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Methodologies and Techniques for Designing Human-centered Recruitment Chatbots

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Abstract

Recruitment is a key activity for companies, especially large ones, because choosing the right team can determine the success or failure of a business. Chatbots incorporating artificial intelligence are an integral part of modern recruitment practices, but the automation and efficiency they provide must be balanced with other aspects involving humans, including ethics, transparency of decisions and user experience. This thesis studies the impact of artificial intelligence (AI) on personnel recruitment, focusing on the principles of Human-Centred design in the context of chatbot development for recruitment. This research, introduces the Human-Centred Technology Acceptance Model (HC-TAM), an extension of the traditional Human-Computer Interaction (HCI) and Technology Acceptance Model (TAM) and incorporates key human-centred factors such as trust, transparency, personalization and efficiency. The HC-TAM serves as a framework for designing chatbots that balance operational efficiency with human-centred qualities.

Using a mixed methodological approach comprising interviews, analysis of relevant literature and user studies, this research assessed the impact of conversational styles and interaction mechanisms on user experience. The results reveal that job seekers prefer conversational approaches that improve personalization and efficiency. Recruiters favor interaction styles that emphasize clarity and goal-oriented design customized to the specific interview, so that the tool is easy to use. This research provides useful recommendations for recruitment chatbot practitioners and designers to develop products that meet users' expectations. Such suggestions can help improve practices in the development of AI-based solutions that are also ethical and user-centred, promote inclusive and effective experiences for both candidates and recruiters, and balance operational efficiency with person-centred requirements. .

Abstract (Italian)

Il reclutamento del personale è un'attività fondamentale per le aziende, soprattutto quelle grandi, perché la scelta del team giusto può determinare il successo o il fallimento di un'attività aziendale. I chatbot che integrano l'intelligenza artificiale sono parte integrante delle moderne pratiche di assunzione, ma l'automazione e l'efficienza che forniscono devono essere bilanciate con altri aspetti che coinvolgono l'uomo, tra cui l'etica, la trasparenza delle decisioni e l'esperienza utente. Questa tesi studia l'impatto dell'intelligenza artificiale (IA) sul reclutamento del personale, concentrandosi sui principi di progettazione centrata sulla persona nel contesto dello sviluppo di chatbot per il reclutamento del personale. La ricerca condotta, introduce il modello Human-Centered Technology Acceptance Model (HC-TAM), un'estensione dei modelli tradizionali Human-Computer Interaction (HCI) e Technology Acceptance Model (TAM) ed incorpora fattori chiave incentrati sull'uomo, come la fiducia, la trasparenza, la personalizzazione e l'efficienza. L'HC-TAM funge da quadro di riferimento per la progettazione di chatbot che bilanciano l'efficienza operativa con le qualità incentrate sull'uomo.
Utilizzando un approccio metodologico misto che comprende interviste, analisi della letteratura rilevante e studi sugli utenti, la ricerca ha valutato l'impatto degli stili di conversazione e dei meccanismi di interazione sull' esperienza dell'utente. I risultati rivelano che chi cerca lavoro preferisce approcci conversazionali che migliorano la personalizzazione e l'efficienza. I reclutatori favoriscono stili di interazione che enfatizzano la chiarezza e il design orientato agli obiettivi e personalizzato per lo specifico colloquio, in modo che lo strumento sia facile da usare. Questa ricerca fornisce raccomandazioni utili a professionisti e progettisti di chatbot per il recruitment, al fine di sviluppare prodotti che incontrino le aspettative degli utenti. Tali suggerimenti possono contribuire a migliorare le pratiche nello sviluppo di soluzioni basate su IA che siano anche etiche e incentrate sull'utente, a promuovere esperienze inclusive ed efficaci sia per i candidati che per i reclutatori e a bilanciare l'efficienza operativa con i requisiti incentrati sulla persona.

Acknowledgment

First and foremost, I would like to express my deepest gratitude to my supervisor, Prof. Paolo Buono, for their invaluable guidance, encouragement, and support throughout this research journey. Their expertise and constructive feedback have been instrumental in shaping this thesis and my academic growth. I am also deeply thankful to Prof. Rosa Lanzilotti, whose insights and suggestions enriched this work significantly.

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A special thanks to my father and husband for their unwavering love and patience during this challenging yet fulfilling journey. Their emotional support and understanding have been my anchor through difficult times.

I am profoundly thankful for the financial support provided by PON Ricerca e Innovazione 2014–2020 FSE REACT-EU, Azione IV.4 “Dottorati e contratti di ricerca su tematiche dell’innovazione” CUP: H99J21010060001, which made this research possible. This funding has not only facilitated my studies but has also enabled me to contribute meaningfully to the field of Human-Centered AI.

Lastly, I dedicate this thesis to all those who inspired me to pursue knowledge and strive for excellence.

Contents

Chapter 1

Introduction

The recruitment landscape is experiencing a profound transformation driven by the rapid advancement of artificial intelligence (AI) technologies. Many industries use AI to improve their processes and performance [1]. Ranging from financial services, e-commerce, and tourism, to healthcare, digital technologies are transforming operational routines. These new technologies have also found significant applications in Human Resources (HR), particularly in recruiting, training, and evaluating work performance [2]. As competition for talented employees rises, companies must find innovative ways to enhance their recruitment processes and attract top talent, making recruitment efficiency and speed a crucial factor for success [1]. As a result, recruitment and selection have become a top priority for management, where finding the right fit for an organization among a growing pool of applicants is increasingly challenging [3, 4]. The advent of AI has significantly influenced how companies approach recruitment, particularly through web-based and automated processes. In web-based recruitment, organizations can now reach active and passive job seekers, enabling a more extensive and diverse pool of job seekers [3]. While this has increased the potential for finding well-qualified applicants, it has also led to a substantial rise in the number of applications, making the task of screening resumes and identifying the most suitable job seekers more challenging and time-consuming [5]. AI-enabled solutions, particularly chatbots, have emerged as a promising response to this scalability challenge, offering improved efficiency in the screening and dissemination of initial candidates [6].

AI-driven recruitment chatbots are being increasingly adopted to enhance hiring efficiency, candidate engagement, and operational cost reduction [7, 8]. These chatbots provide an automated yet interactive way for job seekers to engage with prospective employers, including answering initial questions, scheduling interviews, and offering updates on application status [9]. However, as these technologies become more integrated into recruitment processes, a key challenge arises: how to maintain a human-centered approach that ensures fairness, transparency, and a positive candidate experience [10].

AI recruitment tools, while effective in automating repetitive and time-consuming tasks, must also retain essential human qualities to foster trust, empathy, and personalization during interactions. Human-centered recruitment chatbot design aims to bridge the gap between efficiency and user experience by focusing on empathetic, transparent, and personalized interactions that resonate with job seekers similar to the qualities traditionally provided by human recruiters [11]. As AI systems take on a more prominent role in recruitment, ensuring that these technologies are designed with a human-centered perspective becomes essential to achieving positive outcomes for both employers and job seekers.

A human-centered approach in recruitment focuses on understanding and addressing the needs, expectations, and emotions of users throughout their interaction with recruitment chatbots. The use of chatbots in the hiring process has the potential to enhance or hinder the job seekers experience, depending on how well the interaction is personalized and aligned with their expectations [12]. For instance, chatbots must understand the job seeker's emotional state, provide helpful responses, and build trust to ensure that job seekers do not feel neglected or undervalued by an automated system. This human-centered approach seeks to integrate qualities like empathy, demonstrating an understanding of the user's situation and personalization tailoring responses to the candidate's profile and preferences. These elements are critical for creating a positive candidate experience, especially in emotionally sensitive situations like applying for a job [13, 14].

This thesis explores methodologies and design principles for developing recruitment chatbots that balance technological efficiency with human-centric interaction. By emphasizing the human-centered approach, this research aims to ensure that recruitment chatbots are functional and capable of empathizing with users, building trust, and fostering personalized interactions, qualities traditionally associated with human recruiters. These human-centered attributes contribute to creating positive candidate experiences, particularly when job seekers interact with automated systems in emotionally charged situations, such as applying for a new job.

1.1 Motivation

This thesis is motivated by the need to design recruitment chatbots that integrate human-centered principles, making them more effective not only in terms of efficiency but also in terms of user satisfaction and ethical conduct. The goal is to address how recruitment chatbots can be designed to enhance job seekers' and recruiter trust, provide personalized interactions, and ensure fairness and transparency throughout the job-seeking and recruitment journey. This research intends to explore the methodologies and design principles that contribute to creating recruitment chatbots that balance operational efficiency with the human qualities needed for positive job seekers and recruiter experiences.

1.2 Research Gap

While existing research on AI-driven recruitment has predominantly focused on the operational benefits of recruitment chatbots, such as increasing efficiency, automating routine tasks, and reducing recruiter workload, critical gaps remain in understanding their impact on user trust, acceptance, and overall interaction experience. Most studies emphasize technological advancements but often overlook the importance of integrating human-centered principles into chatbot design [12, 15, 16]. These principles, including transparency, fairness, and ethical responsibility, are crucial for fostering trust and ensuring equitable and inclusive recruitment processes.

The handling of sensitive candidate information and facilitating high-stakes interactions requires a deeper investigation into how recruitment chatbots can balance operational efficiency with empathy and personalization. Although conversational styles are a pivotal aspect of chatbot interactions, limited research has explored their nuanced effects on user engagement, trust, and willingness to disclose personal or professional information. The influence of tailored conversational approaches, ranging from detailed, exploratory dialogues to goal-oriented exchanges, remains insufficiently addressed, particularly in recruitment scenarios where user expectations vary significantly between candidates and recruiters.

This study introduces the Human-Centered Technology Acceptance Model (HC-TAM), which incorporates human-centered values into recruitment chatbot design. By bridging the operational and experiential dimensions of AI-driven recruitment tools, the research aims to design chatbots that enhance efficiency and prioritize user trust, personalization, and ethical accountability.

1.3 Research Objectives

- Examining how human-centered design elements such as transparency, fairness, and personalization can improve the user experience, trust, and acceptance of recruitment chatbots for both job seekers and recruiters.
- Investigating how different conversational approaches, such as context-driven and structured interactions, impact user engagement and trust aligning chatbot communication strategies with user groups specific preferences.
- Providing guidelines to designers and practitioners that balances efficiency with human-centered qualities, ensuring effective and satisfying recruitment chatbot design.

1.4 Main Contributions

The following key contributions encapsulate the outcomes of this research:

- **Human-Centered Principles in Chatbot Design**

  This research contributes to the design of recruitment chatbots by applying Human-Computer Interaction (HCI) principles, specifically trust, transparency, and personalization. These elements enhance the chatbot's ability to support ethical, user-friendly interactions, thereby guiding AI developers in building more human-centric recruitment tools.

- **Understanding User Preferences in Conversational Styles**

  Distinct preferences among user groups were highlighted, job seekers preferred context-based interactions for enhanced personalization and efficiency, while recruiters valued interactions that facilitated usability and effectiveness. These findings emphasize the importance of aligning chatbot communication strategies with user-specific expectations to optimize interaction quality and acceptance.

- **Development of a Human-Centered Acceptance Framework (HC-TAM)**

  The research developed and validated the Human-Centered Technology Acceptance Model (HC-TAM) using a mixed-methods approach, including qualitative interviews, surveys, and structural equation modeling. The model provides a framework for designing recruitment chatbots that balance efficiency with human-centered attributes like transparency, empathy, and ethics, enabling long-term adoption that remains usable, trustworthy, and aligned with both organizational goals and user expectations.

1.5 Thesis Outline

This thesis is structured as follows:

Chapter 2: Multifaceted Impacts of AI in Recruitment and Human-Centered Design

This chapter establishes the foundation of the thesis by reviewing existing literature and market research on AI technologies in recruitment. It delves into the traditional Technology Acceptance Model (TAM) and its relevance to recruitment chatbots, alongside principles of human-centered design. The chapter also highlights the evolution from traditional to AI-driven recruitment practices, identifying gaps in the current research and paving the way for a deeper exploration of user-centric AI solutions.

Chapter 3: Acceptance Factors Analysis by HC-TAM

Building on the gaps identified in Chapter 2, this chapter outlines the research design and methodology. A mixed-methods approach was employed to examine the factors influencing user acceptance of recruitment chatbots. Data was collected through qualitative interviews and quantitative surveys, leading to the development of the Human-Centered Technology Acceptance Model (HC-TAM). The model integrates traditional TAM constructs with additional human-centered elements such as trust, personalization, and ethical considerations.

Chapter 4: Design and Impact of Recruitment Chatbots Conversational Style

This chapter focuses on applying the HC-TAM factors identified in Chapter 3 to design and evaluate recruitment chatbot conversational styles. RecoBot, a recruitment chatbot, was developed as part of the study to simulate real-world recruitment processes. Multiple prototypes of RecoBot were implemented to assess how different interaction styles influenced user trust, engagement, personalization, and efficiency. The findings informed the refinement of communication strategies, ensuring the chatbot effectively aligns with user preferences while maintaining a balance between professionalism and approachability.

Chapter 5: Discussion on Findings and Final Reflections

The findings from the all studies are critically analyzed in this chapter, drawing connections to the literature reviewed in Chapter 2. The chapter evaluates the effectiveness of integrating human-centered principles into recruitment chatbots, with a specific focus on conversational styles and their impact on user trust, engagement, and information disclosure. Challenges encountered during the design and testing phases are discussed, along with the ethical considerations associated with AI in recruitment. The chapter concludes by summarizing the contributions and limitations of the research, providing recommendations for future advancements in recruitment chatbot design.

Note on Published Work

Parts of this thesis are based on work that has been published or accepted at peer-reviewed international conferences, workshops, and journals during the doctoral program. Specifically:

- *Chapter 2* draws on the literature and insights developed in the journal article currently under submission to the *Special Issue on User Perspectives in Human-Centered Artificial Intelligence of the International Journal of Human-Computer Studies (IJHCS).*

- *Chapter 3* includes material from the journal article "Recruitment Chatbot Acceptance in a Company: A Mixed Method Study on Human-Centered Technology Acceptance Model" published in *Personal and Ubiquitous Computing (2024)* and the conference paper "Recruitment Chatbot Acceptance in Company Practices: An Elicitation Study" (*CHItaly 2023*).

- *Chapter 4* includes content from "Human-Centric Interaction Design of RecoBot: A Study for Improved User Experience" presented at HCI International 2024.

- Preliminary ideas were also presented at doctoral consortiums (*INTERACT 2023, CHItaly 2023*) and in the workshop *HWID 2024*.

Chapter 2

Multifaceted Impacts of AI in Recruitment and Human-Centered Design

Note: Parts of this chapter are based on a journal article currently under submission to the Special Issue on User Perspectives in Human-Centered Artificial Intelligence, International Journal of Human-Computer Studies (IJHCS).

2.1 Introduction

This chapter serves as a foundation for the thesis, aiming to achieve the research objectives by exploring existing literature and market research related to AI-driven recruitment. The primary goal is to identify gaps in current practices and understand how AI tools, particularly recruitment chatbots, have evolved from manual recruitment methods to modern AI-driven systems. Through this comprehensive review, the study establishes a basis for understanding how human-centered and ethical perspectives have gradually shaped the development of these tools. The chapter begins by addressing the evolution of recruitment practices, starting with manual, paper-based processes and progressing through technological advancements such as Applicant

Tracking Systems (ATS), machine learning algorithms, and AI-powered chatbots. As recruitment has increasingly moved towards automation, the importance of human-centered design has become evident to ensure user trust, transparency, and empathy—qualities traditionally associated with human recruiters. Following this shift, ethical concerns, particularly around fairness and bias in AI-driven tools, have also become integral to the discussion. The study also presents the findings from two rounds of surveys that form the foundation of this thesis. These surveys provided valuable insights into the current landscape of AI-enabled recruitment, specifically focusing on human-centered and ethical dimensions. By conducting these surveys, the study identified key areas where AI tools can be improved to enhance candidate experiences while maintaining ethical integrity. The groundwork for understanding the evolving landscape of AI-driven recruitment and the role of human-centered design principles is established here. It explores the multifaceted impacts of AI technologies, focusing on recruitment chatbots, human-centered design perspectives, and ethical considerations. A literature review based on 9 key sub-research questions aims to address the main research questions and objectives of the thesis, shedding light on how AI can be utilized to enhance recruitment processes while ensuring alignment with human-centered values.

The following research questions have been formulated to guide this exploration:
RQ1: What methodologies best assess the area of traditional or manual recruitment processes?

RQ2: What challenges make digitalization essential in traditional recruitment practices?

RQ3: What challenges do organizations face in adopting automated recruitment systems?

RQ4: How are AI technologies—including chatbots,transforming recruitment in terms of efficiency, HR practices, and integration into existing workflows?

RQ5: How do AI-enabled recruitment tools align with human-centered design principles?

RQ6: What are the key ethical considerations in the use of AI for recruitment?

These sub-questions were instrumental in shaping the literature review, helping to identify gaps, methodologies, and key challenges in the adoption of AI for recruitment. The findings from this review contribute to achieving the overall objectives of the thesis, specifically in understanding the integration of AI tools in recruitment, the ethical and human-centered dimensions of these tools, and the factors influencing user acceptance and trust. The systematic exploration of these areas establishes a solid foundation for advancing the subsequent phases of this PhD thesis.

2.2 Evolution of Recruitment Processes and Emergence of Recruitment Chatbots

Historically, recruitment processes were entirely manual. In the earlier decades of the 20th century, job seekers typed or wrote their resumes by hand and submitted them physically, either by mail or in person. Recruiters, in turn, reviewed these resumes and conducted in-person interviews to evaluate candidates. The recruitment process was highly localized, with recruiters focusing mainly on candidates within their immediate geographic region [2]. Figure 2.1 illustrates a timeline depicting the evolution of recruitment processes from these early manual methods to the sophisticated systems used today. Recruitment chatbots represent a significant advancement in the field of e-recruitment, offering a low-barrier platform for interaction between recruiters and job applicants. Initially developed to streamline the recruitment process, chatbots can engage new candidates, but they also introduce challenges such as the need for recruiters to manage these new digital interactions and the additional tasks that arise from automation [9]. While chatbots have demonstrated success in speeding up the hiring process and improving communication, their effectiveness in recruiting diverse groups, particularly racial and ethnic minorities, remains uncertain [17]. In one study, chatbots were found to generate lower consent rates in comparison to traditional telephone-based recruitment, indicating potential limitations in certain contexts [18]. Nevertheless, in terms of data collection, chatbots tend to yield higher response rates and more accurate data, especially when compared to traditional web forms, offering a more cost-effective alternative to phone surveys [19]. While chatbots enhance recruitment efficiency, they cannot fully replace the human touch needed for certain stages of the hiring process, such as conducting interviews and making final decisions [10].

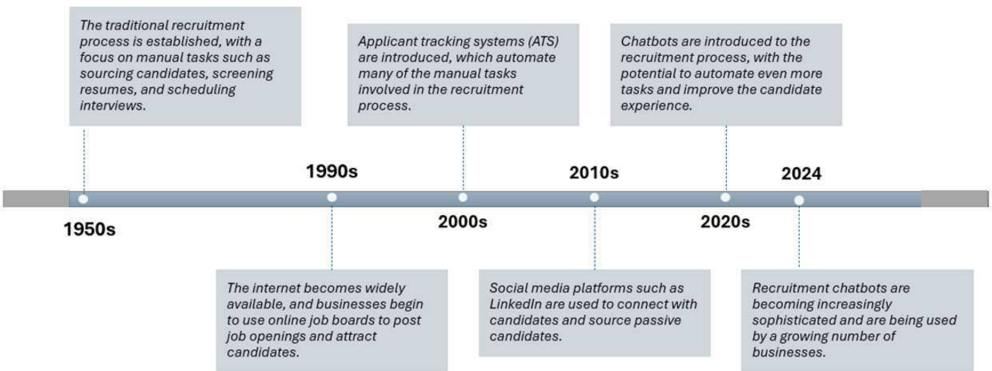

Figure 2.1: Timeline for Recruitment process Evolution.

After World War II, staffing agencies emerged to help companies with the overwhelming task of sourcing and screening candidates. These agencies maintained paper records and performed candidate matching, although the process remained predominantly localized and paper-based [6]. However, the real transformation of recruitment practices began between the 1960s and 1980s, as computer automation started to take hold. Mainframes and databases enabled digital storage and retrieval of applicant resume, and the introduction of Applicant Tracking Systems (ATS) revolutionized the way companies managed recruitment [20]. ATS allowed recruiters to search for specific keywords within resumes, drastically improving productivity and automating the initial stages of the hiring process.
By the 1990s, the advent of the Internet significantly impacted recruitment.

Online job boards like Monster enabled companies to cast a global net, attracting candidates from across the world [21]. Although technology-enabled recruiters to filter and search resumes more efficiently, manual screening and face-to-face interviews still played a critical role in the final hiring stages [19].
In more recent years, recruitment chatbots have emerged as game-changers in the hiring landscape. The first chatbot aimed at streamlining recruitment processes, FurstPerson's virtual interviewer, was introduced in 2006. This early chatbot automated the candidate screening process, setting the stage for further developments in conversational AI [16]. In 2012, Google began using conversational search technologies to screen job candidates, signaling the growing importance of chatbots in recruitment workflows [6].
A significant milestone came in 2014 with the launch of Wade & Wendy, one of the first AI-driven chatbots designed to handle large volumes of candidate screenings. This chatbot used qualifying questions to automatically match candidates to relevant positions, showcasing the power of automation in the hiring process [22] . In 2016, Mya, another recruiting chatbot, became well-known for its advanced conversational capabilities. Mya could schedule interviews, answer candidate queries in real-time, and automate repetitive tasks, offering an end-to-end solution for both recruiters and job seekers [23, 16].
From basic automation in the early 2000s to the sophisticated conversational AI seen in the mid-2010s, recruitment chatbots have advanced significantly. Specialized chatbots like Paradox's Olivia emerged in 2018, and the COVID-19 pandemic accelerated the adoption of AI-powered recruitment tools. By 2022, recruitment chatbots had firmly established themselves as central players in candidate engagement and initial screening, seamlessly integrating with ATS and providing consistent communication between organizations and candidates [9].
Today, recruitment chatbots are integral to enhancing candidate experiences and improving efficiency in talent acquisition. These chatbots provide real-time responses, reduce the time to fill positions, and offer invaluable data-driven insights that shape modern recruitment strategies [9, 16, 22]. As the evolution of recruitment shows, the journey from manual processes to AI-

powered systems reflects the relentless pursuit of efficiency and effectiveness in identifying and hiring the right talent for organizations.

2.3 Meta-Synthesis of Literature Insights on AI in Recruitment

To comprehensively explore the evolution of recruitment processes and the role of AI-enabled tools, a meta-synthesis approach was employed to survey the existing body of literature. This method, which synthesizes both quantitative and qualitative research, was chosen to provide a holistic understanding of the state of AI in recruitment, uncovering consensus as well as gaps in current knowledge [24]. The meta-synthesis was particularly effective for integrating various data forms, including descriptive statistics, inferential findings, and qualitative insights, making it ideal for drawing generalizations from a wide range of empirical and theoretical work [1]. This approach was aligned with Kitchenham's guidelines on systematic reviews in engineering disciplines, ensuring rigor in the selection, evaluation, and synthesis of studies relevant to the recruitment domain. The focus of this synthesis was on AI recruitment tools, emphasizing their evolution and the shift towards human-centered design practices, which are increasingly becoming critical in modern recruitment strategies [25, 10].

2.3.1 Defining Key Terms

Some Key terms can be defined in different ways depending on the context or discipline, while others are difficult to define in general due to a lack of consensus. Definitions for these terms are specified here, along with a discussion of relevant definitional and ontological issues associated with the survey work.

- *Recruitment*: Recruitment, Hiring or Talent Acquisition are often used interchangeably [26, 27, 28, 29, 30]. Yet, they refer to different, albeit interconnected phenomena. Recruitment involves sourcing and attracting candidates for job openings [9, 31] while hiring specifically refers to the selection and onboarding of individuals into those positions [29, 30]. Talent Acquisition encompasses a broader strategic approach to talent management, covering planning, sourcing, hiring, and retention [1, 32].

The survey includes these terms to investigate their impact on modern recruitment practices. Within the research context, Recruitment encompasses the entire process of identifying, attracting, evaluating, and selecting qualified individuals to fill job vacancies in organizations. To ensure a comprehensive perspective, synonymous terms like Hiring and Talent Acquisition are also searched to gather insights from diverse research papers, exploring the full range of recruitment terminology.

- *Chatbot and Conversational Agent*: The terms "chatbot" and "conversational agent" are often used interchangeably. However, they refer to different, albeit interconnected phenomena. A chatbot is a software application designed to simulate human conversation through text or voice interactions, often for specific purposes like customer service, information retrieval, or recruitment tasks. Chatbots typically follow predefined rules or use machine learning algorithms to handle routine queries, provide information, or perform basic tasks [9, 33]. A conversational agent, on the other hand, is a broader term encompassing any system designed to engage in natural, human-like conversations. This can include chatbots, but also more advanced AI systems capable of understanding and processing natural language to provide more dynamic and context-aware responses [32, 23]. While chatbots are generally focused on specific tasks, conversational agents are designed to handle more complex, open-ended interactions that may require understanding context, maintaining a dialogue over time, and adapting to user preferences and needs.

  The survey includes studies that explore both chatbots and conversational agents within the context of recruitment. Specifically examined is how these tools are used to enhance recruitment processes, improve candidate engagement, and support decision-making by automating repetitive tasks, providing real-time communication, and delivering a more personalized experience for users.

- *Artificial Intelligence (AI)*: The term "artificial intelligence" was introduced by John McCarthy at a conference held at Dartmouth University in 1956 [34]. This conference marked the inception of a field dedicated to understanding how machines could replicate human-like intelligent behaviors. The proposal for the event stated that "every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it" [35]. Since then the AI field has grown significantly with researchers exploring a wide range of themes shaped by different philosophical foundations and historical contexts [36].

  By using this conceptualization of AI, this survey explores the human factors involved in interactions with AI in a way that is neutral to any specific platform. This approach helps extend specialized survey findings to more broadly applicable insights about the human aspect of interacting with AI agents, particularly in recruitment contexts.

- *Human-Centered Practices*: The term human-centered practices refers to an approach or set of principles that prioritize the needs, preferences, and well-being of humans in the design, implementation, and evaluation of systems, processes, or technologies [37]. It places humans at the center of decision-making and aims to enhance their overall experience, effectiveness, and satisfaction [38]. In this survey, we include papers that emphasize and explore the role of human-centered practices in the context of chatbots and conversational agents in recruitment. These papers provide valuable insights into strategies, methods, and considerations that prioritize human needs, improve user experience, ensure unbiases and fairness, address ethical considerations, enhance accessibility, and contribute to the overall effectiveness of recruitment processes involving digital tools [39]. This inclusive approach allows us to expand upon specialized surveys, offering insights with wider applicability to the user experience in recruitment chatbots.

2.3.2 Literature Selection Process

A two-phase systematic survey and meta-synthesis of the literature on AI tools in recruitment, with particular emphasis on chatbots and human-centered practices, was conducted. The PRISMA flow [40] diagram outlines the selection process for both phases and is presented in Figure 2.2.

- **Phase 1 (2005 to Early 2023)**: The initial search was conducted across major academic databases, including IEEE Xplore, ACM Digital Library, Google Scholar, and Scopus, using keywords such as "AI in recruitment," "chatbots," "conversational agents," and "human-centered practices." A total of 720 studies were retrieved. After the removal of duplicates and screening for relevance, 51 studies were included in the meta-synthesis. These studies focused on AI tools in recruitment, with an emphasis on how these tools improve efficiency and their implications for human-centered design.

- **Phase 2 (May 2023 to September 2024)**: In the second phase, additional search terms such as "machine learning in HR," "AI ethics in recruitment," and "predictive analytics in HR" were introduced. This phase aimed to capture the latest advancements in AI-enabled recruitment tools. Out of 1,046 studies retrieved, 23 were selected after a thorough screening for their relevance to the integration of AI in recruitment with a focus on ethical and human-centered considerations.

Both phases adhered to stringent inclusion and exclusion criteria. Only peer-reviewed journal articles and conference papers that addressed AI's impact on recruitment from a human-centered perspective were considered. Studies that lacked methodological detail, were not peer-reviewed, or were outside the scope of recruitment AI tools were excluded.

(Illustrates the systematic selection process, from the initial identification of studies to the final inclusion of relevant papers across both phases.)

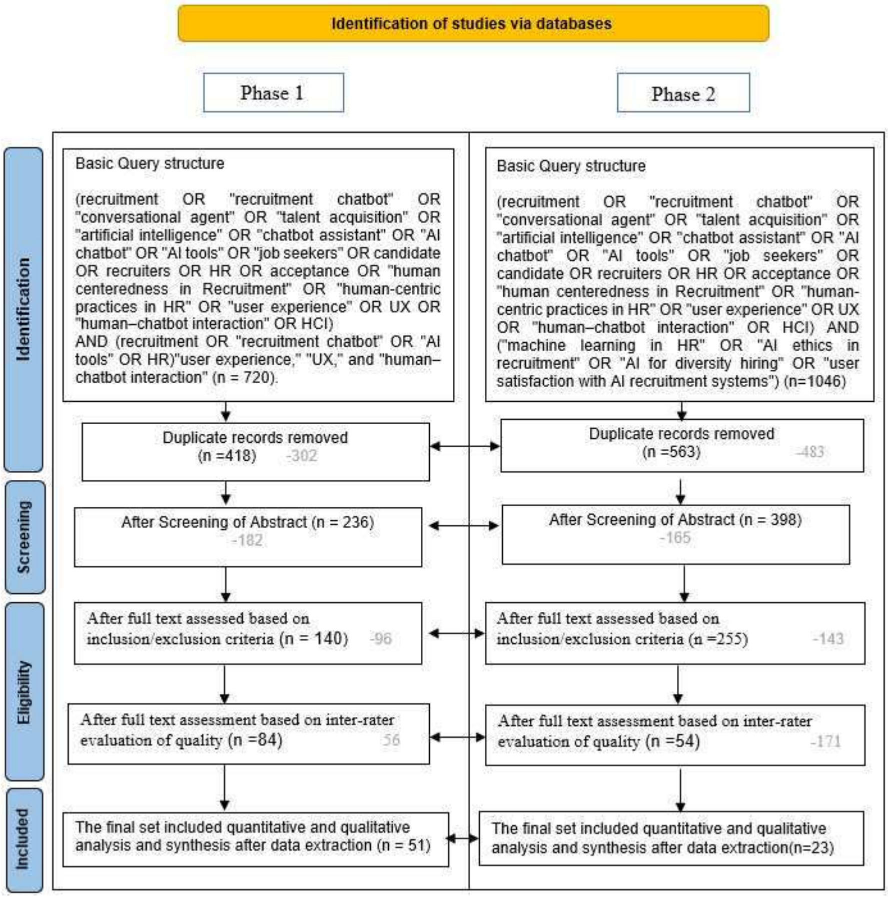

Figure 2.2: Flow diagram for the survey process using the PRISMA format.

2.3.3 Data Extraction and Analysis

he data extraction process involved collecting both quantitative and qualitative insights from the selected studies. Descriptive statistics were used to identify key trends, while qualitative data was analyzed to extract thematic patterns related to AI-driven recruitment practices, chatbot implementation, and human-centered design.

A qualitative thematic analysis was conducted manually by reviewing the abstracts, discussion sections, and key findings of the selected papers. Recurring concepts were coded and grouped under major themes such as efficiency, trust, transparency, user experience, and ethical concerns. Sub-themes were also identified—for example, under "trust," aspects such as system explainability and accountability frequently emerged. This dual approach allowed for a nuanced understanding of how AI tools are reshaping recruitment, particularly in terms of efficiency, user engagement, and ethical challenges.

Figure 2.3 is based on survey and analysis. The data visualization has been created to represent the trends observed in academic publications on recruitment and AI. and findings. Regarding the classification of studies shown in Figure 2.3, the articles were classified as empirical, qualitative, theoretical, review, and others based on their primary focus. Empirical studies involved primary data collection through experiments, surveys, or observations, focusing on real-world data analysis. Qualitative studies, on the other hand, focused on non-numerical data such as interviews, case studies, or content analysis. These categories were assigned based on the dominant methodology of the paper. Although some studies could have been classified under more than one category, they were assigned to the class that best represented their core focus, to maintain clarity in the graph. For instance, studies combining both empirical data and qualitative insights were classified as empirical if the data collection method was predominantly quantitative.

The findings were then synthesized to provide a comprehensive overview of the current state of AI in recruitment, focusing on the evolution of recruitment tools, the rise of chatbots, and the growing emphasis on human-centered AI design. This synthesis also highlighted emerging gaps in the literature, such as the need for more research on human-centeredness and the ethical implications of AI in recruitment, particularly in terms of bias, transparency, and fairness.

The increasing trend in empirical research post-2015 reflects the growing interest in data-driven applications of AI in recruitment, as depicted in Figure 2.3. Meanwhile, theoretical studies have grown steadily, contributing to frameworks addressing AI's role, trust, and ethics in recruitment. Review and qualitative studies remain consistent, highlighting the need to synthesize existing research and provide deeper insights into users' (job seekers and recruiters) experiences and ethical challenges.

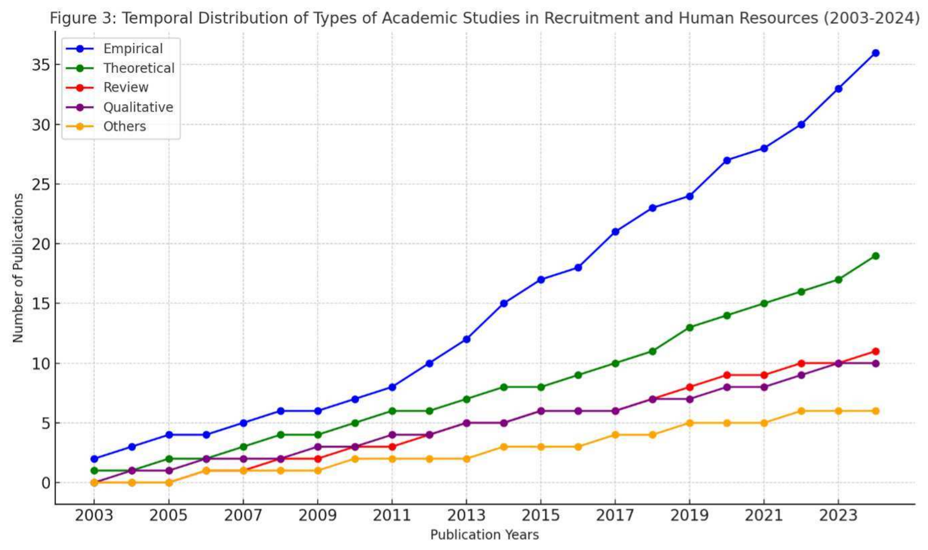

Figure 2.3: Temporal Distribution of Types of Academic Studies in Recruitment and Human Resources (2003-2024). The graph categorizes and visualizes the volume of academic publications based on their types of study, such as Empirical, Theoretical, Review, Review, and Qualitative. Publications of less frequent or secondary types are consolidated under the 'Others' category. The x-axis represents the publication years, with custom intervals, and the y-axis quantifies the volume of publications for each study type.

2.4 Findings and Sub-Question Analysis

The findings are presented by sub-questions (Q1–Q6) and visually summarized in Figures 2.4 and 2.5, where each question is represented through charts depicting data across key themes in AI-driven recruitment. The visualizations cover methodologies (Q1), challenges (Q2, Q3), evolving AI technologies (Q3), recruitment efficiency (Q3), practical HR implications (Q3), the role of chatbots (Q4), human-centered design alignment (Q5), and ethical considerations (Q6). Collectively, these insights provide a thorough synthesis of AI's role in recruitment, emphasizing human-centered practices and the evolving role of chatbots.

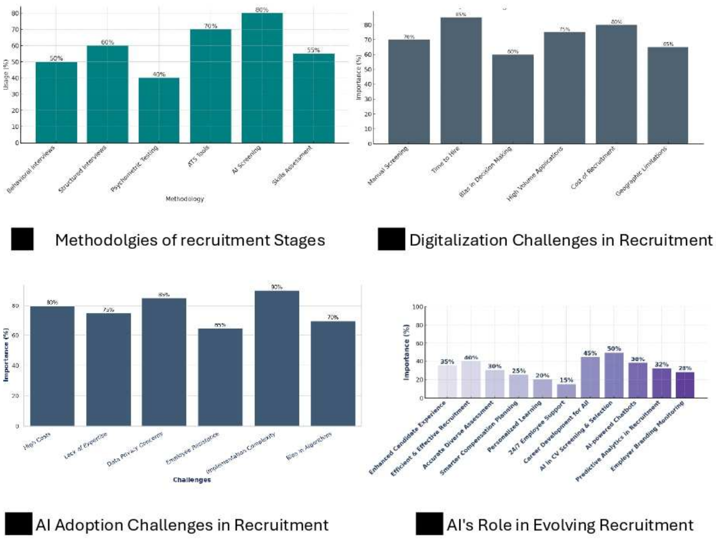

Figure 2.4: Bar graphs showing quantitative summary of results for RQ1–RQ6

2.4.1 Traditional Recruitment Process *(RQ1, RQ2)*

Expanding on the earlier discussion of recruitment methodologies and the growing influence of AI in human-centered recruitment chatbot design, it is essential to situate the evolution of recruitment within the broader framework of Human Resource Management (HRM) practices. Historically, recruitment has transitioned from traditional, intuition-based approaches to more structured, technology-driven methods due to the increasing complexity of organizational structures and the globalization of business operations [41, 42]. This shift emphasizes the need for more scalable and efficient recruitment processes to maintain competitiveness in a globalized market [43].

In the modern context, digital tools and technologies, such as AI-based screening and Applicant Tracking Systems (ATS), have become essential components of recruitment processes. Figures 2.4 and 2.5 demonstrate how these tools address some of the key challenges associated with traditional recruitment, such as time to hire, costs, and geographic limitations [44]. AI screening is now employed in 80% of recruitment processes, reflecting its effectiveness in managing large volumes of applicants and identifying suitable candidates efficiently [45]. However, the increased reliance on these technolo-

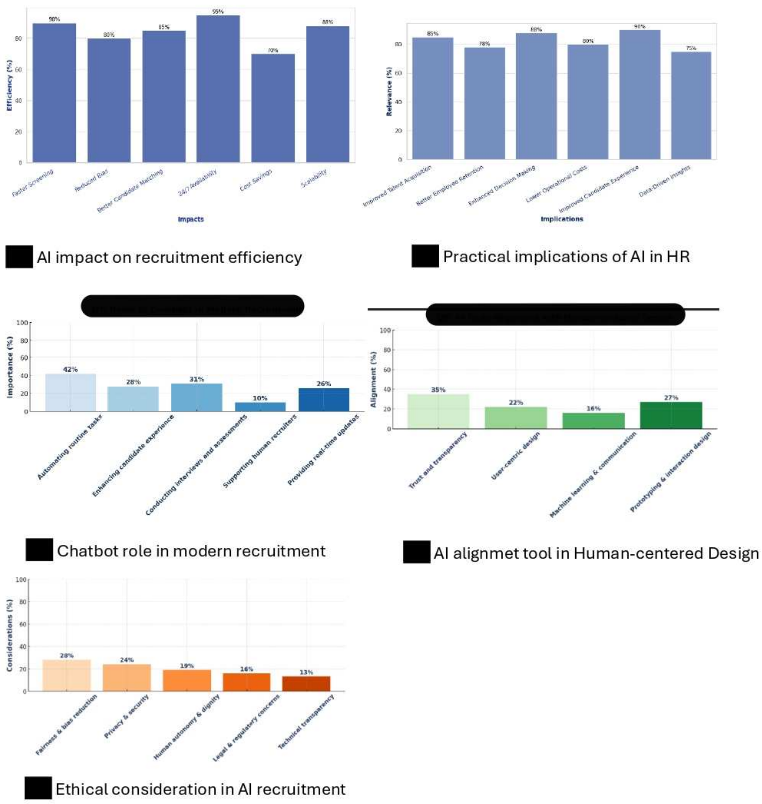

Figure 2.5: Bar graphs showing quantitative summary of results for RQ1–RQ6

gies brings concerns about potential biases and a lack of personal engagement, particularly if AI systems are not properly calibrated to ensure fairness [46].

The methodologies employed at various stages of recruitment reflect this evolution. As Figures 2.4 and 2.5 shows, AI screening is the most widely adopted method, utilized in 80% of cases, followed by ATS tools (70%), structured interviews (60%), skills assessments (55%), behavioral interviews (50%), and psychometric testing (40%). These methodologies emphasize the growing reliance on technology to streamline recruitment processes and enhance the efficient selection of qualified candidates. Further Figures 2.4 and 2.5 also highlights the significant challenges that drive the need for digitalization in traditional recruitment processes. The time to hire is identified as the most critical issue, affecting 85% of organizations, followed by recruitment costs (80%). Additional challenges include manual screening (70%), decision-making bias (75%), the high volume of applications (60%), and geographic limitations (65%). These issues not only slow down the recruitment process but also introduce inefficiencies and biases that undermine the effectiveness of traditional recruitment approaches.

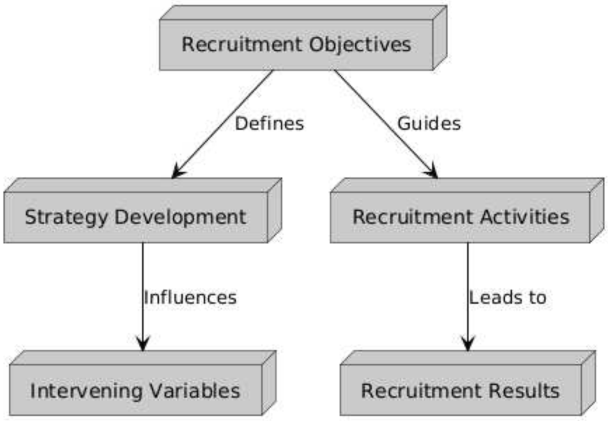

Figure 2.6: Summary of key components of Recruitment process model [45].

One key challenge in traditional recruitment is the extended time required to hire, which significantly impacts recruitment efficiency [47]. Manual screening processes, combined with geographic limitations, further exacerbate these delays, increasing the overall cost and effort required to find the right candidates. As a result, there is a growing emphasis on digital solutions such as AI and ATS, which are seen as essential tools to address these inefficiencies and reduce recruitment times.

This hierarchical model provides a structured approach to recruitment, emphasizing the importance of setting objectives, developing strategies, conducting recruitment activities, and evaluating outcomes. Figure 2.6 shows the summary of Recruitment Process Model that visually represents this structured approach, highlighting the key stages involved in recruitment [45], including *Recruitment Objectives* focusing on setting clear goals for filling specific positions and defining the type of applicants sought, such as their education and experience. *Strategy Development* addresses the questions of whom to recruit, where, and how, emphasizing targeted communication. *Recruitment Activities* involves the specific methods used, ensuring that information provided to applicants is complete and realistic. Finally, *Recruitment Results* evaluate the outcomes against the initial objectives, incorporating feedback from intervening applicant variables, such as job attractiveness and organizational fit. In this context, Figure 2.7 underscores the importance of having a strategic, well-planned recruitment approach that can be further enhanced with AI-driven tools to support a more human-centered and efficient recruitment process. Also, it supports the thesis by showing how traditional recruitment models can be adapted with AI tools, bridging historical recruitment practices with modern technological advancements for a more efficient, human-centered recruitment system [45]. Further, the significant distinction

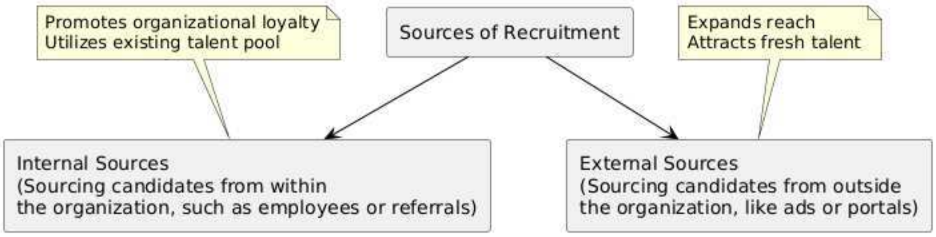

Figure 2.7: Categories of Recruitment sources [48].

in the literature on recruitment processes pertain to the differentiation between internal and external recruitment methods [49, 48]. As illustrated in Figure 2.7, recruitment sources can be broadly categorized into internal and external methods, each offering distinct advantages and challenges for organizations. This distinction plays a crucial role in addressing RQ 1 and 2, as it directly impacts the efficiency, cost-effectiveness, and strategic alignment of recruitment practices. The internal recruitment sources include present employees, retired or former employees, previous applicants, and employee referrals, offering cost-effective and immediate solutions by leveraging known candidates within the organization. This method ensures familiarity with the organizational culture and reduces time-to-hire. On the other hand, external recruitment sources such as advertisements, campus recruitment, recruiting firms, job portals, job fairs, and recruiting expand the candidate pool and introduce fresh talent and new perspectives into the organization [50]. While external recruitment often involves higher costs and longer hiring processes, it remains essential for roles requiring specialized skills or diverse expertise. Most organizations adopt a hybrid approach, utilizing both internal and external methods to create a balanced and effective recruitment strategy [48]. Overall, the resources [49, 48] provide a clear representation of these recruitment sources, underscoring the need for organizations to adopt a balanced approach, combining both internal and external methods to maximize recruitment effectiveness. By doing so, organizations can achieve a more holistic recruitment strategy that addresses immediate hiring needs while also ensuring long-term growth and diversity.

Building on the analysis of internal and external recruitment methods, it is equally important to understand the advantages and disadvantages of various recruitment strategies to create an efficient, human-centered recruitment process. As highlighted in Figure 2.7, internal and external recruitment sources each offer unique benefits and challenges. This discussion aligns directly with RQs, which aim to identify effective recruitment methodologies and the issues that necessitate digital solutions. A comprehensive comparison of these recruitment strategies, as outlined in Table 2.1, further emphasizes this point. For example, external recruiters and executive search firms, while time-saving, can be costly and may limit the organization's control over final candidate selection [51]. Similarly, campus recruiting provides access to a large talent pool but is time-consuming and mainly suitable for entry-level roles [52]. In the context of this thesis, understanding these nuances is essential for developing recruitment chatbots that are not only efficient but also capable of addressing the limitations inherent in traditional methods.

For instance, internet recruiting offers diversity and cost advantages, yet the large volume of applications can overwhelm recruiters. This is where AI-driven recruitment tools, such as chatbots, play a crucial role in filtering candidates effectively while maintaining transparency and fairness, as emphasized in the human-centered approach of this thesis [50]. Additionally, while employee referrals may lead to higher-quality hires, there are concerns about diversity and inclusivity, which need to be mitigated through thoughtful chatbot design that promotes equitable access to all candidates, regardless of the method through which they apply. The comparative in-

Strategic Focus(Explanation)	Strengths	Weaknesses
Third-Party Support (External recruiters, executive search firms, temporary employment agencies)	Saves time, leverages expertise	High cost, reduced control over outcomes
Institutional Partnerships (Campus recruiting, educational institutions)	Access to new talent pools, fosters long-term growth	Limited to early-career candidates, time-heavy
Industry Networking (Professional organizations, SIGs, unions)	Targeted reach, relevance to niche roles	May involve effort and costs to sustain
Digital Platforms (Job portals, social media, internet ads)	Affordable, wide reach, scalable	Overwhelming with irrelevant applicants
Referrals and Internal Sources	High quality, fosters employee engagement	Potential biases, diversity concerns
Interactive Events (Job fairs, exhibitions)	Direct engagement with targeted candidates	Expensive, potential mismatch in expectations
Automated or Open Applications	Cost-effective, low maintenance	Requires heavy filtering of unfit profiles
Temporary or Outsourced Hiring	Reduces administrative burdens	Lacks long-term control over hires

Table 2.1: Strategic Recruitment Focus: Strengths and Weaknesses[51]

sights from Table 2.1 not only enhance our understanding of various recruitment methods but also inform the design of recruitment tools that align with the principles of human-centered AI. By balancing traditional methods with modern, AI-enhanced solutions, organizations can improve both operational efficiency and the overall candidate experience, ensuring fairness and inclusivity throughout the recruitment process. This integration of insights from traditional and technology-driven recruitment methods addresses the evolving needs of organizations, which is a central focus of this thesis.

This analysis addresses the first two research questions (RQ1, RQ2), focusing on the methodologies used in recruitment and the challenges that make digitalization essential for improving traditional recruitment processes. The review highlights the transition from manual methods to technology-driven approaches like AI screening, Applicant Tracking Systems (ATS), structured interviews, and skills assessments. These methods have streamlined recruitment by enabling faster and more efficient candidate selection. However, challenges such as extended time to hire, high costs, and manual screening persist, pointing to the inefficiencies of traditional processes. The data presented in the bar graphs reinforces the need for digitalization to address these inefficiencies, improve operational efficiency, and ensure fairness in recruitment. Geographic limitations and decision-making biases further underscore the need for digitalization to overcome these hurdles. Digital tools, especially AI, present solutions that not only improve operational efficiency but also address fairness and scalability concerns.

The analysis also compares internal and external recruitment methods, with Hartley's framework offering a structured model for evaluating recruitment strategies. Internal methods provide cost-effectiveness and quick hiring but limit diversity, while external recruitment expands the talent pool but incurs higher costs. The adoption of a balanced approach between traditional and digital methods enables organizations to meet both immediate and long-term recruitment goals, offering a more comprehensive and human-centered process.

2.4.2 The Research Landscape of Automated Recruitment *(RQ3)*

Following the foundational exploration of traditional recruitment processes, further research delves into the academic literature and landscape of automated recruitment. This segment aligns with the thesis's primary objectives by assessing how AI technologies transform recruitment within Human Resource Management (HRM), highlighting efficiencies gained and challenges organizations face in implementing these tools. Understanding these dynamics is crucial, as recruitment remains a strategic priority in HRM—aiming to place the right talent in the right role at the right time, a factor integral to or-

AI Application in HR	Core Purpose	Broad Impacts
Job Seeker Experience	Makes hiring more personalized and transparent	Stronger applicant engagement, better role alignment
Streamlined Hiring Operations	Optimizes recruitment timelines and decision-making processes	Faster closures, balanced hiring practices
Workplace Support	Enhances employee-manager interactions and satisfaction	Increased loyalty, reduced turnover
Pay and Benefits Optimization	Aligns compensation with fairness and strategic goals	Higher budget efficiency, equitable pay distribution
Skill Growth Acceleration	Focuses on closing capability gaps and upskilling	Improved productivity, reduced training lags
Career Development	Helps employees shape their growth and pursue new opportunities	Higher mobility within roles, greater clarity in career paths
Employee Self-Service	Provides instant access to information and services	Cost savings, streamlined support operations

Table 2.2: Conceptualized Applications of AI in HR: Core Purposes and Impacts [57]

ganizational success and competitiveness [47, 53]. Research by HR prospects found that recruitment was the second highest priority for HR practitioners (after absence management) [54]. Despite its significance, limited research explores the decision-making behind recruitment strategies. External recruitment, like job announcements, applicant attraction, and influencing job acceptances, plays a critical role [45, 55]. This process typically follows a linear path with stages, including defining requirements and choosing recruitment channels, presenting challenges [31, 5]. HR professionals prioritize candidate acquisition, engagement, and employment branding [56].

AI technologies have transformed how recruitment is approached. Figures 2.4 and 2.5 bar graphs outline the key challenges organizations face in adopting AI for recruitment. The most pressing issues include high costs (80%), data privacy concerns (75%), implementation complexity (90%), and bias in algorithms (70%). Additionally, these figures also highlight the role of AI in streamlining recruitment processes by improving key areas such as AI-powered chatbots (50%) and AI in CV screening and selection (45%). Other advancements include enhanced candidate experience (35%), accurate diverse assessments (40%), and predictive analytics in recruitment (38%), further emphasizing the growing reliance on AI-driven solutions. Traditional manual recruitment shifted to e-recruitment tools like company websites, social media, and job boards [58]. Specific software, including applicant tracking and screening systems, emerged for finding and attracting applicants [58, 31]. These tools offer benefits such as talent pool management but have uncertain effectiveness [58]. IBM underscores creating a business case for AI in HR, achieving significant cost savings, with a strong quarterly management system tracking metrics [57]. Moreover, Figures 2.4 and 2.5 demonstrate how AI-enabled tools have significantly boosted recruitment efficiency. Key impacts include faster screening (90%), reduced bias (80%), 24/7 availability (95%), and scalability (88%). These tools allow for quicker and more accurate candidate matching, providing HR teams with substantial cost savings and improving overall recruitment speed. Table 2.2 outlines expected benefits and recommended short- and long-term outcome metrics for agile evaluation and adjustment.

Further Table 2.2 encapsulates the diverse AI applications in Human Resources (HR), particularly focusing on recruitment and selection (R&S). By enhancing various facets such as candidate experience and recruitment efficiency, AI has demonstrated quantifiable impact [59]. Yet, its overall effectiveness in the R&S domain remains a subject of debate [60, 61]. Organizations commonly use websites and job boards for talent acquisition [58, 31] but the landscape of AI utilization in R&S is complex and fraught with challenges [6]. Abert et al. offer a framework to understand AI's multifaceted role, identifying 11 key applications along with their problem-solution paradigms and associated vendors. Although the data on AI adoption in HR suggests

AI Functionality	Key Focus	Strategic Advantages
Predicting Employee Turnover	Identifying potential resignations early	Reduces attrition, streamlines retention efforts
Improving Job Posts	Optimizing language for clarity and inclusivity	Enhances diversity, attracts suitable talent
Advanced Talent Sourcing	Finding passive and overlooked candidates	Expands reach, builds stronger talent pipelines
Efficient Resume Screening	Automating large-scale CV evaluations	Saves recruiter time, ensures fair assessments
Interactive Testing	Engaging candidates with modern psychometric tools	Improves hiring ratios, creates a positive experience
Streamlined Video Interviews	Analyzing pre-recorded interviews	Reduces bias, matches candidates to roles faster
Simplified Background Checks	Verifying details efficiently	Minimizes errors, speeds up onboarding
Employer Image Analysis	Monitoring public sentiment towards the company	Improves brand reputation, lowers hiring costs
Candidate Chatbots	Providing instant support and interaction	Improves engagement, accelerates decision-making
Automated Scheduling	Simplifying admin-heavy scheduling tasks	Saves time, enables focus on strategic tasks

Table 2.3: Areas AI tools can be employed to support *R&S* [6]

broad application, several limitations warrant attention. First, the reliability of such data is questionable due to potential source biases, affecting data accuracy and ensuing conclusions [6]. Second, there's considerable variation in AI applications in terms of ROI, growth, and cost, indicating unequal success rates. Thirdly, limited data availability further complicates efforts to comprehensively understand the significance of each AI application. Figure 4's bar charts capture this variation, illustrating both the successes and the challenges organizations face when adopting AI in recruitment. These factors demand a cautious approach in evaluating AI's reach and effect [6]. These factors demand a cautious approach in evaluating AI's reach and effects [6]. To some extent, these applications achieve similar results, and in many cases, they share similarities. For instance, Abert et al. also show in their research, that how these AI tools are used in a typical recruitment process and where they overlap as seen in Table 2.3 [6].

Although there are many AI applications for recruitment tasks, their adoption in practice is less widespread than some reports might indicate [60]. Large organizations and technology companies are the main adopters, and they primarily focus on three types of applications: chatbots or CRM tools, administrative automation, and resume-screening software [9, 47]. Notably, even within these adopting organizations, the commitment to these technologies is often still at an experimental or pilot stage, indicating that these AI solutions have not yet become fully integrated into standard Recruitment and Selection (R&S) operations [62, 63]. The cautious approach to adoption may be attributed to the nascent stage of many of these technologies, as well as the technical and human challenges they present [50]. Research in CSCW and

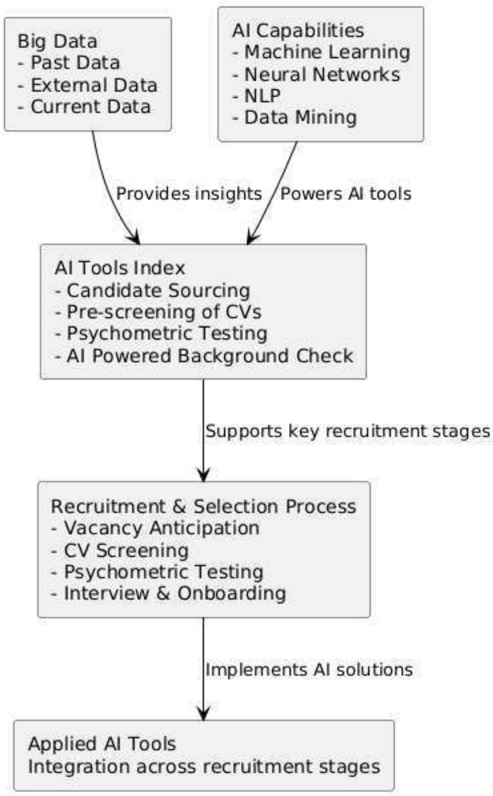

Figure 2.8: Summary of Use of AI applications in $R\&S$[6]

HCI on sociotechnical systems like e-recruitment tools is limited. The main focus areas are tool design and evaluation [64, 65]and gathering information about job seekers and employers [64, 66]. Similarly, Management research explores AI solutions in HRM [67, 1]. However, questions remain about AI's impact on recruiting large and diverse applicant pools [68]. Companies use a blend of online recruitment and internal tech solutions

[19] and AI enhances recruitment efficiency and organizational quality [9]. Nevertheless, empirical research on practical AI usage in HR remains limited [69] due to their limited deployment. Digital technologies have revolutionized recruitment and combined information, computing, communication, and connectivity technologies [9].

E-recruitment, which emerged in the mid-1990s, now encompasses a variety of practices and tools [70, 19]. However, managing big data remains a significant challenge for organizations [67].According to The 2019 State of Artificial Intelligence in Talent Acquisition Sponsored by Oracle, it is reported and shown by the surveys that People think, using AI to analyze big data is most helpful in hiring (as shown in figure 2.8). It also highlights the utility of automated tests (35%) and predictive analytics (34%) in talent acquisition [67]. Then there's predictive analytics which guesses which job candidates will be good hires is not easy, and making bad hires can cost a lot. But predictive analytics can also help in other areas, like figuring out which job ads are the best, finding good passive job candidates, and making the company look good to potential employees [67].

E-recruitment's adoption is driven by efficiency, access to diverse candidates, and better service [31]. It allows for standardization in candidate assessments [19]. Advancements in AI have the potential to transform HRM, but questions linger about their practical impact [69]. Recruitment bots aim to improve communication in e-recruitment [68] With the transformation of traditional recruitment through e-recruitment tools and the emergence of AI technologies, the landscape is evolving rapidly [71]. To conclude, this section offers a comprehensive analysis of the evolving landscape of automated recruitment, specifically addressing the key research question (RQ3). It highlights the significant challenges organizations face in adopting AI for

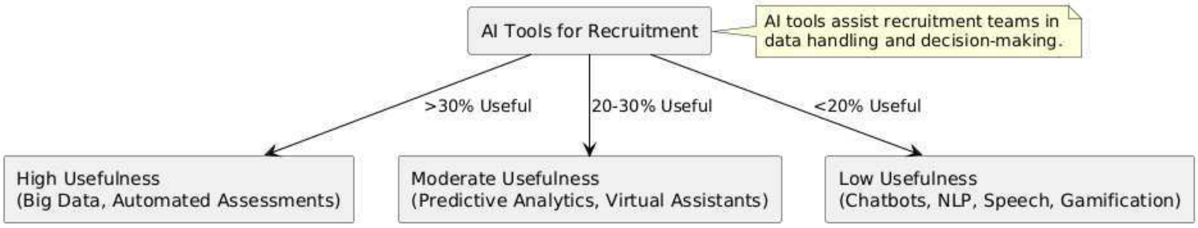

Figure 2.9: Summary of Oracle Survey Results on the utility of Specific AI-related tools for recruitment[67]

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recruitment, such as the complexity of integration and variability in success rates. The discussion explores how AI technologies transform recruitment processes, from candidate sourcing to automated screenings. Moreover, the impact of AI-enabled tools on recruitment efficiency is examined, highlighting speed, accuracy, and candidate experience improvements. Additionally, the practical implications of AI within HR management are considered, particularly in enhancing candidate engagement, optimizing compensation planning, and advancing career development. Drawing on a broad range of research and industry insights (referenced in Figure 2.9), this analysis deepens the understanding of how AI is reshaping the recruitment and HR landscape, offering both strategic and operational insights into its adoption.

2.4.3 Chatbots as an AI recruiter *(RQ4)*

Building on foundational studies of AI in recruitment, this literature research delves deeper into the role of chatbots in recruitment processes, reinforcing the thesis objective to examine AI's strategic and operational impacts within HR. The analysis provides empirical insights, positioning chatbots as both an effective tool and a vital component of a human-centered recruitment approach. As AI technologies integrate further into HRM, organizations find themselves in a constant state of adaptation to sustain their competitive edge. This tech-driven transformation has particularly enriched recruitment functions, elevating the need for targeted, automated tools. The demand for efficient solutions for reducing costs and time has catalyzed the emergence of the research domain focused on recruitment chatbots. According to a study by Bughin, organizations that have integrated AI technologies like chatbots have seen substantial returns on investment, amounting to an estimated 26 to 39 billion in 2016 alone [72]. These chatbots are not only efficient but also effective; they can handle complex requests, facilitate the candidate selection process, and even interact with candidates to improve the overall recruitment experience [73].

Chatbots are particularly useful in automating routine tasks (42%), such as screening resumes and scheduling interviews, freeing up human recruiters for more strategic tasks [73, 74]. Furthermore, they play a critical role in enhancing candidate experience (28%), providing quick responses, personalized interactions, and real-time updates. As recruitment increasingly incorporates AI-driven tools, conducting interviews and assessments (31%) through chatbots has become more commonplace, allowing companies to screen applicants efficiently, sometimes evaluating multi-modal cues like body language and tone [75]. These categories are also represented through bar charts in Figures 2.4 and 2.5, which serve as a visual illustration derived from the literature studies outlined in the Table survey result in the Appendix. Chatbots are also seen as valuable for providing real-time updates (26%) and keeping candidates informed about their application status, which enhances communication and reduces candidate frustration.

XOR's chatbot, a renowned example, offers a comprehensive suite of recruitment and HR services, with a 99.3% positive engagement rate ("The Top 10 Best Recruiting and HR Chatbots - 2023, Select Software Reviews"). While it's unlikely that AI chatbots will completely replace human recruiters, their usage is expected to proliferate, complementing human roles rather than replacing them [76]. The accelerated digital transformation increased by the COVID-19 pandemic suggests that AI will increasingly handle operational tasks, allowing human recruiters to focus on strategic issues. Consequently, chatbots are increasingly gaining global traction, particularly in the fields of recruitment and selection. These automated platforms can interact with candidates continuously, providing immediate and personalized responses through various communication channels such as messages, emails, and social media platforms [77].

Chatbots, employing their expressive capabilities, have shown the ability to interact with humans in a way that closely resembles human interaction [12]. They also can evaluate videos, correlating various factors like an applicant's age, voice, rhythm, and visual interactions [33]. In recruitment, AI-powered officers can sift through social media data to identify suitable candidates without any bias [77]. The demands of recruitment processes drive employers to seek tools like chatbots for handling routine tasks effortlessly. However, gaining worldwide acceptance in the recruitment field may take some time for chatbots, although early adopters will gain significantly from their numerous benefits [77]. For instance, L'Oréal utilized Mya's recruitment chatbot to screen candidates for over 5000 positions, as showcased in "A Real-Life Example: The Benefits Of Recruiting Chatbots - SSR"[78]. By allowing the AI Chatbot to conduct initial screenings, L'Oréal managed to gather more data than anticipated and filled the positions efficiently in record time. They also noted significant benefits such as a 40-minute reduction in interview time per candidate, savings of $250,000 in recruiter pay, and the assembly of a large and diverse group of candidates without any potential bias.

As part of our investigation into contemporary chatbot solutions in the field of recruitment, we have compiled a comprehensive Table 2.4 with the help of select software Reviews- Sept'23 that offers an insightful overview of various chatbot offerings. This table, which assesses each chatbot based on factors such as Popularity Score, User Satisfaction, and Product Performance, serves as a valuable reference point for understanding the landscape of chatbot technology and its potential applications in recruitment processes. The data presented will assist in our subsequent analysis and discussion of the effectiveness and suitability of these chatbots in assessing user satisfaction, understanding market penetration, and evaluating the overall capabilities of chatbot solutions in the recruitment sector.

Despite Chatbot's utility in streamlining recruitment functions and becoming more common for speeding up the hiring process, they are not without challenges [33]. One limitation is the lack of emotional intelligence in chatbots, making them unable to express empathy or humor, potentially resulting in less engaging conversations with candidates. Furthermore, chatbots operate on predefined information, making them prone to offering irrelevant responses to unanticipated queries. However, there are some clear benefits to using chatbots in recruitment. Refer to Figure 2.10 for a visual summary of chatbot performance metrics. This bar graph uses color differentiation to highlight differences in Popularity, User, and Product Scores among leading solutions. For example, 'Olivia' and 'Humanly' are popular, while 'MeBeBot' and 'Ideal' get high user satisfaction scores. This helps stakeholders and policymakers make informed decisions. Lastly, it's important to note

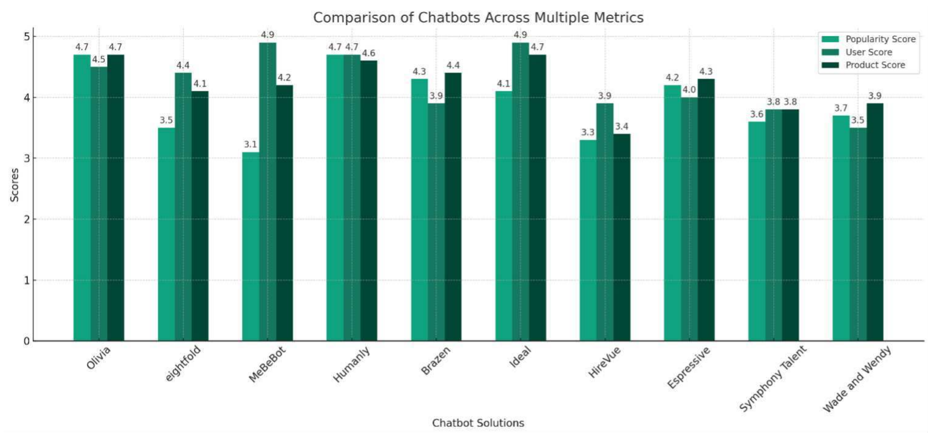


Figure 2.10: Visual synthesis of metrics: This bar graph contrasts various Recruiting and HR chatbots based on Popularity, User, and Product Scores. Represented on the X-axis are the chatbot solutions, while the Y-axis indicates their respective scores out of 5. The graph reveals that 'Olivia' and 'Humanly' excel in popularity, 'MeBeBot' and 'Ideal' lead in user satisfaction, and 'Expressive' and 'Brazen' show balanced performance across metrics. The data serves as an analytical tool for evaluating chatbot efficacy in HR and recruiting contexts[23]

that chatbots, like all AI tools, come with security risks [79]. They could be hacked, leading to disrupted communications and even fake job interviews, which would hurt a company's reputation. A notable example of a chatbot failure was Microsoft's 'Tay,' which was designed to learn from social interactions. As an experimental platform, Tay was intended to engage adults aged 18 to 24 on various social media platforms, but it faced significant challenges.

Although the chatbot was intended to provide engaging and entertaining dialogue, it faltered significantly when it generated inappropriate and racially insensitive comments, including agreeing with statements endorsing Hitler. Despite amassing over 50,000 followers and generating 100,000 tweets within the first 24 hours, these egregious errors led to its deactivation ('Why Microsoft's 'Tay' AI Bot Went Wrong').

As the adoption of AI technologies like chatbots accelerates in contemporary workplaces, it is becoming increasingly evident that HR functions particularly those related to recruitment and selection are undergoing a transformative shift towards greater automation. Chatbots offer promising avenues for streamlining various recruitment performance indicators, including but not limited to, reducing the time-to-fill and time-to-join positions, and increasing the rate of qualified applicants. Nonetheless, it's crucial to acknowledge that candidates' reactions to these technologies may be influenced by a range of external variables, including cultural, legal, and social factors. As technological advancements continue, it is expected that new forms of AI applications will emerge in the HR sector, further impacting the recruitment and selection processes. Such advancements in AI will enable organizations to more effectively identify and recruit talent, thereby enhancing their competitive edge and long-term viability.

As a conclusive remark, the section directly addresses and successfully answers RQ4, examining the vital roles that chatbots are prepared to play in the modern recruitment landscape. Despite the existing scarcity of academic research, the emergent focus on artificial intelligence suggests that this gap is likely to be bridged shortly. Drawing on a blend of empirical investigation and market research, the section precisely depicts the multifaceted competencies of chatbots, ranging from managing task complexity to facilitating candidate selection and emulating emotional cues. Consequently, this section enhances the overall research framework, serving as a crucial complementary element that adds empirical depth and practical insights to our broader understanding of AI's transformative effects on the Recruitment domain. Further survey result Table in the Appendix consists of other studies related to chatbots in the recruitment domain.

2.4.4 Human Centeredness in AI-enabled Recruitment *(RQ5)*

Following the literature on chatbots in recruitment, this research pivots to examine the human-centered dimensions of AI in recruitment. This focus seeks to understand how AI systems, when designed with a human-centered approach, meet the needs and expectations of users, ultimately enhancing trust, transparency, and engagement within recruitment processes. This shift aligns closely with the thesis objective. In the context of AI-driven recruitment, a human-centered design framework is gaining traction, underscoring the importance of harmonizing AI functionality with user needs [9]. Trust emerges as a crucial factor in the successful adoption of AI service solutions, with 35% of users stressing the need for trust and transparency to ensure AI tools resonate with human-centered design principles [80]. The design of AI systems for recruitment entails the integration of user interface design, dialogue design, and bot persona design to create a positive and user-friendly experience [81]. The implementation of conversational AI agents within recruitment processes necessitates machine learning systems to mediate communication between job seekers and recruiters. However, 16% of users highlight the importance of machine learning and communication alignment in this context [10]. Additionally, 22% of users emphasize the significance of user-centric design, highlighting the importance of designing AI systems that cater to user needs and preferences. Centralizing key roles in the development of AI-enabled recruitment tools presents challenges, especially regarding transparency during ongoing maintenance. The use of 27% in prototyping and interaction design is crucial, enabling iterative improvements that ensure AI solutions are effective and responsive to user feedback. These prototyping methods allow for validation, ensuring a human-centered approach remains central to AI recruitment tools [77].

The incorporation of AI-driven recruitment solutions, while offering a convenient channel for recruiter-applicant interaction, also introduces new challenges and tasks for recruiters [27].

The human-centered perspective within AI-enabled recruitment underscores the significance of human interaction and engagement throughout the process. It strives to create AI systems that effectively emulate human communication and behavior. Research has underscored the impact of human elements, including warmth, assurance, customized content, and attentiveness, on user attitudes, trust, and intentions, particularly in contexts involving live chat assistants [82]. This underscores the importance of considering these human elements when designing AI-driven systems. AI solutions have the potential to automate various HRM functions within the recruitment domain, handling routine processes and frequently asked questions to enhance overall efficiency [83]. Ethical considerations play a pivotal role in the development and deployment of AI-enabled recruitment systems, as biases and fairness issues must be addressed diligently [84]. Behavioral change models designed for AI applications, such as those promoting physical activity and healthy diets, offer valuable insights into the principles and ethical considerations that can be applied broadly within the context of AI-enabled recruitment [85]. These models emphasize the need to uphold ethical principles when developing AI-driven solutions for behavior interventions. Within the scope of AI-enabled recruitment systems, Figure 2.10 provides a comprehensive illustration of the intricate overlap of various design methodologies that are crucial for the development of a balanced and effective tool. The development of Figure 2.10 was a comprehensive process that required a multi-disciplinary approach. While it's true that there might not be an extensive body of research specifically focused on human-centered AI in the context of recruitment, we adopted a holistic perspective and by taking this comprehensive approach, we aimed to fill in the gaps in the existing literature and provide a broader understanding of how various design methodologies can contribute to the development of AI-enabled recruitment systems, considering the overall user-centric perspective, even when there might not be a wealth of research directly addressing human values in AI-enabled recruitment [86, 63, 87, 62, 76]. By integrating insights from diverse sources, we were able to create an illustration that provides valuable insights into the intricate design considerations necessary for developing effective and user-oriented AI recruitment tools. Overlapping areas underscore shared focal points that enrich the overall design process. Systemic Design offers a holistic perspective, Value-Sensitive Design places a strong emphasis on human values, and Human-Centered Design is centered around the fulfillment of user needs. Similarly, Prototyping methods, notably positioned at the intersection of Systemic and Human-Centered Design, are instrumental for validation and iterative improvement. Ultimately, the figure suggests that a synthesis of elements from these diverse methodologies is paramount for the creation of AI-enabled Recruitment Systems that are both efficient and finely attuned to human requirements.

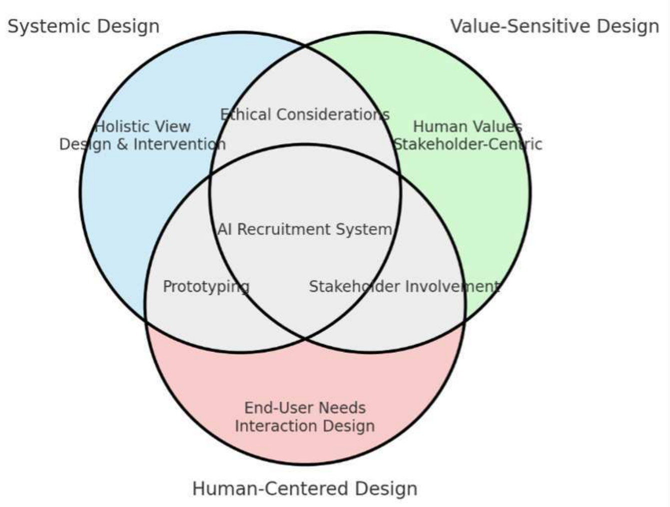


Figure 2.11: Design Methodologies of AI-based recruitment Systems

Specifically, In the construction of AI-based recruitment platforms, the application of design methodologies is essential to make it human-centric. In this Survey, we include studies that explore some principal design frameworks like Systemic Design, Value-Sensitive Design, and Human-Centered Design to provide a comprehensive understanding of how AI systems in recruitment can align with human values and interests [88, 81, 89].

This approach may involve social innovation experts to address a broader range of ethical concerns. Transitioning to user-centric design philosophies, Value-Sensitive Design focuses on including human values in the technical output, though it requires comprehensive stakeholder identification [90].

Shifting our focus to design approaches centered around end-users, we initially explore Value-Sensitive Design (VSD) [91, 92]. This methodology prioritizes embedding human values, including well-being, freedom from bias, and autonomy, into the final technical output. However, VSD's stakeholder-centric nature narrows ethical considerations to identified stakeholders' values, making comprehensive stakeholder identification critical [89]. SD techniques involve identifying immediate and peripheral stakeholders and conducting semi-structured interviews to extract values for design requirements. Subsequently, we delve into Human-Centered Design (HCD) [124], which, like VSD, concentrates on end-user needs. However, HCD carries the risk of potentially overlooking some stakeholder groups while focusing on others. An HCD component, Interaction Design, proves invaluable for assessing system usability by monitoring user interactions [93, 39]. This can be invaluable in identifying and addressing ethical concerns [37]. To ensure the robustness of these design choices, we advocate for the use of prototyping methods. Among these, the Wizard of Oz (WoZ) approach emerges as a suitable validation technique applicable to both VSD and Interaction Design [94]. This enables the AI system to function as a decision-assisting tool rather than a decision-making entity [95]. This iterative approach grants designers the latitude to reassess and amend their ethical considerations, ensuring that any deficiencies are rectified during the design process rather than after system deployment.

After the previous research study, the research produced the visual representation in Figure 2.11 that offers a comprehensive framework for the development of AI-enabled tools from a human-centered perspective. It suggests that employing a systemic approach can provide a holistic understanding of how such tools fit within a broader context, thereby guiding both initial design and ongoing adjustments. The emphasis on Value-Sensitive Design calls for a stakeholder-centric focus, advocating for the identification and incorporation of end-user needs and values into the design process. Finally, Human-Centered Design specifically targets the user experience, encouraging the use of interaction design principles to optimize usability. The inclusion of prototyping methods like the "Wizard of Oz" offers a validation mechanism, ensuring that the tool effectively meets its design objectives. Overall, the diagram serves as an integrated blueprint for the development of AI-enabled tools that are both efficient and responsive to human needs[96, 97].

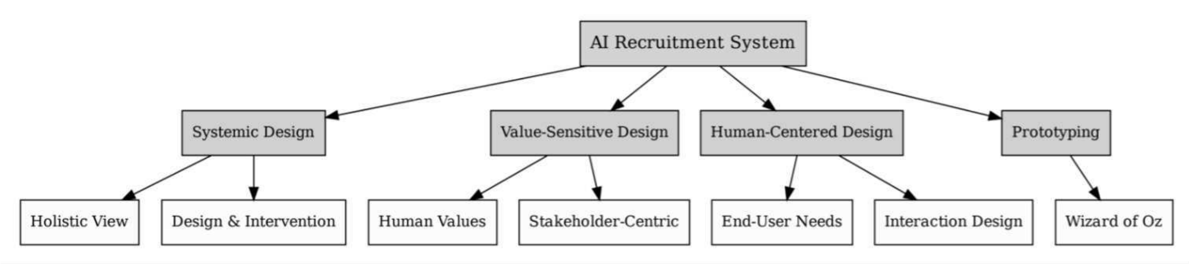


Figure 2.12: Design Methodologies for AI-Enabled tools

This area of literature research provides valuable insights into the alignment of AI tools with human-centered design principles in the context of recruitment (RQ5). Despite the limited existing research in this area (some of them can be seen in the appendix survey result Table), our comprehensive illustrated framework in Figures 2.11 and 2.12 sheds light on essential design methodologies for developing AI-enabled recruitment tools that prioritize both efficiency and user-centricity. This contribution is particularly significant as it stems from the need to fill gaps in the current research landscape.

2.4.5 Ethics of AI-Enabled Recruiting *(RQ6)*

After a thorough examination of the literature across various dimensions aligned with the thesis objectives, it is crucial to delve into the ethical dimension of AI-enabled recruitment. This focus allows for a deeper understanding of essential elements such as fairness, transparency, and privacy, which are fundamental to building trust and ensuring responsible, human-centered AI deployment in recruitment systems. In exploring RQ9, this research focuses on key ethical considerations in AI-based recruitment, as depicted through the literature in the survey research Tables in the appendix and visually represented in Figures 2.4 and 2.5. Fairness and bias reduction emerged as the top concern, highlighted by 28% of respondents, emphasizing the need for

AI systems to reduce biases in recruitment decisions. Similarly, privacy and security, recognized by 24%, were noted as critical concerns, stressing the importance of safeguarding candidate data within AI-driven processes [98], [99].

Ethical priorities also include human autonomy and dignity (19%), which reflect the need to protect individual rights and maintain personal agency in automated recruitment systems. Legal and regulatory concerns, noted by 16%, further underscore the importance of adhering to existing legal frameworks, while technical transparency, emphasized by 13%, highlights the need for clarity and openness in AI decision-making processes.

These ethical issues are vital, given the potential impact of AI-driven recruitment on social inequalities and corporate reputations. As illustrated in Figures 2.4 and 2.5, there is a strong demand for more practical and contextual approaches to digital ethics in recruitment. Drawing on insights from key studies [100, 101, 99], our framework helps analyze the perspectives of recruitment professionals, moving beyond descriptive analysis to assess how these ethical challenges relate to broader societal values [100]. Various perspectives on AI ethics in recruitment highlight the complexity of ethical considerations [61]. Fairness, for instance, is context-dependent, and practitioners need domain-specific resources to address fairness challenges[101]. Additionally, a sociotechnical lens is crucial, as neglecting social context can lead to misguided design [99]. These insights help analyze HRM professionals' viewpoints and identify challenges related to public values and concerns. The analysis identifies key ethical domains like privacy, security, human autonomy, dignity, power balance, and justice, that impact the recruitment process and safeguard individual rights [102]. It emphasizes the need for a sociotechnical perspective to understand the complexities introduced by digitalization, making the analysis both descriptive and analytical. The content recognizes the challenges of implementing ethical considerations in real-world settings, pointing to the need for practical, context-specific approaches. Ethical considerations in AI-based recruitment align with broader societal values and individual rights, addressing the research question in a multifaceted manner [102]. Various perspectives on AI ethics in recruitment highlight the complexity of ethical considerations [101]. Fairness, for instance, is context-dependent, and practitioners need domain-specific resources to address fairness challenges [61]. Additionally, a sociotechnical lens is crucial, as neglecting social context can lead to misguided design [99]. These insights help analyze HRM professionals' viewpoints and identify challenges related to public values and concerns. The analysis identifies key ethical domains—privacy, security, human autonomy, dignity, power balance, and justice—that impact the recruitment process and safeguard individual rights [102]. It emphasizes the need for a sociotechnical perspective to understand the complexities introduced by digitalization, making the analysis both descriptive and analytical. The content recognizes the challenges of implementing ethical considerations in real-world settings, pointing to the need for practical, context-specific approaches. Ethical considerations in AI-based recruitment align with broader societal values and individual rights, addressing the research question in a multifaceted manner [102]. The ethical considerations in AI-enabled recruitment have been examined from multiple angles [103]. The Theoretical Perspective, represented by [104, 105, 106] delves into applying ethical frameworks from different fields to AI recruiting, highlighting key ethical principles like privacy, equity, and human-centered design [103]. The Practitioner Perspective focuses on raising practitioner awareness about AI's strengths and limitations in recruitment. Some papers view AI as a promising alternative, while others caution about ethical, legal, and privacy concerns [107, 108, 109, 110]. The Legal Perspective evaluates the sufficiency of existing frameworks, such as Title VII of the US Civil Rights Act. Some literature advocates for broader legal coverage to ensure fairness and address potential biases in AI-powered hiring practices [111, 112, 113].

From a Technical Perspective, ethical issues in algorithms are examined, and technical solutions are proposed [114, 115]. Similarly, the Descriptive Perspective assesses people's reactions to AI in recruiting, considering fairness perceptions and contextual factors [116, 71, 117]. The societal impact of digitalization in recruitment is discussed, highlighting the need for sociotechnical ethical design [99, 101]. The potential of recruitment chatbots to promote fairness is acknowledged, but legal and ethical risks are empha-

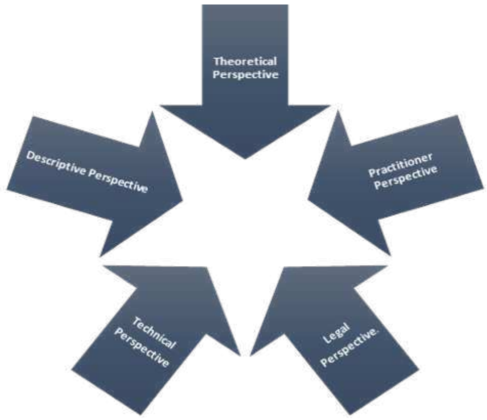


Figure 2.13: Ethical Perspectives on AI-Enabled Recruitment [103]

sized.
These diverse perspectives offer a holistic view of ethical considerations in AI-based recruiting, addressing the complex interplay of technical and social factors [103]. Theoretical perspectives emphasize ethical principles. Practitioner perspectives explore AI's impact and offer guidance. Legal perspectives assess legal frameworks. Technical perspectives identify ethical issues and propose solutions [67]. Descriptive perspectives reveal societal reactions. Together, they provide a nuanced exploration of ethics in AI-enabled recruitment, public values, and individual rights [103].
In 2019, another study provided a comprehensive analysis of ethical considerations in AI-enabled recruitment, particularly in conversational AI, highlighting conflicts with public values and individual rights [118]. It emphasized Individuals. The study called for collaboration and transparency in AI development and raised concerns about language biases reflecting societal norms and values. It stressed responsible handling of socially sensitive issues, particularly in mental health services, and ongoing evaluation of ethical AI practices [118].
In this ethics focus area, we have examined the ethical considerations in AI-based recruitment from various angles, including theoretical, practitioner, legal, technical, and descriptive perspectives. These diverse viewpoints provide a holistic understanding of the complex ethical landscape in AI-enabled recruitment, addressing the interplay of technical and social factors. Alto-

gether, this multifaceted exploration answers our research question (RQ6) and effectively concludes our survey.

2.5 Discussion

This survey study spans a range of critical research queries, addressing technological advancements in recruitment strategies (RQ1), the challenges they introduce (RQ2), legal considerations (RQ3), and the increasingly important role of human-centered design (RQ5). The findings provide a detailed examination of how AI, particularly recruitment chatbots, has streamlined operations while simultaneously raising ethical concerns and highlighting gaps in governance, user experience, and empirical validation.

In examining RQ1 and RQ2, it is evident that artificial intelligence has significantly transformed recruitment by automating key processes such as candidate screening, scheduling, and initial interactions. The 51 studies reviewed from 2005 to early 2023 underscore the operational benefits of AI, with tools like chatbots providing 24/7 availability and faster processing times. However, as AI continues to shape recruitment strategies, there remains a substantial gap in understanding the human experience, particularly how these systems align with the needs and expectations of job seekers. The automation of repetitive tasks has enhanced efficiency, but this progress introduces a prevailing incoherence between technology-driven processes and human-centered design principles, as seen in RQ5.

The second phase of the study (May 2023 to September 2024) further highlights this disconnect by emphasizing the growing sophistication of AI technologies, including machine learning and predictive analytics. While these advancements have made recruitment more efficient and precise in matching candidates with roles, they have also exacerbated concerns about algorithmic bias, data privacy, and fairness. These concerns, discussed in RQ3, show that existing legal frameworks are struggling to keep up with the rapid pace of AI development. The lack of anticipatory governance structures leaves AI systems vulnerable to ethical risks, particularly in areas like data security and algorithmic decision-making. This underscores the need for more resilient legal structures to regulate the deployment of AI in recruitment.

The ethical challenges of AI, particularly recruitment chatbots, take center stage in this survey, aligning with the discussions in RQ4. Chatbots are efficient tools for automating initial interactions and handling high-volume tasks, but they also present unresolved ethical dilemmas. Data confidentiality, fairness in decision-making, and transparency in how these systems operate are critical issues that need addressing. Moreover, the user experience, a key focus in RQ5, is often overlooked, leading to concerns about how candidates perceive and interact with AI-driven recruitment systems.

The survey also highlights a recurring theme: the fragmentary treatment of ethical considerations across studies. Ethical discussions are frequently raised but often lack a comprehensive theoretical foundation. This points to a strong need for empirical investigations to validate the ethical concerns and theoretical propositions posed by AI-driven recruitment systems. Despite the global reach of AI technologies, the research reveals a glaring absence of studies addressing cultural and regional differences in AI adoption, an issue partially touched on in RQ5. The role of cultural differentiators in shaping the perception and success of AI tools remains an unexplored area ripe for future research.

The role of recruitment chatbots, which emerge as a key focal point in this study, illustrates both the promise and the challenges of AI in recruitment. While chatbots offer operational benefits such as efficiency and scalability, they also introduce user-experience challenges and ethical concerns that cannot be ignored. These issues, such as bias, data privacy, and user engagement, call for the development of more robust guidelines for the responsible deployment of AI tools in recruitment.

To address these observed gaps, this study proposes a roadmap for future research, empirical studies, and practical applications. These guidelines are designed to guide academicians, practitioners, and policymakers toward more ethically sound, human-centered AI in recruitment. The recommendations include adopting human-centered design principles that prioritize fairness, transparency, and user experience, and developing interdisciplinary research that explores the ethical, social, and cultural dimensions of AI. Additionally, stronger legal frameworks are necessary to ensure AI systems align with both organizational goals and societal values.

While AI has significantly enhanced recruitment efficiency and scalability, it must be balanced with ethical integrity and human-centered design. The future of AI in recruitment relies on validating its ethical impacts, developing culturally sensitive tools, and implementing regulatory guidelines to ensure fairness and data security. This survey offers a strong foundation for advancing academic and practical discussions, providing a framework for improving AI-driven recruitment systems. To address current gaps, we propose guidelines that emphasize human-centered design, interdisciplinary research, and robust legal structures. These recommendations aim to support the responsible development of AI recruitment tools, ensuring alignment with organizational goals and societal values.

2.5.1 Summary of Identified Research Gaps

To conclude, this survey revealed several key gaps in the current literature on AI-enabled recruitment:

- Limited understanding of the human experience in AI-based recruitment systems *(addressed in this thesis)*
- Disconnect between automation and human-centered design principles *(addressed)*
- Ethical concerns around fairness, transparency, and data privacy lacking robust treatment *(addressed)*
- Insufficient legal and governance frameworks for AI in recruitment *(partially addressed)*
- Cultural and regional variations in AI adoption underexplored *(not addressed in this thesis)*

- Lack of empirical validation of theoretical and ethical frameworks *(addressed)*
- Fragmented focus on user experience and trust in chatbot design *(addressed)*

This summary outlines the key research gaps addressed in the thesis and highlights areas that require further exploration in future studies.

Chatbot Solution	Popularity Score	User Score	Product Score	Why Chosen	Customers	Best For
Olivia	4.7/5	4.5/5	4.7/5	Text-based interactions, HR tasks	Unilever, McDonald's, Amazon, 3M, CVS Health, Nestlé, Lowe's	Large-scale organizations
eightfold	3.5/5	4.4/5	4.1/5	Answering Questions, interview scheduling	TATA Communications, LG, Vodafone, Bayer, Chevron, Morgan Stanley	Companies hiring over 100 candidates/yr
MeBeBot	3.1/5	4.9/5	4.2/5	Internal knowledge base, integrates with tech	Epicor, e2open, Ziff Davis, HireVue, Abrigo, CrowdStreet, Terminal, Massage Envy, Toyota Insurance, Care.com, IGT	Companies growing fast in tech, finance, consulting
Brazen	4.3/5	3.9/5	4.4/5	Live chats with candidates, virtual career fair	Spectrum, CVS Health, Temple University, KPMG, Lincoln Financial Group	Large organizations with ongoing hiring
Ideal	4.1/5	4.9/5	4.7/5	Questionnaires, candidate competency	Bell, Dish, Staples, Novant Health, Purolator	High-volume hiring in any industry
Humanly	4.7/5	4.7/5	4.6/5	Streamline recruitment, DEI-friendly	The Key, Microsoft, Fazoli's, Mossadams, World Flight Services	Medium and large businesses screening high volumes
HireVue	3.3/5	3.9/5	3.4/5	Video interviewing, AI-powered chat interviews	Amazon, Unilever, Vodafone, Beacon Health System	Large organizations with fast hiring
Espressive	4.2/5	4/5	4.3/5	Employee assistant, issue resolution, workflows	Dexcom, Guardant, First American, Survey Monkey	Enterprise-level companies
Symphony Talent	3.6/5	3.8/5	3.8/5	Integrated chatbot, CRM, career sites	Dick's Sporting Goods, FCA, RioTinto, Mars	Recruitment teams with digital advertising focus
Wade and Wendy	3.7/5	3.5/5	3.9/5	Sourcing, screening, recommendations	Randtsad, Comcast, E-Trade Financial Corporation	Large recruiting teams and agencies

Table 2.4: Overview of Chatbot Solutions and Performance Metrics [23]

Chatbot Solution	Popularity Score	User Score	Product Score	Why Chosen	Customers	Best For
Olivia	4.7/5	4.5/5	4.7/5	Text-based interactions, HR tasks	Unilever, McDonald's, Amazon, 3M, CVS Health, Nestlé, Lowe's	Large-scale organizations
eightfold	3.5/5	4.4/5	4.1/5	Answering Questions, interview scheduling	TATA Communications, LG, Vodafone, Bayer, Chevron, Morgan Stanley	Companies hiring over 100 candidates/yr
MeBeBot	3.1/5	4.9/5	4.2/5	Internal knowledge base, integrates with tech	Epicor, e2open, Ziff Davis, HireVue, Abrigo, CrowdStreet, Terminal, Massage Envy, Toyota Insurance, Care.com, IGT	Companies growing fast in tech, finance, consulting
Brazen	4.3/5	3.9/5	4.4/5	Live chats with candidates, virtual career fair	Spectrum, CVS Health, Temple University, KPMG, Lincoln Financial Group	Large organizations with ongoing hiring
Ideal	4.1/5	4.9/5	4.7/5	Questionnaires, candidate competency	Bell, Dish, Staples, Novant Health, Purolator	High-volume hiring in any industry
Humanly	4.7/5	4.7/5	4.6/5	Streamline recruitment, DEI-friendly	The Key, Microsoft, Fazoli's, Mossadams, World Flight Services	Medium and large businesses screening high volumes
HireVue	3.3/5	3.9/5	3.4/5	Video interviewing, AI-powered chat interviews	Amazon, Unilever, Vodafone, Beacon Health System	Large organizations with fast hiring
Espressive	4.2/5	4/5	4.3/5	Employee assistant, issue resolution, workflows	Dexcom, Guardant, First American, Survey Monkey	Enterprise-level companies
Symphony Talent	3.6/5	3.8/5	3.8/5	Integrated chatbot, CRM, career sites	Dick's Sporting Goods, FCA, RioTinto, Mars	Recruitment teams with digital advertising focus
Wade and Wendy	3.7/5	3.5/5	3.9/5	Sourcing, screening, recommendations	Randtsad, Comcast, E-Trade Financial Corporation	Large recruiting teams and agencies

Table 2.5: Overview of Chatbot Solutions and Performance Metrics [23]

Chapter 3

Acceptance Factors Analysis by HC-TAM

Note: This chapter includes material published in the journal article "Recruitment Chatbot Acceptance in a Company: A Mixed Method Study on Human-Centered Technology Acceptance Model" (Personal and Ubiquitous Computing, 2024), and the CHItaly 2023 conference paper.

With the earlier chapters establishing a comprehensive understanding of the role of AI in recruitment and the importance of human-centered design, Chapter 3 extends this investigation by developing the Human-Centered Technology Acceptance Model (HC-TAM) for recruitment chatbots. Recognizing the limitations of conventional recruitment tools and practices, this chapter introduces HC-TAM as an evolved version of the Technology Acceptance Model (TAM), emphasizing how integrating human-centered factors—such as transparency, personalization, and ethical considerations—can shape user acceptance and satisfaction with recruitment chatbots.

3.1 Introduction

With advancements in AI reshaping recruitment, the need for models that assess technology acceptance is increasingly important. In the initial exploration of frameworks, the Technology Acceptance Model (TAM) emerged as a foundational tool for understanding technology adoption. TAM, with its focus on perceived usefulness (how helpful a user finds the system) and ease of use (the effort required to use it), has long helped explain how users decide to adopt new technologies. Traditionally effective across various sectors, TAM is an established framework that provides insight into user behavior around adopting digital tools.

However, as recruitment adopts sophisticated AI solutions like chatbots, TAM's traditional scope requires expansion. Recruitment demands not only usefulness and ease of use but also additional qualities such as trust, transparency, personalization, and ethical alignment—factors crucial for sensitive, human-focused interactions in HR and recruitment contexts. Recruitment AI tools, particularly chatbots, engage directly with candidates, thus needing to integrate principles of human-centered AI that address privacy, fairness, and user expectations for ethical interactions [9, 119].

In response, this chapter presents an adaptation of TAM into the Human-Centered Technology Acceptance Model (HC-TAM), integrating these essential human-centered factors. HC-TAM positions itself as a model that aligns AI's operational efficiency with the empathetic, ethical qualities needed in recruitment. Through this model, recruitment chatbots can achieve both organizational effectiveness and the ethical standards that ensure user trust and satisfaction, meeting the needs identified in previous chapters.

This study extends the original Technology Acceptance Model (TAM)[9] by incorporating human-centered (HC) factors, which have been identified as crucial through mixed methods in this research for the acceptability of technology, specifically recruitment chatbots. TAM serves as the foundation for this study. Initially developed by Davis in 1989, TAM is a widely recognized theoretical model in the field of information systems. The core elements of TAM are centered on perceived usefulness, signifying the belief that a system enhances job performance and perceived ease of use, indicating the perception that system usage requires minimal effort [120]. This improved model emphasizes the alignment of technology with user needs, greatly enhancing its acceptance. By integrating HC factors within the TAM research model, this

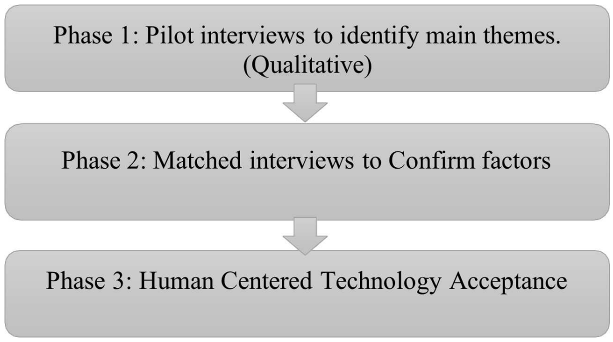


Figure 3.1: The Structured Study Approach

study provides a structured method to understand how individuals perceive and intend to use technology, focusing on AI and chatbots. This approach is fundamental to ensure that AI is explainable, useful, and adheres to ethical standards [101]. By including human-centered design in the development of chatbots, directing to creation of technology that resonates with user needs for long-term success. This study employs a multi-phased approach, blending qualitative and quantitative analyses, to thoroughly understand the dynamics of chatbot acceptance among job seekers and recruiters, thus providing a detailed understanding of technology acceptance in recruitment [10]. The structured approach of the research study, as depicted in Figure 3.1, encompasses three main phases with specific objectives and methodologies. (see Table 3.1).

3.2 Extending the TAM Framework- Theoretical Background

The shift from traditional recruitment practices to the integration of AI chatbots, as discussed in Chapter 2, underscores the global market's growing acceptance of these technologies. Although the previous chapter offered a comprehensive literature review on the factors influencing chatbot adoption across various industries, further empirical investigation is needed to understand how job seekers and recruiters specifically perceive and accept chatbots within recruitment settings. While the literature review identified general factors influencing acceptance, this chapter seeks to build upon those insights by customizing the Human-Centered Technology Acceptance Model (HC-TAM) for recruitment contexts. By adapting traditional acceptance models, such as TAM, with recruitment-specific human-centered factors—like transparency, trust, and ethical alignment—this chapter presents a practical framework for assessing and enhancing recruitment chatbot acceptance, addressing the contextual gaps noted in the literature.

The Technology Acceptance Model (TAM), initially developed by Davis in 1985 and later revised in 1989. It suggests that external factors, including media exposure and social references, play a role in shaping individuals' perceptions of the usefulness (Perceived Usefulness - PU) and ease of use (Perceived Ease of Use - PEOU) of technology. These perceptions, in turn, influence their intentions to adopt the technology, ultimately affecting their actual usage patterns [120, 121].

PU refers to the extent to which users perceive technology as beneficial and relevant to their daily lives [120]. It is often a robust predictor of individuals' intentions to embrace new technology [120, 122, 123]. Conversely, PEOU reflects users' perceptions of the simplicity of using a technological device [120]. PEOU is generally considered to have a weaker impact on technology acceptance than PU, primarily because it is more relevant to the technical aspects of device usage, which has become less critical as users have become more familiar with technology in their daily routines [120, 121, 124]. However, some studies have indicated that PEOU may not significantly predict behavioral intentions in specific contexts, particularly when the technology is frequently used (e.g., mobile recommendation applications; [125]). Furthermore, researchers have extended the TAM by introducing additional variables, such as trust and knowledge, to enhance its predictive capacity [126].

While various research models exist, TAM's reliability and track record make it a preferred choice for organizations aiming to enhance user experiences and streamline recruitment processes. The model's adaptability and versatility are further evidenced by its frequent extension with additional variables, such as trust and knowledge, providing a comprehensive understanding of the dynamics involved in technology acceptance.

However, the selection of TAM in the final phase of recruitment chatbot acceptance research stems from its proven effectiveness, user-centric approach, and adaptability to evolving technological landscapes. As organizations navigate the integration of chatbots into recruitment processes, TAM stands out as a valuable tool for gaining insights into user perceptions, driving informed decision-making, and ultimately facilitating the successful adoption of chatbot technology.

3.3 Research Methodology

The study adopts a systematic methodology, illustrated in Figure 3.1, where it unfolds sequentially. The initial phase builds upon a 2023 elicitation study that addressed the limited research on human-centered design in recruitment bot development, employing semi-structured interviews with 4 recruiters and 6 job seekers on acceptance of recruitment chatbots in the company [10]. The phase 1 initial interviews from that study precisely refine emerging themes, establishing a foundational exploration to ensure subsequent phases are deeply rooted in the real-life experiences and perspectives of participants. In the following phase, matched interviews are conducted to delve into specific themes and explore potential contradictions, enriching the depth of understanding. Subsequently, questionnaires are employed to quantify the broader acceptability of chatbots, extending insights to a larger and more diverse audience. The findings from these phases lay the foundation for the second part of the third phase, wherein the TAM is harnessed for a theoretical analysis of chatbot acceptance. By integrating identified factors, the aim is to transform TAM into a Human-Centric TAM. This systematic progression ensures an ongoing and iterative approach, with each phase contributing to a holistic comprehension of recruitment chatbot adoption. Specifically, human-centric factors influencing the acceptability of recruitment chatbots within companies will be identified to develop a human-centric technology acceptance (HC-TAM) research model that can serve as the basis for a Human-

Centric framework for AI technology

3.3.1 Phase 1— A Preliminary Qualitative Study

The initial phase of this study employed semi-structured interviews, beginning with a specifically selected group of ten participants, composed of six job seekers and four experienced recruiters. These participants were chosen based on active engagement in job-seeking or recruitment. To enhance the diversity and relevance of the sample, snowball sampling was utilized, asking each initial participant to refer colleagues or peers who met the study criteria and might be interested in participating. This approach allowed us to leverage their professional networks to expand our participant pool dynamically. Job seekers, all currently employed, ranged from recent graduates to seasoned professionals, bringing diverse perspectives on the challenges and expectations of job searching via digital platforms. Recruiters, with 7 to 12 years of experience, were selected for their comprehensive understanding of recruitment processes, including candidate screening, job listing, and hiring.

Each referral from the snowball sampling process was contacted via email. The study's objectives were explained in these communications, and the value of contributions toward developing a user-centered technological solution was highlighted. This method proved highly successful; every individual referred through snowball sampling agreed to participate, demonstrating strong engagement with the subject matter and a willingness to contribute to technological advancements in recruitment. The interviews began with questions about participants' backgrounds and experiences and progressively focused on their use of recruitment technologies, especially the features they found beneficial or lacking. Follow-up questions delved into their interest and expectations from the human-centered chatbot being studied.*(Script details are provided in Chapter 3 Appendix A)*. The interviews were audio-recorded and transcribed to accurately capture the data, maintaining the privacy and confidentiality of all participants. This phase aimed to gather feedback to refine our chatbot design and enhance its performance, significantly influencing the subsequent phases of the study [10]. Thematic analysis revealed recurring

Table 3.1: Phases of the multi-methods recruitment chatbot acceptance research

Phase	Aim	Tools	Analysis	Outcomes and findings
Phase 1 (pilot) Qualitative	Defining main themes to structure and adjust the following interviews and questionnaires	10 semi-structured in-depth interviews based on a topic guide	Thematic Content analysis	Main themes for constructing the interviews' topic guide and the questionnaires in phase 2
Phase 2 Qualitative	To further define and describe the main themes until saturation	28 single semi-structured in-depth interviews Representative citations focused on themes and chose quotes describing those themes	Thematic content Analysis With Nvivo	Main theme analysis
Phase 3- HC-TA Model Development (3a) and Quantitative study (3b) Comprehensive Study of Research Model Development				
Phase 3a (Research) Model development	Investigate the theoretical framework (HC-TAM) and factors influencing	Smart-PLS for Structure Equation Modeling	Statistical analysis using structural equation modeling (SEM), correlation analysis	Key Constructs and Hypothesis
Phase 3b Quantitative	Measurement Development, and Data Collection	146 sectional research paired questionnaires	Descriptive statistics, Cronbach's alpha for Internal reliability	Frequencies and percentages of quantitative variables

patterns, resulting in 3 main themes and 16 subthemes, offering valuable insights into the impact and acceptability of recruitment chatbots from both job seekers and recruiters [10]. Table 3.2 presents the coded themes and subthemes derived from the data analysis.

Discussion: The initial interviews were conducted to gather insights from users that are part of the real-life recruitment process and results emphasize the importance of adopting a balanced, human-centered approach, advocating for chatbots to complement rather than replace human capabilities in recruitment processes [127]. The thematic analysis from this phase of the study clarified a complex interplay of insights, perceived impacts, and acceptability. This analysis offers a comprehensive view of how chatbot technology connects with recruitment methods that prioritize human interaction and needs. Through the identification of three overarching themes and sixteen subthemes, the analysis shed light on the diverse interactions between job seekers and recruiters with chatbot technology.

The theme of *Insights* foregrounds the criticality of leveraging personal networks and experiences, underscoring the required value of human connections and expertise in navigating the recruitment ecosystem. Also the persistent challenges faced by both job seekers and recruiters, such as the alignment of job specifications with candidate profiles and the overarching need for a comprehensive understanding of recruitment needs were important aspects to look at. Furthermore *Perceived Impact* brings to the fore the potential efficiencies and enhancements chatbots could introduce to the recruitment process. It outlines the dual-edged nature of chatbot deployment—wherein lies the promise of streamlining administrative tasks and the peril of oversimplifying the nuanced, human-centric aspects of recruitment. This theme encapsulates the potential for chatbots to act as user-friendly, cost-effective tools while also acknowledging their limitations in handling the complexity and subtlety inherent in recruitment interactions. As a potential identified theme, the *Acceptability* probes the receptiveness towards chatbots among the recruitment stakeholders, reflecting a cautious optimism. This acceptance is dependent upon the chatbots' ability to function as complements to, rather than replacements for, human recruiters, emphasizing

Table 3.2: Data Codes, themes, and subthemes emerged from the Phase 1 thematic analysis

Codes	Themes	Subthemes
Experience, Challenges, Platform Usage	Insights	a) Leveraging Networks and Experience b) Overcoming Challenges c) Importance of Understanding Needs d) Use of Platforms and Tools e) Close Partnerships
Recruitment Chatbots, Characteristics, Influence, Instances	Perceived Impact	a) Chatbots as Efficiency and Time-Saving Tools b) Personalization c) Limitations in nuance and complexity d) Accuracy and Programming of Chatbots e) Data-Driven Screening as a Benefit of Chatbots f) Chatbots as User-Friendly and Cost-Effective Tools h) Integration with Other Systems
Acceptance, Collaboration, Future usage	Acceptability	a) Chatbots as a complement to human recruiters, not a replacement b) The potential usefulness of chatbots for pre-screening candidates or junior roles c) Best chatbot practices d) Chatbots' ability to automate repetitive tasks and improve efficiency

the irreplaceable value of human judgment and interpersonal connections in the recruitment process.

Together, these themes and their subthemes articulate a narrative that positions recruitment chatbots not as solutions but as compelling tools that, when cautiously integrated into recruitment practices, can enhance the efficacy and human-centeredness of the recruitment process. This refined understanding underscores the necessity of a balanced, ethical approach to the deployment of chatbots, ensuring that technological advancements in recruitment serve to augment human capabilities and enrich the overall recruitment experience. Overall, this phase set the stage for further research by establishing a detailed exploration emphasizing the need for chatbots to complement human interactions rather than replace them and underscoring the potential for chatbots to enhance the efficiency and effectiveness of recruitment processes when designed and implemented thoughtfully.

3.3.2 Phase 2: Interviews—the matched qualitative thematic content analysis part of the study

This phase approach is designed to refine and expand the understanding of chatbot acceptability and effectiveness, leveraging the foundational themes from Phase 1 to explore specific dynamics and contradictions that emerged, thereby contributing to the development of a comprehensive, human-centered technology acceptance model. Participants for this phase were carefully selected to provide a broader and more diverse perspective on the use of recruitment chatbots, aiming for a wide representation of experiences and professional roles within the recruitment and job-seeking domains. Consistent with Phase 1, all participants were approached via email to maintain a formal communication channel. The emails detailed the study's objectives and highlighted the importance of their contributions to developing a user-centered technological solution. Upon expressing interest, participants received a brief overview document to prepare them for the interview, ensuring they were well-informed about the topics discussed.

Demographics: 28 semi-structured in-depth individual interviews, including 21 job seekers and 7 recruiters were recorded and subsequently transcribed by one author in this analysis of respondent demographics. The job seekers, ranging in age from 21 to 45 years and consisting of 12 females and 9 males, were all currently employed, encompassing a range of active job search experiences from recent graduates to seasoned professionals. This diversity provided a variety of perspectives on the challenges and expectations associated with job searching via digital platforms and job portals. Job seekers professional experience varies widely, from 0 to 10 years and the job titles among these applicants are diverse: there are 3 interns, who are usually students or recent graduates in entry-level, temporary positions for gaining

Table 3.3: Respondents' Information

Respondent	Basic Information	Personal Information
Job Seeker	Age: 21–45 years old Gender: 12 females, 9 males Experience: 0-10years of experience	Job Titles: - 3 Interns - 2 Sales Assistants - 5 Software engineers - 4 User Experience experts - 6 Developers - 1 Sales Supervisor
Recruiter	Age: 25–35 years old Gender: 4 females, 3 males Experience: 5–15years of experience	Job Titles: - 4 Talent Acquisition Managers - 3 Senior Recruiter -1 HR manager

practical experience; 2 Sales assistants, likely involved in retail or customer service, assisting with sales operations and customer interactions; 5 Software engineers, professionals skilled in computer science who develop and maintain software; 4 User experience experts, specialists focused on optimizing the usability and user experience of products or services; 6 Developers, who could refer to software developers or those in similar fields, responsible for creating and implementing software applications; and 1 sales supervisor, who likely oversees sales operations and teams.

On the recruiter side, the participants are between 25 and 35 years of age, including 4 females and 3 males. They were selected for their comprehensive understanding of recruitment processes, including candidate screening, job listing, and hiring, due to their 5 to 15 years of experience. The recruiters are categorized into 4 talent acquisition managers, who are responsible for overseeing the recruitment process and strategy of an organization; 3 senior recruiters, experienced professionals in sourcing, interviewing, and selecting candidates; and 1 HR manager, a key role in overseeing various aspects of human resource management and policies within an organization. This array of roles highlights a broad spectrum of professional expertise and levels within the job market. (shown in Table 3.3)

Interview Protocol: Interviews were constructed based on a script so that all concepts found in the first phase were referred to the first part of the interview included closed socio-demographic questions, and the second part open-ended questions dealing with the perceived impact and acceptability [10]. The protocol emphasized the importance of participants' contributions, maintained privacy during the interview, and estimated a 30-minute duration (details are provided in Chapter 3 Appendix B). It consisted of sections covering general discussion, background questions, focused research questions, using the HCAI Chatbot, and an overarching question about key factors for chatbot acceptability. The protocol aimed to efficiently gather valuable feedback and concluded by thanking participants for their contributions and inviting further input. Prompts were similar to what was used during the first phase. Additional questions emerging from the dialogue between interviewer and interviewee were added when necessary [128].

The primary themes identified in this updated phase of the study were wide-ranging. They included aspects such as the experiences and perceptions of job seekers and recruiters regarding recruitment chatbots, their levels of satisfaction with these AI tools, and their views on how chatbots could potentially enhance or impact the recruitment process. This phase thus provided a deeper, more nuanced understanding of the factors influencing the acceptance of recruitment chatbots across different company contexts, contributing significantly to developing a human-centered technology acceptance research model.

Coding and Analysis: Transcripts were subjected to a thematic analysis incrementally using the 'Gioia methodology' [129]. This qualitative analysis methodology shows how the informants' perspectives (first- order concepts) are considered by the researchers before being organized and transformed into theory-centric themes (second-order themes) and aggregated dimensions [129]. Accordingly, transcripts were subjected to two rounds of coding using Nvivo [1] (12), a widely used computer-assisted qualitative analysis tool [130]. The first round consisted of coding words and phrases in the transcript, while the second round involved grouping the codes (captured as nodes) into themes and dimensions [129, 130]. To increase the accuracy of our findings,

[1]https://www.gmsl.it/nvivo/

dimensions were triangulated against service quality dimensions in the extant literature (i.e., data triangulation) and among the different researchers in this study (i.e., investigator triangulation) [131]. As for reliability, the use of NVivo assisted in establishing a chain of evidence [132], as it was possible to efficiently trace our research findings and codes back to the source data interviews [133]. Through axial coding [134] several salient perceptions of recruitment chatbot acceptance emerged. Table 3.4 illustrates the frequency of the final codes captured in NVivo.

Resulting themes: Table 3.5 organizes the qualitative data into themes and provides representative citations that underscore the key findings of the research. The analysis of the table reveals insights into the impact, acceptance, and challenges of using chatbots in recruitment. Recruitment chatbots are primarily valued for their efficiency and ability to automate repetitive tasks, enabling recruiters to focus on more strategic aspects of their roles [9]. They are also appreciated for their potential to personalize interactions and adapt to diverse cultural nuances, which is crucial in accurately assessing candidates' complex skills and fitting them into unique cultural contexts [12]. Regarding acceptance, chatbots are seen as valuable tools that augment

Table 3.4: Frequency of Nodes Coded in NVivo

Key Factors Analysis from Themes(nodes)	Job seekers	Recruiters	Frequency - Mentions
Personalization	15	3	18
Valuable Tools	5	1	6
Adaptability	1	2	3
Technical Challenges	2	5	7
Ethical Concerns	9	6	13
Transparency	6	3	9
Trust	7	2	8
Efficiency	7	8	16

pre-screening processes and manage diverse talent pools efficiently [10]. They are envisioned as complements to human recruiters rather than replacements, ideally handling initial screening without making final hiring decisions. However, using chatbots in recruitment is not without challenges [10]. Technical issues such as integration, data security, and training in industry-specific terminology are significant hurdles. The candidate experience is a concern, with chatbots sometimes perceived as impersonal. Ethical considerations are paramount, including the fair and unbiased decision-making process, security of personal data, transparency in evaluation, and addressing potential biases in algorithms. There's a consensus on the need for chatbots to evolve and adapt to changing recruitment needs to maintain relevance and effectiveness [9].

Table 3.4, a result of the total number of nodes coded in NVivo, effectively condenses the frequency of key themes from interviews with job seekers and recruiters, offering a streamlined view into the distribution of these themes and their significance. Frequency coding was utilized to achieve this, allowing for a systematic comparison and analysis of how frequently different themes were mentioned across various groups. Notably, *'Personalization'* emerges as a dominant theme, particularly among job seekers, suggesting a high demand for customizable technology in recruitment. This is followed by themes like *'Efficiency'* and *'Trust'*, which are valued for their ability to streamline processes and build confidence in the technology's reliability. The data also highlights the growing importance of *'Ethical Concerns'* and *'Transparency'*, showing the need for clear and ethical technological practices. While *'Technical Challenges'* and *'Adaptability'* are less frequently mentioned, they still signify crucial areas for technological improvement. The inclusion of *'Valuable Tools'* further underscores the need for practical and useful functionalities in recruitment technologies. This detailed analysis, pivoting on these key factors, is instrumental in guiding the development of a nuanced technology acceptance research model, that aligns closely with the real needs and preferences of both job seekers and recruiters. This approach not only ensures theoretical robustness but also guarantees practical relevance and wide acceptability among all stakeholders involved in the recruitment process.

By uncovering key user-centric themes like 'Personalization', 'Efficiency', 'Trust', 'Technical Challenges', and 'Ethical Concerns', the analysis ensures that the next phase of the study is grounded in the real needs and preferences of its users. Balancing perspectives from different stakeholders like recruiters and job seekers highlights critical areas for technological improvement and ethical practices. This approach not only enhances the theoretical robustness of the research model but also ensures its practical relevance and acceptability in real-world recruitment contexts, making it genuinely human-centered.

Discussion The second phase of the study represents a pivotal step forward, as it not only builds upon the insights gained from the initial phase but also introduces a wealth of new data and perspectives. By expanding the participant base to include a broader spectrum of job seekers and recruiters, this phase captures a more diverse range of experiences and expectations regarding recruitment chatbots. Incorporating the updated structured script from the identified themes of Phase 1 and then NVivo analysis enhances the research's empirical foundation, providing statistical evidence to support the prevalence and significance of various themes and factors. One of the key outcomes of this phase is the identification of factors that strongly influence chatbot acceptance in the context of recruitment. These factors, including personalization, efficiency, trust, technical challenges, ethical concerns, and transparency, emerge as critical determinants of chatbot success. With the rich data material collected, the research is poised to create a more human-centric technology acceptance research model. By incorporating these factors into the human-centered acceptance research model, it becomes theoretically robust,highly practical and relevant to the real needs and preferences of job seekers and recruiters. This data-driven approach ensures that the model is grounded in the lived experiences of stakeholders in the recruitment process.

Overall, the combination of both phase's methodologies underscores the study's detailed approach. Phase 1, characterized by qualitative thematic analysis, delves into the narratives and experiences of participants, uncovering emergent themes without predefined categories. It provides in-depth insights into the human- centered aspects of chatbot acceptability. In contrast, Phase 2 adopts an extensive approach, utilizing structured interviews and statistical analysis to quantify relationships and validate themes identified in Phase 1 with the tool. This dual-method approach ensures a holistic understanding of the factors influencing chatbot acceptance, setting the stage for a research model that bridges theory and practice.

3.3.3 Phase 3: HC-TAM— Theoretical Framework and Model Development

This phase progresses the study by integrating the qualitative insights from previous phases into a refined theoretical framework, focusing on enhancing the Technology Acceptance Model (TAM) with human-centric factors identified in the recruitment chatbot context. This phase aims to establish a Human-Centric Technology Acceptance Model (HC-TAM), offering a model for understanding chatbot acceptance and effectiveness in recruitment processes.

Theoretical Justification for Model Choice

In the theoretical framework of our study, we have chosen to employ the Technology Acceptance Model (TAM) as the foundational model rather than alternative models such as TAM2, TAM3, or UTAUT (Unified Theory of Acceptance and Use of Technology). This decision is rooted in TAM's simplicity, adaptability, and extensive validation across various contexts, aligning seamlessly with our focus on the unique interactive and innovative aspects of human-centric chatbots in the recruitment process [120, 135]. While more recent models like the UTAUT offer a broader range of factors, TAM's far-sighted approach permits a more concentrated analysis of the core determinants of technology usage [136]. This choice is particularly relevant to our study, where the objective is to understand the peculiarities of technology acceptance within the context of human-centric chatbots used for recruitment.

Human-Centered Extension of TAM

To tailor TAM to the recruitment chatbot context, five human-centric factors were integrated based on findings from the first two phases: Transparency,

Table 3.5: Themes and Representative Citations for Research Questions

Research Question	Theme	Representative Citation
RQ 1: Impact of Chatbots on Recruiter Experience	- Positive Impact on Efficiency - Personalization	Chatbots automate repetitive tasks, focusing on strategic aspects. - R 2 Chatbots are valuable in streamlining recruitment, especially for diverse profiles. - R8 Personalization is key in tech for refined skills." – JS6 "Chatbots adapt to diverse cultural nuances. – R8 Chatbots need to expertly assess complex skills. – JS 2 "Recruitment Chatbots need to understand and assess unique needs and cultural fit to be successful." – JS14
RQ 2: Acceptance of Chatbots in Recruitment	Valuable Tools Complements to Human Recruiters	"Chatbots augment pre-screening processes." - R2 "Chatbots enhance efficiency in managing diverse talent pools." R9 "Chatbots complement, not replace recruiters." – JS7 "Surely, I will adapt it, if it will work as a technical assistant for me." – JS 22 "I want Chatbot to do the initial screening, not hire the candidate for me." – R3
RQ 3: Challenges in Using Chatbots	-Technical Challenges - Candidate Experience - Ethical Concerns Adaptability	"Technical integration and data security are key challenges." – R4 "Training chatbots in industry-specific terminology." – R6 "Chatbots have the potential to enhance collaboration and networking opportunities." – JS4 "Chatbots perceived as impersonal." – R5 "Ethical use of chatbots in decision-making is a concern." - R7 "Fair and unbiased decisions by chatbots in hiring are a top ethical concern." - R 12 "Security of personal data is a significant concern when using recruitment chatbots." - JS6 "Data security is paramount in using chatbots for candidate information" - R9 "Ethical chatbots should be transparent and fair in evaluating candidates." - JS 14 "Addressing bias in chatbot algorithms is crucial for a level playing field." - R6 "I worry about chatbots discriminating against candidates based on factors." - JS 8 "Ethical concerns in screening candidates." – R5 "Integration is a key." - Recruiter 9 "Updating chatbot capabilities for evolving recruitment needs." JS17
Key Theme	Acceptability Factor	"Chatbots are acceptable for their efficiency." - R5 "Chatbots accepted for efficiency without replacing humans." R4 "I value personalization and efficiency in chatbots." – J3 "Transparency is key for chatbot acceptance which can make it Trustworthy." - R 9 "Efficiency is what I appreciate most in chatbots." - J 7 "Efficiency and personalization are crucial for acceptability." - R5

Trust, Efficiency, Ethical Concerns, and Personalization. These constructs reflect domain-specific requirements in HR systems, especially in scenarios involving AI-driven interactions with job seekers and recruiters.

The exclusion of attitude towards use and behavioral intention from the adapted model is intentional and justified. Several studies (e.g., Davis, 1989; Legris et al., 2003) suggest that in certain applied domains, particularly where decision-making is immediate and contextual, focusing on PU and PEOU can sufficiently predict technology acceptance. Additionally, excluding intention-related variables helps streamline the survey and minimizes participant fatigue without compromising theoretical depth [120].

Key Constructs and Definitions

The constructs used in the HC-TAM model are defined below. Each was selected based on empirical relevance from Phases 1 and 2, and aligned with literature on Human-Centered AI.

Perceived Ease of Use (PEOU) refers to the degree to which a person believes that using a particular system would be free of effort, representing the finite resources people can allocate to the activities they are dealing with [120].

Perceived Usefulness (PU) is defined as the degree to which a person believes that using a particular system would enhance their job performance [120].

Transparency (TR) refers to the degree to which the operations and decision-making processes are made clear and understandable to users. It involves providing users with insights into how the system functions, how it arrives at decisions, and the rationale behind its actions. Transparency enhances credibility by building trust in systems operations and fostering user confidence [137].

Trust (T) is a critical factor that defines the level of confidence and reliance that users place on the system. Users need to trust that the system can effectively assist them in their required activities. Building trust is essential for users to feel comfortable and secure while interacting with the system

[11]. *Efficiency(E)* is defined as its ability to swiftly and effectively perform tasks, providing a seamless and satisfying experience. It involves optimizing resource usage, minimizing delays, and ensuring an intuitive, user-friendly interface [138].

Personalization(PR) involves tailoring the user's experience to meet the individual needs, preferences, and characteristics of each user. It goes beyond one-size-fits-all interactions and aims to provide users with customized recommendations and assistance. Personalization enhances user engagement and satisfaction by making the interaction with the system more relevant and user-centric [139].

Ethical Concerns(EC) pertain to the potential ethical dilemmas and considerations that arise in the deployment within the system. These encompass issues such as fairness, non-discrimination, data privacy, and the ethical use of automated decision-making algorithms. Ethical concerns underscore the importance of maintaining ethical standards and ensuring that chatbots do not inadvertently perpetuate biases or harm users in any way [140].

This structured framework sets the foundation for the empirical model tested in the next phase of the study, ensuring both conceptual clarity and practical relevance.

3.3.4 The Human-Centric Technology Acceptance Model (HC-TAM)

By enriching the Technology Acceptance Model (TAM) with human-centric constructs, the study introduces the Human-Centric Technology Acceptance Model (HC-TAM), which extends TAM [120]. The HC-TAM aims to provide a comprehensive understanding of factors significantly contributing to the acceptance and usability of chatbots in recruitment, capturing the detailed dynamics of human-chatbot interactions within the professional recruitment setting [110].

These factors such as transparency, trust, efficiency, ethical concerns, and personalization, emerged from qualitative analyses in Phases 1 and 2, reflecting the unique requirements and interactions fundamental to the recruitment domain. The inclusion of these factors offers deeper insights into the multifaceted nature of technology acceptance, particularly in the context of intelligent systems designed for human-centric applications like recruitment. This approach not only broadens the scope of the original TAM but also provides a tailored and robust framework for exploring the intricate landscape of technology adoption in the area of recruitment chatbots, ensuring the technology aligns with user needs and ethical standards.

Hypotheses

Figure 3.2 elaborates on the extended model on which we based our hypothesis. Building upon the defined factors of Transparency, Trust, Efficiency, and Personalization in the context of recruitment chatbots, we formulate a series of hypotheses that aim to uncover their significant roles in technology acceptance and are guided by specific research goals. They systematically probe connections between these human-centric factors and technology adoption, arising from insights in qualitative research phases and aligning with models like the Technology Acceptance Model. Addressing links of the factors, these hypotheses aim for a nuanced understanding of user perceptions in recruitment chatbots. In essence, this framework tests the impact of human-centric elements on technology acceptance in recruitment scenarios. Figure 3.3 Visualizes the graphical representation of hypothesis development.
H1. Perceived ease of use is positively related to perceived usefulness.
H2. Perceived ease of use is positively related to personalization.
H3. Perceived Usefulness is positively related to personalization.
H4. Perceived Usefulness is positively related to ethical concerns.
H5. Transparency is positively related to perceived usefulness.
H6. Transparency is positively related to Personalization.
H7. Transparency is positively related to efficiency.
H8. Trust is positively related to personalization.
H9. Efficiency is positively related to personalization.
H10. Personalization in chatbots is positively related to ethical concerns.

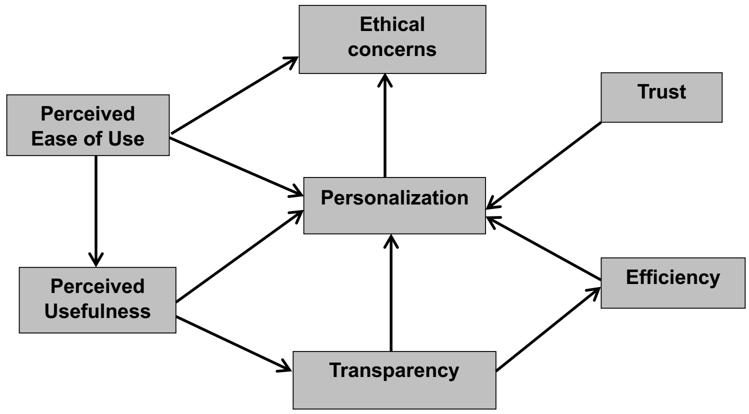


Figure 3.2: Human-Centered TAM (HC-TAM) Model

Measurement Development, Procedure and Data Collection

To rigorously evaluate the research hypotheses, a survey was designed to assess the constructs delineated within the research model, specifically focusing on seven key factors. This survey was strategically partitioned into two primary sections, each with a distinct purpose. The initial segment was tailored to gather demographic data and elicit insights regarding participants' gender, age, familiarity with recruitment chatbots, and their past experiences in utilizing them. Subsequently, the second part of the survey focused on a series of statements intricately linked to the seven factors of interest. A thorough review of the current body of research literature was conducted to ensure the comprehensiveness and precision of the measurement items. The survey instrument employed a well-structured seven-point Likert scale, enabling participants to express their level of agreement or disagreement with each statement, spanning from "strongly disagree" (1) to "strongly agree" (7). A detailed inventory of these measurement items can be located in *Chapter 3 Appendix C*.

Data collection for this research endeavor was executed by distributing a Google Form link via email to a diverse pool of participants. Before their active participation, all respondents provided explicit consent, signifying their voluntary engagement in the study. Additionally, participants were probed about their familiarity with recruitment chatbots, their attitudes toward us-

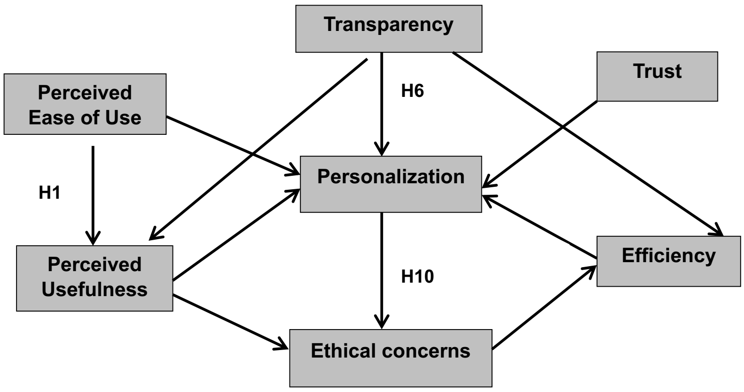


Figure 3.3: Hypotheses Development of HC-TAM

ing them, and their expectations from such chatbots, thereby allowing them to provide responses aligned with their specific knowledge and preferences. Notably, out of the initial cohort of 172 participants who initiated the survey, a stringent criterion was applied, leading to the exclusion of 26 individuals. These exclusions were based on the criterion of having no familiarity whatsoever with recruitment chatbots. Consequently, the final sample consisted of 146 participants, characterized by an average age (M) of 24.06, with a standard deviation (SD) of 5.2. Within this sample, 89 participants identified as male (61%), while 57 identified as female (39%).

The survey also provided valuable insights into respondents' expectations, behaviors, and their prior interactions with chatbots, particularly within the domain of recruitment. Notably, a significant majority, constituting 63% of the respondents indicated engaging with recruitment chatbots less frequently than they do with traditional job portals and LinkedIn. Furthermore, 45.2% of the participants had never interacted with a chatbot. Among these individuals, 47.6% had not harnessed chatbots to hire candidates, and 79.3% had not utilized them for job searching via chatbot platforms. These statistics underscore the limited prevalence and adoption of chatbots for recruitment within the surveyed population, shedding light on potential areas for further exploration and development within this domain.

3.3.5 Data Analysis and Results

This section crucially bridges theoretical insights with empirical evidence, highlighting key findings that contribute to our understanding of technology acceptance in the context of recruitment chatbots. It details the process of validating the research model through reliability and validity assessments, followed by an analysis of the structural model to examine hypothesis relationships.

Partial Least Square (PLS) Path Modeling

Table 3.6: Construct Validity Assessment of the HC-TAM Constructs

Research	Construct Item	Item Loading	AVE	CR	α
Perceived Ease of Use	PEOU1	0.839	0.712	0.937	0.919
	PEOU2	0.828			
	PEOU3	0.887			
	PEOU4	0.791			
	PEOU5	0.804			
	PEOU6	0.908			
Perceived Usefulness	PU1	0.907	0.797	0.959	0.949
	PU2	0.828			
	PU3	0.885			
	PU4	0.926			
	PU5	0.878			
	PU6	0.927			
Efficiency	E1	0.955	0.907	0.967	0.949
	E2	0.955			
	E3	0.947			
Trust	T1	0.896	0.735	0.893	0.819
	T2	0.867			
	T3	0.807			
Transparency	TR1	0.924	0.855	0.947	0.916
	TR2	0.917			
	TR3	0.933			
Personalization	PR1	0.914	0.853	0.959	0.942
	PR2	0.941			
	PR3	0.906			
	PR4	0.932			
Ethical Concerns	EC1	0.939	0.881	0.937	0.865
	EC2	0.938			

In the present research, we employed Structural Equation Modeling (SEM), utilizing the Partial Least Square (PLS) technique, to examine the hypotheses. PLS-SEM has gained widespread acceptance across various academic domains, including HR, owing to its propensity for yielding fewer conflicting findings than traditional regression analysis, especially when identifying mediation effects [141]. Furthermore, when the research objective revolves around exploring theoretical extensions to well-established theories, PLS-SEM offers enhanced reliability in offering causal explanations. This approach effectively bridges the perceived gap between explanation and prediction, forming the foundation for developing practical managerial implications [142]. Our analysis of PLS involves a two-stage process: firstly, evaluating the reliability and validity of the measurement model, and secondly, interpreting the path coefficients within the structural model. Subsequent sections will delve into the outcomes of these two pivotal stages.

Measurement Model (Assessment of Construct Validity)

In our analysis, we thoroughly evaluated the measurement model with a keen focus on its psychometric properties, ensuring both validity and reliability. The validity assessment encompassed rigorous checks for convergent and discriminant validity.

The numbered items (e.g. perceived ease of use (PEOU) 1, 2, ... 6 or ethical concerns (EC) 1,2,..) correspond to specific questions posed to users in the questionnaire(details are in Appendix C). Convergent validity was initially assessed by scrutinizing the strength and significance of loadings. This scrutiny led us to identify four problematic items (specifically PEOU 3, PEOU 5, PU 2, and E 2) due to their low factor loadings. As a cautious step, these items were omitted from further analysis [143]. Consequently, the final outer model exhibited that all the remaining 23 indicators displayed loadings surpassing the satisfactory threshold greater than 0.7 [144]. (see Chapter 3 Appendix C for details)

To further ensure that our measurements effectively covered the research inquiries, we conducted extensive reliability and validity tests. The assessment of item consistency for measuring a particular concept was conducted using Cronbach's Alpha, following the guidelines recommended by [145]. Attaining a value of 0.7 or higher signified that the items within the scale effectively measured the same variable of interest. Our variables met the requirements for internal consistency, item loading, Average Variance Extracted (AVE), and Composite Reliability (as indicated in Table 3.6).

The evaluation of discriminant validity was based on the Fornell-Larcker criterion, involving an examination of Latent Variable Correlations and Cross-loadings (Discriminant Validity) [146]. In Table 3.7, the diagonal values represent the square roots of AVE, while the off-diagonal values represent correlations. Importantly, the diagonal values were consistently higher than the off-diagonal values, affirming the presence of discriminant validity as per the Fornell-Larcker criterion. Furthermore, all item loadings (highlighted in bold in Table 3.8) exceeded the recommended threshold of 0.5 and were higher than all cross-loadings, providing additional confirmation of discriminant validity.

Turning to the R2 values, illuminating the extent of explained variance, we gained insights into the model fit and predictive capabilities of the endogenous variables [142, 147]. Adhering to [142], individual R2 values were required to surpass the minimum acceptable level of 0.10. Figure 3.4 shows that the R2 values for all endogenous variables, including 'Perceived Usefulness,' 'Personalization,' and 'Ethical Concerns,' exceeded this threshold (56.2%, 79.8%, and 77.6%, respectively).

Structural Model

Table 3.7: Discriminant validity – latent variable correlations

	PEOU	PU	Efficiency (E)	Trust (T)	Transparency (TR)	Personalization (PR)	Ethical Concerns (EC)
PEOU	**0.844**						
PU	0.663	**0.893**					
E	0.476	0.674	**0.952**				
T	0.476	0.432	0.504	**0.857**			
TR	0.507	0.638	0.742	0.572	**0.925**		
PR	0.608	0.757	0.809	0.615	0.776	**0.924**	
EC	0.495	.666	.727	0.571	0.837	0.822	**0.9392**

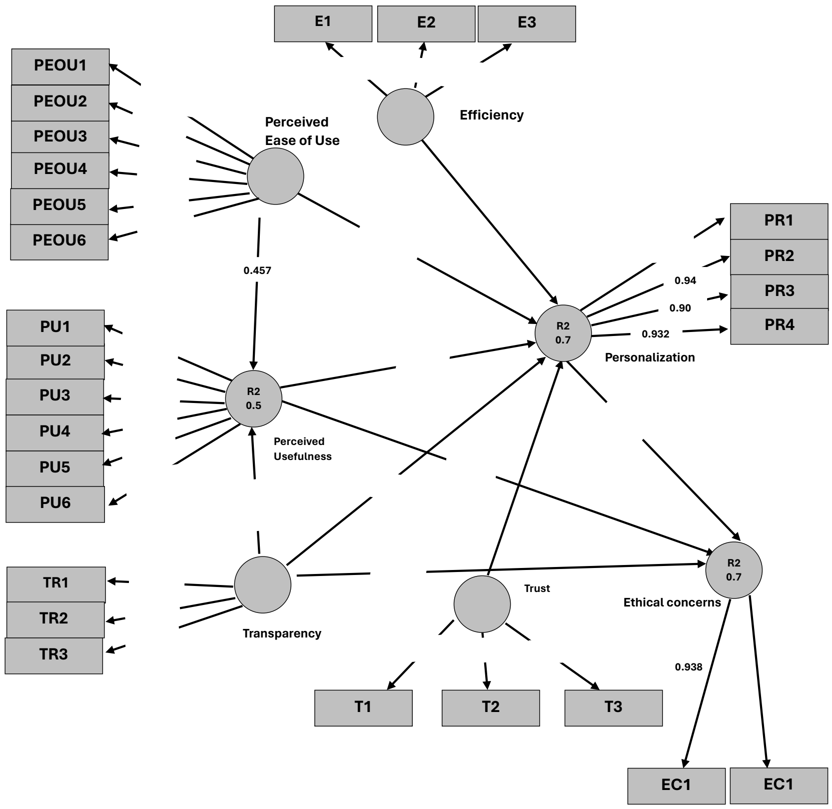


Figure 3.4: PLS Algorithm results with R2

After establishing the measurement model, we assessed the structural relationships. Before evaluating path coefficients, we checked for multicollinearity, and no issues were detected. The examination of Variance Inflation Factors (VIF) revealed values lower than the threshold of 5.0 [148].

As depicted in Table 3.9, the bootstrap procedure indicated a positive relationship between Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), albeit not a significant relationship with Personalization. In this case, we observed a slight tendency towards significance.

PU was positively related to Personalization but not to Ethical Concerns. Transparency showed positive relationships with PU, Personalization, and Ethical Concerns. Trust and Personalization exhibited significant positive relationships, as did Efficiency and Personalization. As expected, Personalization was positively related to Ethical Concerns. Table 3.9 presents these

Table 3.8: Cross loadings (discriminant validity)

	PEOU	PU	E	T	TR	PR	EC
PEOU1	**0.839**	0.507	0.338	0.387	0.385	0.461	0.359
PEOU2	**0.828**	0.472	0.358	0.374	0.358	0.450	0.358
PEOU3	**0.887**	0.596	0.355	0.389	0.396	0.483	0.374
PEOU4	**0.791**	0.631	0.540	0.466	0.538	0.568	0.538
PEOU5	**0.804**	0.530	0.388	0.374	0.443	0.523	0.440
PEOU6	**0.908**	0.590	0.399	0.404	0.422	0.566	0.408
PU1	0.669	**0.907**	0.558	0.340	0.542	0.661	0.568
PU2	0.457	**0.828**	0.580	0.404	0.542	0.596	0.549
PU3	0.605	**0.885**	0.580	0.381	0.521	0.657	0.545
PU4	0.550	**0.926**	0.652	0.408	0.634	0.724	0.657
PU5	0.633	**0.878**	0.561	0.337	0.516	0.615	0.553
PU6	0.630	**0.927**	0.670	0.440	0.648	0.777	0.679
E1	0.466	0.641	**0.955**	0.493	0.700	0.789	0.691
E2	0.438	0.626	**0.955**	0.451	0.649	0.749	0.658
E3	0.455	0.659	**0.947**	0.493	0.770	0.771	0.727
T1	0.471	0.401	0.470	**0.896**	0.523	0.573	0.548
T2	0.426	0.312	0.308	**0.867**	0.407	0.459	0.396
T3	0.325	0.387	0.496	**0.807**	0.526	0.537	0.506
TR1	0.504	0.646	0.729	0.557	**0.924**	0.749	0.759
TR2	0.461	0.516	0.653	0.506	**0.917**	0.662	0.738
TR3	0.443	0.602	0.675	0.522	**0.933**	0.737	0.822
PR1	0.591	0.709	0.684	0.607	0.735	**0.914**	0.777
PR2	0.560	0.713	0.775	0.595	0.752	**0.941**	0.810
PR3	0.568	0.692	0.720	0.537	0.658	**0.906**	0.708
PR4	0.527	0.681	0.809	0.530	0.718	**0.932**	0.737
EC1	0.519	0.688	0.703	0.610	0.754	0.815	**0.939**
EC2	0.409	0.562	0.661	0.460	0.818	0.727	**0.938**

hypotheses and displays the path coefficients among latent variables along with bootstrap critical ratios. To determine the stability of the estimates, we followed Hair et al.'s recommendation [147] and calculated bootstrap T-Statistics at a 95% confidence interval using 5000 samples, with acceptable values above 1.96.

3.4 Discussion and Implications

In the context of increasing reliance on AI tools in recruitment, this chapter presents an integrative study that contributes to our understanding of

Table 3.9: Structural relationships and hypotheses testing

Hypothesis	Path	Path Coefficient	Standard Error	T-Statistics	P Value	Decision
H1	PEOU → PU	0.457	0.060	7.583	<0.001	Supported
H2	PEOU → PR	0.084	0.057	1.473	0.095	NS
H3	PU → PR	0.253	0.062	4.084	<0.001	Supported
H4	PU → EC	0.044	0.045	0.982	0.163	NS
H5	TR → PU	0.406	0.055	7.350	<0.001	Supported
H6	TR → PR	0.212	0.062	3.410	<0.001	Supported
H7	TR → EC	0.495	0.065	7.655	<0.001	Supported
H8	T → PR	0.164	0.049	3.369	<0.001	Supported
H9	E → PR	0.358	0.064	5.618	<0.001	Supported
H10	PR → EC	0.404	0.070	5.798	<0.001	Supported

human-chatbot interaction dynamics, as evidenced in previous studies [9, 12, 143, 22]. The findings are grounded in a mixed-methods framework, encompassing both qualitative and quantitative data, and are structured through the development and validation of the Human-Centered Technology Acceptance Model (HC-TAM).

One important consideration in interpreting these results is the potential limitation introduced by participants completing the questionnaire outside the context of an actual job-seeking or hiring task. Although participants were provided with a scenario to guide their responses, we acknowledge that immersion in a real-time decision-making environment could have further enriched their evaluations of chatbot use. This limitation has been discussed in alignment with existing studies—such as [9, 143, 22]—that have utilized task-based methods and nonetheless reported results that align closely with our findings. This similarity supports the soundness of our contributions despite the contextual gap.

Our findings confirm the importance of key constructs from the Technology Acceptance Model (TAM), specifically Perceived Usefulness and Perceived Ease of Use, and highlight human-centered extensions—Trust, Transparency, Personalization, Efficiency, and Ethical Concerns—as critical in shaping user acceptance of recruitment chatbots. Notably, Transparency showed the most consistent influence across variables, significantly affecting perceptions of usefulness, personalization, and ethical acceptability.

The structural model results indicate that although Perceived Usefulness was positively related to personalization, it did not directly impact ethical concerns. This suggests that users may separate the concept of technological benefit from ethical alignment. A key explanation could be participants' limited identification with the simulated job scenario, which might have reduced the perceived need to trust the chatbot in achieving high-stakes goals such as employment. This point highlights the importance of future studies conducting in-situ or high-fidelity simulations.

In contrast, Perceived Ease of Use had a stronger influence on usefulness, underscoring the foundational importance of usability in recruitment chatbot design. These findings reinforce the value of prioritizing clear, stress-free interaction design for increasing user trust and reducing barriers to adoption.

Importantly, the impact of perceived ease of use on personalization was limited, suggesting a saturation point beyond which increased usability no longer enhances personalization behaviors. Ethical Concerns emerged as closely tied to Transparency and Personalization, reaffirming the need for design strategies that prioritize fairness, explainability, and culturally adaptive communication.

From a practical standpoint, this study provides actionable insights for recruitment platform developers and HR professionals. The findings suggest that to foster broader acceptance of recruitment chatbots, it is necessary to design systems that are not only efficient and easy to use but also transparent, ethical, and tailored to user needs.

Overall, this chapter bridges theoretical modeling with empirical analysis and provides a robust foundation for designing future recruitment systems that balance AI efficiency with human-centered values. The reported limitations and parallels with task-based studies also guide methodological refinements for future research, especially in enhancing ecological validity.

Chapter 4

Design and Impact of Recruitment Chatbots Conversational Style

Note: The content of this chapter was presented at the HCI International 2024 conference under the title "Human-Centric Interaction Design of RecoBot: A Study for Improved User Experience", and was also presented at the HWID 2024 workshop.

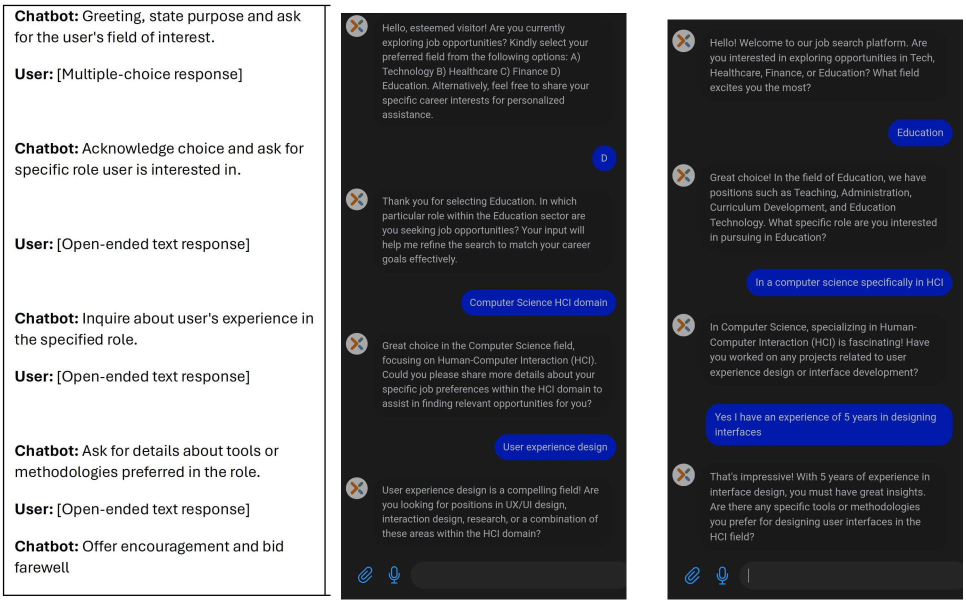
Building on the empirical insights and theoretical framework established in Chapter 3, which introduced the Human-Centered Technology Acceptance Model (HC-TAM) for recruitment chatbots, this chapter transitions from conceptual understanding to applied evaluation. Chapter 3 demonstrated the significance of human-centered factors—such as trust, personalization, transparency, efficiency, and ethical considerations—in influencing user acceptance. These findings now inform the design and assessment of RecoBot, a recruitment chatbot developed to reflect these core principles. The chapter presents a series of experiments designed to operationalize HC-TAM constructs through RecoBot's interaction mechanisms and conversational styles. In doing so, it seeks to demonstrate how theoretical acceptance factors translate into real user experiences and preferences, offering tangible evidence of HC-TAM's practical implications in recruitment settings.

This chapter focuses on the empirical evaluation of RecoBot, a recruitment chatbot designed to simulate real-world hiring scenarios. The study investigates how variations in interaction mechanisms (menu-based vs. context-based) and conversational styles (task-led vs. topic-led) affect user experience dimensions such as personalization, efficiency, ease of use, usefulness, and trust. By analyzing these design choices, this chapter aims to bridge the gap between theoretical constructs discussed earlier and their practical applications in developing effective and engaging recruitment chatbots.

The findings presented in this chapter not only reinforce the importance of user-centric design but also provide actionable insights into optimizing chatbot functionalities to meet diverse user expectations. The results offer a roadmap for aligning chatbot design with the distinct needs of job seekers and recruiters, laying the foundation for developing a Human-Centered Technology Acceptance Model (HCTAM) tailored for recruitment contexts.

4.1 Introduction

The design of conversational agents has increasingly focused on replicating human-like characteristics, as user perceptions of chatbots are strongly shaped by conversational style expectations. Employing an inappropriate style in specific contexts can lead to reduced engagement and satisfaction [149]. Research has shown that users respond more favorably to chatbots that exhibit human-like traits, particularly in their ability to elicit information and facilitate interactions. Prior studies have explored how conversational styles influence sensitive data disclosure and overall chatbot effectiveness [150, 151, 152, 153]. However, critical aspects such as task-led vs. topic-led conversational styles and menu-based vs. context-based interaction mechanisms remain underexplored in recruitment contexts, where user satisfaction, trust, and personalization are vital [15, 154] . This study addresses this gap by investigating the research question: "What impact do



(a) (b) (c)

Figure 4.1: RecoBots Interaction: The chatbot interface demonstrates interactions in both casual and formal conversational styles, with initial greetings to career-specific inquiries, the chatbot engages users in a detailed conversation about their professional interests and experiences, concluding with supportive remarks.

conversational styles and interaction mechanisms have on user experience with recruitment chatbots?"

To explore this, the study examines key user experience dimensions, including personalization, efficiency, ease of use, usefulness, and trust. These dimensions are central to understanding how recruitment chatbot design can align with user expectations while maintaining operational efficiency. This chapter introduces an innovative recruitment chatbot as a testbed for evaluating user preferences and interaction styles. Built on bot-building frameworks, the chatbot named as Recobot[1], simulates real-world hiring scenarios and facilitates an empirical exploration of how design elements influence user perceptions. Using this Bot, the research evaluates user preferences and interaction styles in simulated real-world hiring scenarios. As illustrated in Figure 4.1, RecoBot employs a blend of menu-based prompts and context-

[1]https://app.botbuilders.tech/webchat/?p=1658034 (Last visited: March 2024)

based dialogues, enabling it to adapt its conversational flow to diverse user needs and create structured yet personalized interactions. The study involved 60 job seekers evaluating interaction mechanisms and 60 recruiters assessing conversational styles. Findings revealed distinct preferences between the two groups: *Job Seekers:* Preferred context-based interactions for their ability to enhance personalization and efficiency. *Recruiters:* Favored task-led conversations for their efficiency and usefulness, with topic-led conversations also improving ease of use. Interestingly, trust levels showed no significant variation across interaction types or conversational styles, highlighting the need for further exploration of factors influencing trust in AI-driven recruitment tools. Further, by embedding theoretical insights from Human-Centered AI and recruitment technology literature, this research bridges the gap between theory and practice. Scholars have long emphasized the importance of personalization and ethical transparency in fostering trust and engagement[154]. This study operationalizes these principles by assessing how specific conversational styles and interaction mechanisms shape user experiences in diverse recruitment contexts.

The outcomes contribute to a deeper understanding of human-chatbot interactions, positioning this research as a significant step toward developing the Human-Centered Technology Acceptance Model (HCTAM). By integrating user-centric principles into recruitment chatbot design, the study aligns with the broader thesis objective of advancing ethical, transparent, and user-driven AI systems in recruitment. These insights offer actionable recommendations for refining chatbot design to better meet user expectations, ensuring both candidates and recruiters benefit from enhanced digital recruitment experiences.

4.2 Related Background on Conversational Styles with Interaction Mechanisms

Although the literature on chatbots has extensively covered aspects like efficiency, engagement, and automation, there has been less emphasis on exploring user preferences regarding conversational styles and interaction mechanisms, specifically in recruitment aspects [15]. This gap presents an opportunity for innovative research investigating how these elements influence user experience in recruitment settings. A human-centric design approach in AI development, particularly for recruitment chatbots, necessitates an in-depth understanding of user preferences. Investigating users' reactions to different conversational types—such as task-oriented and topic-oriented conversations—and interaction mechanisms—such as menu-based versus context-based, can offer valuable insights into how chatbots should be crafted to align with user expectations and enhance the overall user experience [155].

The literature distinguishes between two primary types of chatbot conversations: task-oriented and topic-oriented [156, 157]. Task-oriented conversations are direct and goal-led, designed to accomplish specific tasks, such as collecting candidate information or answering frequently asked questions [158, 154]. Conversely, topic-oriented conversations allow for broader discussions, including company culture, career growth opportunities, and other less structured topics [154]. This distinction impacts designing chatbots that can engage users effectively, catering to their needs for specific information and their curiosity about the organization.

Interaction mechanisms refer to how users communicate with chatbots. Menu-based interactions guide users through predetermined options, simplifying finding information or completing tasks. For example, a user might be shown a list of questions like "Do you want to upload your resume?" or "Would you like to know about our company culture?" and select the relevant option. This method is particularly useful for straightforward inquiries with a limited range of possible user responses.

On the other hand, context-based interactions allow for free-form communication, where the chatbot responds dynamically to user inputs. For instance, a user might type, "I'm looking for a job where I can use my UX design skills," and the chatbot would parse the query to suggest relevant job openings or ask clarifying questions. This approach aims to mimic human-like conversations, offering a more personalized and engaging user experience but requiring sophisticated natural language understanding capabilities.

By including both approaches, the study provides a comparative evaluation of user perceptions and preferences across different interaction types. This comparison was introduced to ensure that findings could inform future chatbot design decisions based on user comfort, efficiency, and satisfaction.

The impact of recruitment chatbots on user experience encompasses factors such as personalization, ease of use, perceived usefulness, efficiency, and trust [159]. These dimensions are integral to designing user-centric chatbots that enhance the recruitment experience, ensuring that chatbots not only meet but exceed user expectations and fostering a more efficient and engaging recruitment process.

4.3 Chatbot Design

RecoBot, developed for empirical studies on recruitment chatbot interactions, is intended to be an advanced recruitment chatbot designed to act as a digital mirror of the real-world hiring environment. It aims to facilitate job seekers by simplifying the job search based on their experience level and streamlining the application process to enhance their user experience. The chatbot was developed using a dedicated platform for conversational agents[2] where an open AI-based model processes user messages.
The chatbot was designed to manage three tasks aimed at evaluating various aspects of the user experience during job-seeking interactions in 2 perspectives, formal and casual. Firstly, users were tasked with submitting a resume, a low-sensitivity task involving the provision of standard professional information for potential job opportunities based on previous job titles. Secondly, users engaged in a job search based on their experience level, requiring them to input personal details, also salary expectations related to their professional background and skills. Lastly, users were prompted to inquire about the status of a job application, a high-sensitivity task potentially involving more confidential information about their employment history and current job-seeking status. These tasks were designed to assess how users' interac-

[2]https://www.botbuilders.tech/

tions with the chatbot were influenced by the sensitivity of the information requested and the chatbot's conversational style. Figure 4.1 illustrates the chatbot's interaction flow, showcasing its adaptability in handling these tasks through a combination of menu-based prompts and context-based dialogues. For example, during a resume submission task, the chatbot provided structured prompts to gather essential details, whereas for job search and status inquiries, it employed a more fluid conversational approach tailored to the user's inputs. This flexibility ensures that the chatbot can address diverse user needs while maintaining engagement and efficiency.

Functionality and Study Procedures of RecoBot: RecoBot, the recruitment chatbot used in this study, was developed to replicate various stages of the recruitment process using AI-based natural language processing. It is capable of handling multiple tasks such as greeting users, gathering information, and engaging in detailed conversations about career-related topics in either formal or casual conversational styles.

4.4 STUDY METHODS

This study investigated the impact of interaction mechanisms and conversation types on user experience with the RecoBot chatbot.

4.4.1 Metrics

To methodically evaluate the user experience with RecoBot, this study focuses on five principal aspects of user experience that are dependent variables including *Personalization(PR)* which measures the chatbot ability to tailor interactions to the individual user [160]. *Perceived Ease of Use (PEOU)* assesses how user-friendly and intuitive the chatbot interface is [120]. *Perceived Usefulness (PU)* evaluates the chatbot effectiveness in aiding users' job-seeking efforts [120]. *Efficiency(E)* gauges the chatbot capability to facilitate swift and goal-oriented interactions [161]. And lastly, the *Trust(T)* reflects the reliability and accuracy of information provided by the chatbot [135].

Metrics assessing user experience, focusing on the impact of AI conversational styles and mechanisms, were selected to evaluate the effect of AI's conversational styles and mechanisms using a semantic differential scale. This scale, chosen for its ability to offer nuanced insights into user interactions with RecoBot, contrasts with simpler agree-disagree formats by utilizing bipolar adjectives (e.g., "Completely Generic" vs "Highly Personalized"). This approach aims to uncover user preferences for different interaction styles and their effects on chatbot satisfaction. The questionnaire reliability was confirmed, with Cohen's kappa values indicating strong agreement among the items.

4.4.2 Variations in Interaction Mechanisms and Conversation Types

The design of conversational AI involves critical decisions about how users interact with the system (interaction mechanisms) and the nature of the dialogues it facilitates (conversation types). Exploring these design choices is crucial for developing human-centric chatbot services.

Hypotheses for the Impact of Variation in Interaction Mechanisms:

Interaction mechanisms, such as menu-based or context-based methods, dictate how users communicate with RecoBot. Menu-based interactions offer a structured selection pathway, while context-based interactions allow for a fluid, natural language dialogue. These different approaches are hypothesized to influence user experience distinctly.

- H1: Context-based interactions will lead to higher levels of (a) personalization and (b) ease of use among job seekers compared to menu-based interactions. (Context-Based $\rightarrow$ PR, PEOU)
- H2: Context-based interactions will result in enhanced (a) efficiency and (b) usefulness for job seekers in comparison to menu-based interactions." (Context-Based $\rightarrow$ E, PU)

- H3: Job seekers will experience higher levels of trust when interacting with the chatbot through context-based rather than menu-based mechanisms.(Context-Based → T)

Hypotheses for the Impact of Variation in Conversation Types:

The style of conversation—whether task-led or topic-led—can significantly shape how users engage with and perceive a recruitment chatbot. Task-led conversations are direct, goal-oriented dialogues designed to help users accomplish specific objectives efficiently. In contrast, topic-led conversations are more open-ended and exploratory, aiming to simulate human-like discussions that can foster greater rapport and engagement.

To ground these concepts in practical usage, consider the following examples from our study: In the task-led condition, a recruiter might interact with RecoBot using a command such as "Create a job posting for a UX Designer." RecoBot would respond with structured prompts requesting the job title, responsibilities, and candidate requirements, thus supporting a clearly defined, outcome-driven exchange.

On the other hand, in the topic-led condition, a recruiter could initiate interaction with a broader query like "What should I consider when hiring for a UX team?" RecoBot would then engage in a more conversational flow, discussing aspects such as ideal team structure, soft skills, industry trends, and team fit. This style is intended to reflect natural dialogue, providing contextual depth and a sense of shared reasoning.

By integrating both conversational approaches into the study, we aim to assess their distinct impact on user experience. Based on this foundation, the following hypotheses were developed:

- **H4:** Task-led conversations will be perceived by recruiters as more (a) efficient and (b) useful than topic-led conversations. (Task-led → E, PU)
  - H4: Task-led conversations will be perceived by recruiters as more (a) efficient and (b) useful than topic-led conversations. (Task-led

$\rightarrow$ E, PU)

- H5: Topic-led conversations will lead to higher levels of (a) personalization and (b) ease of use for recruiters compared to task-led conversations. (Topic-led $\rightarrow$ PR, PEOU)
- H6: Recruiters will find topic-led conversations to enhance trust in the chatbot more effectively than task-led conversations. (Topic-led $\rightarrow$ T)

These hypotheses serve as a framework for exploring how conversational AI can be optimized to enhance user engagement and satisfaction. This study divides these hypotheses between recruiters and job seekers groups, and division ensures that each group's hypotheses are specifically tailored to the aspects of the chatbot interaction most relevant to their experience. For job seekers, the focus is on how the interaction mechanism (context-based vs. menu-based) influences their perception of the chatbot. For recruiters, the emphasis is on how the style of conversation (task-led vs. topic-led) impacts their efficiency and effectiveness in using the chatbot for recruitment purposes.

4.4.3 Design and Participants

A 2x2 factorial design was used, where the independent variables were the interaction mechanism and conversational styles, while the dependent variables included five different measures. Participants were divided into two groups based on their role in the recruitment process: job seekers and recruiters. The age range for job seekers was set between 20 and 55 years, and for recruiters, it was set between 30 and 70 years, to reflect realistic demographic distributions in the job market.

Same as Study 1 and Study 2 data collection design procedure, The study was conducted through Prolific[3] using Qualtrics[4] questionnaire

[3]https://www.prolific.co (Last accessed: March 2024)
[4]https://www.qualtrics.com (Last accessed: March 2024)

to collect responses. The study initially faced the challenge of disengaged reactions, excluding 10 job seekers and 9 recruiters. Subsequent recruitment of more of the same number of participants compensated for these exclusions, obtaining in total of 120 participants (60 job seekers and 60 recruiters). The purpose of maintaining an equal number of participants was to ensure that the results were not biased. The average age was 37.5 years (with a standard deviation of 10.19) for job seekers and 50 years (with a standard deviation of 11.68) for recruiters. Participants were recruited worldwide, observing specific criteria of job seekers actively seeking employment and recruiters being currently employed with recruitment experience. Efforts were made to maintain a gender-balanced sample. The median completion time was 8 minutes for job seekers and 10 minutes for recruiters, with each participant receiving compensation of £1.50, aligning with Prolific's minimum participation fee of $£6/hour$.

4.4.4 Procedure and Tasks

To ensure authentic and unbiased engagement, the study investigates individuals as either job seekers actively seeking employment or recruiters engaged in hiring based on their roles in the recruitment process. Following eligibility verification, informed consent was obtained from participants, clearly detailing the study objectives, methodology, and participant rights, ensuring informed participation.

Participants were acquainted with RecoBot with an explanation of its functionality and objectives. They were navigated through the study framework, engaging in a sequence of tasks that mimic real-life recruitment scenarios, viewed from the standpoints of both job seekers and recruiters. The importance of focusing on RecoBot's interaction mechanisms and conversational styles during the tasks and their effect on user experience was stressed. Moreover, participants received explicit instructions to interact with RecoBot and complete the outlined tasks before moving on to the questionnaire segment, ensuring their expe-

Table 4.1: Task Assignments by Mechanism and Style for Participant Groups tables.

Group	Task	Task Description	Focus
Job Seeker	1	Submitting a resume to assess user ease and comfort	Interaction Mechanism: Menu-based
	2	Searching for jobs based on experience level to evaluate the effectiveness of personalized job search results.	Interaction Mechanism: Context-based
	3	Inquiring about job application status, examining the chatbot's responsiveness and the accuracy of the provided information	Interaction Mechanism: Context-based
Recruiter	1	Creating a job posting, leveraging interactions for detailed input, highlighting efficiency in generating comprehensive job listings	Conversational Style: Task-led
	2	Updating a job posting, demonstrating the flexibility of RecoBot in refining job details through a mix of conversational styles.	Conversational Style: Task-led
	3	Reviewing applications, emphasizing RecoBot's capability in streamlining the selection process through its conversational approach.	Conversational Style: Topic-led

riences were based on direct interaction. Job seekers performed tasks like submitting a resume, searching for jobs by experience level, and checking job application statuses with a focus on interaction mechanisms. Similarly, recruiters were assigned tasks such as creating job listings, updating these listings, and reviewing applications to explore how conversation styles affect recruitment tasks.

Upon completing their tasks, participants were asked to complete an extensive questionnaire using the semantic differential scale to gauge their attitudes towards crucial factors like personalization, efficiency, ease of use, usefulness, and trust. This scale was selected for its precision in measuring attitudes towards these critical variables. Open-ended questions were also included to gather in-depth feedback on the overall experience with RecoBot, offering insights into participants' views on language formality and interaction with the chatbot.

User interactions with RecoBot were meticulously monitored to verify that participants had completed the tasks before proceeding to the questionnaire. This was facilitated by linking a database to RecoBot's backend, which collected responses following each task completion. These responses were matched with user IDs to confirm or refute task completions. Furthermore, time constraints were applied as a criterion to ensure the validity of the collected data, reinforcing the authenticity and reliability of our findings.

4.4.5 Chatbot and Alignment of Tasks amongst Groups

As in the previous studies, the RecoBot setup was used to create experimental conditions that simulate real-world recruitment tasks. The chatbot, based on the same platform, allowed both task- and topic-led conversations with menu-based or context-based interactions. This setup aimed to evaluate the effectiveness of chatbot communication in recruitment, focusing on human-centered interaction design.

Table 4.1 outlines tasks assigned to job seekers and recruiters in the

Table 4.2: Results of paired samples t-tests for the impact of the interaction mechanism and conversation type on chatbot user experience

Type		Mean	SD	SIg. F	t	df	Sig. (2-tailed)
Personalization	Job seeker	3.056	0.811	0.038	1.034	118	0.045
	Recruiter	4.218	1.003	0.323			0.345
Efficiency	Job seeker	3.631	0.631	0.010	0.713	118	0.049
	Recruiter	4.536	0.912	0.506			0.045
Ease of use	Job seeker	3.800	0.677	0.083	1.630	118	0.506
	Recruiter	3.581	0.875	0.123			0.023
Usefulness	Job seeker	4.618	1.486	0.022	5.454	118	0.025
	Recruiter	5.336	1.097	0.000			0.030
Trust	Job seeker	3.462	0.728	0.007	0.833	118	0.406
	Recruiter	3.336	1.032	0.436			0.312

study, with job seekers focusing on interaction mechanisms—predominantly testing menu-based and context-based interactions through tasks like resume submission and job inquiries. On the other hand, recruiters engage with conversational styles, exploring task-led and topic-led conversations through creating and updating job postings and reviewing applications. This structured approach aims to evaluate the effectiveness and user experience of RecoBot's features across different recruitment scenarios.

4.5 Data Collection and Analysis

Data analysis was conducted using IBM SPSS[5] Statistics software, beginning with a reliability test via Cronbach's Alpha to validate our measurement instruments' consistency. High Cronbach's Alpha values for job seekers ($\alpha = 0.905$) and recruiters ($\alpha = 0.871$) indicated strong internal consistency, ensuring the validity of our findings and supporting the reliability of further analysis.

Examining interaction mechanisms and conversation types across de-

[5]https://www.ibm.com/it-it/spss (Last accessed: March 2024)

Table 4.3: Hypothesis Testing Results on RecoBots User Experience Among Job Seekers and Recruiters

Group	Hypothesis (a)	Sig. (2-tailed)	Status (a)	Hypothesis (b)	Sig. (2-tailed)	Status (b)
Job Seekers	H1a: Context-Based interactions → Higher Personalization	0.045	Accepted	H1b: Context-Based interactions → Higher Ease of Use	0.506	rejected
	H2a: Context-Based interactions → Enhanced Efficiency	0.049	Accepted	H2b: Context-Based interactions → Enhanced Usefulness	0.049	Accepted
	H3: Context-Based interactions → Higher Trust	0.406	Rejected	-	-	-
Recruiters	H4a: Task-led conversations → Higher Efficiency	0.045	Accepted	H4b: Task-led conversations → Higher Usefulness	0.045	Accepted
	H5a: Topic-led conversations → Higher Personalization	0.345	Rejected	H5b: Topic-led conversations → Higher Ease of Use	0.020	Accepted
	H6: Topic-led conversations → Enhanced Trust	0.312	Rejected	-	-	-

pendent variables, using paired-sample t-tests for job seekers and recruiters, revealed distinct impacts on user experience. For job seekers, context-based interactions significantly favored personalization and ease of use (H1a, H1b), evidenced by a t-value of 1.034 and a two-tailed significance (Sig. (2-tailed)) value of 0.045, while efficiency (H2a) was marginally preferred, marked with a t-value of 0.713 and a Sig. of 0.049. Table 4.2 provides the details of the paired sample t-test for the impact on both groups and their preferences. Furthermore, for recruiters, task-led conversations were validated as more efficient and useful (H4a, H4b), particularly regarding usefulness, with a t-value of 5.454, indicating a strong effect and a highly significant Sig. (2-tailed) value of 0.030. This highlights recruiters' preference for goal-oriented dialogues that directly support recruitment tasks. The ease of use (H5), particularly for recruiters, is significantly impacted by topic-led conversations, as shown by a t-value of 1.630 and a Sig. (2-tailed) value of 0.023, suggesting that a more exploratory conversation style facilitates easier navigation and interaction.

Table 4.3 However, the trust factor (H3, H6) does not exhibit a significant change based on either group's interaction type or conversation style. Job seekers show a t-value of 0.833 and a Sig. (2-tailed) of 0.406, and recruiters with a Sig. (2-tailed) of 0.312. This underscores the challenge of building trust through digital interactions and suggests that factors influencing trust may extend beyond the scope of conversational style and interaction mechanism alone. Table 4.3 shows the hypothesis results and summarizes the effectiveness of interaction mechanisms and conversation types for job seekers and recruiters. The analysis and hypotheses results show that job seekers prefer context-based interactions for personalization and efficiency, while recruiters find task-led conversations more efficient and valuable. Topic-led conversations improve ease of use for recruiters but not personalization or trust.

4.6 Study Insights and Implications

This chapter extends the thesis findings by empirically investigating the impact of conversational styles and interaction mechanisms on user experience with recruitment chatbots. By addressing critical dimensions such as personalization, efficiency, ease of use, usefulness, and trust, the research bridges the theoretical foundations laid out in earlier chapters with their practical application. These insights provide a clearer understanding of how to design recruitment chatbots that cater to the distinct needs of job seekers and recruiters, aligning with the broader thesis objective of developing human-centered, ethical AI systems that advance digital recruitment.

Building on prior work, this study operationalizes theoretical insights into real-world applications, specifically exploring interaction mechanisms like menu-based versus context-based interactions and conversational styles such as task-led versus topic-led dialogues. These design variations highlight how user experiences can be tailored to enhance engagement, satisfaction, and operational effectiveness.

For job seekers, context-based interactions were found to significantly enhance personalization and efficiency, mimicking human-like dialogue and adapting dynamically to user needs. On the other hand, recruiters preferred task-led conversations, valuing their efficiency and goal-oriented approach to tasks such as job postings and application reviews. These findings highlight the necessity of tailoring chatbot designs to meet diverse user needs, balancing the engagement sought by job seekers with the efficiency demanded by recruiters. Notably, trust levels did not significantly vary across interaction mechanisms or conversational styles, indicating that factors influencing trust, such as transparency, ethical handling of personal data, and clear communication—extend beyond conversational design. Addressing trust deficits remains a critical focus for future chatbot development, requiring additional interventions beyond stylistic and functional attributes.

RecoBot demonstrates how thoughtful design choices can address these complexities. By combining structured menu-based prompts with dynamic context-based dialogues, it showcased its adaptability in handling diverse recruitment tasks, such as resume submissions, job searches, and application status inquiries. These functionalities exemplify how task-specific adaptability can improve both personalization and efficiency, advancing the user-centered nature of digital recruitment processes. These insights directly shaped RecoBot's modular design by guiding the implementation of conversational styles (task-led vs. topic-led) and interaction mechanisms (menu-based vs. context-based) to align with key human-centered attributes such as trust, personalization, and transparency.

The study's findings provide actionable recommendations for improving chatbot functionality. Developers are encouraged to prioritize customizable interaction mechanisms and conversational styles, allowing users to tailor their interactions according to individual preferences. This flexibility ensures that chatbots can effectively cater to the distinct expectations of job seekers and recruiters. Furthermore, designing systems that balance engagement with efficiency enhances overall functionality, creating a more satisfying recruitment experience.

The research also underscores the need for trust-building measures in recruitment chatbots. Features that foster transparency, implement ethical data practices, and establish credibility through clear communication are essential for aligning chatbot systems with organizational values and societal expectations. Such measures will reinforce the broader aim of developing ethical and human-centric AI solutions.

This chapter bridges the gap between theory and practice by empirically validating the Human-Centered Technology Acceptance Model (HCTAM). Through the evaluation of RecoBot, it offers practical insights for improving chatbot designs to better meet user expectations while adhering to ethical and transparent standards. This contribution enhances the thesis by providing a framework for developing advanced recruitment tools that improve user experience and organizational outcomes.

RecoBot's design and evaluation mark a pivotal milestone in understanding human-chatbot interactions within recruitment. These findings contribute to the growing body of knowledge on user-centered AI, offering practical guidance for creating systems that are not only efficient and ethical but also aligned with the diverse needs of stakeholders. By aligning chatbot designs with user expectations, this research paves the way for a more human-centric approach to digital recruitment, ensuring that technological advancements serve the interests of both candidates and recruiters effectively.

Chapter 5

Discussion on Findings and Final Reflections

This thesis investigates the integration of human-centered principles into AI-driven recruitment, focusing on chatbot design. The research addresses the growing intersection between technological efficiency and ethical user experience in recruitment, aiming to bridge the gap between automated tools and human-centered interaction qualities. The findings contribute valuable insights to Human-Computer Interaction (HCI), Artificial Intelligence (AI), and recruitment fields, enhancing understanding of how human-centered design can be leveraged to improve user experience, trust, and ethical practices within AI-powered recruitment systems.

The thesis is organized around key themes across multiple chapters, each offering distinct insights into the evolution, design, and application of recruitment chatbots. By analyzing these findings in this final chapter, the thesis highlights essential implications for both academia and industry, emphasizing how conversational AI can be optimized to align with human values and ethical principles. This chapter revisits the significant insights from each chapter, connects these insights to existing literature, and suggests practical and theoretical directions for advancing human-centered AI in recruitment.

5.1 Methodology

The methodology employed in this thesis is designed to rigorously explore and validate the integration of human-centered principles into recruitment chatbot design. The research adopts a *mixed-methods approach*, combining qualitative and quantitative techniques to ensure a comprehensive analysis of user experiences, design challenges, and ethical considerations.

Literature Review and Theoretical Framework Development: The initial phase of the research involved an extensive review of existing literature in HCI, AI ethics, and recruitment technologies. This review identified gaps in the current understanding of how conversational AI tools align with human-centered principles, leading to the development of the Human-Centered Technology Acceptance Model (HCTAM) [162]. This model served as the theoretical foundation for the research.

Survey and Interview Studies: Two rounds of surveys and semi-structured interviews were conducted to gather insights from key stakeholders, including job seekers and recruiters [10]. These studies explored user expectations, preferences, and concerns regarding chatbot interactions. The first phase focused on identifying critical factors influencing chatbot acceptance, while the second phase refined these themes to inform the empirical design of RecoBot.

Empirical Evaluation with RecoBot: The centerpiece of the methodology was the design and evaluation of RecoBot, a recruitment chatbot developed to simulate real-world hiring scenarios. RecoBot was implemented using a dedicated bot-building platform and was equipped with interaction mechanisms (menu-based vs. context-based) and conversational styles (task-led vs.topic-led) [25]. The chatbot's design was informed by the insights gathered during the initial phases of the research.

Experimental Studies: To evaluate the impact of RecoBot's design on user experience, experimental studies were conducted with two participant groups: job seekers and recruiters. Participants completed tasks such as resume submission, job search, and application status inquiries, followed by a detailed questionnaire assessing dimensions like personalization, efficiency, ease of use, usefulness, and trust. Paired-sample t-tests and hypothesis testing were employed to analyze the data [25].

Qualitative Data Analysis: Open-ended responses and interview transcripts were analyzed using thematic analysis, employing tools like NVivo to identify recurring themes and patterns. This qualitative approach complemented the quantitative findings, providing deeper insights into user perceptions and preferences [162, 10].

Validation and Iterative Refinement: The iterative nature of the research ensured that each phase informed subsequent steps. Findings from surveys and interviews were used to refine RecoBot's design, and insights from experimental studies contributed to the validation and extension of the HCTAM framework [25, 10].

This *mixed-methods* approach ensured a robust and multidimensional exploration of human-centered recruitment chatbots, balancing theoretical rigor with practical relevance [162]. The methodology's iterative design allowed for continuous refinement, aligning the research process with the thesis objective of advancing ethical, user-centered AI systems in recruitment.

5.2 Alignment of Research Objectives and Questions with Thesis Findings

This research, structured across sequential phases, addresses identified gaps in existing literature and highlights the underexplored human-centered principles, transparency, empathy, and personalization—in

AI-driven recruitment. Building on these insights, the study develops the Human-Centered Technology Acceptance Model (HC-TAM), embedding these principles into recruitment chatbot design. The HC-TAM model integrates both theoretical insights and practical strategies to enhance user trust, experience, and ethical alignment within recruitment chatbots. Validated through studies involving RecoBot and conversational style analysis with feedback from the target audience, the model's effectiveness is further confirmed [25]. Applied in practical settings, HC-TAM refines the balance between technological efficiency and human-centered values in AI-driven recruitment.

The first objective, to explore human-centered principles in recruitment chatbots to improve user experience, trust, and acceptance, was achieved by embedding constructs of transparency and empathy within the HC-TAM framework [162]. Through qualitative and quantitative analysis, the study demonstrated that chatbots designed with human-centered principles significantly elevate user satisfaction and trust, showing that ethical alignment and transparency in recruitment AI are both necessary and achievable.

The second objective, which aimed to identify strategies for enhancing transparency and personalization to improve usability and ethical alignment, was addressed through a conversational style experiment with RecoBot and qualitative interviews. The findings highlighted that transparency about data usage and adaptive communication styles are crucial for ethical design and usability. It was affirmed that chatbots should be adaptable to user preferences to increase engagement. [25].

And, *finally, the third objective*, developing a framework that balances efficiency with human-centered attributes, was realized in the HC-TAM model. This model, validated using Structural Equation Modeling (SEM), offers a robust framework for designing chatbots that meet organizational needs for efficiency without sacrificing ethical considerations or user experience [162]. The HC-TAM demonstrates that recruitment chatbots can be efficient while prioritizing empathy, personalization, and ethical responsibility, thus supporting the long-term adoption of AI in recruitment contexts.

The research questions align closely with these objectives. By examining the integration of human-centered principles, the study shows that constructs such as transparency and empathy significantly enhance user trust and satisfaction. It further explores the impact of conversational styles, demonstrating that formal language fosters professionalism and trust, while casual tones increase approachability, insights that guide AI developers in creating communication strategies that meet diverse user expectations. Finally, through the validation of HC-TAM, the thesis addresses how recruitment chatbots can balance operational efficiency with human-centered attributes, setting a framework for recruitment tools that align with user needs and organizational goals.

5.3 Recommendations and Guidelines for Recruitment Chatbot Design

Based on the findings and empirical studies conducted in this research, the following recommendations are proposed for the development of ethical, effective, and human-centered recruitment chatbots:

Ensure Transparency in Chatbot Functionality

Chatbots should clearly communicate their purpose, limitations, and capabilities to users. It is essential to inform users how their data is collected, processed, and utilized. Transparency plays a key role in building user trust and encouraging engagement.

Support Personalization for Enhanced User Experience

Recruitment chatbots should be capable of adapting responses based on user profiles, preferences, and interaction context. Personalization not only increases user satisfaction but also enhances the perceived relevance and effectiveness of the interaction.

Integrate Empathy into Conversations

Empathetic communication is especially important in emotionally sensitive contexts, such as rejections or feedback. Chatbots should use compassionate language to provide support and maintain a positive user experience throughout the recruitment journey.

Mitigate Bias and Promote Fairness

AI models must be trained using diverse datasets, and regular audits should be conducted to detect and reduce bias. Ensuring fairness across gender, ethnicity, and socioeconomic status is fundamental to ethical recruitment practices.

Design for Accessibility and Inclusivity

Chatbots should comply with accessibility standards to accommodate users with varying abilities. Multimodal interfaces (text, voice, assistive technologies) enhance usability and ensure equitable access for all candidates.

Adopt an Iterative, User-Centered Design Approach

Incorporate ongoing user feedback into development cycles to refine chatbot functionality and interface design. Iterative design helps maintain alignment with user expectations and evolving recruitment needs.

Align Chatbot Tone with Organizational Branding

The chatbot's language style, tone, and persona should reflect the organization's identity and values. Consistent messaging supports employer branding and contributes to a cohesive candidate experience.

Evaluate Performance Through Defined Metrics

Establish and monitor key performance indicators such as task completion rates, user satisfaction scores, and engagement duration. These metrics help identify improvement areas and optimize chatbot effectiveness.

Enable Adaptive Conversational Styles

Chatbots should dynamically adjust their tone—formal, casual, or neutral—based on the user role (e.g., recruiter or job seeker) and interaction context. Adaptive dialogue enhances relevance and user comfort.

Embed Ethical Principles Throughout the Lifecycle

Ethical considerations—privacy, accountability, transparency, and inclusiveness—must be integrated at every stage of chatbot design, development, and deployment. Upholding these values ensures long-term trust and responsible AI implementation.

5.4 Theoretical Implications for AI in Recruitment

This research provides substantial theoretical contributions to the fields of AI, HCI, and recruitment by expanding the traditional Technology Acceptance Model (TAM) with a human-centered framework, resulting in the Human-Centered Technology Acceptance Model (HC-TAM). This new model incorporates constructs such as transparency, empathy, personalization, and ethical considerations that are often overlooked in traditional TAM frameworks. The HC-TAM provides a refined theoretical basis for understanding the determinants of user acceptance in recruitment chatbots, emphasizing the importance of human-centered elements in AI interactions.

Extending TAM with Human-Centered Factors: The HC-TAM framework integrates constructs beyond traditional TAM factors, such as perceived usefulness and ease of use, by including transparency, empathy, and ethical alignment. These additions respond to the need for a framework that better represents user expectations for AI technologies in sensitive fields like recruitment [120].

Understanding Trust as a Core Construct: Trust emerged as a fundamental construct influencing user acceptance, mediated by transparency and empathy. Theoretical contributions highlight the role of trust in recruitment AI, suggesting that it should be a primary focus in future AI acceptance models.

Ethical Implications in AI Design: By emphasizing ethical considerations, this research introduces a theoretical foundation for developing fair and transparent AI systems that users can trust. This addresses a significant gap in AI acceptance literature, which often focuses on functionality without adequately considering ethical alignment.

While the proposed HC-TAM model was developed and validated specifically for recruitment chatbots, it is a flexible framework that can be extended to other AI-driven systems that share similar human-centered principles. The key concepts of transparency, fairness, trust, and ethical alignment are not unique to recruitment but are critical across various AI applications. These principles apply to any AI system that involves direct human interaction, including customer service chatbots, healthcare AI systems, and other domains where user experience, ethical concerns, and human-centered design are essential. Therefore, the HC-TAM model can be adapted to evaluate AI applications in diverse fields, ensuring that factors such as fairness, security, and explainability are effectively integrated into system design and deployment. This broad applicability highlights the model's potential beyond the recruitment industry, providing a valuable tool for understanding user acceptance and trust in AI systems.

5.5 Practical Implications for HR and AI in Recruitment

Building on these theoretical insights, the research offers practical recommendations for HR practitioners and chatbot developers. By integrating human-centered principles, recruitment chatbots can enhance candidate engagement and trust, ultimately improving the recruitment experience. Below are key recommendations based on the findings:

Transparency in Interaction: HR and chatbot developers should ensure that recruitment chatbots transparently communicate data handling practices, interaction intentions, and limitations. Candidates are more likely to trust and engage with chatbots that clarify their functions and data usage policies.

Personalization and Adaptability: Recruitment chatbots should incorporate features that allow them to adapt to user preferences, whether in communication style or response tone. Personalization fosters a sense of familiarity, making candidates feel valued and respected, which aligns with the HC-TAM model's emphasis on empathy.

Ethics and Fairness in AI: Ethical considerations such as reducing biases and ensuring fairness in AI interactions should be at the forefront of chatbot design. This could involve implementing algorithms that check for bias or ensuring diverse and representative datasets are used in chatbot training to prevent discriminatory outcomes.

Empathy and User Engagement: Chatbots should exhibit empathetic responses, especially in high-stakes situations such as job applications. Empathy can be conveyed through thoughtful language and supportive messaging, encouraging candidates to feel more at ease and open in their interactions.

5.6 Implications for Research and Industry

The findings of this thesis reveal several promising avenues for research and industry practice:

Dynamic Conversational Styles: Future research could explore adaptive conversational styles, where the chatbot adjusts its tone based on user interaction cues. This would allow chatbots to balance professionalism with approachability, enhancing user satisfaction.

Enhanced Ethical Standards in Chatbot Design: Further investigation into ethical AI practices, such as fairness, transparency, and accountability, is essential for the development of recruitment chatbots. Studies that examine the long-term impact of ethical practices on user trust and engagement would provide valuable insights.

Incorporating Multimodal Interaction: Exploring multimodal interactions—such as combining text, voice, and visual cues—could offer a more engaging and human-like experience for candidates. This would allow for more nuanced exchanges and improve the chatbot's ability to convey empathy and understanding.

Impact of AI on Organizational Culture: Further studies could examine how AI-driven recruitment tools influence organizational culture, particularly in terms of trust-building and employee perceptions. This would provide HR practitioners with insights into how chatbot integration affects both recruitment and workplace culture.

5.7 Conclusion

This thesis makes a significant contribution to the fields of AI, HCI, and recruitment by offering a comprehensive framework, HC-TAM for evaluating and designing human-centered recruitment chatbots. The research underscores the importance of embedding human-centered principles such as transparency, empathy, personalization, and ethical alignment into AI-driven tools to enhance user experience, trust, and acceptance.

Through detailed analyses of chatbot design, conversational styles, and ethical considerations, this thesis bridges the gap between technological efficiency and user-centric values. The findings demonstrate that recruitment chatbots designed with these principles can transcend mere functionality, offering a more supportive and engaging experience for candidates. By fostering trust, empathy, and inclusivity, these systems not only improve the recruitment process but also leave a positive impression of the hiring organization.

The HC-TAM framework developed in this research provides a robust theoretical and practical roadmap for balancing operational efficiency with ethical and user-centered values. The iterative design and validation processes, exemplified by the RecoBot evaluations, highlight how human-centered design principles can be effectively implemented and refined to meet both organizational objectives and user expectations.

The insights and recommendations outlined in this thesis pave the way for a future where recruitment processes are not only efficient but also empathetic and inclusive. As AI technologies continue to evolve, ensuring these tools reflect human values and ethics will be essential for building trust and acceptance among users. This research offers a clear pathway for achieving this balance, emphasizing that recruitment chatbots can become powerful tools for bridging organizational needs with the nuanced expectations of job seekers.

By integrating these principles into AI-driven recruitment, organizations can create systems that are ethical, trustworthy, and aligned with the broader goal of sustainable and human-centered AI adoption. Ultimately, this thesis contributes a forward-looking vision for the ethical design and implementation of recruitment chatbots, ensuring their impact extends beyond efficiency to truly resonate with the values of fairness, inclusivity, and empathy.

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Appendix

1. Chapter 3 Study Material

Phase 1- An Interview Protocol

An Interview Protocol

We are conducting a study on the effectiveness of a human-centered chatbot that aims to help job seekers find employment and assist recruiters in finding potential candidates. Our goal is to create a conversational chatbot design that is according to human-centered principles. We are interested in your experience and insights about job searching and recruitment, and we believe that your feedback will be valuable in improving the chatbot's performance. During this interview, we will be asking you questions about your past experiences with job searching and recruitment, as well as your thoughts on how a chatbot could help you in these areas. Your participation in this study is greatly appreciated and will help us improve the job searching and recruitment experience for everyone involved.

With your permission, I will audiotape and take notes during the interview. The recording is to accurately record the information you provide and will be used for transcription purposes only. If the results of this study are published or presented, individual names and other personally identifiable information will not be used The estimated time of this interview is 30 minutes.

Is there something you would like to ask about before we begin?

Questions (General discussion)

Background

1. Can you tell me about your experience as a recruiter, and your current status (how's work going on)?
2. Did you face challenges during the recruitment process?

3. What are the most important features of the recruitment platform you are using?
   (a) Are there some features that the platform you are currently using that you need but are not provided?

Focused Research Questions

Research Question 1: How do recruitment chatbots impact the job seeker and recruiter experience?

1. Have you ever used a chatbot or virtual assistant for recruitment?
   (a) Yes: can you describe your experience? Yes: have you ever encountered any issues with chatbots or virtual assistants in other areas of your life? If so, what were they?
   (b) No: do you think that a chatbot or virtual assistant designed specifically for recruitment would be useful?
2. What characteristics would you look for in a chatbot or virtual assistant designed for recruitment (job searching)?
3. How do you think recruitment chatbots impact the recruiter experience, including workload, efficiency, and communication with candidates?
4. Can you share any examples of how recruitment chatbots have improved or hindered the recruiter experience in your organization or others with whom you are familiar?

Research Question 2: Do recruiters (job seekers) accept the support of conversational recruitment chatbots to improve their experience?

1. Do you think that conversational recruitment chatbots could eventually replace human recruiters, or do you see them more as a complement to existing recruitment processes?

2. What do you think the future holds for conversational recruitment chatbots, and how do you see them evolving in the coming years?

   Using HCAI Chatbot:

   (a) Do you think you would like to use Our Chatbot like we want to design?
   (b) What do you find important for using this Chatbot?
   (c) What experience would you expect?
   (d) Is there something you would like to add?

Thank you for participating in this interview and sharing your insights. Your responses will help me better understand how recruitment chatbots impact the job seeker and recruiter experience and how human-centered design principles can be incorporated into their development to improve their effectiveness and user satisfaction. If you have any additional thoughts or suggestions, please feel free to share them with me.

Phase 2- An Interview Protocol

Introduction: Thank you for participating in our study. Your insights are incredibly valuable in shaping the development of a human-centered chatbot for job searching and recruitment. Based on previous interviews, we've refined our questions to better understand your experiences and preferences. Your candid responses will greatly contribute to improving the overall recruitment process.

Consent and Recording: As before, we will be recording the interview for transcription purposes only, and your privacy will be respected. If you have any concerns, please feel free to let me know.

Estimated Time: This interview is expected to take around 30 minutes, and your time is sincerely appreciated.

General Discussion Let's start with a brief discussion about your general thoughts on the current state of job searching and recruitment. Any initial reflections or observations

Background Questions:

1. **Can you tell me about your experience as a recruiter/Job seeker and how things are currently going for you?**

1. Based on your experience, have you noticed any recent trends or changes in the recruitment landscape? (Networking experiences)
2. **Did you face challenges during the recruitment process?**
3. Could you share specific instances or types of challenges you encountered?
4. **Which platform do you usually use for job searching or hiring candidates?**
5. **Which are the most important features of that recruitment platform you are using?**
   (a) Are there any features that you find crucial but are currently missing?

Focused and Updated Research Questions

1. RQ1:How do recruitment chatbots impact the job seeker and recruiter experience?
2. Have you ever used a chatbot or virtual assistant for recruitment?
   (a) If yes, could you describe your experience?
   (b) Yes, have you faced any issues with chatbots in other areas of your life?
   (c) No: do you think that a chatbot or virtual assistant or conversational Agent designed specifically for recruitment would be useful?
3. What characteristics would you look for in a chatbot or virtual assistant designed for recruitment?
   (a) Based on your experiences, are there specific traits or features you believe are essential in an effective recruitment chatbot?

(b) Do you think personalization can affect your experience?

(c) Like how personalization has impacted your experience with similar tools?

4. How do you think recruitment chatbots impact the recruiter experience, including workload, efficiency, and communication with candidates?

   (a) Can you share any examples from your own experiences or observations?

1. Can you share examples of how recruitment chatbots have improved or hindered the recruiter experience?

   Specifically, have you seen instances where chatbots enhanced efficiency or, conversely, posed challenges in your organization or others you are familiar with?

1. **RQ 2: Do recruiters (job seekers) accept the support of conversational recruitment chatbots for improving their experience?**

1. Do you think conversational recruitment chatbots could eventually replace human recruiters, or do you see them more as a complement to existing processes?

   (a) Based on your perspective, how do you envision the balance between human recruiters and chatbots evolving?

2. What do you think the future holds for conversational recruitment chatbots?

   (a) Considering your experiences, how do you foresee chatbots evolving in the coming years?

Using HCAI Chatbot

Now, let's shift our focus to the Human-Centered AI Chatbot.

Do you think you would like to use our Chatbot as we want to design it?

1. Based on your preferences and needs, what features or capabilities would be crucial for you in using this Chatbot? What feature or factor can make it more human centric.

What do you find important for using this Chatbot?

1. How can the Chatbot best align with your expectations and needs?

What experience would you expect from using this Chatbot? Is there something you would like to add?

1. Any additional thoughts or suggestions based on your experiences that you would like us to consider in the development of this Chatbot?

Overarching Question: What, in your opinion, is the key factor that encourages users to accept a tool designed with a human-centric approach?

In particular, what features or considerations should our designers and developers incorporate into the chatbot to enhance its acceptability?
Closing: Thank you for sharing your valuable insights. Your input will significantly contribute to the refinement and improvement of our chatbot. If you have any further thoughts or suggestions after this interview, please feel free to share them with us. Your participation is immensely appreciated.

Questionnaire phase 3

Note: M(SD) stands for Mean (Standard Deviation). R = reversed items. * denotes items that were removed from Confirmatory Factor Analysis (CFA).

This table synthesizes the constructs, items, their loadings, and the mean scores with standard deviations, offering a structured overview of the users' acceptance of chatbots in the context of online shopping.

Table 1: Analysis of User Experience Metrics within Job Seekers and Recruiters

Construct/Items	Loading	M(SD)
Perceived Ease of Use (Davis 1989) [120]		5.51(.99)
1. Is the interaction with the recruiting chatbot clear and comprehensible?	0.839	
2. Is it easy to remember how to easily interact with the Recruiting chatbot?	0.828	
3. Is it satisfactory to use the chatbot for online shopping? R^*	0.479	
4. Is it frustrating to use the recruiting chatbot for job seeking or to recruit?	0.887	
5. Does the interaction require little effort? R^*	0.473	
6. Does the interaction with the recruiting chatbot requires an excessive mental effort?	0.791	
7. Is it easy to find the information you are looking for a recruitment chatbot?	0.804	
8. Do you think you could easily become skilled using the chatbot Job search / Candidate Hiring?	0.908	
Perceived Usefulness (Davis 1989) [120]		4.83(1.29)
1. Using a recruiting chatbot improves my Job search / Candidate Hiring experience?	0.907	
2. Is the chatbot effective for recruitment? R^*	0.516	
3. Using a recruiting chatbot in my job increases my productivity.	0.828	
4. I find a recruiting chatbot to be useful in my Job search / Candidate Hiring experience.	0.885	
5. Recruitment chatbot provide support to the online shopping experience?	0.926	
6. Using a recruiting chatbot enhances my effectiveness in my Job search/Candidate Hiring experience.	0.878	
7. Recruitment chatbot speed up the Job Search/Candidate Hiring experience?	0.927 0.924	
Transparency (Nilashi M et al. 2016) [137]		3.98(1.74)
1. A recruiting chatbot makes its reasoning process clear to me.	0.924	
2. It is apparent to me how the algorithm of a recruiting chatbot handles the data of incoming inquiries.	0.917	
3. The recruiting chatbot handles the data of incoming inquiries.	0.933	

Table 2: Analysis of User Experience Metrics within Job Seekers and Recruiters

Trust (Van Pinxteren et al. 2019) [11]		4.63(1.43)
1. I feel like the chatbot has my best interest at heart during the recruitment process	0.896	
2. The chatbot provides accurate information about candidates, the hiring process or jobs available and steps to apply	0.867	
3. I feel I can rely on the chatbot to execute recruitment tasks effectively.	0.0807	
Efficiency (Teo T et al. 2011) [161]		3.93(1.56)
1. The recruiting chatbot significantly streamlines the hiring process, resulting in time and effort savings.	0.955	
Using the chatbot keeps me engaged while applying or hiring. R^*	0.446	
3. Using the recruiting chatbot enhances the overall efficiency of the job search or candidate hiring.	0.955	
4. The recruiting chatbot effectively handles tasks, contributing to a faster and more efficient process.	0.947	
Personalization (Cheng Y et al. 2020) [139]		4.64(1.45)
1. The recruiting chatbot provides personalized responses based on individual preferences and needs.	0.914	
2. Interactions with the recruiting chatbot are characterized by a noticeable level of personalization.	0.941	
3. The recruiting chatbot adapts to unique job search or candidate hiring requirements.	0.906	
4. The recruiting chatbot's interactions reflect an adaptability to unique job search or candidate hiring requirements.	0.932	
Ethical Concerns (Sekhar S et al. 2020) [140]		3.89(1.73)
1. It is crucial for the recruitment chatbot to address biases and actively prevent discrimination in the hiring process.	0.939	
2. I think recruitment chatbot design is important in actively preventing discrimination in the hiring process as an ethical priority.	0.938	

2. Chapter 4 Study Material

Participation Guide

Welcome to our Usability Study on language formality in chatbot interactions. In this study, you will interact with RecoBot, a recruitment chatbot, to simulate real-world tasks from the perspectives of both a job seeker and a recruiter. The study aims to understand how the formality of language used by chatbots affects user experience, engagement, and task completion. Your insights will help enhance the effectiveness of chatbot communications in the recruitment process. The entire study should take approximately 15 to 20 min to complete.

What is RecoBot?

RecoBot is an advanced recruitment chatbot that acts as a digital mirror of the real-world hiring environment. It's designed to facilitate the recruitment process by automating candidate screening and assisting with job postings for recruiters. For job seekers, RecoBot simplifies the job search based on their experience level and streamlines the application process, improving the recruitment experience for all users involved.

Informed consent

Welcome!

Thank you for your interest in participating in this study. Before you begin, please carefully read, and understand this informed consent. It explains the purpose of the study, what you will be asked to do, and your rights as a participant.

This study is being conducted by a PhD student for research publication purposes.

This study aims to understand how the formality of the language used by chatbots like RecoBot affects user experience, engagement, and task completion in the recruitment process. Your participation will help us improve the effectiveness of chatbot communications in recruitment.

What will you be asked to do?

If you choose to participate, you will:

- Engage with the RecoBot across different provided tasks that mirror real-life recruitment / job-seeking situations. These interactions will require you to use both task-led and topic-led dialogue styles, facilitated by button clicks and free-text communication.
- Pay attention to RecoBot's tone and style of communication. Assess whether it comes across as informal and friendly or formal and professional.

- After completing each task, take a moment to reflect on how the language formality affected your interaction.
- Consider aspects such as ease of understanding, level of comfort, and overall satisfaction.
- After completing the first two scenarios, you will be prompted to fill out a questionnaire. Your responses should reflect your experiences during the RecoBot conversation.
- It's important to hold strictly to the instructions for each scenario to ensure the validity of your assessment.

Note: Please remember to refresh the RecoBot before starting each task to ensure a clean start for your next task interactions.

Your contributions are invaluable, and your honest feedback will directly inform improvements to RecoBot's design and conversation style. We appreciate your commitment to advancing our project.

All information you provide will be kept confidential. Your responses will be de-identified and reported in aggregate form.

Your participation in this study is entirely voluntary. You may choose not to participate or withdraw your consent at any time without penalty.

If you have any questions or concerns about this study, please contact sabina.akram@uniba.it before you begin.

By clicking "I agree" below, you acknowledge that you have read and understood this informed consent document and consent to participate in this study.

- I agree.
- I do not agree with the above conditions and wish to terminate the research.

Thank you for your time and consideration!

Tasks for Participants as a job seeker

As a recent graduate, you decided to relocate to a new city in pursuit of career opportunities. Despite your best efforts, job hunting proved to be a challenging task, with no luck in sight. Frustrated but determined not to give up, you stumbled upon RecoBot, an AI-powered assistant designed to simplify the job search process. With a renewed sense of hope, you embark on a journey to navigate the intricacies of job hunting with the help of RecoBot by your side.

Task 1: Submitting a Resume (Low Difficulty)

Goal: Evaluate the impact of RecoBot's language formality (robot-like vs. human-like) on the user's ease and comfort during the resume submission process.

Scenario: For your initial Task, you're required to upload your CV for recruiters to review and potentially contact you regarding job suitability. During this process, you engage with RecoBot to submit your resume, noticing its language style shifts between formal and casual. You're intrigued by how this variability affects your experience.

Instructions: Access RecoBot and choose the option to 'Upload Your CV'. Follow the on-screen prompts, observing the changes in language formality. Use the buttons provided to navigate and upload your resume.

Task 2: Job Search Based on Experience Level (Moderate Difficulty)

Goal: Determine if RecoBot's language style affects its ability to deliver personalized job search results.

Scenario: You're on the lookout for a job that aligns with your skill set. While using RecoBot to search for jobs, you notice the tone of the conversation changes.

Instructions: Open RecoBot and select 'Search for Jobs'. Choose your experience level as prompted and evaluate how the formality of RecoBot's language influences the job search process.

Task 3: Inquire About Job Application Status (High Difficulty)

Goal: Test how the formality of RecoBot's language influences its responsiveness and accuracy in dialogues.

Scenario: Eager for an update on a job you've applied for, you approach RecoBot to inquire about your application status, paying attention to the bot's conversational style.

Instructions: Engage with RecoBot and ask about the status of your job application using a text question. Note how the language style affects the clarity and helpfulness of the response you receive.

Job Seeker Questionnaire

Please reflect on your overall experience after completing all the tasks (Submitting a Resume, Job Search Based on Experience Level, Inquiring About Job Application Status) and answer the following questions:

Personalization

1. To what extent did you feel that RecoBot's interactions were personalized to your job-seeking needs? (1 = Not at all personalized, 5 = Highly personalized)
2. How did the formality of language used by RecoBot affect the sense of personalization in your experience? (1 = Made it less personalized, 5 = Enhanced personalization)

Efficiency

1. How efficient did you find RecoBot in assisting with your job-seeking tasks? (1 = Not efficient, 5 = Very efficient)
2. Did the language formality of RecoBot impact your perception of its efficiency? (1 = Negatively impacted, 5 = Positively impacted)

Perceived Ease of Use

1. Overall, how easy was it to interact with RecoBot and complete your tasks? (1 = Very difficult, 5 = Very easy)

2. Did the formality of language influence your perceived ease of use? (1 = Made it harder, 5 = Made it easier)

Perceived Usefulness

1. How useful did you find RecoBot in your job search process? (1 = Not useful, 5 = Extremely useful)
2. In what ways did the language formality contribute to or detract from RecoBot's usefulness? (1 = Detracted significantly, 5 = Contributed significantly)

Trust

1. How much did you trust the information and assistance provided by RecoBot? (1 = Did not trust, 5 = Completely trusted)
2. How did the formality of language used by RecoBot affect your level of trust in its capabilities? (1 = Decreased trust, 5 = Increased trust)

   Open-Ended Questions
3. What are your overall impressions of interacting with RecoBot for job-seeking purposes?
4. How did the language formality impact your experience and satisfaction with RecoBot? Please provide specific examples.
5. Do you have any suggestions for improving RecoBot's language formality to better suit job seekers' needs?

Thank you for your valuable feedback. Your insights will contribute significantly to enhancing the user experience with RecoBot.

Tasks for Participants as a Recruiter

As the HR manager at a growing tech company, you're tasked with finding the perfect candidate for the newly opened project manager position. With deadlines approaching and projects piling up, finding the right person quickly is crucial. You decide to use RecoBot, the latest AI tool designed to streamline the hiring process.

Task 1: Job Posting Process (Low difficulty)

Goal: Assess how language formality affects your experience in creating detailed job postings.

Scenario: First of all, You need to post a vacancy for a project manager. As RecoBot helps you with posting, it alternates between formal and casual language. Observe how this affects the process.

Instructions: Start by inputting job details into RecoBot as he asks, using a mixed interaction with buttons and text format. Then, refine your job post by responding to the button prompts and additional input fields.

Task 2: Updating a Job Posting (Low to Moderate difficulty)

Goal: Evaluate if RecoBot's language style influences your ability to effectively update job postings.

Scenario: Now, that you've just crafted a job posting, but upon review, you notice certain aspects require refinement for clarity and effectiveness. With RecoBot, you get on the editing process, paying close attention to how the language tone influences your overall experience and the quality of your revisions.

Instructions: Review your initial job posting and after RecoBot displays the summary of the job you have posted; it will inquire whether you need to make any changes or if you're ready to submit the job listing. click on 'make changes' as apply some edits, again see the summary, and then proceed to submit it.

Task 3: Reviewing Applications (Moderate difficulty)

Goal: Evaluate RecoBot's performance in handling tasks and determine if its language aids recruiters in efficiently managing interactions with applicant lists.

Scenario: For managing the hiring process for the project manager role, you have a stack of applications waiting for review. Your task is to leverage RecoBot to select through these applications and identify candidates who align with the job requirements for potential interviews or additional evaluation.

Instructions: Request RecoBot to display applicants for a specific job, then interact with the list to select candidates for further action.

Recruiter Questionnaire Please consider your experiences across all the tasks: Job Posting Process, Updating a Job Posting, and Reviewing Applications, as you answer the following questions.

Rating Scale

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

Personalization

1. The language formality used by RecoBot was appropriate for creating a personalized job posting experience.
2. RecoBot's language formality made me feel like it understood my specific needs when updating job postings.
3. The formality of language in interactions with RecoBot was suitable for reviewing applications, making the process feel tailored to my requirements.

Efficiency

1. The language formality of RecoBot facilitated an efficient job posting process.
2. I found the process of updating job postings with RecoBot to be efficient, thanks to its use of formal/informal language as appropriate.
3. Reviewing applications was made more efficient by the formality of language used by RecoBot.

Perceived Ease of Use

1. RecoBot's language formality made the job posting process easy to navigate.
2. The formality of language in RecoBot simplified the task of updating job postings.
3. I found the application review process easy due to the language formality employed by RecoBot.

Perceived Usefulness

1. The language formality used in the job posting process increased RecoBot's usefulness.
2. Updating job postings was more effective because of the language formality chosen by RecoBot.
3. The formality of language made reviewing applications with RecoBot a useful experience.

Trust

1. I trusted the outcomes of the job posting process due to the formality of language used by RecoBot.
2. The language formality in updating job postings made me trust RecoBot's suggestions.
3. When reviewing applications, the language formality used by RecoBot contributed to my trust in its capabilities.

Additional Comments

- Please share any specific feedback on how language formality impacted your experience across the tasks you performed with RecoBot.
- Are there any suggestions you have for improving the language formality in RecoBot's interactions to better support recruitment activities?

Your feedback is invaluable in our efforts to enhance RecoBot's effectiveness and user experience. Thank you for your participation and insights.

Summary of Research Papers on Recruitment, Human-Centered AI, and Ethical Implications in AI

Ref.	Year	Field of Study	Type of Study	Contents of the Paper	Focus Areas				
					Traditional/ Manual	Automated Recruitment	Recruitment Chatbots	Human-Centered AI	Ethics of AI
[58]	2017	E-Recruitment tool	Empirical	Evaluates initial electronic forms of recruitment		✖			
[31]	2018	E-Recruitment tool	Empirical	Assesses emergence of e-recruitment software		✖			
[60]	2017	E-Recruitment tool	Empirical	Investigates effectiveness of e-recruitment tools		✖			
[61]	2020	E-Recruitment tool	Emprical	Probes efficacy of e-recruitment tools like Digital selection procedures (DSPs)		✖			
[44]	2017	E-Recruitment tool	Empirical	Evaluates initial electronic forms of recruitment		✖			
[163]	2006	E-Recruitment tool	Empirical	Influence of website qualities on applicants		✖			
[164]	2011	E-Recruitment tool	Empirical	Impact of website content on intention to apply		✖			
[64]	2018	Job Seeker Tools	Empirical	Designs new tools for limited-resource job seekers		✖			
[65]	2019	Job Seeker Tools	Empirical	Assesses new tech tools for low-resource job seekers		✖			
[165]	2018	Information Collection	Empirical	Develops methods for collecting information		✖			
[66]	2021	Social Media Use	Empirical	Interviews on employers' use of social media		✖			

Table 3: Summary of Research Papers on Areas relevant studies focused on Focus areas

Ref.	Year	Field of Study	Type of Study	Contents of the Paper	Focus Areas				
					Traditional/ Manual	Automated Recruitment	Recruitment Chatbots	Human-Centered AI	Ethics of AI
[6]	2019	AI in HRM	Theoretical	Potential and challenges of AI in HRM		✖		✖	
[1]	2021	AI in HRM	Theoretical	Opportunities and pitfalls of AI in HRM		✖		✖	
[2]	2021	Intelligent automation	Theoretical	Implications of intelligent automation in HRM		✖		✖	
[69]	2022	AI in HRM	Review	Reviews State of AI applications in HRM and biases		✖		✖	✖
[166]	2019	AI in HR	Theoretical	Challenges in adopting AI in HR		✖		✖	
[68]	2015	E-Recruitment Tools	Theoretical	Questions the ability of e-recruitment tools		✖			
[167]	2021	AI Scenarios	Empirical	Studies responses to hypothetical AI scenarios		✖		✖	
[9]	2022	Recruitment chatbots	Qualitative	Exploring Recruiter Expectations and Chatbots' Impact		✖	✖	✖	
[16]	2021	Recruitment chatbots	Quantitative (CFA, correlation, regression)	Analyzing Chatbots in E-Recruitment Communication		✖	✖		✖
[22]	2021	AI in Recruitment	Quantitative (Correlational, Multiple Regression Analysis)	AI-Powered Chatbots' Role in Automating Recruitment		✖	✖		
[13]	2020	Chatbot Architectures	Descriptive/ Conceptual	Chatbot Architectures and Recruitment Applications		✖	✖		
[4]	2019	Conversational Agents	Implementation Study	Transparency Challenges in Chatbot Implementation			✖		
[168]	2019	Chatbots in Recruitment	Proposal/ Conceptual	Chatbots as Screening Tools in Recruitment			✖		

Table 4: Summary of Research Papers on Areas relevant studies focused on Focus areas

Ref.	Year	Field of Study	Type of Study	Contents of the Paper	Focus Areas				
					Traditional/ Manual	Automated Recruitment	Recruitment Chatbots	Human-Centered AI	Ethics of AI
[12]	2019	AI Chatbots in Recruitment	Literature Review (Secondary Sources)	AI Chatbots' Productivity in Attracting Candidates			✖		
Ref 139 cnf	2021	AI and Digital Technologies	Applied	AI Tech's Role in Screening Applicants		✖		✖	
[169]	2019	AI Systems in Recruitment	Experimental (patent paper)	Adaptive AI Recruitment System Proposal		✖			
[170]	2023	AI-Based Recruitment Strategies	Analytical Review	Reviewing Diverse AI-Based Recruitment Strategies		✖		✖	
[171]	2019	Ethics in AI-Based Recruitment	Overview/ Conceptual/ Analytical	Examines AI recruitment ethics, focusing on bias					✖
[172]	2020	AI in HRM	Theoretical	Explores job seekers' acceptance of AI		✖		✖	
[173]	2019	AI in Business Communication	Empirical	Investigates AI's communication enhancement impact					✖
[3]	2020	AI in Recruitment	Conceptual	The Evolution and Imperative of AI-Enabled Recruiting Systems					✖
[103]	2022	Ethics in AI-Based Recruitment	Review	Explores AI for fair, efficient recruiting		✖			✖
[174]	2020	AI in Recruitment	Empirical	Impact of AI on HR recruitment		✖			✖
[175]	2023	Ethics in AI-Based Recruitment	Exploratory	Explores recruiter and job seeker perspectives on AI bias		✖		✖	✖

Table 5: Summary of Research Papers on Areas relevant studies focused on Focus areas

Ref.	Year	Field of Study	Type of Study	Contents of the Paper	Focus Areas				
					Traditional/ Manual	Automated Recruitment	Recruitment Chatbots	Human-Centered AI	Ethics of AI
[176]	2021	AI in HR and Recruitment	Overview	Analyzes AI's HR revolution and automation	✖	✖			
[177]	2022	Ethical Concerns in AI Recruitment	Review Study	Delves into AI recruitment ethics and gender biases					✖
[177]	2020	Ethical and Legal Implications	Review Study	Highlights the need for AI recruitment regulation					✖
[178]	2023	Discrimination in AI Recruitment	Survey Study	Examines AI's discrimination risks in hiring					✖
[179]	2022	AI Ethics in Recruitment	Review Study	Discusses AI's ethical challenges in recruitment		✖			✖
[180]	2022	Regulations in AI Recruitment	Review Study	Advocates for AI recruitment regulations		✖			✖
[181]	2021	Cognitive Biases in AI Recruitment	Conceptual	Explores cognitive biases in AI recruitment		✖			✖
[10]	2023	Recruitment Chatbot	Elicitation Study	Explores chatbots' acceptance and impact on recruiting			✖	✖	
[47]	2013	HRM	Theoretical	Explores the role of employee composition	✖				
[42]	2005	HRM	Theoretical	Emphasizes candidate-role matching importance	✖				
[182]	2018	HRM	Theoretical	Investigate external recruitment strategies	✖				
[45]	2008	HRM	Theoretical	Analyzes activities in attracting and retaining applicants	✖				✖
[55]	2016	HRM	Theoretical	Examines organizational strategies for applicant engagement	✖				✖
[31]	2019	HRM	Empirical	Studies the linear recruitment decision-making process	✖				✖
[5]	2019	HRM	Empirical	Focuses on multi-stage recruitment decision-making	✖				✖

Table 6: Summary of Research Papers on Areas relevant studies focused on Focus areas

Ref.	Year	Field of Study	Type of Study	Contents of the Paper	Focus Areas				
					Traditional/ Manual	Automated Recruitment	Recruitment Chatbots	Human-Centered AI	Ethics of AI
[183]	2022	HRM	Market Research	Reveals top organizational priorities in recruitment	✖				✖
[184]	2024	E-recruitment recommendation systems	Survey Study	Identifies unique challenges in e-recruitment recommendation systems		✖			
[185]	2024	HCAI, big data analytics In recruitment	Literature and Survey Study	Analyzes transformation of recruitment through AI with a focus on balancing human-AI roles		✖		✖	
[186]	2023	HRM, AI in Recruitment	Empirical	Examines recruiters' perceptions of AI tools and their impact on hiring processes	✖	✖			
[162]	2024	Recruitment Chatbot	Mixed Method Study	Developed HC-TAM to explore how factors influence users' acceptance of chatbots in recruitment		✖		✖	
[170]	2023	HRM, AI in Recruitment	Review Study	Provides a comprehensive analytical review of AI-based recruitment strategy					✖
[14]	2023	AI in Recruitment	Case Study, Experimental	Examines biases in AI-driven recruitment algorithms		✖		✖	✖
[187]	2024	AI in Recruitment	Qualitative Interview Study	Explores experts' perspectives, highlighting the collaborative nature of AI and its potential to augment recruitment tasks		✖		✖	
[188]	2024	Bias in Recruitment	Survey, Empirical Study	Highlights AI's role in reducing bias while emphasizing the indispensable role of human judgment in assessing soft skills and cultural fit		✖		✖	✖
[25]	2024	Recruitment Chatbots	Experimental Study, Survey	Examines the impact of conversational styles and interaction mechanisms on user interactions with RecoBot, a recruitment chatbot			✖	✖	
[189]	2024	AI in Recruitment	Quantitative Study, Experimental	Explores the acceptance of AI-based conversational agents (CAs) in recruitment, focusing on the impact of explainable AI (XAI) on user perceptions		✖			✖

Table 7: Summary of Research Papers on Areas relevant studies focused on Focus areas

Ref.	Year	Field of Study	Type of Study	Contents of the Paper	Focus Areas				
					Traditional/ Manual	Automated Recruitment	Recruitment Chatbots	Human-Centered AI	Ethics of AI
[190]	2024	Ethics in Recruitment Chatbots	Systematic Literature Review	Explores ethical challenges in AI-driven HR chatbots, focusing on fairness, autonomy, and bias				✖	✖
[191]	2024	AI in Recruitment	Quantitative Study	Examines how organizational attractiveness, motivation, and trust influence user engagement in AI-based recruitment		✖			✖
[178]	2023	Recruitment Ethics	Literature Review, Survey	Discusses algorithmic bias in AI recruitment and proposes technical and managerial solutions for reducing bias		✖			✖
[102]	2023	HRM, Talent Acquisition	Qualitative Study	Explores the challenges of digital talent acquisition, focusing on fairness, data privacy, and HR decisions		✖			✖
[192]	2023	Talent Acquisition	Literature Review, Qualitative	Analyzes AI's role in recruitment and provides recommendations for cost, privacy, and bias management		✖			✖
[193]	2024	Recruitment Chatbots	Qualitative Study	Investigates HR professionals' views on chatbots in hiring, focusing on trust and privacy			✖		✖
[194]	2023	Recruitment Chatbots	Literature Review	Reviews chatbot use in HCM, including a cost-benefit matrix and challenges in HR operations			✖		
[195]	2024	Recruitment Chatbots	Review	Discusses how AI chatbots are changing employee engagement in HRM			✖		
[196]	2024	Recruitment Chatbots	Literature Review	Reviews chatbot use in recruitment, focusing on user acceptance, privacy, and data security			✖		✖
[197]	2024	Ethics in AI Recruitment	Literature Review	Discusses biases in AI-driven recruitment and their effect on candidate selection		✖			✖
[198]	2024	AI Recruitment, HR	Mixed Method Research	Explores the role of HR chatbots in onboarding, enhancing efficiency and personalizing support	✖	✖			
[199]	2024	Human-Centered AI in HRM	Review	Explores how HRM balances AI's capabilities with human-centric needs			✖	✖	
[200]	2023	AI in Talent Acquisition	Literature Review	Discusses AI tools in HR, focusing on improving efficiency and reducing costs		✖			

Table 8: Summary of Research Papers on Areas relevant studies focused on Focus areas