OUT												
PEOU		1.493										
PST		1.477									1.324	
PU		1.870										
PEC											1.849	
RCANX											1.166	
RES												
SWESE												
SWETE												

SWEUE											
RCSE										1.610	
SIMP											
SN	1.641										
SWE			1.333								

Appendix R: Main Study Structure Model Analysis: Full VIF Values

	PU	**PEC**	**RCANX**	**RES**	**SWESE**	**SWETE**	**SWEUE**	**RCSE**	**SIMP**	**SN**	**SWE**
U											
BI											
EIMP	1.223										
INA	1.057										
INAAB											
INABB											
INACB											
REL	2.226										
LIMP	1.167										
OUT	2.478										
PEOU											
PST											
PU											
PEC											
RCANX											
RES	1.753										
SWESE											1.081
SWETE											1.028
SWEUE											1.055
RCSE											
SIMP	1.280										
SN	2.065										
SWE											

Appendix S: Main Study Structure Model Analysis: LVS PLS-SEM T-Statistics and Significance

	Original Sample	Sample Mean	Standard Deviation	T Statistics (|O/SD|)	P Values
EIMP → PU	0.176	0.177	0.035	5.032	0.000
INA → BI	-0.048	-0.049	0.038	1.271	0.204
INA → PU	-0.110	-0.110	0.036	3.087	0.002
LIMP → PU	-0.113	-0.113	0.038	2.934	0.003
OUT → PU	0.211	0.209	0.057	3.689	0.000
PEC → PEOU	0.035	0.038	0.061	0.580	0.562
PEOU → BI	0.140	0.140	0.042	3.306	0.001
PEOU → PU	0.179	0.179	0.049	3.645	0.000
PST → BI	0.088	0.088	0.043	2.054	0.040
PST → PEOU	0.323	0.321	0.052	6.255	0.000
PU → BI	0.351	0.351	0.050	7.059	0.000
RCANX → PEOU	-0.219	-0.219	0.046	4.741	0.000
RCSE → PEOU	0.199	0.199	0.058	3.407	0.001
REL → PU	0.234	0.236	0.052	4.543	0.000
RES → PU	0.020	0.021	0.048	0.412	0.680
SIMP → PU	-0.055	-0.056	0.037	1.505	0.132
SN → BI	0.352	0.351	0.042	8.347	0.000
SN → PU	0.157	0.154	0.051	3.057	0.002
SWE → INA	0.477	0.475	0.046	10.479	0.000

BIOGRAPHY

Name-Surname	Judith Drebert
Academic Background	After finishing her Bacherlor’s degree (B.A.) in “Tourism & Event Management” at the International School of Management (ISM) in Dortmund, Germany, Mrs. Drebert obtained her Master’s degree (M. Sc.) in “E-Business” from the Niederrhein University of Applied Sciences in Krefeld, Germany. At present, she is finishing her Ph.D. thesis as Ph.D. student at the International College of the National Institute of Development and Administration (ICO NIDA) in Bangkok, Thailand in cooperation with the RheinMain University of Applied Sciences (HSRM).
Experience	During her Ph.D. studies, Mrs. Drebert worked as a research associate and laboratory engineer at RheinMain University of Applied Sciences (HSRM) in Wiesbaden, Germany. After completion of the governmentally funded research project “CATS” (Chatbots in Applicant Tracking Systems) she is currently working on administrative digitization as advisor for the Hessian Ministry of Economics, Energy, Transport and Housing in Wiesbaden, Germany. She gives lectures on administrative digitization at the RheinMain University of Applied Sciences.