Tampere University

SAMI KOIVUNEN

Digitalization of Talent Acquisition

Understanding Human Resource Management Professionals' Experiences and Practices

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ACADEMIC DISSERTATION
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Sami Koivunen, Tampere 7.1.2024

ABSTRACT

Human capital is arguably a key asset for organizations. Successful talent acquisition is critical for both organizational success and individuals' pursuit of meaningful work. Today's ongoing digitalization is transforming the way in which Human Resource Management (HRM) professionals attract, assess, and select talent for organizations. Digital tools such as applicant tracking systems (ATSs), sourcing tools, chatbots, and interviewing tools enhance professionals' reach, consistency, and cost-efficiency. However, research has raised concerns, among other things, related to digital ethics, user experience, and reluctance to use advanced digital tools. It has been argued that advanced digital tools have not yet delivered on their promised benefits to organizations.

This thesis investigates the digitalization of talent acquisition by exploring HRM professionals' experiences, work practices, and related processes. While success in talent acquisition increasingly depends on professionals' interactions with digital tools, prior research is scarce. Digital tools also evolve constantly, creating a need to explore current experiences and practices.

The thesis comprises four original publications: three empirical interview studies, and a secondary analysis of their data. The research employs the constructivist-oriented grounded theory method to analyze 47 interviews with mostly recruiters and HR managers. The thesis contributes socio-technical insights into professionals' experiences, practices, and processes to the fields of Human-Computer Interaction (HCI) and Computer-Supported Cooperative Work (CSCW).

Key contributions include descriptions of professionals' experienced challenges, emerging work practices, and early experiences with a new digital tool. In addition, the research identifies opportunities and threats related to the introduction and design of digital tools. The publications provide design considerations to address professionals' decision-making challenges, and to support practices related to assembling innovation teams and utilizing recruitment chatbots. They also identify potential pitfalls and tensions, including counterproductive user interfaces, and requesting detailed data versus respecting privacy. Critically, solutionism tends to drive the market but can backfire for organizations as they may not receive what they need or have to restructure practices. This underscores the importance of

understanding the sociotechnical and processual consequences in addition to issues related to individual tasks or digital tools.

TIIVISTELMÄ

Inhimillinen pääoma on kiistatta keskeinen voimavara organisaatioille. Toimiva rekrytointi on kriittistä sekä organisaatioille että yksilöiden pyrkimyksille tehdä merkityksellistä työtä. Digitalisaatio tuo muutosta siihen, kuinka henkilöstöhallinnon ammattilaiset houkuttelevat, arvioivat ja valitsevat rekrytoitavia. Digitaalisten työkalujen, kuten rekrytointijärjestelmien, työnhakusivustojen, suorahaku- ja haastattelutyökalujen, käyttäminen lisää ammattilaisten mahdollisuuksia saavuttaa hakijoita, johdonmukaisuutta ja kustannustehokkuutta. Tutkimus on kuitenkin nostanut esiin huolia liittyen digietiikkaan, käyttäjäkokemukseen ja kehittyneiden työkalujen käytön vastustukseen. On väitetty, että kehittyneet työkalut eivät ole vielä lunastaneet odotuksia.

Tämä väitöskirja käsittelee rekrytoinnin digitalisoitumista tutkimalla ammattilaisten kokemuksia, käytäntöjä ja prosesseja. Vaikka rekrytoinnissa onnistuminen riippuu enenevästi ammattilaisten vuorovaikutuksesta digityökalujen kanssa, aiempi tutkimus on vähäistä. Digityökalut myös kehittyvät, minkä takia kokemuksia ja käytäntöjä on tärkeää tutkia jatkuvasti.

Väitöskirja koostuu kolmesta empiirisestä haastattelututkimuksesta sekä haastatteluaineiston uudelleenanalysoinnista, joista syntyi yhteensä neljä julkaisua. Tutkimus käyttää konstruktiivista Grounded Theory -menetelmää analysoimaan 47 haastattelua pääasiassa rekrytoijien ja esihenkilöiden kanssa. Tutkimus tuottaa tietoa sosioteknisistä kokemuksista, käytännöistä ja prosesseista ihmisen ja teknologian vuorovaikutuksen sekä tietokoneavusteisen yhteisöllisen työn tieteenaloille.

Tutkimuksen avainlöydöksiin lukeutuu kuvailu ammattilaisten koetuista haasteista, uusista työkäytännöistä ja varhaisista kokemuksista rekrytointichatboteista. Tutkimus tunnistaa myös sekä mahdollisuuksia että uhkia liittyen työkalujen käyttöönottoon ja suunnitteluun. Tutkimusjulkaisut tarjoavat suunnittelumahdollisuuksia vastaamaan ammattilaisten päätöksentekohaasteisiin ja tukemaan käytäntöjä liittyen innovaatiotiimien muodostukseen ja rekrytointichatbottien käyttöön. Ne tunnistavat myös mahdollisia sudenkuoppia ja jännitteitä, kuten kielteisesti vaikuttavat käyttöliittymät sekä yksityiskohtaisten tietojen kerääminen yksityisyyden kunnioituksen sijaan. Kriittisesti tarkasteltuna solutionismilla on tapana ajaa kehitystä ja aiheuttaa organisaatioille haasteita, kun

työkalut eivät vastaa tarpeisiin tai työkäytäntöjä täytyy muuttaa. Onkin tärkeää ymmärtää sosioteknisiä ja prosessivaikutuksia yksittäisten työtehtävien ja digityökalujen lisäksi.

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ABBREVIATIONS

HCI	Human-Computer Interaction
CSCW	Computer-Supported Cooperative Work
HRM	Human Resource Management
E-recruitment	Electronic recruitment
AI	Artificial Intelligence
ML	Machine Learning
LLM	Large Language Model
UX	User Experience
ATS	Applicant Tracking System
HCM	Human Capital Management
DEI	Diversity, Equity, and Inclusion
RQ	Research Question

ORIGINAL PUBLICATIONS

Publication I	**Sami Koivunen**, Thomas Olsson, Ekaterina Olshannikova, and Aki Lindberg. (2019). Understanding Decision-Making in Recruitment: Opportunities and Challenges for Information Technology. *Proceedings of the ACM on Human-Computer Interaction*, 3(GROUP), 22.
Publication II	**Sami Koivunen**, Ekaterina Olshannikova, and Thomas Olsson. (2021). Understanding Matchmakers' Experiences, Principles and Practices of Assembling Innovation Teams. *Computer Supported Cooperative Work (CSCW)*, 30, 589-616.
Publication III	**Sami Koivunen**, Saara Ala-Luopa, Thomas Olsson, and Arja Haapakorpi. (2022). The March of Chatbots into Recruitment: Recruiters' Experiences, Expectations, and Design Opportunities. *Computer Supported Cooperative Work (CSCW)*, 31, 487-516.
Publication IV	**Sami Koivunen**, Otto Sahlgren, Saara Ala-Luopa, and Thomas Olsson. (2023). Pitfalls and Tensions in Digitalizing Talent Acquisition: An Analysis of HRM Professionals' Considerations Related to Digital Ethics. *Interacting with Computers*, 35(3), 435-451.

The authors' contributions to the articles are as follows.

Publication I. The authors planned and designed the interview study collaboratively. Koivunen, Lindberg and Olsson were collaboratively responsible for conducting the interviews and analyzing the data. Koivunen, Olshannikova and Olsson produced the publication. Koivunen was the principal author and was in charge of producing the publication.

Publication II. The authors planned and designed the interview study collaboratively. Koivunen conducted the interviews, and the data was analyzed together with Olshannikova and Olsson. The authors collaboratively produced the publication. Koivunen was the principal author and was in charge of producing the publication.

Publication III. The authors planned and designed the interview study collaboratively. Ala-Luopa and Koivunen collaboratively conducted the interviews and analyzed the data together with Olsson. Koivunen was the principal author and was in charge of producing the publication.

Publication IV. Koivunen, Sahlgren and Olsson planned and designed the secondary analysis. Koivunen conducted the secondary analysis with the help of Olsson, and they produced the publication together with Sahlgren and Ala-Luopa. Koivunen was the principal author and was in charge of producing the publication.

1 INTRODUCTION

This chapter presents the background and motivation of the research, key terminology, the research questions (RQs) and associated knowledge gaps, and the research approach and process.

1.1 Background and Motivation

Human capital is a fundamental asset for organizations, impacting productivity, long-term economic competitiveness, as well as employee wellbeing (Breaugh, 2013; Schneider, 1987; Weller et al., 2019). Nevertheless, effectively finding and selecting the best workers and assembling teams has proven challenging for organizations (Mathieu et al., 2017; Ployhart et al., 2017; Salas et al., 2017). In fact, it seems that talent acquisition processes often lack planning, structure, and strategic approaches (Ployhart et al., 2018). Moreover, the historical discrimination in talent acquisition necessitates maintaining equitable practices that treat all applicants fairly, both morally and legally (Lippens et al., 2023; Quillian & Midtbøen, 2021).

Organizations are increasingly adopting advanced digital tools that can allegedly enhance talent acquisition activities, including talent location, attraction, and assessment (Albert, 2019; Fuller et al., 2021; Koivunen et al., 2019). These tools seem to prioritize improving quality-of-hire, time-to-hire, and talent pipeline growth (Jobvite, 2021). Research highlights practical benefits such as improved reach to candidates, reduced administrative burden, cost-efficiency, indirect employer branding, and overcoming social and technological pressures (Holm, 2014; Koivunen et al., 2022; Nguyen & Park, 2022). Moreover, job seekers now expect the early stages of talent acquisition to take place online (Holm, 2014), and work life trends are shaping both practices and tools (see Section 2.1). For example, organizations are increasingly emphasizing diversity, equity, and inclusion (DEI) through marketing and digital channels, as well as enhancing candidate experience efforts.

However, recent CSCW and HRM research has criticized digital tools and their development. For example, vendors seem to use deceptive claims when promising solutions to purported talent acquisition problems (Roemmich et al., 2023). Some tools may emphasize criteria unrelated to the actual work (Fuller et al., 2021; Tippins et al., 2021), and their validity has not always been on par with traditional methods (Chamorro-Premuzic et al., 2016). From HCI viewpoint, issues related to the user experience (UX), usability, misuse, or reluctance to use digital tools may also undermine their potential benefits (see Section 2.5). In general, it has been argued that advanced digital tools have not yet delivered on their promised benefits to organizations (Cappelli, 2019a, 2019b).

This thesis explores the digitalization of talent acquisition as a crucial function aiming to find the right person for the right job at the right time (Cappelli & Keller, 2014; Ployhart et al., 2018). The focus is on relatively structured processes that attract job applications from the external labor market rather than slotting available work force into open positions with no deliberate process (Keller, 2018). The focus is further defined in Section 1.2.1.

This thesis primarily represents the research traditions of HCI and CSCW. They consider most technical applications to be socially embedded. Thus, this research draws from sociotechnical traditions that seek to understand users' actions in order to create tools that fit with users and their context (Abdelnour-Nocera & Clemmensen, 2019). Due to the need for understanding how professionals experience digitalization in real-world, this research is qualitative and descriptive. The emphasis is to understand sociotechnical factors that ought to be considered in digitalization of talent acquisition. Consequently, this research addresses relatively typical HCI research problems where there is a lack of "understanding about some phenomenon in human use of computing" (Oulasvirta & Hornbæk, 2016).

This thesis comprises four publications that examine the digitalization of talent acquisition from the perspective of HRM professionals. The first publication (P1) focuses on experienced challenges in the recruitment process, while P2 focuses on the experiences and practices in assembling innovation teams. P3 then explores early experiences with recruitment chatbots, and P4 identifies tensions and pitfalls in the process. While P1–P3 specifically focus on recruitment or team assembly, P4 clarifies how the thesis's overarching focus is on talent acquisition (see Section 1.2.1). The decision-making processes and practical work tasks were reasonably similar across the studies, in large part due to the overall emphasis on deliberate and structured processes.

This research contributes empirical understanding and insights into the experiences, practices, and processes, which are practically relevant when designing or utilizing digital tools in talent acquisition. By aligning with HCI and CSCW interests, the research effectively focused on understanding the sociotechnical aspects of talent acquisition while integrating knowledge from diverse disciplines. The research followed a constructivist-oriented grounded theory, which facilitated an exploratory approach that resonates with HCI and CSCW interests, driving the construction of novel and practical contributions.

Improving organizations' talent acquisition practices may have benefits at multiple levels: individuals, employers, the economy, and society (Kremer et al., 2021). For individuals, work plays a crucial role in building personal and social identity, earning a livelihood, enhancing well-being, and fostering a sense of self-worth. As digital tools increasingly influence future career prospects and livelihoods, talent acquisition has been acknowledged as a high-risk decision-making area under the European Union's regulation (AI Act). For society, work fosters cohesion, safety, social and economic development, and influences the allocation of welfare benefits and efforts to address social inequalities.

However, if the employee-organization match does not work out, replacing the employee can cost thousands or even hundreds of thousands of dollars, and may also have indirect costs related to company culture (Tarki et al., 2022). Furthermore, ineffective teams can have a range of negative consequences, including conflicts, faultlines, delays, extra costs, lack of innovation, poor performance, and reputational harm (Gómez-Zará et al., 2020).

1.2 Key Terminology

The following subsections will further introduce the context by defining the key terminology related to talent acquisition and digitalization.

Notably, research on the digitalization of talent acquisition is increasingly emerging, and multiple research communities such as HCI, HRM, HR, and personnel psychology have studied the topic. A substantial portion of the related research cited in this thesis comes from HRM, especially its subfields such as E-HRM, e-recruitment, and e-selection.

1.2.1 Talent Acquisition

This thesis focuses on talent acquisition in organizations as a deliberate and relatively structured market-based process that invites a broad pool of interested *candidates* to apply and considers them *applicants* upon application. Talent acquisition is described as a critical first step of effective talent management, which more broadly covers the entire employee "lifecycle", including learning, development, and performance management (Breaugh, 2021). Successful talent acquisition processes can result in hiring a full-time employee, a freelancer, or a temporary project team member. The scope includes sourcing (or "headhunting") practices, in which promising talent is identified and invited to participate in the process without a direct job offer.

Historically, recruitment and selection have been intertwined but distinct concepts. For example, in a seminal work, Barber (1998) defined recruitment as "aimed at attracting individuals to an organization", and selection as "aimed at identifying the most qualified from among those individuals". However, since the 2010s (Sparrow, 2021), it appears that the term "talent acquisition", which includes both recruitment and selection, is becoming an increasingly preferred term in both the literature and organizations (Breaugh, 2021). This thesis adopts a processual view in which both "attracting individuals" and "identifying the most qualified" are included as part of the stages of the process, with P4 introducing the term "talent acquisition". As the terms "talent acquisition" and "talent management" are relatively new, their definitions are still evolving. For example, talent management can be defined "from a variety of perspectives depending on the context, unit of analysis, and level of analysis" (Tarique, 2021).

Sections 4-4.2 define the stages, related tasks, and potential digital tools in the talent acquisition process. Previous process conceptualizations and findings from the publications highlight that while conceptualizations imply a sequential temporal process, digitalization has made processes more flexible, allowing applicants to be at different stages simultaneously (See Sections 4-4.2). In addition, digital tools often aim for consistency and reuse relevant information beyond a single hiring assignment. For example, they can be "on-tap" (e.g., company websites, or LinkedIn), or connected to other organizational systems (e.g., application tracking systems, ATSs).

Notably, this research excludes other ways of hiring, such as internal recruitment, indeliberate hiring practices, and hiring based on professional relationships: e.g., hiring directly from competitors, early career affiliations, or clients/suppliers of the organization (Kehoe et al., 2022). In 2017, a national survey conducted by Sitra found that the most common paths to employment in Finland are applying for an open position (27 percent), being approached by an employer (25 percent), approaching an employer directly (24 percent), and moving internally within an organization (18 percent) (Sitra, 2017). This suggests that although structured processes are prevalent, also unstructured and ad hoc approaches are popular. In addition, practices that occur after selecting the most suitable talent, such as onboarding and retaining talent, are beyond the scope of this thesis.

While the term "talent" is sometimes considered to refer to only high-potential workers (Lumme-Tuomala, 2019), this work adopted an inclusive "everybody is talent" approach, which regards all individuals as talent (Breaugh, 2021; Wiblen, 2019). Due to the potential ambiguity of the term, researchers have been urged to clarify their interpretation (McDonnell et al., 2023). The term "alternatives" was used in P1 when defining the stages of the recruitment process, but "talent" became the used term in the introductory part in order to harmonize and clarify the terminology. Furthermore, whereas the interviewees represented a variety of job roles, the primary target group in all publications remained HRM professionals.

1.2.2 Digitalization

Digitalization refers to the transitions whereby human lives, organizational processes, cultural infrastructures etc. are restructured by IT infrastructures, and digital tools, including artificial intelligence (AI) tools (Brennen & Kreiss, 2016). The term emphasizes the transition from manual practices to incorporating digital products within the process, signifying the integration of digital technology into the sociotechnical context. As Wiblen and Marler (2021) observe, the terminology related to the use of information technology in the HRM context has evolved since the 1990s, keeping pace with emerging technological innovations. Terms such as "human capital technology" and "electronic human resource management (e-HRM)" have been used. Wiblen and Marler (2021) propose that the term "digitalised talent management" complements the growing e-HRM literature. Similarly, this thesis focuses on the digitalization of talent acquisition.

Strohmeier (2020) provides conceptual clarification of the use of the term "digitalization" in the HRM context. The digitalization process typically begins with the adoption of digital tools to enhance operational efficiency, aiming to increase speed, reduce costs, and improve the quality of operations. As an organization progresses on its digitalization journey, the focus shifts towards aligning digital tools to support the execution or formulation of strategic goals. Importantly, digitalization is not a one-time event; it is an ongoing process that involves the continuous adoption, use, and evolution of digital tools, along with their accompanying sociotechnical changes.

Notably, there are various kinds of relevant digital tools, including software (e.g., ATSs), web sites (e.g., job boards, LinkedIn), as well as technologies and features that the tools use (e.g., augmented writing and job advertising optimization). For example, Section 4.4 explores large language models (LLMs) as a specific emerging technology.

1.3 Research Questions and Research Gaps

Overall, this thesis aims to understand HRM professionals' experiences of digitalization in talent acquisition, their practices, and the emerging opportunities and challenges. The following presents the two research questions and a summary of the associated research gaps. The summary of background literature in 2.6 also highlights research gaps.

RQ1: How do HRM professionals experience and practice talent acquisition with digital tools?

Digital tools have been argued to have radical impact on talent acquisition, influencing existing practices, as well as introducing new practices and challenges (Allal-Chérif et al., 2021; Holm, 2012). As the success of talent acquisition increasingly depends on professionals' interactions with digital tools, it is noteworthy that the research on how HRM professionals experience and adapt to digitalization is scarce (R. Johnson et al., 2017). Consequently, various disciplines call for understanding professionals' experiences and practices considering the influence of both digital tools and intuition (see Section 2.2 and summary in Section 2.6).

In contrast to studying HRM professionals' perspectives, prior research has studied job seekers' perspectives (Highhouse, 2008; McCarthy et al., 2017). Notably, Dillahunt and colleagues have explored opportunities for technology to support marginalized groups in job seeking in HCI and CSCW (Dillahunt, 2014; Dillahunt et al., 2016, 2018; Dillahunt & Hsiao, 2020; Dillahunt & Lu, 2019; Lu & Dillahunt, 2021; Ogbonnaya-Ogburu et al., 2019; Wheeler & Dillahunt, 2018). Furthermore, prior research tends to focus on the *expectations* rather than the *experiences* of new digital tools. For example, a substantial body of quantitative research has studied job seekers' expectations related to AI tools (see Section 2.5). While this thesis explores professionals' future expectations of the capabilities of digital tools (P1 and P3), the emphasis is on understanding their experiences and work practices (P1–P3).

Moreover, P2 addresses the gap in research on how professionals assemble innovation teams from external talent using digital tools. Existing research on teams has mainly studied team effectiveness *after* the teams have been assembled (Gómez-Zará et al., 2020). Furthermore, while HCI and CSCW research have studied specific team assembly tools (Gómez-Zará et al., 2020; Harris et al., 2019), they have not explored professionals' practices, such as their tactical approaches to composing teams. Also, research on practices related to assembling teams from external talent is generally limited (Munyon et al., 2011).

Finally, P3 is one of the first qualitative studies to explore user experiences of recruitment bots from the perspective of HRM professionals. Chatbots are popular, but the related user needs and motivations are often poorly understood. HCI scholars have called for more context-specific research on chatbots' purposefulness (Brandtzaeg & Følstad, 2018; Følstad & Brandtzaeg, 2017).

RQ2: What opportunities and threats does the digitalization of talent acquisition entail?

Digital tools are constantly evolving (Chapman & Gödöllei, 2017). Therefore, it is crucial that researchers continue to study processes, opportunities and threats related to digitalization, particularly focusing on critical areas such as digital ethics (Raghavan et al., 2020; Sánchez-Monedero et al., 2020).

Previous research on how talent acquisition processes are organized is relatively limited (see Sections 4-4.2). P1, P4, and Section 2.4 elaborate the process by detailing the stages, tasks and opportunities for digital tools. Furthermore, P1–P3 identify opportunities for design based on their context-specific findings.

Digitalizing work involves balancing different goals, values, possibilities, and tools, which creates tensions and pitfalls. While HCI has studied digital ethics, particularly fairness and autonomy (Holstein et al., 2019; Mulligan et al., 2019), the understanding of the considerations emerging in the context of talent acquisition is still in its infancy (Köchling & Wehner, 2020). P4 addresses the gap by identifying tensions and pitfalls related to digitalization, and the related values and value tensions.

Section 4.3 synthesizes the developments and provides practical implications related to introducing and developing digital tools in talent acquisition. Section 4.4 then reflects the key findings about the emerging large language models technology.

1.4 Research Approach and Process

This thesis comprises three interview studies along with a secondary analysis of the data obtained from these interviews. The research is qualitative, empirical and exploratory. The research method is constructivist-oriented grounded theory, utilizing abductive reasoning influenced by pragmatism (Bryant, 2017). However, the research paradigm is firmly aligned with constructivist and interpretative views. The research philosophy and methodology of the thesis is described in further detail in Chapter 3.

The data consists of 47 interviews with 46 professionals. One participant was interviewed twice in separate studies. These individuals represented a variety of job roles, including recruiters, HR managers, CEOs of companies developing the relevant digital tools, recruitment consultants, and facilitators of innovation teams. All the participants had a strong professional track record in either conducting talent acquisition activities or developing digital tools for talent acquisition. P4 contains a table that presents all the participants with a short description of each one's work role.

Figure 1 presents the research process. Each publication builds upon knowledge from previous publications. P1 served as a general introduction, providing an overview of the application area and familiarizing the authors with the topic. Subsequently, P2 focused on team assembly activity, which includes specific team composition considerations. In P3, the research centered on studying the experiences of professionals of an emerging technology. After the three interview studies, the authors realized that the interview data had unused potential in terms of describing the pitfalls and tensions related to digitalization and digital ethics. Therefore, a secondary analysis was conducted to explore the topic in more depth. To ensure methodological rigor, several steps were taken. These steps included utilizing uncoded, clean transcripts from the parent studies (P1–P3) and applying a novel analytic framework in which the transcripts were purposefully read from a new perspective.

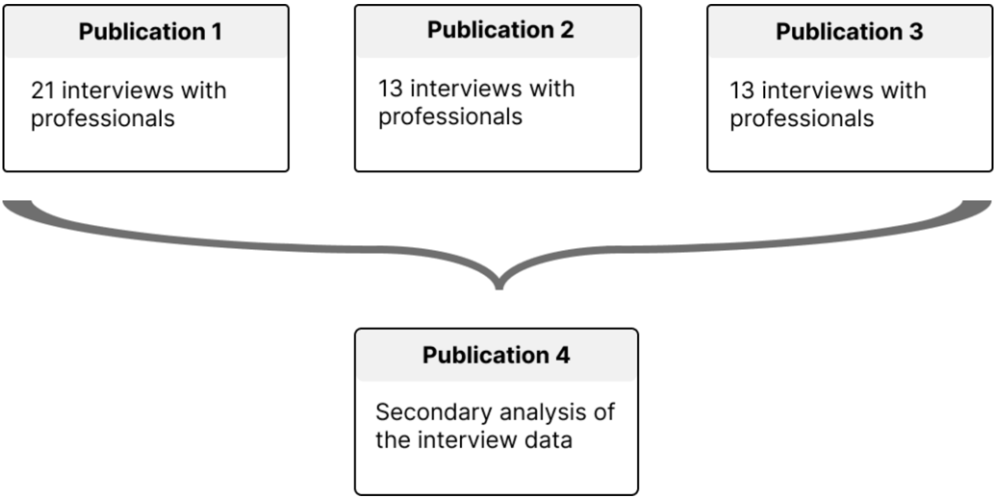

Figure 1. Publications and the analyzed data.

The publications that followed P1 enriched the knowledge base by focusing on specific contexts, digital tools, or factors. As the research process unfolded and the application area became more familiar, interest in exploring aspects that had not been thoroughly studied in the earlier publications grew. This natural development of the research process enabled the identification of potential avenues for new research.

2 DIGITALIZATION OF TALENT ACQUISITION

Chapter 2 provides the theoretical and conceptual background and defines the practical context of the research. The brief summaries below indicate roughly the relevance of the background in each subsection concerning RQ1 (professionals' experiences and practices), RQ2 (opportunities and threats of digitalization in talent acquisition), or both:

- Section 2.1 introduces work life trends that are shaping talent acquisition practices and priorities, thereby motivating digitalization efforts. The trends necessitate studying emerging challenges and identifying arising tensions.
- Section 2.2 presents the variation of practices and the role of human judgment, particularly pertinent to RQ1.
- Section 2.3 offers a historical review of digitalization in talent acquisition, thus giving background for the context of the thesis, and particularly for addressing RQ2.
- Section 2.4 continues with a detailed overview of digital tools that can be used to support talent acquisition, providing further understanding of digital tools in this context related to RQ2.
- Section 2.5 outlines the critique towards the use of digital tools presented in recent literature across disciplines, being relevant background for both RQs.
- Section 2.6 summarizes the previous sections, raising topics from literature that are particularly relevant for this research.

2.1 Work Life Trends Shaping Talent Acquisition Processes

This section introduces four significant work life trends, including a relatively recent phenomenon known as the Great Reshuffle, as well as enduring challenges like the war for talent. These trends substantially influence the processes, priorities, and practices within talent acquisition. For example, organizations may strategically focus on improving DEI or the candidate experience. Concurrently, vendors are innovating and introducing digital tools to address these evolving trends.

First, **amidst a persistent worker shortage and dynamic macro conditions, organizations face intense competition for talent**. For example, economic uncertainties, rising inflation, the Covid-19 outbreak, and geopolitical conflicts have recently contributed to a volatile labor market (Martínez-Matute & Urtasun, 2022). At the same time, a lack of available skills is hampering investment projects in Europe (European Investment Bank, 2023). Consequently, organizations are adapting their practices to attract qualified workers, and they are increasingly filling non-entry level job openings externally to bring in new knowledge and foster innovation (Breaugh, 2021; Cappelli & Keller, 2014).

Second, **the Great Reshuffle (or Great Resignation) is driving workers to seek jobs with increased purpose, flexibility, and empathy** (I. Cook, 2021). Research by the Pew Research Center revealed common reasons for quitting, including low pay, limited advancement opportunities, and feelings of disrespect at work (Parker & Horowitz, 2022). Approximately one out of five workers in the United States plans on looking for a new job within six months, but only one-third of them believe it will be easy (Parker & Horowitz, 2022). Many individuals are quitting to prioritize family care and personal well-being (De Smet et al., 2022). In a study by MIT Sloan, toxic work cultures were found to be by far the strongest predictor of turnover, and the Great Reshuffle is affecting both blue and white collar workers equally (Sull et al., 2022). Over time, employee tenure has declined, leading to reduced employment stability in both private and public sectors (Hollister, 2011). This increased workforce mobility necessitates organizations to frequently turn to the external labor market to find talent (Kehoe et al., 2022).

Survey data by McKinsey show that employees are shifting into different industries (48 percent of job leavers) and embrace nontraditional work arrangements, such as temporary, gig, or part-time roles, or start their own businesses (De Smet et al., 2022). Alternative work arrangements (also nonstandard, contingent, temporary or externalized arrangements) drive most of the job growth in the labor market (Boudreau et al., 2015; Spreitzer et al., 2017). Freelancers, who are typically self-employed and hired for specific tasks, are a growing portion of the workforce (Watson et al., 2021; Wilkins et al., 2022). Freelancer growth is driven by technology advancements (e.g., mobile applications) and lifestyle changes (e.g., a preference for flexible work) (De Ruyter & Brown, 2019; Watson et al., 2021). Side hustles, income-generating work alongside full-time jobs, are also gaining popularity (Sessions et al., 2021). In the US, around 40 percent of people have side hustles, especially adults around 30 years of age (Bankrate, 2022). In Finland, 8,1 percent of 16-64 year olds had multiple jobs simultaneously between 2010 and 2016 (Järvensivu & Haapakorpi, 2022).

Third, **job seekers are becoming increasingly aware of their value in the job market, leading them to demand faster processes and information about culture** (Chambers, 2022). Transparency is more important than ever, as applicants expect fair, unbiased assessments and prompt feedback. Google, for instance, optimized its hiring process to include only four rounds of interviews, realizing that additional rounds were not worth the investment and could lead to losing potential individuals (Google, 2017).

Fourth, **organizations are increasingly advocating diversity, equity, and inclusion (DEI) to improve workplace conditions**. For example, balanced gender diversity has been linked to improved economic performance (Ferrary & Déo, 2022). However, a SHRM study found that 63 percent of US employers spend "little to no" resources on DEI (SHRM, 2022), and tech layoffs have hit one of the least diverse industries hard, for example (Gonzales, 2022). Many HRM professionals saw job applicants reject offers for lack of diversity (Jobvite, 2021), linking this to the trend of job seekers' increased awareness and willingness to change jobs. Vendors may also claim to promote DEI. For example, talent marketplaces (see Section 2.4.2) are believed to foster DEI by providing visible and defined project opportunities (Deloitte, 2021)

2.2 Complexity of Talent Acquisition

This section explores the complexity of talent acquisition, examining its diverse forms and interdisciplinary approaches taken by researchers. The aim is to underscore the importance of studying this topic and provide background information to enhance understanding of the context. The presented related work selectively focuses gaining insights into the complexities of the context, typical decision-making structures, and the perceptions related to interactions with digital tools (or, "algorithms").

In terms of motivating organizations to seek the most suitable talents and effective team compositions, Aguinis and colleagues introduced the concept of "star performers", who have a disproportionate impact on an organization's overall success (Aguinis & Bradley, 2015; Bradley & Aguinis, 2022; O'Boyle & Aguinis, 2012). Their research highlights the crucial differences between the best and second-best candidates. Additionally, team composition significantly influences innovation processes, with different competences being required at various steps of innovation (Fonseca et al., 2019).

Talent acquisition **is characterized by uncertainty, and the related practices vary and change over time** (Brändle et al., 2022). It also has different meanings for organizations and people (Ployhart et al., 2018), and these practices are shaped by both national and organizational culture. Various organizational constraints come into play, such as policy issues (e.g., salary issues preventing hiring), internal challenges (e.g., inadequately trained practitioners or unclear requirements from managers), market conditions (e.g., scarcity of talent or unrealistic expectations), resource and technological limitations (e.g., difficulties accessing or acquiring tools for candidate outreach), and financial constraints (e.g., lack of capital for investing in technology). Furthermore, the restructured practices resulting from digitalization must adhere with professional, ethical and legal standards (Tippins et al., 2021). Moreover, **digitalization is an ongoing process, making it a historically moving target**. Consequently, research tends to lag behind practice, unable to keep up with the developments in the field (Chapman & Gödöllei, 2017).

Brändle et al. (2022) conducted a study to examine changes in hiring behavior and policies within German private sector organizations with at least 50 employees from 2012 to 2018. The research focused on talent acquisition practices and strategies. They observed an increase in the use of social networks like LinkedIn and Xing to find workers (from 27 percent in 2012 to 54 percent in 2018), while the utilization of personality and cognitive ability tests declined. The study also revealed a strong association between an organization's size and the adoption of formalized talent acquisition practices. However, while the characteristics of an organization "are correlated with different facets of hiring behavior", there is no homogenous pattern and "substantial amount of variation in recruitment practices remains unexplained".

While this thesis focuses on the organization's perspective, it is important to acknowledge that the hiring process is influenced by noise stemming from the applicant side, such as individual differences contributing to test success that may not necessarily correlate with job success (Highhouse & Brooks, 2023). This noise can arise from factors like the applicant's financial situation, chance, test-taking skills, ability to comprehend instructions quickly, and level of fatigue. Individuals are inherently complex, capable of unpredictable behavior, and their performance may vary based on the context. Consequently, making decisions about applicants is a challenging task.

Neumann et al., (2023) noted that decision-making in talent acquisition is typically a team effort. The process involves various stakeholders, including executives, consultants, managers, and future team members. The level of structuredness in the practices appears to be associated with the size of the company, with larger organizations dedicating more time to assessing applicants (Brändle et al., 2022). For instance, Rivera (2012a) identified a deliberate separation between recruitment activities and hiring decisions in elite law firms, investment banks, and management consulting companies. In these cases, "revenue-generating professionals", such as bankers and lawyers, took charge of assessing applicants during interviews and making selection decisions, while HR staff managed the process and handled administrative aspects.

Behavioral decision research has offered insight into numerous systematic limits in rationality and provided understanding of the cognitive processes relevant in talent acquisition (Kahneman, 2011). This literature reveals that much of decision-making relies on fast, intuitive reactions (Kahneman, 2011). In addition, several factors such as attractiveness, race, sex, and dress style have been identified as influencing factors in the interpersonal process (H. Wang et al., 2022). While providing a comprehensive review of judgment biases (systematic judgment deviations from a standard) in talent acquisition is impractical, a few practical examples can help illustrate the context.

Especially interviews have garnered significant scholarly attention as one of the most used assessment methods. Some relevant judgment biases include seeking confirmatory information over disconfirming information (i.e., confirmation bias) (Dougherty et al., 1994) and sensitivity to irrelevant information (Highhouse, 1996). For example, Lepistö and Ihantola (2018) found that recruiters in management accounting look for applicants who appear sociable and credible, emphasizing overall personality and appearance in the process. They note that while it is crucial that the overall background and "profile" are suitable for the job, employers increasingly rely on their feelings and impressions from interviews to make decisions. A recent meta-review shows that while structured interviews are the strongest predictor of job performance, the overall selection predictor–criterion relationships are considerably lower than previously believed (Sackett et al., 2021). Recent research is particularly critical regarding "cultural fit", "curiosity", "creativity", or "community involvement", considering them as constructs that likely stem from personal beliefs, experiences, and professional literature rather than empirical evidence associated with good job performance (Neumann et al., 2021).

To make job performance predictions and selection decisions, HRM professionals need to combine information from simulations, assessments, and interviews. This data can be combined either holistically (e.g., utilizing human judgment), or mechanically (e.g., using algorithms). Earlier surveys and scarce qualitative research suggest that decisions in this area are typically made using holistic methods (Miles & Sadler-Smith, 2014; Ryan & Sackett, 1987). While the research remains scarce, a recent study by Neumann et al. (2023) suggest that selection decisions are still mostly made holistically, with algorithms mainly used for attracting, identifying and comparing applicants rather than making selection decisions. Notably, algorithmic decision-making has received substantial research interest in other contexts, especially in terms of fairness (e.g., (Lepri et al., 2018; Veale et al., 2018)), accountability (e.g., (Cobbe et al., 2021)), and perceptions (e.g., (R. Wang et al., 2020)).

Meta-analysis by Kuncel et al., (2013) shows that personnel selection literature consistently shows improved job performance prediction by over 50 percent when data is combined mechanistically rather than holistically. In other words, research consistently demonstrates that decision accuracy is better with mechanical methods. Currently, mechanical methods are already utilized when algorithms provide scores based on performance in gamified assessments or asynchronous interviews, or when offering hiring recommendations (Landers & Sanchez, 2022).

Neumann et al., (2023) identified various reasons for the reluctance to use algorithms, including stakeholders' resistance, fear of negative evaluations, reluctance to quantify information, unavailability of algorithms, and concerns about reduced status or autonomy when using algorithms. They highlighted a science-practice gap, as professionals often lack awareness of evidence-based decision-making practices, including the benefits of structured and mechanical approaches. Professionals primarily seek information from other HRM professionals and consult sources such as blogs, videos, websites, and magazines (e.g., Harvard Business Review), rather than academic literature. There was a positive correlation between the use of algorithms and professionals who read academic literature and possess an assessment license. Surprisingly, despite this correlation, these professionals also preferred holistic prediction.

The complexity of algorithms can vary from relatively simple rules that are based on practitioners' knowledge to complex machine learning (ML) approaches. Neumann et al., (2023) found that professionals were more inclined to use simple algorithms, valuing their transparency and potential for higher fairness perceptions. In focus group discussions, professionals considered that many decisions were too complex for algorithms, but if used, variables should be well-measured and evidence-based (Neumann et al., 2023). The authors speculated that the fact that many participants thought algorithms are unavailable might be due to the assumption that algorithms must be complicated.

It should be noted that while research on algorithmic decision-making is emerging sociological research on employer decision-making, for example, tends to focus on outcomes rather than the actual processes and experiences when evaluating and assessing applicants (Rivera, 2020).

Practitioners are likely to utilize heuristics in uncertain decision-making environments: "rules of thumb that economize on information gathering and processing" (Lejarraga & Pindard-Lejarraga, 2020). Research on ecological rationality (decisions are ecologically rational when they are adapted to the decision maker's environment) aims to determine when certain heuristics are effective and, consequently, when they should be employed (Gigerenzer et al., 2022). Many organizations employ a multi-hurdle approach where applicants are screened out in each stage corresponding with "fast-and-frugal trees" heuristics (Gigerenzer et al., 2022). Another example is "one-clever-cue", which involves selecting an applicant based on a single key factor, such as general mental ability, performance in structured interviews, or work samples (Gigerenzer et al., 2022). "Delta inference" is another heuristic that involves comparing two applicants by prioritizing cues based on their validity (Luan et al., 2019)).

Despite their widespread practical use, heuristics are sometimes presented as a source of bias and are not always acknowledged in decision-making processes. Researchers recognize the need to understand heuristics and decision-making approaches used by practitioners to design effective decision aids (e.g., digital tools) (Lejarraga & Pindard-Lejarraga, 2020; Luan et al., 2019). Decision aids that align with natural tendencies and task environments have been successfully developed in other disciplines, such as medicine (Luan et al., 2019).

While evidence supports mechanical (algorithmic) methods in data combination, it seems that practitioners may be underutilizing algorithms, demonstrating a preference for human forecasters instead. In other words, practitioners are "algorithm averse". In a prominent study, Dietvorst et al., (2015) conducted experiments that demonstrated that people tend to prefer human judgment even after witnessing that algorithms outperform humans. To overcome algorithmic aversion, practitioners might be more willing to use algorithms if they have some control over the mechanical combination, either by designing the algorithm based on their personal beliefs (Nolan & Highhouse, 2014), or by giving even a small degree of control in adjusting the algorithm's forecasts (Dietvorst et al., 2018). Interestingly, Neumann et al., (2023) highlight that the existing literature has extensively discussed "algorithm aversion", while "algorithm appreciation" has received much less attention.

In an economics research study, Hoffman et al., (2018) highlighted the potential impact of new technologies on managerial mistakes or biases in hiring. They found that managers who made exceptions to algorithmic recommendations in hiring workers in the service sector were more likely to hire workers who left their jobs quickly. This suggests that managers may wrongly believe that they can create valid exceptions to a mechanical approach, exhibiting bias or misjudgment.

Furthermore, Kahneman (2021) emphasizes the importance of a structured (or mechanical) approach to mitigate the severely underestimated role of noise in hiring judgements. Initial impressions from resumes and tests can significantly influence interviews and lead to imaginary patterns from meaningless answers. To reduce noise, Kahneman (2021) suggested adding structure to the process, decomposing decisions into components, collecting information independently for each assessment, and delaying holistic judgment in noisy unstructured interviews.

Feldkamp et al., (2023) conducted a scenario where participants imagined being hiring managers and receiving decision-support from either human colleagues or algorithms. The study revealed that although algorithms were perceived as less biased, they were trusted less compared to humans. While algorithms were perceived as more consistent, their suggestions were more frequently rejected than those from humans, suggesting underlying moral judgments. The study illustrates that although algorithms offer consistency and are perceived to be less biased, there are recognized issues related to trust and fairness.

Recently, scholars have presented different views on whether adding stakeholders (i.e., aggregation) is the correct direction for interview assessments, considering that organizations may conduct multiple interview rounds with various stakeholders (Kahneman et al., 2021). Gigerenzer et al., (2022) proposed that aggregating judgments is counterproductive since adding a second interviewer, after the best interviewer has already gone first, never increases accuracy. However, Highhouse and Brooks (2023) argued that the assumption of individual differences in interview accuracy, on which the counterproductive argument is based, lacks empirical evidence and "seems highly unlikely given research in other domains". This underlines the uncertainty around best practices, especially concerning (human) judgments.

2.3 The Brief History of Digitalization in Talent Acquisition

While today most job seekers expect that the attraction of talent takes place online (Holm, 2014), it was not until mid-1990s when web-based application channels became popular among candidates (I. Lee, 2007). The advent of the Internet in the early 1990s made applying to jobs more accessible for many. The first online job boards–websites employers use to advertise their jobs–appeared in the mid- and late-90s, notably including Monster.com, Elance (now Upwork) and Netstart (now CareerBuilder). The first ATSs began in the late 90s, for example, Taleo Recruiter WebTop. The 2000s then saw the launch of several prominent job boards, social media websites (e.g., LinkedIn), job ad aggregators (e.g., Indeed), freelance marketplaces (e.g., Fiverr). LinkedIn was launched in 2003[1], Indeed in 2004[2], Glassdoor in 2007[3], Fiverr in 2010[4], and ZipRecruiter in 2010[5].

During the 1990s and early 2000s, organizations began adopting internal e-recruitment systems, employing two primary approaches. Some implemented separate systems solely dedicated to recruitment, while others integrated HR functions into organization-wide Enterprise Resource Planning (ERP) suites (R. D. Johnson et al., 2016).

In research, Lee (2007) classified "e-recruiting sources" such as general-purpose job boards like Monster.com, niche job boards catering to highly specialized job markets, hybrid recruiting service providers serving both recruiters and job seekers through traditional media, and corporate career websites. Later, Lee (2011) defined the process involving digital tools as "a hiring process that utilizes a variety of electronic means and technologies with the primary purpose of identifying, attracting, and selecting potential employees". They provided practical and still relevant examples of digital tools that "help recruiters and job applicants to complete their tasks more efficiently and effectively by automating recruiting processes and providing the information necessary for making appropriate decisions". These include career web sites, ATSs, prescreening/self-assessment tools, talent management system, candidate relationship management systems, and social media.

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[1] https://about.linkedin.com/

[2] https://www.indeed.com/about/our-company

[3] https://www.glassdoor.com/about-us/glassdoorcom-launches-public-beta-opening-doors-employee-salaries-bonuses-reviews-ratings-company-free/

[4] https://www.fiverr.com/news/fiverrs-founders-are-creating-an-online-marketplace

[5] https://www.ziprecruiter.co.uk/about

Lang et al., (2011) conducted a literature review that identified 23 publications from 1990-2010 exploring the drivers, consequences and challenges related to the implementation of e-recruiting systems at organizations. Despite the expansion of literature since then, the identified themes have remained reasonably relevant. The drivers included:

- Cost savings
- Time savings
- Increased number of applicants
- Independence of space and time (e.g., finding job advertisements and applying)
- Easier identification of qualified staff
- Improved employer image
- Enhancement of efficiency and effectiveness (to manage a high number of applications)
- Provision of additional organizational information
- Usability and user-friendly application process

Similarly, **potential challenges** associated with e-recruitment encompassed the following:

- Excluding potential applicants due to factors like the digital divide
- Ensuring the security of applicant's data
- Faking in assessments
- Coping with increased effort and costs
- Managing applications with low qualifications
- Selecting the appropriate application channels

Later, Chapman and Gödöllei (2017) identified **potential benefits** of e-recruitment, including:

- Efficiently managing the increased volume of applicants
- Enhancing the quality of applicants
- Reaching passive candidates who may not actively seek job opportunities
- Signaling that the organization is media savvy or trendy

- Providing positive first impressions, for example, through aesthetically pleasing, up-to-date, and easy-to-navigate career pages
- Applicants potentially responding positively to novel tools

Kuncel (2017) further emphasized that an effective e-recruitment tool has the potential to attract candidates who might otherwise be considered out of the organization's league.

As the 2010s progressed, the number of vendors increased dramatically (Cappelli, 2019b). The prevailing work life and technology trends have enticed investors to invest more in HR technology, leading to an increase in venture capital investments each year[6]. Vendors increasingly created tools for more specific tasks, including optimizing job descriptions, programmatic job advertising for targeted online advertisements of open positions, conducting video interviews, using gamified assessments, scraping social media profiles, conducting background checks, scheduling interviews, and employing chatbots (Albert, 2019; Koivunen et al., 2022; Nguyen & Park, 2022; Raghavan et al., 2020). Practically, these tools are becoming ever more efficient in analyzing data from sources like video interviews, supporting the generation and modification of targeted text for candidates, analyzing performance in assessments, sending messages about open positions to a large population simultaneously, and providing customer service for frequently asked questions.

On a broader scale, the market appears to be consolidating, with larger vendors acquiring smaller ones, particularly since the 2010s (e.g., Recruit acquiring Indeed and Glassdoor, Microsoft acquiring LinkedIn, SAP acquiring SuccessFactors, and Workday acquiring Peakon and Adaptive Insights).

New tools are visioned to foster and nurture the relationship between employers and talent (Allal-Chérif et al., 2021; Nguyen & Park, 2022), encouraging employers to strengthen their digital presence to increase their attractiveness. As a result, new tasks have emerged for professionals, often requiring digital skills such as designing webpages, sending newsletters, maintaining social media, writing blog posts, and participating in professional communities (Allal-Chérif et al., 2021). The management of social networks and talent communities serves various purposes, including reaching passive candidates, gaining valuable insights into candidates' qualities (e.g., soft skills) and the job market, promoting the organization's values and culture to attract higher-quality applicants, and establishing a direct and friendly

[6] https://www.bcg.com/publications/2022/billion-dollar-opportunity-in-hr-technology

channel for communication with potential future employees (Allal-Chérif et al., 2021).

The use of digital tools has become widespread, with major employers integrating new tools alongside traditional processes (Rieke et al., 2021). Job boards, ATSs and social media continue to serve as the primary tools for reaching and managing talent. Nearly all employers are using ATS, for example, to conduct increasingly complex background checks, resume screening, applicant ranking tasks, and assessment tests (Upturn, 2021). Social media usage is estimated to range from 40 to 80 percent among HRM professionals (Hartwell et al., 2022; Hartwell & Campion, 2020). In terms of candidates, commercial survey data from the U.S. shows a rising trend in the usage of job boards, company career pages, and social media in 2021 compared to 2017 (Jobvite, 2021).

While digital tools have gradually become more complex and sophisticated, they are primarily used to support decision-making rather than fully automatize it. Holm (2012) found no evidence that sophisticated tools could feasibly pre-screen applicants, and Sánchez-Monedero et al., (2020) noted that very few decisions are taken without human intervention. Specific limitations of advanced AI solutions in HRM include small data size, a limited number of data points, and a lack of diversity in data (Tambe et al., 2019).

Nevertheless, digital tools are progressively assuming a larger *role* in decision-making, with AI features commonly integrated during organizations' digitalization projects (Brock & von Wangenheim, 2019). The CEO of ZipRecruiter estimated that 75 percent of submitted resumes in the US are read by algorithms in 2022, using the term "robot recruiting" to describe this phenomenon (Schellmann, 2022). Major platforms like LinkedIn, ZipRecruiter, Indeed, CareerBuilder, and Monster prominently claim on their webpages that they utilize AI to support various work tasks. Ore and Sposato (2021) interviewed 10 recruiters and found that perceived opportunities of AI included increased efficiency through automating sourcing and screening tasks, improved data analytics on applicants, and enhancing candidate experience with timely feedback. Laurim et al. (2021) interviewed 15 stakeholders to find practical acceptance criteria for AI in talent acquisition. Their findings included job relevance (e.g., AI can support the creation of a job description if it saves time and works with ATS), sense of control (e.g., AI should provide detailed reasoning, with humans making final decisions) and complexity (recruiters seek for clear and clear results).

As an extreme example of the current pursuits of organizations, media sources have recently reported that Amazon has allegedly been developing technology that "aims to predict which job applicants across certain corporate and warehouse jobs will be successful in a given role and fast-track them to an interview–without a human recruiter's involvement" (Del Rey, 2022). The technology operates by identifying similarities between the resumes of high-performing employees and those of applicants who have applied for similar positions. This new technology allegedly does not show bias against race, or gender, which had been an issue with a previously infamous AI tool that Amazon tested and subsequently discontinued in the mid-2010s. By implementing the new technology, Amazon aims to alleviate a significant task previously performed by HRM professionals–evaluating job applicants and determining who should proceed to the next stage.

2.4 Work Tasks and Overview of Digital Tools in Talent Acquisition Now

This section presents a detailed overview of common digital tools used by HRM professionals, categorizing them into stages based on the tasks they support. The aim is to show how various digital tools can support the professionals' work in the process. This chapter strives to provide clarity and concreteness to support the findings in the publications.

The overview presents examples of established or innovative digital tools and their features. A bottom-up approach is used, studying existing solutions from the perspective of vendors and service providers, and supplementing with relevant literature on related tasks. Sources for the review included academic articles, online articles, and the vendors' homepages. Commercial research was useful in providing directions on what the most prevalent vendors and solutions are. This practical approach was chosen to gain a comprehensive understanding of the market, providing background for the empirical publications.

While other works have covered the process with examples of digital tools (e.g., (Chapman & Gödöllei, 2017; Nguyen & Park, 2022), this overview provides more in-depth insights by describing potential digital tools in each stage of the process, along with the key vendors and features of the most relevant digital tools. Digital tools can usually be categorized by their purpose and features, but it seems that vendors sometimes may avoid using established terminology to emphasize uniqueness in their marketing.,

Under each subsubsection, the text presents typical work tasks and potential digital tools to support them. The text also refers to related literature, if suitable. Key vendors and their tools' key features or latest features are elaborated based on commercial surveys or information from vendors' homepages.

2.4.1 Establishing Requirements

Work analysis, also known as job analysis, is the process of collecting and analyzing information about the tasks, responsibilities, and skills required for a job (Brannick et al., 2012; Breaugh, 2017). It is a classic topic in industrial-organizational psychology (Morgeson et al., 2020), and important for gathering the critical information required for developing a strong talent acquisition process (Breaugh, 2017). Work analysis yields two main outcomes: **a job description**, and a list of **job specifications** (or **job requirements**). The job description outlines work-related activities like typical duties, tasks, and responsibilities of a position. The job specifications encompass worker attributes, detailing knowledge, skills, abilities, and other characteristics (KSAOs) an employee should possess to excel in the job (Breaugh, 2017; Holm & Haahr, 2019).

Digital tools can assist in the work analysis process by facilitating data collection and communication (Brannick et al., 2012; Holm & Haahr, 2019). For example, online databases that provide descriptions and classifications of occupations, such as the US Occupational Information Network (O*NET), can be used as a reference when creating job descriptions. However, these databases should not be the only source of information, as jobs with the same title may differ across organizations (Stone et al., 2013).

The **job opening** should have a clear and descriptive job title, a summary of the job's purpose and major duties, and a list of qualifications and requirements that allow candidates to self-screen (Morgeson et al., 2020). The content and language used in job openings (or job advertisements) that present both job description and job specifications, influence greatly who will apply for the job. However, it has been found that employers "hardly ever evaluate how information in these job ads is perceived by different job seekers" (Koçak et al., 2022). Research has shown that specific wording in job openings can discourage candidates based on age (Koçak et al., 2022), gendered wording can discourage women from applying even if they have the required skills and there is no discriminatory intent (Gaucher et al., 2011; Wille & Derous, 2018), and personality requirements can slightly discourage well-qualified ethnic minorities (Wille & Derous, 2017). Wille and Derous (2018) found that using behavior-like wording instead of qualifications-based wording can attract a more gender-diverse applicant pool.

Job advertisements are an essential, but often overlooked, component that can enhance the employer image and awareness among potential candidates (Petry et al., 2022). Job advertisements may serve as the primary source of information about an employer, especially for those who are not familiar with the organization. Job seekers who are new to the market tend to value information about career advancement opportunities and high salary levels, which can compensate for the lack of familiarity (Petry et al., 2022). Some recent trends in job ad writing include skill-based hiring, which involves removing degree requirements for many middle-skill and some high-skill roles (Fuller et al., 2022), and disclosing salary information more frequently than before[7]. Moreover, in 2023, a new EU legislation requires that job ads and titles must use gender-neutral language[8].

There are tools that can automatically transform text-only job advertisements into "visual candidate experience". For example, Rootly claims to be able to transform "old school, text-only job postings" into interactive ones "with zero extra work for recruiters"[9].

Previous research has highlighted the benefits of communicating **realistic information** about the open position. For example, it can help to reduce the turnover rate of new hires, even if it means fewer applications are received (Baur et al., 2014). Conveying realistic picture is also regarded as an "ethical imperative" for professionals (Buckley et al., 1997).

Tools that use **augmented writing** technology claim to help professionals create job descriptions that are more interesting, engaging, inclusive, and bias-free. For example, Textio is one of the first and most well-known tools for augmented writing. It analyzes the text and compares it with millions of other documents. It suggests alternative ways of writing phrases or words and generates new text "that has worked before in this context" and provides "real-time detection of unconscious social bias in writing, so you can see exactly how your language appeals to different groups"[10].

Augmented writing tools have become more prominent recently, driven by advancements in LLM development. For example, in 2023, LinkedIn started testing

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[7] https://indeed.force.com/employerSupport1/s/article/Indeed-pay-transparency-salary-estimates?language=en_US

[8] https://www.europarl.europa.eu/news/en/press-room/20230327IPR78545/gender-pay-gap-parliament-adopts-new-rules-on-binding-pay-transparency-measures

[9] https://www.ruutly.com/

[10] https://textio.com/products/recruiting

"AI-powered job descriptions" that creates drafts from basic information such as the job title, company name, job type, and location. The user can then review and edit the generated draft[11]. Section 4.4 further details developments and possibilities related to the use of LLMs in the process. Apart from job advert-focused tools, general-purpose writing tools like Grammarly, and Wordtune may also be used to improve the language in job advertisements.

2.4.2 Identifying Talent

The subsequent step after defining the requirements is to proactively identify the sources of talent, or proceed to attract talent (Section 2.4.3). Holm and Haahr (2019) stress the importance of understanding the current state of the labor market, especially the availability of qualified workers. Organizations may have to target passive job seekers or talent from talent marketplaces if there are no suitable talents among active job seekers who are looking for a full-time job.

Talent intelligence tools provide insights into talent in competitors, regions, or the home organization. These tools can conduct searches across large volumes of data and provide insights based on the searches. The results can present trends in the talent market, such as demographics. Organizations can use the information for talent acquisition planning and discovering existing skills. For example, Retrain.ai analyzes job market data against local company data[12]. Moreover, Eightfold AI has "a patented deep learning AI" in their talent intelligence platform that can "rapidly staff the right contingent labor based on skills and availability, with direct sourcing and redeployment capabilities built in" and "automatic recommendations to update job roles based on skills and market trends"[13].

In addition, Boolean searches (using operators like "AND", "OR", "NOT") in LinkedIn and Google (a practice known as Google X-Ray) can be used for talent intelligence. Based on limited evidence from interviews with HR professionals and headhunters, Boolean searches seem to be one of the most popular ways to identify new talent (Li et al., 2021).

Entelo and SeekOut are **sourcing tool vendors** that offer search engines to find talent from various data sources (e.g., LinkedIn). They have many search options to

[11] https://www.linkedin.com/business/talent/blog/talent-acquisition/linkedin-tests-ai-powered-job-descriptions

[12] https://retrain.ai

[13] https://eightfold.ai/learn/talent-intelligence-platform/

find candidate profiles, including Boolean searches. Entelo has a feature called "more likely to move", which uses predictive variables to surface candidates who are open to new opportunities, such as those with a new degree or underpaid[14]. Entelo also has a browser extension for sourcing that enables actions when viewing a candidate's profile or social media[15]. Users can see a summary view of the candidate's skills and career, email them directly, or export their profile to ATS.

Layoff lists and trackers, such as Layoffs.fyi and Layoffs Tracker, have emerged as a way to directly locate employee information. Layoffs.fyi tracks tech startup layoffs and links to publicly posted, crowdsourced Google Sheets with employee names, roles, and contact information[16].

Talent marketplaces (also "freelance marketplaces", "online freelance platforms", "gig economy platforms", or "freelancing platforms") are popular online platforms that facilitate direct, digitally enabled contingent work arrangements (Blaising & Dabbish, 2022). Professionals can use them to find and engage workers for specific work arrangements. They can help meet temporary workload needs, boost productivity, save money, and access hard-to-hire or specialized talent. Unlike "work services platforms" (e.g., Uber and DoorDash), talent marketplaces focus on facilitating labor relationships rather than providing the outcome.

Some of the most popular talent marketplaces are UpWork, Fiverr, and Freelancer (Bersin, 2021). For example, Fiverr claims to be the largest marketplace for digital services. On their website, "sellers" create "gigs" and set a price for "buyers"[17]. Some popular gigs are logo design, WordPress customization, voice over services, and social media management. Fiverr has a matching feature that uses "a smart algorithm" to match sellers with the most relevant offers from buyers. Gigged.AI is another example of a talent marketplace that uses AI to match companies with talent from their talent pool[18]. Furthermore, **internal talent marketplaces** are gaining popularity. A survey by MBO Partners with 504 HR professionals found that 85 percent were aware of internal talent marketplaces, 42 percent were very familiar with them, and 54 percent were using them (MBO Partners, 2022).

Digitally enabled contingent work arrangements have gained research interest in HCI and CSCW communities. Talent marketplaces can support flexible remote

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[14] https://blog.entelo.com/5-signs-a-candidate-is-more-likely-to-move

[15] https://www.entelo.com/products/platform/entelo-chrome-extension

[16] https://layoffs.fyi/

[17] https://www.fiverr.com/support/articles/360010558038-How-Fiverr-works

[18] https://gigged.ai/enterprise/

work, entrepreneurship, control in work-life, career exploration and mobility, and skill development (Alvarez de la Vega et al., 2021; Sannon & Cosley, 2022). However, individuals may face challenges related to platform management, algorithmic control, performance evaluation, unpaid labor, work simplification, and information finding (Alvarez de la Vega et al., 2021; Blaising & Dabbish, 2022; Sannon & Cosley, 2022; Wilkins et al., 2022). Barriers also include power and information asymmetries that relate to platform surveillance, freelancer-client ratio, algorithm function and impact, and community building (Kinder et al., 2019). Blaising and Dabbish (2022) interviewed 27 freelancers using Fiverr and Upwork, finding that they have to overcome self-doubt, learn self-management and build credibility when transitioning from other work. While the research has produced understanding of how freelancers use talent marketplaces and what the barriers are, there seems to be little research on how HRM professionals are utilizing them.

2.4.3 Attracting Talent

Identifying talent and attracting talent are two closely related processes that can be conducted separately or together. If an organization decides to attract applications, some relevant channels include job boards, organization's websites, and LinkedIn.

Job boards connect job seekers and employers (Hennig-Thurau et al., 2004). They can aggregate, analyze, match and support candidates who look for jobs (Bersin, 2021). For employers, job boards can provide a channel to market and promote jobs, as well as to find candidates. The main feature is usually the job search box for job seekers. Notably, the first international workshop on computational jobs marketplace was held in 2022 as a part of ACM international conference on web search and data mining[19].

The first job boards in the 1990s were practically online versions of newspaper job advertisements where employers paid to promote jobs. In the 2000s, niche job boards, geographically focused generalist boards (e.g., Job Market Finland and Seek in Australia), aggregators (e.g., Indeed), and hybrid sites combining job board features with other content (e.g., Oikotie) emerged. Nowadays, the most popular job boards include Glassdoor, Indeed, ZipRecruiter, and Monster.com. LinkedIn started

[19] https://compjobs.github.io/

as an open resume database, but according to Staffing Industry Analysis, had globally the biggest market share in job advertisement business in 2022 based on revenue[20].

Indeed is a job site that aggregates job postings from other websites (e.g., job boards, and organizations' career sites) but also allows job seekers to apply to jobs directly on their website. It is owned by the Japanese company Recruit Holdings, along with Glassdoor. According to Indeed's website, it is the most popular job site in the world with 300 million unique visitors every month[21]. Recently, the website introduced a major change in their pricing model as they are planning to move from a pay-per-click plan to a pay-per-application model[22]. For employers, this means that they only pay when the applicant starts an application, rather than when a candidate has clicked a job advertisement[23]. Glassdoor is a website where employees can review companies anonymously and job seekers search for jobs. It has 67 million visitors per month, and nearly 50 million reviews for over one million companies[24].

US-based ZipRecruiter is an employment marketplace that has a job board and also posts jobs to other job boards. Employers can add screening questions, integrate it with ATSs, and search candidates from their resume database[25].

Targeted job advertising optimization (or automated or programmatic job advertising) is "the use of automated technology for buying, placing and optimizing job advertising" (Nguyen & Park, 2022). Vendors like PandoLogic and Recruitics claim to target the right candidates at the right time and platform. They promote jobs automatically across a large network of job boards and buy and place ads on specific websites. The goal can be to adjust visibility, increase applications, or find a niche job board. PandoLogic claims to use historical data to determine the best job board and duration for each job[26]. It can also reduce visibility for jobs with enough applications and increase it for hard-to-fill jobs. Targeted job advertising optimization can use rule-based buying to stop spending on campaigns that meet the application goal. This may help organizations prioritize and align their spending with their hiring goals.

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20 https://www2.staffingindustry.com/Editorial/Daily-News/Online-job-advertising-market-revenue-rises-16-five-largest-firms-65581

21 https://www.indeed.com/about

22 https://www.shrm.org/resourcesandtools/hr-topics/talent-acquisition/pages/indeed-shifts-pricing-to-pay-per-application.aspx

23 https://indeed.my.site.com/employerSupport1/s/article/What-is-cost-per-application-pricing?language=en_US

24 https://www.glassdoor.com/employers/resources/hr-and-recruiting-stats/

25 https://support.ziprecruiter.com/s/

26 https://pandologic.com/recruiting-with-ai/candidate-targeting/

Organizations use their websites to attract talent. Chapman and Gödöllei (2017) identified four features that affect candidate perceptions: aesthetics, navigability, content and interactivity:

- Aesthetics refer to the design, layout, and graphics of a website. There is no clear guidance on how to make a website pleasing for job seekers.
- Navigability refers to the ease with which job seekers can find the information they need on a website. Early research suggests that job seekers' perceived ease of finding relevant information is an important predictor of their attitude towards a website (Lin, 2010). Chapman and Gödöllei (2017) suggest that organizations ensure that their primary landing pages have a link to their career content.
- Content refers to the messages related to talent acquisition, including job advertisements. Chapman and Gödöllei (2017) summarize that while the quality of the content has been acknowledged to be important, it is not clear how to make the content attractive for candidates.
- Interactivity refers to the ability of job seekers to interact with the website and the organization. Websites are evolving to create new opportunities for two-way interaction between candidates and organizations.

The application process for job seekers typically begins with reading or watching the job ad, followed by providing contact information and answering screening questions (e.g., multiple choice questions about the applicant's interests and qualifications). The screening questions can become more detailed and open-ended as the process progresses. Applicants may also be able to submit video, audio (which could be transcribed in the application), or text responses to explain their motivation. Resource Solutions consultants (2023) reviewed 100 UK companies by applying to one of their jobs. The report found that, on average, completing an application took 4 minutes and 42 seconds, required 40 clicks, required filling out 24 mandatory fields, and 76 percent of companies required creating a user account. The fastest application system took about one minute, while the slowest one took about 5-6 minutes.

Vendors and ATSs provide solutions for creating career sites and application processes. For example, myInterview can track the source where applicants are coming from (i.e., it can measure the engagement of applicants from specific sources, such as a social media channel), and allow applicants to submit their application after each screening question (the applicant can complete the application at their convenience)[27]. Tools may use recruitment marketing metrics to measure success, such as conversion rate (also known as apply rate), which is the ratio of applications to visits on the job opening page.

VR environments (e.g., metaverse) are a new way to host recruitment fairs online (Jones, 2022). For example, PwC's "virtual park" platform enables candidates to create avatars, network with recruiters in one-to-one and small group chats, and learn about PwC's work culture on their career pages[28].

Recruitment chatbots can provide customer service and/or attract applications from passive job seekers. Some examples of recruitment chatbots are Olivia by Paradox[29] and Talkpush[30]. The latter can be integrated into popular messaging applications, such as WhatsApp or Facebook Messenger. These chatbots possess natural language understanding, they can ask pre-screening questions, and collect applicant information. Users can also inquire about the hiring organization and schedule interviews.

While **TikTok** and **Instagram** have gained popularity as channels for attracting applicants (Jobvite, 2021), **LinkedIn** remains a core tool for many organizations. The professional network platform was launched in 2003 and acquired by Microsoft in 2016. In 2022, it had over 875 million members, driven by its mission to "connect the world's professionals to make them more productive and successful"[31]. Unlike other social media sites, LinkedIn is specifically designed for individuals and organizations to facilitate their professional goals.

While often classified as a social networking site, LinkedIn Business provides various products. LinkedIn's "Talent Solutions" includes tools for sourcing, hiring, and managing talent[32]. For example, "LinkedIn Recruiter" is a "tool to source, contact, and hire the right candidates", which represents a solution for organizations to source talent from LinkedIn's large database. "Jobs" is "a platform for companies to post their jobs on LinkedIn". "Talent Insights" is "a platform for smart real-time workforce and hiring decisions".

Recently, LinkedIn has introduced several new features, including (1) recommended matches in Recruiter (automatically recommends up to 25 candidates

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[27] Co-founder Benjy Gillman in a YouTube interview: myInterview Demos Video Interview Software https://www.youtube.com/watch?v=Y_ps82lr4WA

[28] https://www.pwc.co.uk/careers/early-careers/ourevents/virtual-park.html

[29] https://www.paradox.ai/solutions/retail

[30] https://talkpush.com/

[31] https://about.linkedin.com/

[32] https://business.linkedin.com/talent-solutions/product-overview

per day to employers, based on their sourcing activity in the active project); (2) companies can showcase their values on company page; (3) diversity nudges in Recruiter (alerts in real-time if a search yields less than 45 percent of male or female candidates, and recommends locations, skills, or companies that can improve the gender balance); and (4) employers can hide the names and photos of candidates in their search results with the intent of reducing biases. (Hilgers, 2022; LinkedIn, 2022):

Early research has found that LinkedIn profiles can be used to assess candidates' cognitive ability in a quick, practical, and economical way (Roulin & Stronach, 2022). However, assessments have limited validity, and LinkedIn is not optimal for assessing experienced workers' personalities (Roulin & Stronach, 2022).

2.4.4 Tracking Applicants

An Applicant Tracking System (ATS) is a core tool for many organizations that helps them manage the job and applicant information in a common database (Phillips & Gully, 2015). An ATS can be a stand-alone system or a module in a cloud-based suite of HR applications, such as Human Resources Information System (HRIS) or Human Capital Management (HCM) (Holm, 2020). According to a survey by HR.com in 2020, 73 percent of HR professionals use an ATS (HR.com, 2020). Among them, 35 percent use a stand-alone solution and 44 percent use a module that is part of their HCM. Also, in 2019, Jobscan determined that 99 percent of Fortune 500 companies use an ATS (Hu, 2019).

According to Sapient Insights Group's (2021) data from 2177 organizations, the most popular ATSs are Workday (the most popular option by a big margin), SAP SuccessFactors, iCIMS, Oracle Taleo, Cornerstone, and Avature. The report also projected that Greenhouse and iCIMS would increase their market share in the future. Ongig (2020), an HR tech provider, analyzed the ATSs of their 1063 employer clients and reported similar results. Workday, Oracle Taleo, SAP SuccessFactors, iCIMS, and Greenhouse were the most popular systems among their sample.

Many ATSs can integrate add-ons that extend their capabilities beyond tracking applicants. An example of such add-on is Phenom, which can be integrated with Workday or SAP SuccessFactors[33]. Phenom's key features include creating a career site that can dynamically personalize job recommendations for candidates based on their browser history, a recruitment chatbot to "automate sourcing, screening, and

[33] https://www.phenom.com/

scheduling while answering candidate FAQs", video assessments, and a content management system to create career sites. Many ATS vendors and integrations are continually updating their offerings. As a result, the term ATS can refer to a range of solutions with slightly different features (Holm, 2020).

ATSs can typically perform a variety of tasks, including storing job descriptions, generating job requisition analyses, automatically storing all applications and resumes submitted via the internet, scanning resumes, creating applicant profiles, generating automatic responses to applicants, scheduling and tracking interviews and other assessments, producing statistics and cost analyses, generating mail lists and labels, and performing other data processing operations (Phillips & Gully, 2015). However, empirical studies investigating the experiences, efficiency, or effectiveness of these systems are scarce (Eckhardt et al., 2014; Holm, 2020; Laumer et al., 2015).

Candidate relationship management software is typically used to attract, engage, and nurture candidates over time. It can be used to create recruiting campaigns, manage candidate engagement, and track the performance of recruiting efforts. Workday distinguishes between candidate engagement and recruiting by delegating sourcing and engagement activities to candidate relationship management software, and applying and hiring activities to ATS. Workday Candidate Engagement software helps organizations "build quality talent pipelines by connecting and nurturing prospects & candidates"[34]. It can be used to create tailored landing pages, track recruiting campaigns, and build relationships with candidates. As the functionalities overlap with ATS software, candidate relationship management is often integrated with ATS (see the following subsections. For example, similarly to Workday, iCIMS's software includes the ability to create talent pools, use machine learning to match candidates with jobs, and track the performance of recruiting campaigns[35].

Workday, SAP, and Oracle are large companies that provide comprehensive HCM solutions, in which the ATS is just one application in a larger ecosystem of tools for HR processes such as compensation management, performance management, time-tracking, payroll, and learning. The following paragraphs will introduce three prominent ATS vendors and features they have introduced recently, followed by related candidate relationship management solutions.

First, Oracle used to have a popular ATS called Taleo, but the company now encourages shifting to Oracle Recruiting, which is a module in the Oracle Cloud

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[34] https://forms.workday.com/en-gb/webinars/coffee-mornings-with-workday-talent-acquisition-fy23/form.html?step=step1_default

[35] https://marketplace.icims.com/en/apps/254368/icims-crm

HCM[36]. According to marketing materials, Oracle Recruiting offers built-in candidate relationship management tools, ML-based candidate recommendations, self-learning digital assistants for candidates, and time-to-fill predictions[37]. The software seems to have four release updates per year[38]. For example, update 22B (the second update in 2023) added more options for career sites customization, and recruiting campaigns (i.e., email marketing campaigns). Oracle introduced a new tool called "Recruiting Booster" in 2022 to extend the capabilities of Oracle Recruiting[39]. The Recruiting Booster can:

- Create and market hiring events in career sites, with prescreening questionnaires for candidates.
- Communicate with applicants via text and email messages.
- Enhance Oracle Digital Assistant (a chatbot) with new capabilities for candidates, such as signing up for and checking into recruitment events, receiving job recommendations based on preferences and qualifications, answering prescreening questions, scheduling interviews, and conducting candidate surveys.

Second, Workday is a US-based company that currently delivers features through weekly updates and, since 2019, feature releases twice a year called R1 and R2, respectively[40]. Workday does not officially disclose much information about new features or changes, but some consultant firms offer overviews of the changes. For example, Tietoevry has hosted release event webinars where the feature release changes are presented[41]. According to consultant sources, 2022 R1 included[42]:

- Job requisition notes, allowing members of the recruiting process to create comments to the job description within the system.
- Candidate job application, allowing members of the recruiting process to create notes to individual job applications.

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[36] https://www.oracle.com/human-capital-management/taleo/

[37] oracle.com/human-capital-management/recruiting/

[38] www.oracle.com/webfolder/technetwork/tutorials/tutorial/cloud/r13/wn/recruiting/new-recruiting-wn.htm

[39] https://www.oracle.com/be/news/announcement/ocw-recruiting-booster-2022-10-19/

[40] https://blog.workday.com/en-us/2019/workday-changes-product-release-naming-convention-and-schedule.html

[41] https://www.tietoevry.com/en/events/2022/Get-Ready-For-Workday-2022-R2/

[42] https://www.altura.consulting/blog/top-workday-2022-r1-updates#recruiting

Workday uses ML in their integrated "Skills Cloud" feature within Recruiting software[43]. This skills ontology deconstructs and interconnects skill elements, backed by a dataset of "five billion skills". It aims to help organizations understand their skills gaps and needs. Intriguingly, "Workday messaging" provides support for text messages, touted as more efficient for candidate outreach than emails. Text messages can be used to provide status updates, background checking, and reference checking[44][45]. Another example of Workday's own extension to the Recruiting tool is the Candidate Engagement product. With this tool, organizations can build email recruiting campaigns, create landing pages for candidates, and track how the pages perform in terms of candidate engagement[46].

Third, SAP is a German-based software company that acquired SuccessFactors in 2012. SuccessFactors is one of the biggest providers of cloud-based HCM software, with more than 191 million users in early 2023[47]. SuccessFactors Recruiting is a module in their HCM solution that has two key feature releases per year, H1 and H2. SAP's Recruiting module includes sourcing tools for distributing job openings globally, automating job advertising, and creating applicant pools[48]. Like Oracle and Workday, it also has candidate relationship management tools for running email marketing campaigns, creating targeted landing pages for candidates, and progressively profiling candidates to improve conversion rates.

In 2022, SAP SuccessFactors introduced a new module to Recruiting called "dynamic teams". "Dynamic team is a group of people with different skills, strengths and working styles, coming together to get a mission done. Once the work is done, the team disbands". With the new feature, administrators can assemble new teams by sourcing suitable people from the "opportunity marketplace", where employees can opportunistically present their skills, competencies, and capabilities to the organization. Administrators can also set objectives and key results for the teams, and employees can track their progress or apply to teams.

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[43] https://blog.workday.com/en-us/2022/how-workday-delivering-next-generation-skills-technology-scale.html

[44] https://www.workday.com/en-us/products/platform-product-extensions/workday-messaging.html

[45] Workday Messaging: Enabling SMS for Recruiting, https://youtu.be/BvQJOKZhj50

[46] https://forms.workday.com/en-us/other/workday-candidate-engagement/form.html

[47] https://www.sap.com/uk/products/hcm/about-successfactors.html

[48] https://www.sap.com/products/hcm/recruiting-software/features.html

2.4.5 Assessing Talent

Tippins (2015) defined technology-enhanced assessments as "the use of any form of technology in any aspect of testing or assessment". They pointed out the need for research on the factors that affect test performance, such as the environment, the equipment, and the device type. In practice, different technologies and devices can be used to assess applicants, such as games or questions in mobile, desktop, or VR environment (Raghavan et al., 2020).

Job simulation is a test that asks the applicant to perform a typical work task for the job they are applying for. There are different formats of job simulation, such as situational judgment tests, work samples, role-playing, and home assignments.

VR environments have been proposed as a way to conduct job simulations. Kotlyar and Krasman (2022) developed a high-fidelity virtual simulation called Skill Simulator[49], which uses chatbot technology to create realistic team situations. The participants had to interact and collaborate with bots that acted as their team members for 40 minutes, facing increasingly difficult challenges. The system automatically analyzed their natural language responses and generated a report with scores on various teamwork factors, such as conflict management, communication, and collaborative problem solving. The study found that the score was a significant predictor of peer-ratings of teamwork skills, producing promising early evidence of the effectiveness of this assessment method.

Automated personality tests are a recent trend in talent acquisition that use different data sources to measure personality traits. Emerging work has studied the use of such tests in analyzing asynchronous video interviews (Hickman et al., 2019, 2022). In addition, a growing body of literature is studying the use of, and the opportunities of automated personality tests based on social media content (Alexander et al., 2020; Roulin & Stronach, 2022).

Pymetrics is a vendor that provides **gamified behavioral assessments**. The vendor claims to reduce human biases by using cognitive and behavioral data instead of resumes or questionnaires[50]. They have calculated that over one million candidates have "gone through pymetrics". The vendor has 12 core games and four additional games that measure various traits, such as risk tolerance, decision-making, attention, focus, learning, and generosity. The games take 25 to 35 minutes in total. The vendor also has an integrated video platform for candidates and recruiters. Wilson et al., (2021) audited the tool in terms of fairness given the constraints by ethical,

[49] https://skillsimulator.com/

[50] https://www.pymetrics.ai/

regulatory, and client demands. In a newspaper interview, Wilson emphasized that while pymetrics generally passed the audit in terms of "the technology produced unbiased choices", the general validity (i.e., whether the selected applicants would turn out to be good hires) was not tested (Vogel, 2022).

Cyber-vetting is the practice of assessing job candidates based on their social media profiles. Candidates may view this practice as unfair and privacy-invasive (R. Cook et al., 2020). However, recent studies utilizing LinkedIn as a data source have found that candidates perceive cyber-vetting on this platform as fairer and less privacy-invasive (R. Cook et al., 2020). Roulin and Stronach (2022) demonstrated that hiring professionals can reliably assess personality, cognitive ability, and likelihood to engage in organizational citizenship behaviors based on LinkedIn profiles. They also tested a language-based tool called Receptiviti that assessed personality more consistently with professionals' assessments than targets' (i.e., candidates') self-reports. However, they found that these data sources were not valid for personality assessments of experienced workers. professionals favored longer profiles with many connections, listed skills, and a professional picture. Yet, it seemed that these aspects were not valid indicators of the measured qualities.

There have been proposals to structure social media assessments in order to improve their validity, reliability, reactions of users, and legality (Hartwell et al., 2022). One example of a tool that performs social media assessments is VN Secure[51], which claims to use AI to screen public social media accounts for specific activities, such as racial slurs or discriminatory language.

Professionals may utilize tools for **background checking** to streamline the process of validating the information that applicants provide for assessment, such as their resume. Additionally, a background check at the initial stages might discourage the so-called fake applicants from submitting applications[52]. Background checking tools can sometimes be integrated with an ATS. For example, Zinc is a vendor that offers various services related to background checking. Some of the features of Zinc are[53]: (1) criminal record checks that search for criminal records or convictions; (2) ID verify that checks the accuracy and integrity of applicants to prevent fraud or misrepresentation; (3) education check where the staff of Zinc go directly contact the source to confirm details; (4) employment reference checks where either the dates of prior employment periods can be checked or "a professional reference" can be obtained;

[51] https://www.viralnation.com/vn-secure/

[52] https://www.hr-brew.com/stories/2023/03/27/how-isolved-developed-a-way-to-ferret-out-fake-applicants

[53] https://zincwork.com/

(5) adverse media check that searches "for negative or potentially damaging information about a candidate reported in the media"; and (6) adverse financial checks "to gain insight into applicants financial stability and responsibility".

Reference checking tools serve to automate the reference collection process. This encompasses obtaining selected references from applicants and the feedback from referees. Ideally, the tools can save time by reducing the time required (e.g., eliminating the need for scheduling and conducting phone calls), standardize the process by posing the same questions to each referee (rather than using unstructured or semi-structured phone calls), and present results visually using statistics instead of relying on notes based on a phone call. Typically, professionals need to create the questionnaire (either from a template or customized) that are presented to both the applicants and references, and (2) review the results that are usually analyzed by an algorithm and presented using graphs and statistics. For example, Refapp[54] sends the applicants a request to enter the contact details of their references, and then the application automatically sends a competency-based questionnaire via email and/or text message to the referees (or schedules a phone call, if preferred). When all referees have completed the questions, the app generates a report and notifies the professionals. Similar software include SkillSurvey Reference[55], and Xref[56] (claiming to have over 1 million users).

Job interviews are often an essential part of the process. Employers tend to rely on the subjective impressions formed during face-to-face encounters when making hiring decisions (Rivera, 2015). This section focuses on video interviews due to the proliferation of new solutions and research. Telephone interviews were the first to emerge, and more recently, video interviews enabled the use of non-verbal cues. Videoconferencing technology has also been around for a while, but video interviews have become more popular recently, especially due to the COVID-19 pandemic.

Employers can conduct synchronous (live, using the internet connection) or asynchronous (one-way, time-delayed) video interviews. Synchronous video interviews (SVIs) are similar to an in-person interview, whereas in asynchronous video interviews (AVIs) applicants usually record and submit answers to either individual questions or in free form where they can emphasize their strengths (Raghavan et al., 2020). The advantages of AVI are lower traveling costs and scheduling flexibility. However, participants lack cues to regulate their communication and they may underrate their own performance (Castro &

[54] https://www.refapp.com/industries-recruitment

[55] https://www.skillsurvey.com/products/reference-checking-solution

[56] https://www.xref.com/solutions/reference-checking

Gramzow, 2015). While there is a chance to carefully answer specific questions, video interviews may favor an applicant with technical skills related to video presentation. Also, automating interactions with applicants diminish their opportunities to ask counterquestions and clarifications.

Recent research has studied particularly the fairness perceptions related to video interviews. Suen et al., (2019) found that neither asynchronous video interviews (AVI) paired with AI algorithms nor traditional synchronous video interviews (SVI) elicited fairness concerns. Mirowska and Mesnet (2021) interviewed professionals who raised justice issues with video interview tools, whereas Basch and Melchers (2021) found that recruiters tended to view these tools skeptically, and face-to-face settings are perceived to be fairer than conducting technology-mediated interviews (particularly AVI). Koch-Bayram et al., (2023) conducted experiments and concluded that algorithms violated applicants' fairness perceptions and reduced organizational attractiveness when they were used to evaluate digital interviews. They also found that applicants with experience of discrimination viewed algorithm-based decisions more favorably.

Using an Australian-based AVI vendor's archival data set of over 2,5 million responses from 627 999 applicants Dunlop et al., (2022) found that AVIs were used for small applicant pools (10 applicants per AVI), most of the interviews consisted of four to five questions, and the applicants had on average 30 seconds to prepare a response and two minutes to record it. Applicants provided a mean total of 259 seconds of footage and seldom had the opportunity to preview questions or rerecord responses.

Kappen and Naber (2021) experimented with AI in video assessments by training ML on candidates' introspective judgments. With the developed model, they measured the applicants' motivation to work for the mock company that the experiment presented. The study found that the ML model successfully identified the most motivated applicants, while the recruiters made poor judgments about the motivation in terms of correspondence with applicants' introspective suggestions and reliability of nonverbal video-recorded behavior. The study was the first attempt to focus on dynamic facial behavior captured from a video.

Recently, Griswold et al., (2022) conducted a study with an industry partner that provides video interview software. Their data included 644 905 participants (33 552 participants completed SVI and 650 418 completed AVI) from 46 countries, collecting the data from an optional survey after an interview for a real job. They found that applicants perceived AVIs as slightly less effective globally and were slightly less satisfied with them than SVIs, supporting the findings from Suen et al., (2019). They concluded that both AVIs and SVIs were safe choices for recruiters, as applicants generally viewed them positively and the cultural interaction effects were relatively small.

BrightHire is a vendor that provides "interview intelligence" tools, including "AI interview notes"[57]. According to their websites, their tools can automatically create structured interviews, provide live guidance and feedback during the interviews, record and transcribe interviews (allowing key moments to be replayed and shared), and analyze key patterns from the interviews (giving interviewers personalized feedback, such as speaking rate and talk ratio). The tool sends highlights to ATS or inbox after every interview. The AI interview notes tool can integrate with ATS and generate a summary during the interview.

HireVue is a vendor established in 2004 that offers video interview and hiring assessments solutions, claiming to reduce bias and increase diversity and fairness[58]. In 2020, they discontinued a controversial visual analysis feature that assigned traits and qualities based on applicants' facial expressions, raising obvious ethical concerns regarding privacy (and potentially transparency) (P4). Later, HireVue stated that they "will never evaluate a candidate's personal appearance, eye contact, what they are wearing, or the background where they are taking the interview" (Marks, 2022). They also avoid detecting emotions that were previously implemented in a feature "that attempted to measure the perceived tone of someone's voice" (Marks, 2022).

2.5 Criticism Related to the Use of Digital Tools

In addition to various business drivers, it has been argued that well-designed and tested decision automation and other digital tools can outperform even the most experienced humans in decision-making (Kuncel et al., 2013). The literature further highlights the potential of digital tools to improve consistency in the process and assessments, provide timely feedback to applicants, efficiently deliver relevant information (e.g., through career pages), and manage large applicant populations simultaneously (Hunkenschroer & Luetge, 2022). Vendors selling digital tools are also claiming to enhance fairness by mitigating human bias (e.g., in support of organizations' DEI efforts) (Raghavan et al., 2020; Sánchez-Monedero et al., 2020), and accurately identify high-performers (Wilson et al., 2021).

[57] https://brighthire.com/ai-interview-notes/

[58] https://www.hirevue.com/

However, it has been noted that **the claims are typically vague and abstract** (Raghavan et al., 2020; Sánchez-Monedero et al., 2020). As Selbst and Barocas (2018) summarize, these tools can produce results that are "unnerving, unfair, unsafe, unpredictable, and unaccountable"**.** Raghavan et al., (2020) found that vendors are not transparent about their practices due to business reasons. In a seminal study, Wilson et al., (2021) audited pymetrics, a gamified assessment tool, for algorithmic bias and reminded us that we should not assume digital tools are bias-free or neutral. Previous research has also uncovered signs of algorithmic racial and gender biases on job boards and freelance marketplaces (e.g., Indeed, Monster.com, CareerBuilder, TaskRabbit, and Fiverr) (Chen et al., 2018; Hannák et al., 2017). For example, Hannák et al. (2017) showed that in both TaskRabbit and Fiverr, social feedback from customers was biased against workers perceived to be black, and the search algorithms may have incorporated this biased feedback.

Furthermore, Roemmick et al. (2023) recently studied the public-facing websites of hiring services that claim to use AI to generate inferences about applicants' emotions and other affective phenomena. The authors critique that these services' claims "dangerously obscure the potential harms […] and reinforce exclusionary hiring practices despite their concurrent claims of debiasing hiring processes and outcomes". They identified three purported hiring problems that the vendors market their technologies to address: (in)accuracy, (mis)fit, and (in)authenticity. The following paragraphs present these claims and the associated values highlighted by the authors.

The most salient claim was improving *accuracy* in hiring. Vendors argue that their services can correct the subjective and biased features of human decisions, and that this is a moral imperative in the context of data-driven decision making and continuous improvement. This reflects the value of "**techno-omnipresence**" – the idea that these services can and should access places previously inaccessible.

Second, a common claim is that "*fit*" in terms of values, beliefs, character, and culture is an organizational imperative. Vendors promise that they can identify "perfect hiring fits with absolute precision" and automatically exclude misfits. Vendors tend to describe their technology "powerful" (e.g., "AI-powered"), and that they "secure" the best "fit-to" the organization. This reflects the value of "**techno-omnipotence**" – the idea that "technology can and should have the power to determine hiring "fits" and exclude hiring (mis)fits".

Finally, vendors claim that organizations achieve truth in hiring when they are fully and deeply able *to authenticate* an applicant. They promise that organizations can avoid decisions based on untrustworthy or faked information, and that this will allow them to make "truly informed" decisions. This reflects the value of "**techno-omniscience**" – the idea that "technology embodies all-knowing "intelligence", and its supreme ability to completely know who a person truly is, ought to be used to attain authenticity in hiring".

Fairness is a complex and context-dependent concept, encompassing both procedural (equal treatment of applicants, or fairness in the procedures) and distributive (equal impact on groups) aspects (Gilliland, 1993). In Finland, The Non-Discrimination Act[59] provides that all job applicants are treated equally, prohibiting discrimination based on personal characteristics such as age, skin color, origin, belief, or sexual orientation. Requirements related to qualities that are unrelated to job performance are not allowed. In the US, legal challenges to assessments may arise through disparate treatment (intentional discrimination based on protected characteristics) or disparate impact (neutral policies with adverse effects on protected groups). Raghavan et al., (2020) examined vendors' claims and found that vendors who make claims on equality of outcomes (HireVue, pymetrics, and PredictiveHire) aligned themselves with "the fourth-fifths rule", which states that if the selection rate for one protected group is less than 4/5 of that of the group with the highest selection rate, the employer may be at risk. However, this rule alone does not fully capture bias, as it overlooks the comprehensive evaluation of a system (Raghavan et al., 2020).

Already Cappelli (2001) highlighted the risk of **discrimination** when digitalizing talent acquisition. Köchling and Wehner (2020) noted that while there is enthusiasm for using digital tools to improve efficiency and address labor shortages, there is a risk of discrimination and unfairness. They warned that it is concerning when well-known organizations use digital tools without considering the ethical pitfalls. Concerns about discrimination have since intensified with the introduction of ML tools that aim to differentiate between individuals (Barocas & Selbst, 2016). Hangartner et al. (2021) found that the rate of recruiters' contacts for immigrants and minority ethnic groups on the Swiss public employment service's recruitment platform was 4-19 percent lower, along with a gender-based penalty in professions dominated by another gender.

The U.S. Equal Employment Opportunity Commission (EEOC) recently raised concerns about digital tools that may disadvantage applicants with disabilities[60]. Examples include tests requiring specific input devices for applicants with limited

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[59] https://www.finlex.fi/fi/laki/alkup/2014/20141325

[60] https://www.eeoc.gov/laws/guidance/americans-disabilities-act-and-use-software-algorithms-and-artificial-intelligence

manual dexterity, chatbots filtering out applicants with work history gaps due to disabilities, video interview software biased against applicants with speech impediments, and gamified assessments posing challenges for blind applicants. While employers should be able to provide reasonable accommodations (e.g., accept applications from different sources, or provide assessment materials in alternative formats), it seems that they tend not to provide details about assessments or what kind of accommodations will be available (Rieke et al., 2021).

Building on Selbst et al. (2019) work on describing potential "abstraction traps" that arise from "failing to consider how social context is interlaced with technology in different forms", P4 identified and elaborated three particularly relevant traps in the context of talent acquisition:

- The solutionism trap: the best solution to a problem may not involve technology.
- The portability trap: solutions from one social context may mislead, be inaccurate, or cause harm when applied to a different context.
- The ripple effect trap: inserting technology can change behaviors and embedded values of the pre-existing system.

Cappelli (2019b, 2019a) criticizes that despite heavy marketing, advanced digital tools have not yet delivered the promised benefits for organizations. Professionals receive multiple pitches daily from vendors promoting a "fresh approach to hiring" (Cappelli, 2019a). While there is "a desperate need" for new tools to improve existing practices like unstructured interviews, **many new tools lack an understanding of the complexities of talent acquisition processes**, potentially making things worse (Cappelli, 2019b, 2019a). For example, digital tools may analyze applicants' word choice, facial expressions, or social media comments, but the effectiveness of these measures in identifying top-performing employees is uncertain, and ethical concerns arise (Cappelli, 2019b, 2019a). In addition, Chamorro-Premuzic et al., (2016) highlight that new tools have not demonstrated validity comparable to traditional methods, they may ignore decades of research, cost more than traditional methods, and may inadvertently identify candidates' ethnicity and gender through other signals.

Moreover, ML tools have faced criticism for emphasizing criteria that are unrelated to job performance (Kuncel, 2017; Tippins et al., 2021). A survey by Fuller et al., (2021), found that 88 percent of business leaders believe their hiring systems reject qualified candidates who do not perfectly match the job requirements, raising concerns about **filtering out candidates who are not exact matches**. HR.com's

(2020) report also found that less than half of the 285 surveyed professionals rated their ATS good or very good at matching candidates to job postings. Adding more criteria and skill requirements can make algorithms reject qualified candidates for missing unimportant skills. According to Fuller et al., (2021) employers seem to use "proxies" such as university degrees or continuous work history, to infer candidates' qualities. For example, almost half of the ATSs used by US employers automatically would filter out candidates with more than six months of unemployment, disregarding reasons like parental leaves, illnesses, or relocation. They refer to these candidates as hidden talent who could be valuable additions to organizations.

A substantial body of literature has also explored candidates' expectations regarding the use of AI and algorithmic decision-making in talent acquisition (e.g., (Lavanchy et al., 2023; M. K. Lee, 2018; Wesche & Sonderegger, 2021)). Research suggests that applicant reactions tend to be negative in terms of (procedural) fairness, justice, and organizational attractiveness perceptions (Acikgoz et al., 2020; Folger et al., 2022; Gonzalez et al., 2022; Hilliard et al., 2022; Köchling et al., 2022; Langer et al., 2020; Mirowska & Mesnet, 2021; Newman et al., 2020; Wesche & Sonderegger, 2021). Köchling and Wehner (2023) demonstrated that such negative perceptions could be mitigated by presenting applicants with a video explanation of the advantages of AI instead of written information.

A lack of feedback for applicants during the talent acquisition process remains a well-known challenge, even with modern ATSs that encourage providing such feedback (Rieke et al., 2021). A recent Upturn (2021) report found that this is likely due to fears of liability and accountability for judgments, or assumptions made during the application process. As a result, **applicants may not receive feedback** on their performance in assessments, knowledge of which skills to improve before reapplying, or the ability to challenge unfair or inaccurate assessments.

UX and usability issues can undermine the potential benefits of digital tools. For example, poor design, misuse, and reluctance to use tools can lead to issues. Kuncel (2017) provides examples, such as "the Cassandra problem" (a mythological Greek prophetess gifted with perfect prophecy but cursed never to be believed), where professionals may not believe in the tools due to reasons like going against tradition, sapping autonomy, being confusing, or requiring too much work. Another example is "fool's gold and shiny distractions", where new tests may be added for elegant measurement but do not significantly benefit job performance predictions. For example, adding gamified assessments or fancy narrative information can be risky, as practitioners may be overly influenced by them. Moreover, people may have different perceptions of digital tools (R. Wang et al., 2020). For example, some applicants may prefer a playful or simple tool, while others may expect a more professional approach (Allal-Chérif et al., 2021).

2.6 Summary

This section summarizes previous subsections of this chapter. It highlights the importance of studying digitalization in this context, provides information on what the digital tools are, and presents the challenges identified in relation to their use.

Section 2.1 introduced four work life trends that are shaping talent acquisition work and priorities and, simultaneously, the development of digital tools. The trends are the competition for talent amidst a persistent worker shortage, Great Reshuffle driving job seekers to seek roles with increased purpose and flexibility, job seekers demanding faster processes and information about organizational culture, and an increasing advocacy for DEI.

Section 2.2 elaborated on the inherent complexities of talent acquisition, including uncertainty, organizational variety, dynamic changes, judgment biases, and the presence of noise. Individuals are inherently complex, capable of unpredictable behavior, and their performance may vary depending on the contextual factors. Literature from various disciplines emphasizes the advantages of structuring the process and incorporating mechanical (algorithmic) approaches to support consistency and reduce the influence of noise. This has spurred calls for developing digital tools to support the process (e.g., (M. C. Yu & Kuncel, 2020)) even though recent literature has identified various reasons why professionals avoid using algorithms (Neumann et al., 2023). Concurrently, the literature emphasizes the need for research to understand HRM professionals' practices, considering the influence of both digital tools and intuition (Chua & Mazmanian, 2022; Kuncel, 2017; Lejarraga & Pindard-Lejarraga, 2020; Meijer & Niessen, 2022; Rivera, 2020).

Section 2.3 offered a historical review of digitalization in talent acquisition, revealing what are the drivers, challenges and potential benefits. Furthermore, it revealed that tools increasingly support more specific tasks and also new tasks have emerged for professionals. Job boards, ATSs and social media continue to serve as the primary tools, and these tools are supporting decision-making rather than fully automatizing it. However, with the developments, digital tools are progressively assuming a larger role in decision-making.

Section 2.4 continued with an overview of current digital tools in the process, organizing the findings according to the temporal process. The key findings from the overview are presented in Section 4.2.1 and discussed in Section 4.3.

Section 2.5 showed that while digitalization has benefits, such as consistency and efficiency, vendor claims, especially those about mitigating human biases, are often vague and abstract. Roemmick et al. (2023) analyzed that vendor claims can reflect ideas, such as "techno-omnipotence", where technology can and should have the power to select or reject applicants. Furthermore, there is a risk for discrimination and unfairness, and Selbst et al., (2019) explain abstraction traps like solutionism, which can result from not considering social context when introducing new technology. Many new tools lack understanding of the complexities related to the context, professionals are concerned that digital tools may even reject qualified candidates, and UX or usability issues can undermine the potential benefits.

3 RESEARCH PHILOSOPHY AND METHODOLOGY

The research topic is approached qualitatively with the goal of understanding HRM professionals' experiences with the ongoing digitalization in talent acquisition. The thesis includes three interview studies, a secondary analysis, and an overview of common digital tools. In terms of a philosophical paradigm, this research is based on a constructivist view, and a related method, constructivist grounded theory, was employed to conduct the interviews and to analyze the interview data.

While in the beginning existing theories were explored (e.g., the attraction-selection-attrition model in P1), this research was not guided by a specific existing theory. Existing theories did not adequately consider talent acquisition, digitalization, and professionals' viewpoints together. As a result, this research took an **exploratory** approach. To this end, constructivist grounded theory was a particularly suitable method as it is designed to produce novel theory without a strong influence from existing theories.

In the interviews and analysis of the data, this research drew from **socio-technical** traditions. These traditions underline that looking at a system only from a technical design side is insufficient to design systems for the work and workers; instead, both the social and the technical need to be co-designed, mindful of the characteristics of the context. For example, organizational practices and individual preferences shape how talent acquisition is organized (see Section 2.2). The typical goal of socio-technical analysis is to provide knowledge that can be used to create systems that "fit" with users and their context. To achieve this goal, there is a need for critical sociotechnical analysis that acknowledges that the role of the digital tools is situated, interpretatively flexible and socially shaped and shaping (Abdelnour-Nocera & Clemmensen, 2019). Critical insight and interpretation are crucial when utilizing the grounded theory method.

With a focus on HCI and the research topic, it is essential to identify the conceptual forms of interactions of interest. Building on Hornbæk and Oulasvirta (2017), the focus of this thesis can be identified as "**interaction-as-experience**", described as "shaped by the users' expectations, momentary unfolding of experience, and recounting of episodes of interaction". The authors remind that while experiences may be thought "to be an epiphenomenon, a side effect of sorts", they actually shape how we use digital tools. Especially P1 and P2 did not focus on specific tools but rather on the consequences of interaction such as challenges. By focusing on experiences, it is possible to have a time scale that goes beyond interactions that last a few seconds. In fact, talent acquisition processes can take weeks if not months to complete.

RQ1 includes a focus on understanding **work practices**, aligning with CSCW interests (the W in CSCW). This contrasts with research that would address socio-economic interests, organizational settings, or motives of actors (Schmidt, 2011). Specifically, talent acquisition is the investigated coordinative practice that has domain-specific practices, and digital tools. Talent acquisition often has cooperative work arrangements as the processes typically include several stakeholders within the organization, and, of course, there is the interaction between HRM professionals and applicants. This research aims to involve relevant actors having a variety of practices, thus entailing more than an interest in a specific technology.

The conceptual foundations of CSCW include the "sequential approach" where the first step is to study the current practices, and then provide considerations for future designs (Wulf et al., 2011). Broadly speaking, this thesis followed this approach, and the considerations are discussed in the Discussion sections as "roles for systems supporting decision-making" (P1), "considerations for design" (P2), "towards next-generation recruitment bots" (P3), or "reflections" (P4).

Design considerations are aimed to inform future designs in practical and transferable manner (e.g., P3 proposes design improvements for recruitment chatbots). That said, the primary objective of the publications is to provide insight into the phenomena. Focusing solely on design considerations could trivialize the empirical insight (Dourish, 2006; Oulasvirta & Hornbæk, 2016). Design considerations based on interaction-as-experience research typically provide objectives, ideas, and boundaries for designers, rather than recommendations or guidelines for making design decisions. Moreover, while some contributions (e.g., the conceptualization of the temporal process of talent acquisition) are raised as illustrative examples when introducing the works, practical or theoretical contributions are not typically prioritized one over another.

3.1 Exploratory Research with Constructivist Grounded Theory

Among the three primary variants of grounded theory (Glaserian, Straussian, and constructivist), this research employs the constructivist grounded theory -oriented method. Constructivist grounded theory was introduced and articulated by Kathy Charmaz in the 1990s, and together with Antony Bryant, they continued to develop the method in the following decades. Books that have proven to be very useful are "The Handbook of Current Developments in Grounded Theory" (Bryant & Charmaz, 2019), and "Grounded Theory and Grounded Theorizing: Pragmatism in Research Practice" (Bryant, 2017). Especially Bryant's (2017) practical approach in their book has been influential for this work. Consequently, this research is specifically aligned with the constructivist grounded theory approach as detailed by Bryant in their book (Bryant, 2017).

The research paradigm is constructivist, but notably, Bryant's approach acknowledges elements from both interpretivism and pragmatism. In the broader context, all qualitative research is typically considered interpretative as the researcher creates interpretations that are constructed (Denzin & Lincoln, 2017). An important distinction is that Charmaz and Bryant contrast the constructivist approach with Glaserian and Straussian positivist-objectivist positions (Charmaz et al., 2017). A key positioning is that constructivists view that knowledge (or truth) is constructed, whereas positivists and realists view that knowledge is discovered (Berger & Luckmann, 1966; Bryant, 2017). Comparatively the constructivist approach is more interpretive, viewing individuals as active constructors of both the studied phenomenon and the research process (Charmaz et al., 2017). The approach recognizes the influence of historical, situational, and social conditions on actions, with the researcher actively shaping the data and analysis (Charmaz et al., 2017). In practice, constructivist grounded theorists practice reflexivity concerning their constructions and interpretations of the data, acknowledging the presence of multiple positions and standpoints without asserting a single interpretative truth.

Interpretivism and constructivism are closely related approaches with significant shared intellectual heritage. While this research is positioned in the constructivist camp, it is quite challenging to definitively choose between the interpretivist and constructivist epistemological views. This research integrates epistemological aspects from both approaches, drawing on constructivism's acknowledgment of reality as socially constructed and the examination of how individuals' experiences are constructed within a given context. Additionally, it embraces interpretivism's goal of understanding perceptions and lived experiences of reality, placing emphasis on participants' voices and how interpretations influence their understanding of the social world.

One of the benefits of employing grounded theory is that it provides a set of systematic practices to be followed during the data collection and data analysis. The method emphasizes "constant comparison" which means constantly interacting with the data while being continuously involved with the emerging analyses. Data collection and analysis are proceeding simultaneously and can inform each other. The process should progressively and iteratively make the data more focused, and the emerging analysis more theoretical.

The objective is to construct a theory, which can be understood as models, frameworks, conceptualizations, or taxonomies (Bryant, 2017). Theories in this research are substantive rather than overarching formal theories. They can be judged by their usefulness, as in they need to fit, work, have relevance, and be modifiable (Bryant, 2017). The contributions of this work include conceptualizations, frameworks, and taxonomies (see Sections 4-4.2).

Furthermore, the employed form of grounded theory reflects a profound influence of pragmatism, rejecting the pursuit for absolute certainty. Instead, it places emphasis on judging the concepts and theories based on their usefulness. Furthermore, it highlights the crucial role of **abductive reasoning** in fostering innovative and creative research (Bryant, 2017). Notably, for this research, the use of this method was exceptionally fitting, as it not only permits but also encourages an exploratory approach. In essence, this method fosters openness to serendipity and the production of novel and useful findings (Bryant, 2021). While the method appears well-suited for explorative HCI/CSCW research, it does not seem to enjoy widespread popularity within these communities.

3.2 Overview of Data Collection and Analysis

3.2.1 Practical Context of the Research

The topic of each publication was based on an academic research project. The projects were inspired by the research conducted in prior projects, and each project had several strands where individual thesis workers could focus on their own topics while also helping each other.

Initially, the research aimed to explore organizations' experiences with matching people using digital tools. However, during the interviews and analysis for the first project and publication, the focus centered on studying recruitment. This is typical in constructivist grounded theory research, which begins with a starting point and some initial knowledge about possibly relevant literature, but then uses open-ended questions to allow the most fruitful topic to emerge during the process.

As the focus became clearer during and after the first study, the relevant literature turned out to be slightly different than initially thought. Contextually, particularly relevant background literature comes from HRM studies and its subfield E-HRM. In contrast to the Glaserian variant, the constructivist approach encourages reviewing literature in the early stages of the process. In the final stages of the study, the literature is then reviewed with a more specific aim, considering the target outlet (Thornberg & Dunne, 2019).

3.2.2 Interviews and Sampling

Data was collected by conducting in-depth semi-structured expert interviews. Due to the busy schedules of the interviewees, in-depth interviews lasted approximately one hour on average. Interviews were transcribed between the interview sessions.

The interview structures and themes were carefully planned, with the key themes remaining relatively consistent throughout the interviewing period. However, themes were sometimes further clarified during the process, and specific questions yielded fruitful discussions.

In some studies, different interview structures were purposefully employed for different user groups based on their work roles. For example, HR professionals were asked different questions than those involved in the development of relevant digital tools.

The sampling approach was mostly *purposive*, involving the identification and invitation of participants with relevant experience for interviews. Many interviewees represented knowledge industry organizations, though not exclusively. Additionally, *theoretical sampling* was employed in certain studies, where potential participants were identified after conducting initial data analysis. *Snowball sampling* also proved to be useful, specifically in P3. All these sampling methods are common in grounded theory.

The sampling approach prioritized gaining in-depth insights into experiences and practices over population representativeness. This meant that 13-21 interviews were conducted per interview study, which allowed for in-depth exploration of the topic. Participants were typically identified through online searches and contacted via email addresses obtained from their personal websites or organizations' websites.

3.2.3 Data Analysis

The data analysis employed a bottom-up process, involving the creation of codes, categories, and concepts (Bryant, 2017). An important aspect related to grounded theory method is that the codes were derived from the data itself rather than being predetermined before data collection. Initially, the data was thoroughly read, and abductive reasoning was used to generate initial codes (open codes). To facilitate the coding process, Atlas.ti proved to be a useful software. Once the initial codes were ready, they were compared, and eventually categorized after careful examination.

Memoing is a vital component of grounded theory. Researchers extensively commented and reflected on the codes and groups by utilizing Atlas.ti's commenting feature to label them with the date and the creator of each comment. This textual memoing was crucial for identifying the insight and quotes for the publications. Although the exact structure of the categorization process varied across publications, certain sets of codes and categories eventually emerged, forming the basis for articulating the concepts in an article. The structure further evolved during the process of writing the Results section of the publications.

The analysis process was a collaborative effort in most studies with the first author orchestrating the process and being responsible for the open coding (McDonald et al., 2019). It is worth mentioning that grounded theory, in general, does not require inter-rater reliability, and this has been discussed in the context of CSCW and HCI research (McDonald et al., 2019). In P1, three authors actively participated in coding, while in P2, a senior researcher periodically checked and commented on the codes. P3 involved two authors actively coding, with a senior researcher periodically providing feedback on the codes. In P4 another author was actively involved particularly after the open coding.

It should be noted that coding is just one stage in qualitative analysis (O'Connor & Joffe, 2020). The coding stage was usually followed by a series of iterative discussions with team members where the most representative and interesting findings were selected and organized. These discussions also involved other authors providing commentary on the codes in Atlas.ti. The purpose of the communication through discussions and commentary was not solely to reach agreement but to synthesize and generate concepts or theory. The senior researcher, an author in all publications, actively participated and agreed on selected findings during the analysis process.

3.3 Research Ethics and Data Management

The three interview studies were conducted as part of an academic research project adhering to the guidelines set by the Finnish research ethics authority TENK[61] (Finnish National Board on Research Integrity). In terms of data protection, personal identifiable information or data about sensitive topics were not collected. Interview topics and research questions focused on typical work practices and experiences, such as describing the decision-making processes, how digital tools are used, and what the typical challenges in talent acquisition are. The questions are reported in detail in the publications. As per university guidance at the time, the studies were not submitted to an institutional review board due to the absence of sensitive data. However, all research conducted within the Finnish university context must comply with the university's research requirements, which include preparing the study, obtaining informed consent, and ensuring secure data management.

A protocol was established for each interview study prior to conducting the interviews. This protocol outlined the interview structure, questions, and standardized how interviewers informed the interviewees about the research and data management procedures. Before recording, the interviewers briefly explained the goals of the study, interview structure, how data will be collected, and how the interview data will be stored after the interview. Typically, one or two interviewers conducted the interviews, and in one instance, there were three interviewers. All participants gave their informed consent before the start of the interview. They either signed a consent form or provided verbal consent on record for the further use of the interview data. The consent form clarified that interview data would be deleted after transcription and that participants' names or employers would not be disclosed in the publications. In essence, the participants' identities were anonymized in the publications.

The audio data was usually collected using a recorder device, and later transferred to the university servers for storage. Following this, the interview data underwent transcription and analysis using Atlas.ti software, with the Atlas.ti data also stored on the university servers. Since the projects have concluded, and publications have been published, all interview audio files have been deleted.

[61] https://tenk.fi/en/advice-and-materials

4 CONTRIBUTIONS AND DISCUSSION

This chapter summarizes the novel contributions of the thesis and discusses their relevance, validity, and implications. Sections 4.1-4.2 revisit the research questions by summarizing key findings from the publications. Furthermore, the chapter discusses the developments and implications for practitioners (4.3), reflects on learnings with emerging LLMs (4.4), provides directions for future research (4.5), and discusses the limitations of this research (4.6).

Table 1 presents how publications address the RQs. The interview studies (P1–P3) generally explore both professionals' experiences and practices (RQ1), and opportunities for digital tools (RQ2). P4 then generally focuses on threats related to digitalization (RQ2).

Table 1. The link between research questions and publications.

	RQ1: How do HRM professionals experience and practice talent acquisition with digital tools?	**RQ2:** What opportunities and threats does the digitalization of talent acquisition entail?
P1	Experienced decision-making challenges in recruitment (e.g., balancing between diversity and similarity)	Appropriate roles for digital tools (e.g., facilitating transparent and democratic decisions)
P2	Experienced decision-making challenges in team assembly (e.g., taking risks to reach an unreachable optimum) and practices (e.g., tactical approaches in team assembly)	Considerations for design (e.g., interactive views to support team assembly)
P3	Early experiences (e.g., initial suitability of attraction bots) and practices (e.g., new tasks) related to the use of recruitment chatbots	Recruitment chatbot taxonomy and considerations for design (e.g., support for chatbot script planning)
P4	-	Tensions and pitfalls in the process (e.g., requesting detailed data vs. respecting privacy), with related public values (e.g., autonomy and privacy) and value tensions

Table 2 presents theoretical contributions, and the kind of considerations publications have for practitioners (e.g., for designers, developers, or decision-makers at organizations). Following the sequential approach (see Chapter 3), the considerations for design aim to inform future designs in a practical manner. Additionally, Figure 5 in Section 4.2.1 presents a temporal framework with stages, work tasks, and digital tools. Section 4.3 then discusses thesis-level practical implications.

Table 2. Key theoretical contributions and considerations for practice.

	Theoretical contribution	**Considerations for practice**
P1	Conceptualization of a four-stage recruitment process, with a description of key practices and challenges related to each stage	Six potential roles for digital tools to support decision-making in recruitment
P2	Conceptualization of five tactical approaches to assembling innovation teams	Design considerations for new digital tools that support innovation in team assembly with different tactical approaches
P3	Recruitment chatbot taxonomy	Design considerations for next-generation recruitment chatbots
P4	Description of 14 tensions and pitfalls related to the ongoing digitalization of talent acquisition, with related public values and value tensions	Considerations for designing and developing digital tools to support ethically-aware talent acquisition

Figure 2 depicts the four-stage decision-making process that is introduced in P1. This processual conceptualization was necessary to frame the findings, allowing for a focus on details of the process. The conceptualization was further utilized and elaborated in P4. As noted by Holm (2012), the process is less sequential than traditional recruitment, as digital tools facilitate conducting tasks concurrently and different applicants can progress through the process at varying paces. Nonetheless, a temporal model remains useful and illustrative, as each stage has distinct tasks and tools for professionals.

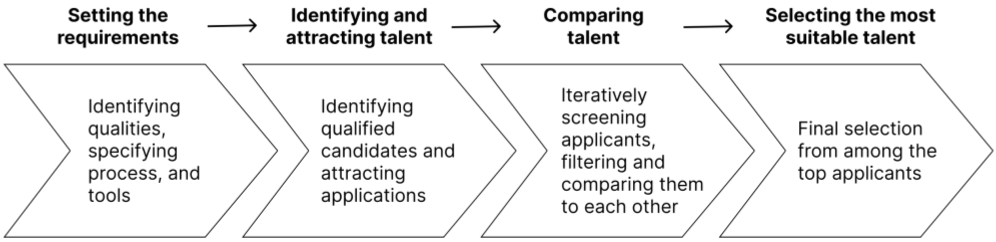

Figure 2. Conceptualization of the talent acquisition process, as defined in P1 and P4.

Foundational work that conceptualizes the process includes contributions from Cappelli (2001), Lee (2011), Holm (2012), Chapman and Gödöllei (2017), and Holm and Haahr (2019). For example, Holm's (2012) findings supported Cappelli's (2001) identification of three key steps in e-recruitment: attracting, sorting, and contacting candidates. Additionally, Cappelli (2001) recognized a step for "closing the deal", though it was considered less significant since it does not involve digital tools.

Holm and Haahr (2019) further detailed the temporal process, including the tasks and subtasks within the stages. The stages of the process included (1) setting hiring objectives, (2) identifying required applicants, (3) attracting applicants, (4) pre-selecting candidates, (5) conducting candidate assessments, and (6) ultimately making candidate selections (note: the terms "applicant" and "candidate" are used oppositely compared to this thesis). This process is largely similar to the latest conceptualization of this thesis, as outlined in Section 4.2.1 in Figure 5. However, Figure 5 further clarifies the tasks, and outlines the associated digital tools.

The next two sections revisit the research questions and summarize the key findings from the publications. These summaries are intentionally brief as the publications themselves provide rich qualitative descriptions. If suitable, they also refer to recent related empirical research that is not covered in the publications. Notably, it appears that related research tends to focus on exploring professionals' expectations and early experiences with emerging AI tools.

4.1 How do HRM Professionals Experience and Practice Talent Acquisition with Digital Tools?

The interview studies **P1–P3** explore HRM professionals' experiences and practices related to the use of digital tools. The following subsections are categorized according to the related key areas from publications' findings: decision-making challenges, work practices, and early experiences with new digital tools.

4.1.1 Decision-Making Challenges

Talent acquisition involves a series of decisions, such as determining the content of the job description, selecting application channels, and choosing among applicants. Human judgment is crucial (see background in Section 2.2), but many decisions are supported by digital tools. **P1** and **P2** identify several decision-making challenges faced by professionals in recruitment and team assembly for innovation.

Figure 3 from **P1** illustrates the key decision-making challenges at each recruitment stage. P1 highlights epistemic asymmetry–where neither professionals nor job seekers know the other's needs or are not even aware of the existence of the other side– as a key challenge that affects decisions across all four stages. Notably, the trend related to the need of conducting faster processes (see Section 2.1), aligns with challenges related to forcing quick, intuitive decisions and having narrow perspectives.

Stages and definitions	Examples of the decision-making challenges from matchmaking point of view
Establishing requirements: Identifying what would make a good match in the given situation and what kind of qualities are sought for.	Lack of clarity in the goals might lead to very opportunistic decisions and hence suboptimal matches. Identifying what complementary viewpoints or competences an organization might benefit from.
Identifying alternatives: Identifying and attracting individuals who would meet the requirements.	Selecting and finding the information about candidates that is the most relevant yet practically available. The spectrum of alternative matching strategies and different individuals' needs are easily forgotten.
Comparing alternatives: Assessing the alternatives in relation to the requirements and each other.	Evaluating the candidates and their qualities from too narrow perspectives and based on self-reported description. Comparing two individuals who fulfill the minimum requirements but have very different strengths.
Selecting the most suitable match: Making a deliberate and as well-informed decision as possible, considering the goals and available alternatives.	Being forced to make fast-paced, intuitive decisions because of time pressure or managerial practices. Increasing diversity in the organization without disrupting harmony or reducing efficiency.

Figure 3. Key challenges in each stage of recruitment, as presented in P1.

P2 explores professionals' experiences in assembling innovation teams, an increasingly common activity due to work-life trends like side hustling (see Section 2.1). It shows that professionals consider the potential roles and responsibilities at the team-level, aligning individuals' qualities with project requirements. Professionals perceive significant freedom in deciding team compositions. However, they experience challenges in processing the large amount of information in applications. Decisions on applicants and team compositions are largely based on expert intuition, like scanning applicant profiles, rather than strict criteria. Applications often lack specific details, making communication and self-expression skills highly valued. This is consistent with Chua and Mazmanian (2022) findings, who also found that evaluators prioritize applicants with "innovation potential", demonstrated through active dialogue and diverse opinions. P2 also notes that while professionals acknowledge their judgement biases, they are open to making risky choices that could yield great results, such as incorporating applicants without substance skills relevant to the project.

4.1.2 Work Practices

Figure 4 from **P2** details five tactics for assembling innovation teams, categorized as arranging and balancing tactics. They involve considerations on different levels: individuals, a single team, and multiple teams. Arranging tactics resemble heuristics (see Section 2.2), entail professionals first filling critical roles and then rounding out the team. For example, a common tactic is to build teams around one or two people who are knowledgeable about the project topic (topic-interest-first tactic). Balancing tactics are employed when assembling multiple teams simultaneously, deciding whether to prioritize teams with high expertise, or distribute talent evenly among teams. Tactical approaches contribute a new perspective to research focusing on team composition decisions (see Discussion in P2), with a particular emphasis on assembling innovation teams.

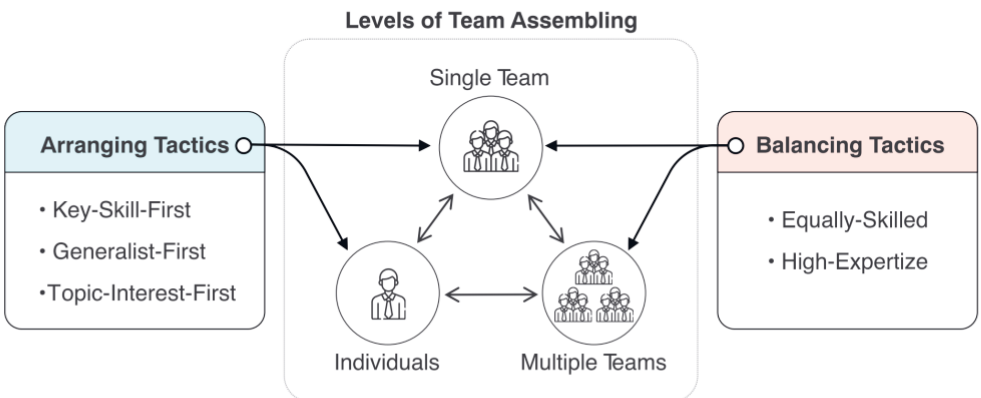

Figure 4. Tactical approaches in innovation team assembly, as presented in P2.

P3 explores emerging practices related to deploying recruitment chatbots. It highlights how chatbots have introduced new practices that necessitate extensive predefining and coordination. When a company deploys an attraction chatbot (which gathers basic applicant data), it is typically the professional's responsibility to create the chatbot script and oversee its operation. While the tools for creating chatbots appear to enable relatively fast creation of chatbots (e.g., within 15-60 minutes), professionals need to be able to design effective conversations. This includes considering aspects such as the order of questions, tone of voice, and response options.

4.1.3 Early Experiences with New Digital Tools

P3 finds that professionals were generally surprised by how well recruitment chatbots met their expectations of increasing the quantity and quality of applications. Attraction bots were perceived as effective and initially suitable for processes where only a few key details are required at the beginning. However, some applicants may prefer a more professional approach over a playful chatbot (see also criticism related to digital tools in Section 2.5). While useful, attraction bots were not integrated with other digital tools like ATS. This separation potentially creates a fast lane for applicants using an attraction bot, because the chatbot sends an email to professionals that may stand out compared to other applications that go directly into ATS. Professionals also expressed concerns about candidate experience and privacy, noting the risk of applicants either oversharing or being hesitant to share information with chatbots.

In a similar vein, Li et al. (2021) interviewed 15 HR professionals who use AI-enabled software for sourcing or assessing candidates. They noted that the use of AI systems is influenced by socio-organizational contexts, including professionals' individual motivation and organizational practices. This highlights the importance of acknowledging complexity of the application area when introducing new digital tools (see Section 2.2).

4.2 What Opportunities and Threats Does the Digitalization of Talent Acquisition Entail?

This RQ seeks to understand both the opportunities and threats related to introducing and using digital tools in talent acquisition. It outlines common digital tools, highlights design opportunities from **P1–P3**, and addresses threats noted in **P4**.

4.2.1 Opportunities

Figure 5 on the next page outlines how digital tools and technologies relate to work tasks in the talent acquisition process, as described in Section 2.4. The stages and task descriptions are drawn upon previous process conceptualizations, including the one presented in Figure 2 and the research by Holm and Haahr (2019). This figure adds new connections and provides updated, specific information about potential digital tools, including technologies such augmented writing. It also includes the recruitment chatbots introduced in **P3**: attraction, customer service, and interview chatbots.

In contrast to earlier frameworks described in the beginning of the chapter, this does not include a separate stage for selecting the most suitable talent, as there does not appear to be specific digital tools for this purpose. Similar to Holm and Haahr (2019), this framework distinguishes between attraction and identification of talent, as they involve different digital tools. Also, the stage "comparing talent" used in P1 and P4 encompasses screening applications (here, under "tracking applicants"), which can occur before, during, or after assessments. Notably, although the frameworks imply a sequential, temporal process, digitalization has made the processes more flexible, allowing applicants to be at different stages simultaneously. Especially ATSs can operate and support various tasks beyond their main function.

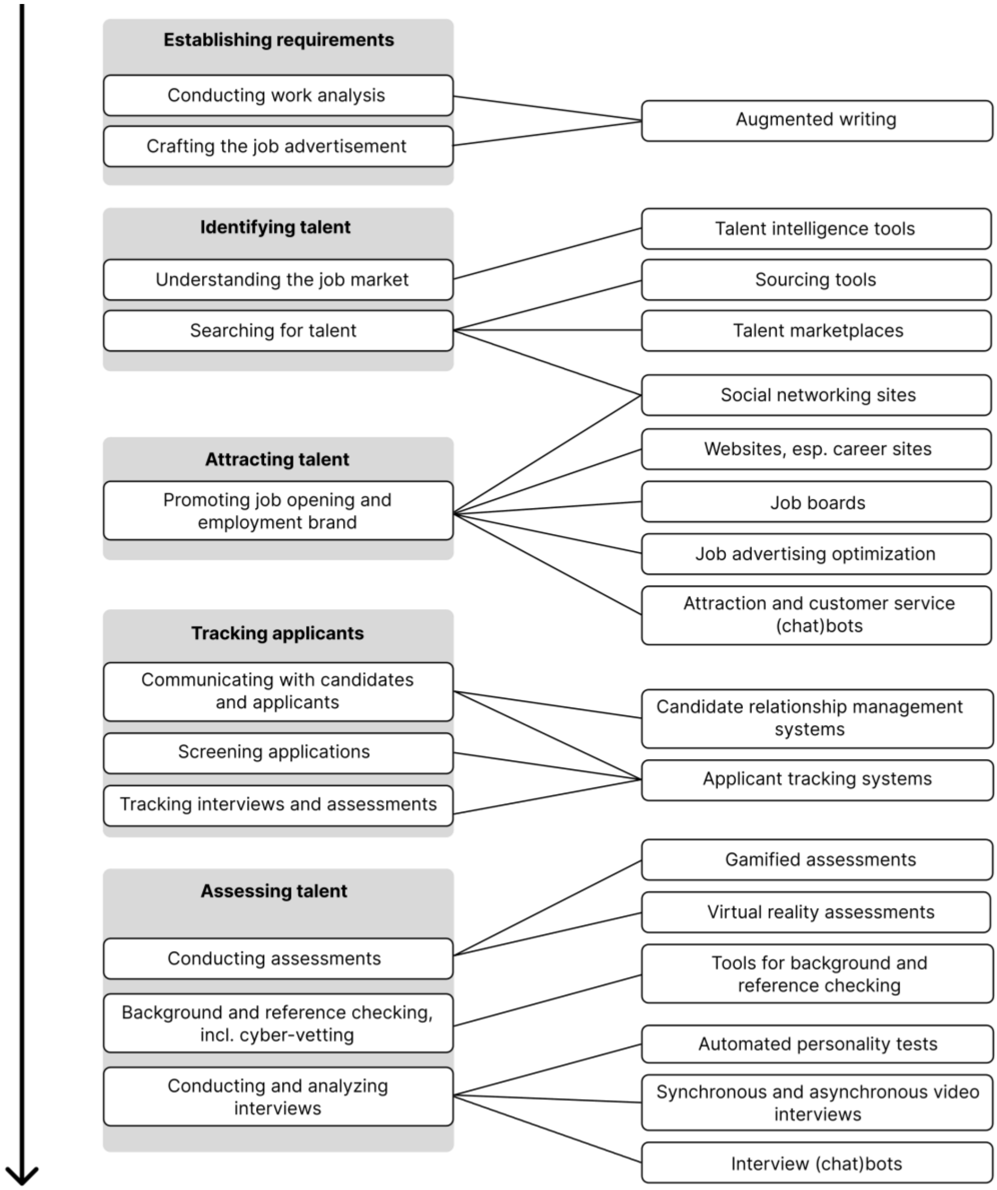

Figure 5. Framework of potential stages, work tasks, and digital tools in a talent acquisition process.

P1 proposes new roles for digital tools in recruitment based on empirical results. Table 3 summarizes them and provides a practical implementation example for each role, as described in the publication.

Table 3. Potential new roles for digital tools and associated implementation examples from P1.

Potential new role for digital tools	Implementation examples
Increasing awareness of various criteria	Checking periodically that the stakeholders' interests are still coherent
Enabling multi-dimensional matching	Considering applicants' deep-level attributes in addition to surface level attributes
Facilitating transparent and democratic decisions	Inviting various stakeholders to the decision-making process
Bridging different forms of epistemic asymmetry	Supporting more active interaction and allowing expressing oneself in free format
Helping to make sense and learn from the data	Considering the optimal number of applicants, and how to analyze applicant data fairly
Finding the balance in diversity and similarity	Identifying the similarities in the existing work community and comparing them with applicants

Similarly, Table 4 presents design considerations from **P2** related to innovation team assembly, and practical implementation examples. A typical process in innovation team assembly follows the one described in Figure 2, where interested talent is invited to apply. However, the professionals often assemble several teams at once, and they need to consider team compositions towards the end of the process. Also, the decision-making levels related to the example of offering interactive views are illustrated in Figure 4.

Table 4. Design considerations to improve innovation team assembly from P2.

Design considerations	Implementation examples
Enhancing user modeling	More nuanced insight about the applicants, e.g., based on big social data
Offering interactive views to help team assembly on different levels	A view for each decision-making level (individual, single team, and multiple teams) to place the applicants effortlessly into teams
Identifying potential team members	Digital tool could highlight individuals, e.g., with interest towards a particular project

Table 5 presents three design considerations for next-generation recruitment chatbots, and provides implementation examples, as described in **P3**.

Table 5. Design considerations for next-generation recruitment chatbots from P3.

Design considerations	Implementation examples
Support for careful planning of the chatbot script	Digital tools could help to define the questions and the order of questions (e.g., easy questions first)
Chatbots support low-threshold interaction but are also a part of external communications	Customer service bots could track applicants' progress, but requiring identification would compromise low-threshold service benefits
Attraction bots can benefit most when targeted at specific job seeker profiles	Candidates using mobile devices without an updated CV could benefit from attraction bots

4.2.2 Threats

Table 6 shows 14 potential tensions and pitfalls **P4** identified using a novel analytical framework on digital ethics. Relevant values (utility, autonomy, fairness and/or balanced power) and value tensions are presented in detail in Table 2 in P4. Tensions and pitfalls mostly stem from uncertainty (see Section 2.2, and epistemic asymmetry in P1), conflicts of interests among stakeholders, and practical constraints, such as tool or workforce availability, high costs, and administrative demands, such as the need for a speedy process (see e.g., trends in Section 2.1).

Table 6. Tensions and pitfalls according to the temporal process from P4. The number refers to the stage of the process (the four-stage process presented in Figure 2).

	Tensions and pitfalls
1	Short-term vs. long-term planning
	Abstract vs. detailed job descriptions
	Ease and speed of applying vs. detailed information
	Uncertainty vs. inclusion
2	Requesting detailed data vs. respecting privacy
	Candidates' data rights vs. tracking their interactions
	Unequal treatment of applicants across application channels
	Counterproductive UIs with unfair advantages
3	Utilizing existing data vs. initiating a new process
	Efficiency vs. quality and fairness of the assessment
	Video interviews may introduce unpredictable conditions
4	Under- or overestimating the value of human decision-making
	Selecting quickly vs. slowly
	Portability trap in copying metaphors

P4 highlights overall tendencies from the interview data, such as the professionals' potential binary divide between the human and automated decision-making. This divide can hinder identifying appropriate ways to manage ethical risks from a process-oriented, sociotechnical systems perspective that considers both digital tools and human-technology interaction. Another challenge is that solutionism tends to drive the market but can backfire for organizations. Organizations may need to restructure practices, or adapted digital tools can be counterproductive. For example, fast-paced and proactive recruitment chatbots can repel potential applicants (see Section 4.2.4 in P4).

With a similar focus, Van den Broek et al. (2019, 2021) conducted a rigorous ethnographic field study with ML developers and HR professionals using the ML service. First, they empirically illustrated how fairness ideals can fall short in accounting for the contextual, temporal, and contestable nature of fairness (van den Broek et al., 2019). In a similar way to P4, they highlighted the importance of considering ethical values in the use and development of digital tools. Second, they described the hybrid practice that emerged through mutual learning between ML developers and domain experts (van den Broek et al., 2021).

Ore and Sposato (2021) also interviewed recruiters and found that perceived risks of AI in talent acquisition involved fear and distrust regarding technology accuracy and reliability, as well as concerns about losing the human touch or human recruiters altogether. Losing the human touch and professionals' autonomy is also discussed in Section 4.4.1 of P4 (the tension "under- or overestimating the value of human decision-making"). Furthermore, Park et al., (2021) found that when introducing AI to the HR context, employees are generally concerned about emotional aspects (e.g., damaging human dignity), mental aspects (understanding and adapting to unpredictable AI), bias (algorithmic bias and discrimination), manipulation (e.g., humans ending up to manipulate AI decisions), privacy (collecting and analyzing sensitive information), and social burden (unexpected or negative changes in the workplace).

4.3 Discussion on Developments and Implications for Practice

This section discusses developments based on the findings of the publications and Section 2.4, with the purpose of showing how this research can inform practice beyond publication-specific design considerations (van Berkel & Hornbæk, 2023). The target audience are organizations and professionals who conduct or are planning to conduct talent acquisition activities.

The core digital tools include standalone ATSs or equivalent HCM modules. Other key digital tools are organizational websites, social media, job boards, talent marketplaces, and assessment tools. Furthermore, emerging digital tools such as augmented writing and talent intelligence tools are gaining popularity. Despite the high number of vendors, the most widely adopted tools, such as Microsoft's LinkedIn, have remained relatively stable for several years.

The capabilities of existing tools are continuously being enhanced through software updates. As noted by Nguyen and Park (2022), these updates often introduce features that enhance interactivity, personalized communication, automation (e.g., customer service bots), and optimization (e.g., efforts to increase conversion rates). One specific recent trend is the widespread adoption of LLM for conducting tasks such as creating job descriptions and summarizing interviews (see Section 4.4).

Chatbots and videos have become more feasible with more use cases. For example, attraction chatbots can be utilized on career sites (see P3), and videos can be used for employee stories, job advertisements, and interviews. In fact, video interview tools have potentially introduced a new sub-stage within the assessment stage, during which applicants' responses to pre-recorded questions via video are analyzed before face-to-face interviews. VR technologies (e.g., for assessments or organizing job fairs) do not seem to be so widely adopted yet.

Professionals who use ATSs or adopt new digital tools need to be prepared to learn new features and develop digital skills. Market leaders in ATS solutions (Section 2.4.4) typically release two to four feature updates annually, with similar trends in the types of features introduced. For instance, Oracle and Workday have recently introduced features to create email recruiting campaigns and landing pages for potential applicants, which may require skills in web design or marketing. Similarly, recruitment chatbots (P3) or LLMs (Section 4.4) require new skills and create new work tasks.

The key practices and digital tools in talent acquisition have remained relatively similar over time, despite vendors' claims of major advancements. Instead of being replaced by new approaches, existing core tools are gradually updating their features. Job boards, career sites, and ATSs have existed since the 1990s (see Section 2.3), serving the same purpose but continuously improving their features. For example, Oracle recently introduced a "recruiting assistant" chatbot that allows candidates to match their resumes with jobs, ask job-related questions, review upcoming interview schedules, and add themselves to a talent pool[62]. Other long-standing practices and tools include online job advertising, telephone interviews, and email communication. Email and telephone communication are practical and versatile ways to support various tasks. Oracle and Workday have even recently introduced features that allow users to send traditional text messages using their ATSs.

While radical changes appear to be rare, organizations and professionals should be cautious when vendors introduce novel features. P4 highlights how vendors' Silicon Valley mentality of "moving fast and breaking things" can lead to introducing features with ethical concerns, such as HireVue's visual analysis and emotion detection features, which were discontinued after concerns were raised. At present, vendors are quick to implement LLM features (see Section 4.4), despite limited research on their implications.

While employers are often portrayed as utility maximizers (Rivera, 2020), the interviews showed that the professionals who do the work are the ones who weigh many practical aspects and balance them when there are tensions between ethical values and utility. Notably, despite the strong criticism of vendors' claims in the literature (Section 2.5), some vendors have conducted algorithm audits (e.g.,

62 https://docs.oracle.com/en/cloud/saas/talent-management/23b/faarb/what-s-recruiting-assistant.html#u30238318

pymetrics (Wilson et al., 2021)) and are now obliged to follow algorithmic level regulations (e.g., AI Act[63] and New York City's Local Law 144[64]).

AI disruption in talent acquisition has been discussed for years. In the 2010s, academics were cautious about the extent of its use (see Chapter 2.3). The general impression from P1–P3 interviews conducted from 2018 to 2020 somewhat supports this view. However, recent developments, and particularly the emergence of LLMs (see Section 4.4), suggest that AI is becoming more widely used and recognized. While professionals might not consider themselves to be using AI, many core tools are already utilizing it. For example, LinkedIn, and popular ATSs, such as Workday Recruiting, Oracle Recruiting, and SAP SuccessFactors, have introduced AI features. The ZipRecruiter CEO has even advised applicants to write "machine-readable" resumes with common templates, no images or special characters, and short "declarative and quantitative" sentences (Schellmann, 2022). This contradicts the desire of professionals to avoid limiting the input of information and to allow more freedom in creating profiles (P1). This thesis does not discuss policies in depth, but it is important to emphasize that organizational and HR policies should consider the fact that AI is built into both emerging and existing tools.

If an organization wants to develop a structured talent acquisition process with digital tools, it could start by focusing on practices related to attracting talent and tracking applications. However, they should be mindful of the tensions that come with digitalizing practices, such as short- vs. long-term planning, and under- or over-estimating the value of human decision-making (see P4). While quick technological fixes may not enhance processes, structured approaches can help with the flaws in human judgment (see Section 2.2). Also, in such a high-risk application area, it is essential that professionals know their tools' capabilities, such as how they filter and combine information. While it can seem obvious, it can be difficult to determine how algorithms screen or rank applicant data, or how vendors have adjusted algorithms to allegedly improve fairness. For example, Marks (2022) pointed out that ZipRecruiter and Oracle are unwilling to discuss how their screening algorithms work. With stricter regulations and more ethical concerns (P4), organizations should be cautious when using or updating digital tools in their practices.

Organizations with structured and organized practices may still face challenges in finding talent, which may lead them to explore new digital tools. However, before

[63] https://www.europarl.europa.eu/news/en/headlines/society/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence

[64] https://rules.cityofnewyork.us/wp-content/uploads/2023/04/DCWP-NOA-for-Use-of-Automated-Employment-Decisionmaking-Tools-2.pdf

deploying new tools, they should critically assess these questions related to experiences and work of HRM professionals:

- How do new digital tools integrate with existing tools? (See the example of recruitment chatbots in P3)
- Do new digital tools introduce new work? (See the example of recruitment chatbots in P3)
- Should the process be conducted internally or outsourced? (See Section 4.1.1 in P4)

For example, organizations that use specific HCM ecosystems (such as Workday, SAP, or Oracle) may face integration challenges. Large vendors seem to be increasingly combining features into one HCM platform, claiming to improve synergy, reduce costs, risks, and complexity. However, P4 discusses how dependence on monolithic digital tools can lead to the need to restructure practices around them, creating mismatches between organizational needs and tool capabilities. Also, while this thesis primarily focuses on relatively advanced or emerging digital tools, it is important to recognize that traditional methods, such as newspaper advertising, face-to-face meetings, and phone calls, can also effectively reach the target populations and help avoid solutionism.

Deploying new digital tools also necessitates understanding their impact on the process and the sociotechnical consequences (discussed in P3 and P4). For example, using LinkedIn can significantly affect who is identified as talent, with unclear implications for the later stages of the process.

Digital tools also seem to increasingly facilitate collaboration, which makes sense because research findings confirm that several stakeholders are usually involved (Chua & Mazmanian, 2022; Neumann et al., 2023; Rivera, 2012b). For example, Workday Recruiting added collaborative note-taking for applicant evaluation (Section 2.4.4). These kinds of features promote transparency and democracy but can also create tension between uncertainty and inclusion (see Section 4.1.4 in P4). Democracy may reduce uncertainty but may also complicate and delay the process. Collaboration features may affect professionals' autonomy and fairness if stakeholders have different expectations of their influence. The benefits of adding stakeholders to conduct assessments (e.g., interviews) are also generally unclear (see Section 2.2). Therefore, organizations should carefully consider stakeholder participation and the deployment of these features.

4.4 Reflecting the Findings with an Emerging Digital Technology: Large Language Models

This section explores how Large Language Models (LLM), as an example of a recent significant technology development, are integrating into digital tools and work practices. This section also provides early considerations based on insight from the publications and Chapter 4. The introduction of ChatGPT by OpenAI[65] in late 2022 and other chatbots based on LLMs has raised questions on how LLM technology could be applied in talent acquisition. The following paragraphs present the technology, study how it is emerging, and discuss how it may change interactions and practices. The focus on LLM technology and chatbots is motivated by the observation that several vendors are either introducing or planning to implement LLM features soon (see Section 2.4), and P3 specifically studied chatbots.

Early examples of LLMs include GPT models by OpenAI, LaMDA by Google, and LLaMA by Meta. In simple terms, LLMs are neural networks that are typically trained with vast amounts of data from the web. Essentially, they can receive a prompt and predict the words that come after it. It is claimed that LLMs can open up novel possibilities and enhance the speed and scalability of existing processes (McKinsey, 2023).

With the latest LLM developments, it seems that vendors are rushing to integrate text generation features into conversational interfaces. Table 7 outlines three ways in which professionals may utilize LLM: (1) Core tools, such as ATSs, may be enhanced with LLM capabilities through the introduction of new features or updates to existing ones; (2) organizations may deploy new integrations with LLM capabilities, or existing integrations may be enhanced with LLM features; or (3) professionals may utilize general LLM tools like ChatGPT in conjunction with their existing tools to enhance their work.

[65] Introducing ChatGPT https://openai.com/blog/chatgpt

Table 7. Three possible approaches for professionals to deploy new technology, with LLMs as an example.

	How the new technology emerges	How the new technology can be accessed	Examples
1. Existing core tools	New features leveraging the new technology	Updating the core tools (typically a HCM module or ATS)	Workday Recruiting, SAP SuccessFactor Recruiting, Oracle Recruiting
2. Integrations or other specific tools	New features leveraging the new technology	Deploying, or updating integrations with new capabilities	LinkedIn, Beamery, SeekOut, Eightfold AI, BrightHire, Metaview
3. External tools	Technology becomes feasible to use and accessible	Using general tools in conjunction with existing tools	ChatGPT, Bing Chat, Microsoft Copilot

The first category includes established core tools, particularly ATSs, which have either announced their intentions or already introduced features leveraging LLM capabilities. For example, Workday envisions using LLM to enable document drafting, including job descriptions[66]. SAP plans to integrate their product with Microsoft Copilot to create tailored job descriptions and prompt interviewers with relevant questions based on applicants' resumes and job descriptions[67]. Oracle then intends to enhance their HCM software with buttons for automated text generation, including a feature for creating job description drafts[68].

The second category includes tools that can be integrated into or used together with core tools. For example, the sourcing tool SeekOut has introduced the "SeekOut Assistant", which generates a list of candidate recommendations based on a provided job description and creates personalized outreach messages that highlight the candidate's qualifications for the role[69]. LinkedIn is testing a feature that can create a job description after the user provides initial information[70]. Eightfold AI has introduced "Recruiter Copilot" which can schedule interviews, send reminders, and generate job descriptions[71]. For interviews, possible use cases include automatically

[66] https://blog.workday.com/en-us/2023/how-ai-and-ml-are-powering-future-work.html

[67] https://blogs.sap.com/2023/05/15/the-future-of-work-is-now-an-update-on-generative-ai-at-sap-successfactors/

[68] https://www.reuters.com/technology/oracle-adds-generative-ai-its-human-resources-software-2023-06-28/

[69] https://www.seekout.com/blog/chatgpt-for-recruiters-seekout-assist

[70] https://www.linkedin.com/business/talent/blog/talent-acquisition/linkedin-tests-ai-powered-job-descriptions

[71] https://www.prnewswire.com/news-releases/eightfold-ai-announces-talent-intelligence-copilots-bringing-generative-ai-to-its-deep-learning-ai-platform-301789607.html

creating structured interviews, generating real-time notes and summaries, providing live guidance and feedback, and analyzing patterns from the interview transcription (e.g., BrightHire described in Section 2.4.5).

The third category includes potential LLM-based external tools that can complement talent acquisition tools, such as ChatGPT, Microsoft Copilot, and Google Docs. These tools can be used for tasks such as suggesting changes to the tone of a job description (e.g., "make it more interesting and exciting"), generating tailored Boolean search strings when sourcing talent from Google Search or LinkedIn, creating personalized messages, or summarizing interviews. Early commercial data suggests that ChatGPT is currently utilized for "mundane tasks", such as crafting job descriptions, interview questions, and candidate follow-ups[72]. Furthermore, the CEO of OpenAI has warned that ChatGPT should not be relied on for "anything important"[73].

The opportunities of LLM-based assistants and copilots include using natural language to ask questions about the data they are trained on, such as resumes, portfolios, social media data, and internal information. P1 suggests that digital tools could learn and interpret data better, even though LLMs were unexpected at the time. Sourcing tools SeekOut (with over 800 million profiles in April 2023[74]), and LinkedIn (with 930 million users[75]) have access to vast candidate databases. Natural language searches could make database searches easier, allowing deeper inquiries into workforce skills and availability.

Another opportunity based on P3 is to use LLM-based customer service chatbots with organizational knowledge. These chatbots could provide more detailed and approachable information with extensive language support. They could also foster diverse conversations, giving valuable information about candidates and their interests to organizations. This would align the interviewees' future expectations of recruitment bots in P3, which include new behavioral data and job market insights for organizations.

However, current LLM tools often require prompt engineering, where users aim to craft optimal textual input. While LLM tools may improve, using them efficiently currently requires professionals to learn prompt engineering, which would probably increase their workload. For example, P3 showed that professionals may need to

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[72] https://www.resumebuilder.com/1-in-4-companies-have-already-replaced-workers-with-chatgpt/

[73] https://twitter.com/sama/status/1601731295792414720

[74] https://www.globenewswire.com/news-release/2023/04/04/2640444/0/en/Introducing-SeekOut-Assist-ChatGPT-for-Recruiters.html

[75] https://about.linkedin.com/

carefully predefine and coordinate the new recruitment bots they use. These kinds of new tasks can complicate the integration of LLM tools into existing workflows.

In addition, P4 warns of "the solutionism trap" that can backfire on organizations. Vendors may offer solutions that are easily integrated but do not consider organization-specific sociotechnical needs for digital tools. This is particularly salient in the case of LLM tools, because of the portability trap: "the possibility that algorithmic solutions designed for one social context may be misleading, inaccurate, or otherwise harmful when applied to a different context" (Selbst et al., 2019). LLM tools have shown portability potential, and vendors have adopted a solutionist mentality of adding LLM features and finding use cases quickly. Therefore, organizations need to be careful when deploying LLM tools.

A final note is reserved for the vendors' claims to adjust and check for biases. For example, Beamery's TalentGPT and SAP's initial visions for LLM tools claim to be adjusted for biases[76][77]. However, they do not explain how they do it (see also general criticism in Section 2.5). While there is a need to mitigate biases related to human judgment (Section 2.2) and professionals are aware of this need (P1–P3), adding more digital tools with algorithm-level adjustments for biases is a potential pitfall. It is challenging to show how biases are systematically avoided with vague safeguards in each tool. Different digital tools may not mitigate biases consistently or similarly, and we should not assume that bias-removing algorithms are neutral or bias free (Tambe et al., 2019). An appropriate approach for mitigating bias in a sociotechnical environment involves layered and processual measures (see Discussion in P4).

4.5 Future Research

This explorative empirical research suggests that ongoing digitalization in talent acquisition warrants further investigation, particularly from a sociotechnical perspective. The following presents promising avenues for future research.

The publications and Chapter 4 identified several specific digital tools that could be in the focus of future empirical research, particularly regarding user experiences. For example, there is almost no empirical research on the experiences of using LinkedIn and ATSs, despite their popularity. Empirical research is also required for

[76] https://www.prnewswire.com/news-releases/beamery-announces-talentgpt-the-worlds-first-generative-ai-for-hr-301781627.html

[77] https://blogs.sap.com/2023/05/15/the-future-of-work-is-now-an-update-on-generative-ai-at-sap-successfactors/

emerging tools, such as VR tools, and new capabilities in existing tools, such as LLM features (see 5.2.1). Avenues for further investigation can be identified from the ATS feature updates of leading vendors, such as Oracle, Workday, and SAP. Recent examples include features related to recruitment campaigns, LLMs, and collaborative note-taking (see Section 2.4.4).

Furthermore, the level of analysis could be varied to explore sociotechnical user experiences in specific processes, stages, or work tasks.

The current research has focused on studying job seekers and HRM professionals, but an especially fruitful area for future research would be to study the collaboration between stakeholders in employer decision-making. Talent acquisition often involves a team effort of various stakeholders in different parts of the process (Neumann et al., 2023). Although several stakeholders (e.g., recruiters, HR managers, headhunters) were interviewed, this research did not specifically concentrate on their collaborative efforts. P1 highlighted the potential role of digital tools in facilitating transparent and democratic decisions, which is still an underexplored aspect in the research.

Studying the challenges and opportunities specific to different user groups is an important and promising area of research that should receive increasing attention. Although there is existing HCI research that focuses on marginalized job seekers, there is still room for exploring specific user groups or industries. For example, studying how immigrants and organizations that hire immigrants experience digitalization in talent acquisition would be a relevant thematic research topic, particularly in the Finnish context.

Finally, other methodological approaches could complement interview studies. For example, an ethnographic study where HR professionals are observed in their natural settings, as in the study by van den Broek (2019), seems like a promising approach. Additionally, experiments or user experience research in a particular scenario, such as an interview, would provide valuable insights into how work and decisions are conducted in practice.

4.6 Limitations

As with any research, this thesis has its limitations. Individual publications address their specific limitations, for example, related to methodology. This section provides a discussion of the identified limitations that mainly result from practical constraints and could potentially lead to misinterpretations of the focus. A case in point is the terminological choice that could cause a misinterpretation of the scope and focus of the research. While the title is "Digitalization of Talent Acquisition", this thesis specifically focuses on deliberate, relatively structured talent acquisition processes that involve external applicants and digital tools are often used to support the work. However, given that organizations and professionals have various ways to hire talent, terminological generalizations were necessary to convey the overall findings of the thesis. To avoid confusion, Section 1.2 defines the key terms as they are understood in this thesis.

This research was qualitative, deliberately avoiding quantifying the findings. From a quantitative viewpoint, the sample size of 47 participants may appear limited, with 13 participants in both P2 and P3. Nevertheless, the emphasis was *to explore* practices, and given the chosen methodology, it seems unlikely that a larger number of participants would have significantly improved the outcome. The analysis had reached a point of theoretical saturation, meaning that the most interesting findings could be presented coherently.

The sequential approach, which provides design considerations after studying current practices, may face the limitation of not fitting well with dynamic real-world practices that constantly change and evolve (Bjørn & Boulus-Rødje, 2015). In addition, ongoing digitalization impacts practices and tools, making especially the practical contributions somewhat time-bound. For example, the reflection related to LLMs in 4.4 demonstrated how this new technology can address some of the proposed design considerations from P3. In some cases, the practical contributions proposed iterative improvements to existing solutions that could be addressed in the near future (e.g., support for planning chatbot scripts in P3, or offering new interactive views for team assembly in P2). As perhaps less time-bound contributions, they also explored new potential roles for digital tools in P1 and analyzed general tendencies in professionals' considerations across interviews in P4.

This research focuses on the Finnish cultural context, commonly seen as a Nordic culture characterized by democratic decision making, high levels of worker autonomy and work ethics, and high levels of digitalization. Many organizations have integrated digital tools, with relatively established practices for both job seekers to find opportunities and employers to attract and assess applicants. Commonly used digital tools include job boards, career sites, LinkedIn, HCM solutions, and ATSs. Furthermore, the purposive sampling led to interviewees mainly from organizations that appeared to be open to improving practices and exploring new digital tools.

4.7 Concluding Remarks

Successful talent acquisition practices are essential for organizational success, and individual well-being. This thesis studies the rapidly advancing digitalization of talent acquisition from the perspective of HRM professionals. By exploring the experiences and new practices of these professionals, this thesis provides insight into the challenges and potential avenues for acceptably introducing digital tools into talent acquisition.

Digitalization has had a radical impact on talent acquisition, influencing work tasks, introducing new practices, and raising ethical risks. While digitalization offers benefits such as improved reach and consistency, professionals also face challenges related to finding suitable and available information, and making quick, intuitive decisions. In addition, several ethical risks relate to digitalization that require careful navigation through tensions and pitfalls across the stages of the process.

While the core practices and digital tools of talent acquisition have remained relatively similar over time, digital tools have progressively integrated new features. Recent years have witnessed the integration of AI functionalities into prevalent tools, the emergence of recruitment chatbots, and the surging popularity of talent marketplaces. Professionals who use ATSs or adopt new digital tools such as recruitment chatbots need to stay up-to-date with new features and cultivate relevant skills.

The findings of this thesis help HRM professionals to comprehend the current landscape and relevant trends amidst the ongoing digitalization developments. In addition, designers and developers may gain insight into UI-level considerations and the abstraction traps that can result from overlooking the sociotechnical context.

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PUBLICATIONS

PUBLICATION
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Understanding Decision-Making in Recruitment: Opportunities and Challenges for Information Technology

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Understanding Decision-Making in Recruitment: Opportunities and Challenges for Information Technology

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Although the composition of individuals can strongly affect the success of professional collaboration, organizations often struggle with their so-called social matching decisions. For example, when recruiting new people to an organization, the decision-making is often reduced to intuitively matching individuals based on vague descriptions of projects or positions. The role of technology in recruiting is typically confined to gathering and presenting simple candidate profiles. We argue that many issues in recruitment boil down to lack of understanding the process of decision-making from social matching perspective, covering aspects like identification of relevant selection criteria and choice of the most suitable candidate. To better understand the appropriate roles of information technology (IT) in this domain, we interviewed 21 expert matchmakers, such as HR specialists and headhunters. Based on qualitative analysis of their experiences, we provide a bottom-up framework of the decision-making stages in recruitment, focusing on the pertinent challenges from the perspective of social matching. The findings indicate that, particularly, the epistemic asymmetry between the recruiter and candidates regarding the expected qualities calls for deliberation throughout the decision-making process. Matchmakers also struggle between contradictory ideals of agility and holistic decision-making. Based on the findings and relevant literature, we propose six roles that IT could play in social matching decisions in recruitment.

KEYWORDS

Social matching, decision-making, working life, collaboration, human resources, recruitment, talent acquisition, head hunting, people recommender systems

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1 INTRODUCTION

In modern knowledge work, collaboration is considered as a universal dogma to reach high levels of innovativeness and performance in organizations. A key question in enhancing collaboration relates to the social composition of individuals: the mutual compatibility of individuals has been found to significantly affect the performance and well-being of both individuals and organizations [51]. In organizations, this question is typically addressed through recruitment and headhunting, that is, at the time of acquiring new personnel. Unfortunately, however, organizations seem to be struggling with their recruitment decisions and the tools they use in the process [11,48].

In Human-Computer Interaction (HCI), the question of optimal social composition has been considered through the concept of *social matching* [52], or simply *matching*, which refers to ways of identifying and facilitating new social connections between people—with or without computational aid. Different computational approaches have been envisioned to support the matching processes in different areas of life. For instance, matching similar profiles at work places to encourage new encounters [17], people recommender systems to find relevant users in social media services [20], online dating systems [60], as well as peers for learning [43]. Contextualizing the general notion of social matching to professional life, a recent paper introduces *professional social matching* as an umbrella term that covers a plethora of vocational matching activities, related to partnering, grouping, mentoring and networking in professional contexts [37]. The authors provide directions for the development of computational approaches to this area, outlining approaches for computer scientists to design for matching.

From a management science perspective, Weller and others [56] define matching as the "process by which individuals are dynamically aligned with roles, jobs, situations, and tasks within organizations". They stress the complexity of matching, considering it as a multilevel and multidimensional process with heterogeneous groups of individuals and organizations and dynamic circumstances that greatly affect organizational performance. We further argue that the importance of choosing suitable collaborators and partners is ever increasing as co-creation chains tend to become more complex and cross organizational boundaries through, for example, ad hoc freelancer groups, micro-entrepreneurship, crowdwork and piecework [1].

Building on the aforementioned two conceptual groundings, this paper considers recruitment as a social matching activity that certain decision-makers, such as HR specialists and managers, perform in organizations. Employee recruitment typically refers to the overall process of attracting, appointing and managing suitable candidates for jobs within an organization, regardless of how and by whom the process is carried out, hence also covering the so-called third-party head-hunting activities [6]. Consequently, as recruitment covers various managerial and administrative activities, the concept of matching provides a more focused perspective to the *selection* of individual(s) to a certain organizational context or activity. In this paper, we use the term *matchmaker* to refer to the key actor from the matching perspective.

While the matching choices are typically made by human decision-making, various applications of Information Technology (IT) are increasingly being used to support such processes, making this an interesting space for HCI research. Prior research on e-recruitment [53] has provided some insight into the decision-makers' use of specific tools, such as online job boards, job ad aggregators, employer websites, mobile recruiting and social media in their matching practices [13]. Recently, the newest wave of computational tools has been strongly criticized [11]. To provide a fresh perspective, we argue for a lack of more general and holistic understanding of the decision-making in relation to matching, which is also acknowledged by Weller et al. [56]. We argue that better understanding of the decision-making process of matching and the challenges therein would be beneficial for developing more appropriate and effective IT solutions for recruitment.

Consequently, the research question driving this study stands: What are the characteristics of the decision-making process and the related challenges of social matching in the context of recruitment? We conducted 21 in-depth interviews with experts who frequently perform matching as part of recruiting activities in organizations. We studied their current practices, different aspects and perceived ideals in the decision-making they perform, and, in particular, the challenges they face in pursuing good decisions.

The analysis revealed a variety of relevant perspectives to decision-making that can be characterized as a process with four distinct stages, each with their specific challenges. For example, the participants were found to often struggle with balancing between contradictory ideals of agility in decision-making and reaching a holistic understanding to allow making thought-through choices. Matching decisions in organizations are considered very delicate, context-dependent and dynamic, and, in the studied sample, such decision-making was found to be suboptimally supported by IT. The decision-making processes in matchmaking remain to be primarily human-based and tend to be driven by intuition. This calls for careful consideration of the optimal roles of IT in assisting the matching processes at different stages.

This paper offers (i) qualitative insight about decision-making in the empirical context of recruiting, focusing on expert matchmakers' perceived challenges, (ii) conceptualization of the decision-making process, and (iii) considerations on what are appropriate roles for IT systems to support matchmakers' work in recruitment.

2 RELATED WORK

HR processes have undergone significant changes due to recent technological advances. Particularly in recruitment, technology is extensively utilized for posting jobs, collecting resumes, and communicating with the pool of candidates. In the following, we discuss prior research perspectives regarding the role of technology in facilitating recruitment practices. As we consider recruitment as a social matching decision that involves various phases, we also provide an overview of theoretical foundations of decision-making in recruiting.

2.1 Optimistic vs. Critical Perspectives to E-Recruitment

Relevant HCI and CSCW research has aimed to understand the role of technology in hiring and job search processes. The "war for talent" [35] and challenges in managing a large number of job applications have motivated the development of various e-recruitment systems. IT-based systems are intended to solve issues in HR management, allowing to target a broad audience of candidates with lower costs, assisting in the analysis of rich CV data, and screening job applications [2]. In general, there seems to be a variance with respect to what kind of agency IT is given in such activities and how optimistic vs. critical mindset the developers and authors take.

The work that we consider to represent the optimistic end of the spectrum looks at the advantages of IT in computational hiring, and hence contributes to e-recruitment or *digital recruitment*, which has been argued as a strategic imperative that organizations should aim for [40]. Thus, IT solutions are seen to serve as a bridge between job-seekers and organizations. The design solutions are typically based on existing organizational, social and personality theories (e.g., [41,59]). Recent examples include sophisticated semantic job-applicant matching techniques [19,28,42] and matching resumes of candidates to job descriptions using machine learning techniques [31,57] . In addition to headhunting services, online workspaces such as GitHub have proved to play an essential role in hiring decisions [32]. The transparency and rich activity traces in such interactive workspaces help decision-makers to infer verifiable signals of practical abilities and passion for working.

The more critical stance tends to highlight the adverse effects of recruiting technologies. Even though there are various services that aim to fulfill the needs of both the recruiters and the job-seekers, evidence illustrates high unemployment rates and organizations' arguments regarding challenges in reaching the right audience for jobs [8]. For instance, Cappelli [9] concluded that hiring processes are poorly optimized due to lack of experience-based training and education of job-seekers as well as overly demanding requirements and expectations of organizations. Such mismatch in demand and supply on the labor market further was found to be fostered by existing hiring technologies that typically utilize overly simplified filtering and screening methods, thus disregarding actual merits in the evaluation of job applicants [49]. To this end, HCI research has particularly investigated the so-called disruptive job technologies [15] that foster inequality of access and use of IT by low-resourced and disadvantaged job-seekers [16,26]. Overall, it seems that many problems in relation to recruitment persist and that the current technological tools suboptimally support the processes and decision-making in recruitment.

Furthermore, it is noteworthy that prior research mainly takes the viewpoint of job seekers aiming to understand their needs and approaches in finding jobs (e.g., [10,25,39]). The recruiters' perspective was taken in regard to facilitating the fast pace of hiring processes via technology, which is typically confined to conveying information about potential matches [21]. At the same time, experiences, practices and decision-making challenges of recruiters remain understudied. Majority of design-oriented HCI research aims at increasing the effectiveness of job-person matching before even knowing matchmakers needs that are worthy to be solved or optimized with IT. In fact, along with advantages, existing job technologies have been found to bring even more issues to the hiring decision-making (e.g., biased hiring, lack of job match quality, cognitive overload) [18], which we also identified in our empirical data. Therefore, more in-depth understanding of the challenges that matchmakers face along the decision-making process can introduce new opportunities for more optimal roles of IT.

2.2 Theoretical Foundations of Decision-Making in Recruitment

The literature on conceptualization and theorization of matching practices is highly segmented across domains of organization research, psychology, and management science. In this paper, we focus on the well-established research area of external employee recruitment. Employee recruitment is defined as a demanding decision-making process consisting of multiple stages including bringing a job opening to the attention of potential candidates, influencing whether the candidates apply, affecting whether they maintain interest during the process and influencing whether the job offer is accepted [6]. As any other decision-making task, matching is susceptible to the limitations of human cognition and bounded rationality, including limited ability to understand the complexity and to sustain logical reasoning [36]. Biases and cognitive shortcuts in decision-making refer to, for instance, the tendency to seek information that confirms existing beliefs and rely on easily available information [27]. In addition, decision-making can be affected by *dualistic perception* discussed by Kahneman [27]: when facing choices, human cognition primarily initiates automated and intuitive selection rather than rational reasoning.

Aiming to assist decision-makers in recruiting tasks, psychology and management researchers have investigated, for example, personnel attraction [12,46] and selection through person-environment fit (P-E fit) theories [50], such as the Attraction-Selection-Attrition (ASA) model [47]. In relation to P-E fit theories, researchers have explored the influence of personality or cognitive qualities in face-to-face hiring decisions, revealing human biases in action [29]. For example, more extraverted applicants are more effective in self-promotion and perceived applicant-interviewer similarity often serves as a determinant factor in hiring decisions. Social factors, individual characteristics, and personality traits also affect the matching of an individual to a group within an organization [33].

A recent review by Weller et al. [56] provides an analysis of the extensive and multidisciplinary literature on matching processes within organizations—covering the life cycle of an employee from recruitment till contract termination. The authors extend the ASA model into a more holistic matching model exploring also selection and adaptation mechanisms. They illustrate the complexity of matching by referring to information asymmetries between job seekers and organizations, heterogeneous nature of labor, and instability of internal and external contexts. The authors address the importance of information flow, organization design and personnel heterogeneity in achieving high-quality matches.

The above-mentioned theories illustrate that behavioral biases are also inherent in decision-making processes within recruitment. Although existing modeling and suitability P-E fit theories contribute to the conceptualization of the recruiting and personnel selection life cycle, they are insufficient to holistically explain what qualities define a good match. The empirical research in this area is often narrowed down either to issues of matching individual characteristics with professional environments or to other specific matching activities, which limits obtaining a general-level understanding of the process of selection and matchmaking. In contrast, this article approaches recruitment from the perspective of decision-makers' experiences by providing an account of perceived challenges in their current practices.

3 METHODOLOGY

To better understand the challenges and practices in recruitment from matchmaking viewpoint, we decided to study the subjective experiences and opinions of people actively involved in the matchmaking process. Qualitatively oriented empirical research based on interviewing was expected to yield a profound understanding of the actual challenges that the central actors face on a daily basis. Instead of studying the experiences of using specific tools, like in some previous work, we wanted to understand the decision-making process on a more abstract level from the perspective of matchmaking. While the interviews touched also other social matching activities, such as team formation and professional networking, the majority of the discussion revolved around recruitment related tasks, which is also the focus in this paper.

3.1 Interview Procedure

We conducted 21 semi-structured, face-to-face interviews in December 2017–March 2018, with one or two researchers present in the interview. In most cases, the physical context was the interviewee's workplace, which created a relaxed atmosphere and helped them to elaborate on their typical practices and experiences.

The first part of each interview we inquired what kind of social matching activities they are involved in. This was followed by questions related to their current practices and technologies they use. Following our focus on perceived challenges, the central part of the interviews focused on various challenges and risks in their matchmaking activities from the decision-making perspective.

3.1.1 Design Fictions

To enrich the discussion and elicit opinions about possible technological futures, we utilized a design fiction approach [4] and scenario-based design [45]. In practice, we generated scenarios that set out narratives of possible uses of IT in the decision-making related to matching.

We prepared two utopic and two dystopic scenarios with respect to possible ramifications of a technological tool. For each interview, we selected one dystopic and one utopic scenario according to the participant's expertise and professional role, and we gave the scenarios to the participants to read in the latter half of the interview. It is noteworthy that two of the four scenarios covered other matching activities than recruiting (i.e., finding a mentor, general networking), so this paper only incorporates the discussion on the two scenarios described below.

The utopian scenario on recruitment envisioned a system that is able to recognize lack of specific skills in an organization and recommend a new position to be filled. This was envisioned to lead to improved well-being at work. Figure 1 illustrates in what form the scenario was presented to the participants. The dystopian scenario is about a system that identifies an ideal team of four people to be recruited to a startup company. Unfortunately, the highly performing team becomes culturally isolated from the rest of the company, which creates social conflicts and leads to drastic personnel changes.

The scenarios were presented in original language. The scenarios were presented as 2-page comic strips with images and text. They helped the participants to envision how the use of information technology in social matching might positively or negatively influence individuals or organizations. Exploring possible futures helped the participants to better articulate their present practices, challenges and to move beyond the familiar towards an imaginative space.

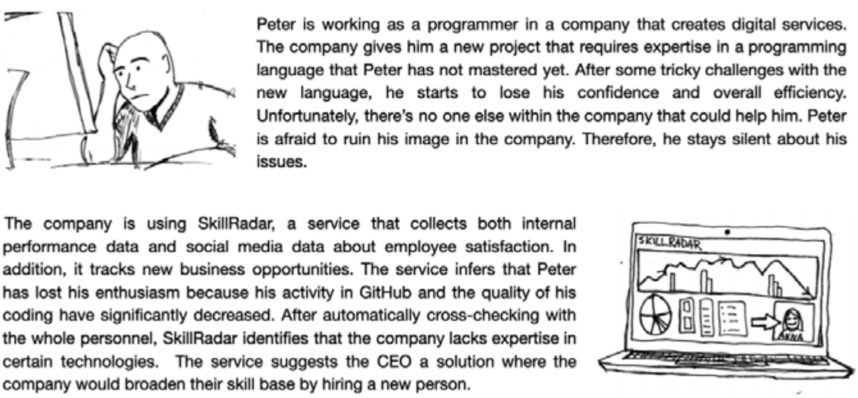

Fig. 1. An excerpt from a utopian scenario on recruitment. The text is translated from the original language.

3.2 Participants and Recruitment

To gather a relevant sample of participants, we first identified candidates from various local organizations and relevant social media forums in Finland. We were explicitly seeking HR experts, people in leading positions, people in charge of teamwork, and other people that are involved in recruitment decision-making within organizations. In addition, we targeted organizations that are interested in matching in general (see Table 1) to be able to discuss the topic also beyond their personal experiences. We inspected each candidate's work profile, social media profiles, as well as approachability for a face-to-face meeting. As a result, we invited 50 relevant people to the interview study via email and, eventually, 10 females and 11 males agreed to participate.

Table 1. Participants' background information.

ID	Gender	Experience (years)	Role
1	F	22	Startup CEO, developing recruiting apps
2	M	2	Startup CEO, developing recruiting apps
3	M	4.5	Startup CEO, analyzing social media
4	M	1.5	Organizer of a student job fair
5	F	1	HR consultant, a job fair organizer
6	M	1.5	Project manager, event organizer
7	M	4	Strategic resourcing and recruiting expert
8	F	8	Head of recruitment and employer branding
9	F	13	HR manager
10	M	2.5	Recruitment consultant
11	F	3	HR consultant
12	F	11	Recruitment team leader
13	F	2	Sales, recruiting and team leader
14	M	17	Journalist, team leader
15	M	2	Responsible for a digital infrastructure
16	F	1.5	Project manager in a mentoring program
17	M	8	Account manager, consultant
18	F	10	People development consultant
19	M	16	User experience team leader
20	F	3	Community manager, career counseling
21	M	7	Social media recruitment trainer

At the time of the study, all the participants were residents of Finland, and the interviews were held in their native language. Their ages varied from 22 and 48 (median 33). On average, they reported having 6.7 years of experience in their current role (in any organization), minimum being one year and maximum 22. In general, we were able to reach a diverse sample in terms of occupation and expertise (see Table 1).

3.3 Data Analysis

All interviews were audio recorded and later transcribed in verbatim. The average length of one interview was 73 minutes, and the total word count of the combined transcription file was 146,880. This provided us with a rich textual data set. We conducted bottom-up coding with the Atlas.ti software. In the coding process, we first employed attribute coding and structural coding, dividing the data roughly into four main categories: current practices in matching, attitudes towards technology-supported matching, ideals in matching decisions, needs for technology, and problems and risks. Then we read data in each category line-by-line and created individual codes with descriptive open coding. After that, we formed larger themes with pattern coding and axial coding and started to look at the structure from different perspectives, one of them being challenges. The analysis was carried out in the same language that the interviews were conducted and the findings were translated into English when preparing the publication.

Throughout the process of data collection and analysis, we utilized the critical interpretation method [4], which allowed us to focus more on gathering experiential heights of individuals rather than on typical or representative experiences. This method was also helpful in expanding our sense regarding feasible versus demanded design opportunities for IT-based solutions. Furthermore, to ensure the credibility of the analysis, we followed a collaborative qualitative coding method with two responsible analysts, first coding independently then cross-checking each other's categorization and emerging topics, and one senior scholar challenging and enriching the analysis process.

4 RESULTS

We organize our findings according to a temporal framework that is synthesized from relevant literature as well as the analysis of the interview data. We unpack the process of decision-making, including stages that could be identified in employee recruitment: (1) establishing requirements for a match, (2) identifying and attracting alternatives, (3) comparing alternatives, and (4) selecting the most optimal match. The process elaborates the ASA theory for recruiting [47], however, shaping it into a more generally applicable process for decision-making. In the following, we identify epistemic decision-making challenges at each stage.

4.1 Stage 1: Establishing Requirements for a Match

This stage relates to the identification of what would make a good match in the given situation (for example, for the task at hand) and what kind of qualities are sought. The importance of this stage increases in long-term, high-risk commitments such as team formation and recruitment. However, it is noteworthy that none of the participants brought up the use of any information systems to facilitate the discussion on and definition of the requirements for a good match.

4.1.1 Unclear Matching Goals and Requirements

A recurrent theme in the interviews was that the goal of matching is often unclear. In recruitment, it is hard to know what an organization needs in the long term. Hence, decision-making processes tend to represent iterative and opportunistic explorations of emerging options rather than the determination of clear criteria and objectives.

The reasons behind the limited understanding about matching needs are manifold. Several participants pointed out that a general goal is to find as innovative and talented people as possible in order to drive company growth. Such generic qualities are, however, not easy to measure and often surface only after several discussions. Participant 20 said that sometimes vague requirements lead to mismatches that affect, for instance, the coworkers the candidate is going to work with. We continue on this aspect in section 4.3.1.

> "There have been a few cases where I have asked the client if they have any specific wishes and how we could really emphasize that and try to find that out during the process (of matchmaking) … Because it is hard to go back to the drawing board and start the process again. It is a puzzle that affects all stakeholders." (P20)

> "You have to be careful when defining the requirements … we think about that a lot and how much it affects the direction the discussion (with the candidate) goes … instead of thinking what problems we are supposed to solve, it is tempting to start thinking about the solutions and then we end up developing all kinds of solutions. We don't even start to think if we are asking the right questions." (P20)

An organizational reason is that the people who create and publish job ads are not familiar with the actual work. In the country where this study was conducted, the matching process was mentioned to be often delegated to HR people who are not involved in the work in question. This lack of clarity was mentioned to lead to very opportunistic recruitment, which can lead to further issues related to mismatch of duties and skills of a recruited person. Time pressure was another persistent issue. A participant whose company is developing an application to match job seekers with a job described this challenge in relation to the pressure of time and competition that recruiters face:

> "If you are not [as a matchmaker] absolutely certain and want to spend more time to learn about the candidate [you get from our service]… that gives someone else time to hire the candidate. We encourage doing decisions fast, and we even send automatic replies to remind that 'first come, first served.''" (P1)

To dodge the lack of clarity of matching goals, one participant mentioned having started to utilize informal essay assignments. The applicants' answers might provide insight about personality characteristics, attitudes and general ways of thinking, and thus allow room for unexpected qualities to surface. This can be seen as a strategy to externalize the definition of requirements to the applicants. However, such qualitative insight and criteria are hard to employ when having a high number of options or having several people to make the matching decision.

> "Someone who is experienced, eager to try new things and can show that s/he has produced some ideas and tested them in practice – those are the qualities we are looking for. Our application process is simply a short essay where we ask for opinions on what is the biggest trend that is going to affect our lives. There we can see how they perceive the world." (P20)

Furthermore, the most important qualities can be hard to identify not only by the matchmakers but also by the people who might be relevant candidates. This lack of knowledge boils down to the typical issue of epistemic asymmetry: neither side knows the needs or is even aware of the existence of the other side.

4.1.2 Lack of Flexibility Causes Compromising and Mismatches

One participant indicated that if the requirements emphasize a few attributes too strongly, it might be that there are no realistic options to fulfill the need. Sticking with the overly demanding primary criteria can hence result in watered-down compromises. At the same time, readiness to change the requirements could have yielded fruitful results. A recurring story in the interviews was that an unsuccessful matching case was preceded by a decision-making process that was far from well thought or systematic. Recruitment decisions are often made under intense time pressure and the decision-making power is limited to a few central people in the organization using merely their own knowledge.

> "The company basically went straight to the interviews and when one candidate quickly seemed like a good employee, the company hired the person then and there. However, the match didn't work out. The work assignment was not suitable and some things from the person's background were found that didn't suit the organization." (P10)

A typical example of a mismatch is when the parties are epistemically too far from each other. One participant was serving as a matchmaker who makes educated guesses on who could benefit from each other in terms of consultancy and information sharing (i.e., recruitment for short-term collaboration). Speaking of results of unclear requirements and lack of flexibility, he gave the following example of a mismatch:

“We match organizational needs and academic excellence. However, academic knowledge is not always understandable for the organizations. Once, I set up a training for nuclear plant workers and I picked a great professor to train them for a few days about very theoretical stuff [...] It turned out to be a bad situation for everyone, the professor felt that it is impossible to make it simpler and the workers felt that this kind of expertise was not needed.” (P17)

Furthermore, participant 1 wanted to remind that taking time to find a new member to a team after someone has left is an opportunity to re-evaluate what the organization needs. Unfortunately, the opportunity is rarely used; several participants stressed that the ordinary, everyday needs of the team to be productive create pressure to recruit a worker that has skills similar to the previous employee.

“Probably the first thing you should do is to take your time and search, because it is such a wonderful opportunity… Of course, it is a bummer that someone leaves but it is a great opportunity to figure out if we need different kind of skill profile for the next challenge.” (P1)

4.2 Stage 2: Identifying and Attracting Alternatives

After defining goals and requirements, stage 2 covers the identification of organizations or individuals who would meet the requirements. Furthermore, as one side or a stakeholder typically initiates matching, it is crucial to ensure that the potential counterparts become aware of and interested in the opportunity, leading to a discussion on possible collaboration.

As an individual’s social network is increasingly valuable social capital, the analysis consolidated the idea that managers and entrepreneurially-minded people tend to network very openly and opportunistically. However, many of the participants found the opportunistic strategy time-consuming. The opportunistic approach was often contrasted with more predefined searching-based strategies to identify matches.

“I’m opportunistically browsing the data and read a lot of things that are not in any way directly linked to me. It takes a lot of time. Then again, a more efficient way is to actively look for people and companies from our own data [...] However, doing that, I have to first decide what I’m looking for and might leave something out when I make decisions.” (P3)

4.2.1 Current Systems Lack Features of Opportunistic and Flexible Matching

The use of IT was discussed particularly in relation to identification of candidates. With IT systems it was easy to conclude that the more info, the better. However, a fundamental real-life challenge relates to selecting and finding the type of information that is the most relevant in the given case, thus keeping the amount of data practically manageable.

“There are certain prescreening categorizations [in our system] which we use to apply certain keywords and select the most interesting applicants. It is possible to include only those who have a graduate degree, for example.” (P9)

It was noted that agile, opportunistic matching decisions during face-to-face encounters are very different from computer-supported processes. In e-recruitment services, the attraction of candidates is typically not a real-time process. Additionally, if a service uses matching algorithms, like in some of the scenarios the participants read, the decision-making logic about the relevancy of candidates might not be considered transparent and trustworthy. After reading the scenarios, a participant was worried that digital solutions that aim at efficiency and simplicity might drastically narrow down the population of suitable candidates:

“This kind of service is often probably made in Tinder style, like: here’s a match for you, take it or leave it. The spectrum of alternatives is easily forgotten.” (P14)

Not surprisingly, LinkedIn was considered as one of the key channels for headhunters to identify potential employees, although some also felt that various social media groups on specific topics are being increasingly utilized. However, what is interesting is that many considered that the users have to cleverly adapt to the way the service works, depending on the openness of personality and practical availability for matching. A few participants further pointed out that the IT system should avoid setting limitations for inputting information and, preferably, give more freedom in building a profile.

“In LinkedIn, the profile the service provides, gives quite one-sided picture about your skills. For a job seeker, a service where you could introduce yourself with YouTube videos and other content would make more sense” (P11)

"Something is done correctly when, instead of forcing you to a promoter format, both the employer and the worker can very informally tell about themselves. Then the [employer and the worker] can maximize their visibility and hit rate." (P3)

“Skilled workers don’t fit into boxes, and the message that you don’t have to fit into a box is what they love.” (P1)

4.2.2 Competition Makes It Challenging to Search for Experts

With a big responsibility to find the best people available, participants noted, usually after reading design fictions, that the most suitable people are often already occupied. The ongoing competition between organizations to get the best professionals has forced to create efficient ways for attracting candidates and collaboration partners.

“Work life is going to a direction where, even if you find suitable persons, it’s ever harder to attract them. If we think about recruitment software, the systems often address the matching [of suitable skills], while the challenge is actually to attract good candidates. Sorting candidates is not the challenge but to get anyone at all to work for you is.” (P12)

If the identified experts are already occupied, the job of a matchmaker increasingly resembles that of a salesperson. The outcome of matchmaking strongly depends on how transparently and attractively one is able to communicate the benefits of potential collaboration to the candidates. Besides, matchmakers often lack a holistic understanding of jobs they try to sell to candidates, which makes the recruiting process even more challenging. Unclear responsibilities and indifference from the matchmaker might also delay the decision-making process.

> "The hardest thing has probably been that no matter how good your tools are and how good you are in your job, the head hunter must often also be a good salesperson. [...] You contact the person who has never heard of you and say that you should come to work for us. [...] For sure very skilled workers can be found in this way but the big question is whether they are interested in what you are offering." (P21)

4.3 Stage 3: Comparing Alternatives

In case of having many options, there might be a prequalification where some of the alternatives are ruled out. Nevertheless, comparing the remaining few alternatives typically takes plenty of effort and involves various pitfalls.

4.3.1 Narrow View to Individuals' Qualities

Drawing from both their real-life experiences and the design fictions, the participants were worried that, with or without digital solutions, candidates are not always able to provide relevant information about themselves and, therefore, it is challenging to find the most suitable matches. For example, it was mentioned several times that comparisons are often based on oversimplified information, such as job titles or personal impressions about suitable people. Participants were concerned that the vast potential in people is not visible in simple lists of names and titles:

> "Currently we define ourselves largely through titles. To me, it is actually the least interesting thing when I recruit people. Something else from your background can be much more interesting to me because it shows that you can bring a unique, new perspective to the discussion." (P20)

> "We use this service that shows all construction projects and people responsible for them [...] however, it is limited only to representation of people in charge. So there are many people who are not nominally responsible of a project but could be really good [for a position]." (P5)

Many existing human resource management systems do not support extensive capture of skills, knowledge, experience and other qualities that a person or an organization has. This might rule out people that have different, complementary qualities, such as experience from another field. The most obvious skills, especially skills related to technology, are underlined while little information is presented regarding the qualities or skills that could make more unique matches or give an advantage in the competition with other people.

Furthermore, even though working in teams has long been a rising trend in knowledge work, it seems that, from the decision-making point of view, more weight is given to individuals' qualities as opposed to teams' qualities. Many participants addressed the need for better means of forming teams, giving more attention to facts about the team as a whole rather than the individuals separately. For instance, the company of participant 18 had been offered to recruit a whole team at once but, so far, their focus has been strictly on individuals:

> "For example, our culture and recruitment focus heavily on individuals. His/her interests, enthusiasm and all other things are the base for virtually everything with us." (P18)

4.3.2 Seeing through Impression Management

Another common theme was that individuals tend to have different faces in different contexts, which complicates gaining a holistic picture of a person. Notably, for an individual who is far from routine matching decisions, the cognitive load of analyzing, comparing and interviewing several candidates one after another can be overwhelming, resulting in mixing individuals and their features. As participant 7 stated, social matching is primarily grounded in impressions people give about themselves, overlooking the fact that one can adjust the impressions because of different interests:

> "There are all kinds of impression management. How credible is the information job seekers provide? For a job seeker, it is usually important to get the job. [...] People are aware that there are criteria that the selection is based on. Understandably many people are tempted to adjust the impression accordingly." (P7)

A project manager who analyzes application letters to form actor-mentor pairs felt strongly that the matching process with such importance needed a human operator who, for instance, could understand the hidden messages between the text lines. In fact, one of the difficulties in her job is to find out if people actually mean what they are writing:

> "You can pretty well sense what they need. Sometimes there are surprises [...] It depends a lot on what the applicants are ready to tell about themselves in the application phase. Some people might think that they have to sound better than they feel just in case because they are used to create job applications where they have to be perfect." (P16)

4.3.3 Need for Readiness to Revise the Requirements

When there are only a few candidates to choose from, it can be hard for the decision-maker to see which one would be the best option. Scenario work and risk analysis were some of the mentioned ways to make a more systematic selection in a seemingly even situation. However, the case of comparing two candidates with very different strengths was considered particularly challenging and required revisiting the original criteria:

> "One thing that we have often discussed is comparing a digitally very capable and innovative person with an experienced domain expert; they can be contradictory in terms of requirements." (P7)

For a matchmaker, contradictory goals cause difficulties in optimization. The originally defined requirements can also change during the process, so another issue at this phase is that one might not be flexible and wise enough to notice that the requirements are indeed not those that were initially set.

> "It is possible that you need to select, at the same time, the most skilled worker, an equal number of young and old applicants and someone who is best at marketing. Therefore, the criteria are not always coherent. It creates challenges to optimize matches." (P7)

4.4 Stage 4: Selecting the Most Suitable Match

Following the challenges in comparing alternatives, the participants pointed out that selection rarely represents a deliberate and well-informed decision.

4.4.1 Need for More Iterative Selection Process and Trial Periods

According to the participants, the matching decisions are often made quickly, for reasons such as lack of time or pressure from the management. There seem to be two contradictory 'forces' in the decision-making process: the need to react to the dynamism of the operational environment and the need for making well-thought decisions. One participant exemplified that the match is more likely to fail when the recruitment is accomplished in one go. The risk decreases if there are more than one interview or pre-tasks but, in turn, this is deemed to take a lot of time:

> "So, the company had basically gone straight to the interview process and when the applicant seemed decent, the company gave the contract straight away. Then the match had not worked out well. The job assignment was not what was expected or something was found from the person's background that did not fit to the organization. With personnel assessment, we try to prevent those kinds of things." (P10)

Participants who complete matching assignments for clients pointed out that the qualification requirements might change before the selection. The separation of responsibilities to search for suitable person/s on the one hand and to make the final decision on the other was seen to increase the risk for rejection and need to restart the process.

> "It happens quite often that we make significant effort to find someone and after we find the person and think that s/he is perfect for the position, the employer or the client thinks after the interview that s/he is not suitable at all." (P5)

> "The situation changes all the time... There might have been several months since we have gone through a client's situation, that they want this and that skill. But things go forward so fast that when I go to offer a good prospect, the situation has already changed and now they want different skills." (P13)

Our impression from the interviews consolidated the general trend towards people and organizations being more flexible in terms of doing freelance or part-time work. This brings a growing need to make quick matches for small tasks. Participant 8 even suggested a system that would allow organizations to treat people as a resource, enforcing more flexibility to move between job assignments. This would enable a more on-demand approach to matching and decrease the organizations' financial risks of making a bad choice. However, in reality, the decision-makers seemed to struggle to attract full-time employed people that would be open for new opportunities. Therefore, they seem to be forced to settle for suboptimal matches.

4.4.2 Balancing between Diversity and Similarity

Interestingly, many participants seemed to share the need for diversity in teams or organizations but said that it is often practically challenging. A few participants noted that sometimes they try to make non-obvious matches to bring fresh viewpoints, for example, to support growth or shift to traditional ways of working. For instance, participant 15 said that he typically aims to find surprising combinations. More generally, the participants considered that introducing diversity might have negative consequences in short-term, but, at the same time, noted that growth does not come without investment in facilitating change, as participant 7 describes below.

> "Sometimes, on purpose, we recruit 'troublemakers' who represent the future we have envisioned for this community. Then the person comes here and starts to railroad change by force. There is going to be bruises but it helps us; the reactions help us to make the transition." (P7)

In the other end of the continuum, a team leader gave a concrete example of how people in his surroundings have a representative similarity; e.g., being roughly the same age, or having biased gender distribution. Friends of a professional are in many cases from the same professional field. He had realized that getting personal recommendations from familiar people may lead to hiring even more people that are similar in that way, basically representing the homophily bias.

> "There is a risk that soon all of us are a little under 40-year-old white males with glasses. That is a big risk I have noticed [...] We currently have five teams [...] In three of them, all look like me. I have talked about this with our HR." (P14)

Furthermore, the cultural fit was mentioned to be of equal importance as personal skills and qualities. A recruitment team leader (P12), for instance, described how an interview is an opportunity to test if there is a cultural match and, if a person is incompatible, the recruiting process can stop straightaway. One participant argued that cultural matching is, however, understood incorrectly, as it is not equal to hiring similar people.

"Cultural matching doesn't mean that you want to hire similar people every time. On the contrary! It's a bad thing if you get clones, people who always think the same way and have similar backgrounds. In the end, that kills the innovativeness. Cultural matching should mean that the sought person is different enough from the people you already have but s/he shares the values, culture and certain personality, for instance. Things like communication, ability to create content, take criticism, and be constructive." (P21)

5 DISCUSSION

We start with a summary and reflection on the key findings in relation to earlier work. This is followed by a discussion on design considerations about what kind of IT solutions would appropriately support the decision-making process and its specific stages. Finally, we discuss the methodological limitations of the study.

5.1 Summary and Reflection on the Key Results

While such qualitative research can yield a variety of insights for different readers, in the following we highlight aspects that we consider the most important from the matchmaking perspective. Our findings are organized according to a process that elaborates the ASA theory for recruiting [47]. However, in contrast to ASA and the work by Weller et al. [56], we focused on the more narrow viewpoint of matchmaking, including stages that could be identified and corresponding challenges. Table 2 provides an overview of the stages and some of the key challenges in recruitment.

Table 2. Summary of the stages and examples of challenges in recruitment and team formation.

Stages and definitions	Examples of the decision-making challenges from matchmaking point of view
Establishing requirements: Identifying what would make a good match in the given situation and what kind of qualities are sought for.	Lack of clarity in the goals might lead to very opportunistic decisions and hence suboptimal matches. Identifying what complementary viewpoints or competences an organization might benefit from.
Identifying alternatives: Identifying and attracting individuals who would meet the requirements.	Selecting and finding the information about candidates that is the most relevant yet practically available. The spectrum of alternative matching strategies and different individuals' needs are easily forgotten.
Comparing alternatives: Assessing the alternatives in relation to the requirements and each other.	Evaluating the candidates and their qualities from too narrow perspectives and based on self-reported description. Comparing two individuals who fulfill the minimum requirements but have very different strengths.
Selecting the most suitable match: Making a deliberate and as well-informed decision as possible, considering the goals and available alternatives.	Being forced to make fast-paced, intuitive decisions because of time pressure or managerial practices. Increasing diversity in the organization without disrupting harmony or reducing efficiency.

In establishing requirements for a match, the most generalizable finding is that the goal of matching is often unclear. This leads to problems in identifying relevant actors as alternatives and choosing the most optimal one. Even the explicitly mentioned requirements might not be thought through but the actors are nevertheless unable to revise them. Lack of flexibility and reactivity about the criteria can cause mismatches and issues in the long run.

Regarding the identification and attraction of alternatives, prior research focuses on attraction and search from the perspective of personality traits and abilities assessment [30,50]. In addition, we identify challenges in defining what personal qualities are the most relevant in each case and what kind of data about the individuals would be best to tell about those. In practice, the current IT systems were argued to fail in supporting fast-paced opportunistic searching (e.g., by providing recommendations from a large population of eligible people).

In the comparison stage, matchmakers may struggle because the candidates fail to express themselves meaningfully and truthfully with current IT. In addition, comparisons are often based on oversimplified information, such as job titles or general impressions about suitable people. While IT has reduced the amount of time needed to catalog alternatives, existing systems do not support capturing the candidates' skills, knowledge, and experience very extensively. In opportunistic searches, the decision-makers might look for alternatives with more vague requirements, which results in unpredictable emerging alternatives and challenges in the process of defining the exclusion criteria.

Finally, the selection of the most optimal match is where the risks of unclear requirements or an opportunistic strategy in finding actors typically actualize: the selections might remain arbitrary and be based on intuitive impressions rather than deliberate reasoning. For instance, hiring with gut feeling against algorithmic recommendations is associated with worse hires, yet matchmakers believe themselves to be better judges of applicants' suitability [22]. Additionally, Rivera [44] found that emotional reactions to applicants are meaningful contributors, in contrast to stances that consider recruiting to be driven primarily by applicant characteristics, such as cognitive skills, social capital, and demographic characteristics.

Overall, matching often brings about conflicts between making deliberate decisions and the available time and ever-changing requirements. In other words, matchmakers struggle between contradictory ideals of agility and holistic, rational decision-making.

5.2 Roles for Systems Supporting Decision-Making in Social Matching

To refine the findings into design considerations for the HCI community, we highlight six potential roles of IT to support matchmaking in recruitment, based on our empirical results as well as prior literature. The identified roles underline central needs and opportunities, and, when possible, suggest computational approaches to support matchmakers to tackle the challenges. In Table 3, we categorize the considerations into two primary categories, which relate to either *cognitive* or *managerial and cultural* decision-making challenges, and map them to the stages of the matching process.

Table 3. Potential roles of IT in relation to the decision-making stages.

	Roles of IT	Stage 1	Stage 2	Stage 3	Stage 4
Managerial & Cultural	1. Increasing awareness of the various criteria.		X	X	
	2. Enabling multi-dimensional matching.		X	X	
	3. Facilitating transparent and democratic decisions.	X			X
Cognitive	4. Bridging different forms of epistemic asymmetry.	X	X	X	X
	5. Helping make sense of and learn from the data.			X	
	6. Finding the balance in diversity and similarity.				X

Our sample of matchmakers had a cautious attitude toward technology that would decrease human interpretation and contemplation in the matchmaking process. The design fictions we presented or the IT systems they had been using in the recruitment process raised questions regarding the appropriateness of the technology. The important aspect regarding the role of technology in the future of matchmaking has not yet been a popular discussion topic in HCI. We believe that IT could assist human matchmakers in several ways: through different kinds of decision support systems (e.g., to reach consensus on the criteria); by providing targeted information on the UI (e.g., using advanced visualizations to highlight various features of people); by being more proactive in giving recommendations about relevant and timely matching opportunities; and ensuring that the stakeholders have up-to-date information and a possibility to revise the criteria in every stage.

5.2.1 Increasing Awareness of the Various Criteria

Making a well-informed decision necessitates seeing how the candidates' qualities are in line with the original requirements, the new requirements that might emerge in the process, and the qualities of the people that are connected to the intended collaboration. Especially in cases where the process lasts long, IT could periodically check if the interests of the candidates, the decision-makers, and the actors who set the original requirements are still coherent. The conventional solutions for online profiling have been proven to fail in delivering up-to-date and contextually relevant information about the candidates [34]. To this end, a system could highlight candidates with incomparable unique qualities that might, for instance, compensate for lacking work experience.

5.2.2 Enabling Multi-Dimensional Matching

Although prior research [28,42] has addressed the need for utilizing more sophisticated and deep-level attributes [5] of the candidates (e.g., personality traits, values, and attitudes). In practice, matchmaking tends to consider mainly surface-level qualities like previous job titles. Key questions are (i) how to find information about the non-obvious but relevant qualities that candidates might have, and (ii) what information is sufficient for a generic profile and with what context-specific profile information should this be enriched in each case. Potential solutions to make the matching decisions more multi-dimensional include, for instance, identification of an applicant's latent qualities through topic modeling of the public documents they have produced in the past and including new, typically relevant factors (e.g., an individual's level of commitment) in the questions the candidates are asked. Previous HCI research has found the need to make applicants' contributions to online services more accessible because of the limited amount of time the matchmakers can spend on one applicant [32]. Moreover, the findings indicate that computational solutions could better support decision-makers by providing means for assessing the qualities of teams instead of the conventional focus on individual qualities. The importance of assessing teamwork qualities has been acknowledged but there are concerns regarding the validity of the assessments [54].

5.2.3 Facilitating Transparent and Democratic Decisions

Matching often means fitting an individual with everyone in the target team. We argue that employing a democratic decision-making process would be ideal in such group-based settings. Therefore, IT could assist decision-makers by involving different team members and stakeholders in the process, thus considering different perspectives to the selection criteria. Groupware technologies such as e-collaborative systems and group decision support systems [55] could be used to gather opinions anonymously and making more transparent decisions. Having said that, it is noteworthy that this study was conducted in a strongly democratic country with low power distance [23]. However, we argue that democratic practices would serve the complex and multi-dimensional decision-making in HR activities particularly well, not to mention their long-term effects on organization culture.

5.2.4 Bridging Different Forms of Epistemic Asymmetry

Epistemic asymmetry is a general challenge that resides between the various stakeholders relevant to a matching decision and hence touches all the decision-making stages. In the early stages of the process, it relates to that between the candidates and the recruiters, while in the later stages it hampers the decision-making within an organization. Considering the gap between the candidates and an organization, they may not even be aware of each other, which is a key reason for the mismatch between job-seekers and vacancies on societal level [3]. Furthermore, they rarely know much about the various qualities and interests of the other party. Our findings imply that IT should support more active interaction and automatic exchange of information between the matching parties and allow expressing oneself in free format rather than forcing to use predefined forms. However, to be able to exchange relevant pieces of information calls for better utilization of existing competence taxonomies as well as development of more specific vocabularies of relevant features in certain domains or professions.

5.2.5 Helping Make Sense of and Learn from the Data

In matchmaking, conventional data sources include, e.g., CVs and portfolios, social media data, and organizations' internal information resources. Interpreting these data to create relevant and manageable representations of competences might become challenging. As the amount of data and number of alternatives increase, the abstraction level tends to raise. To consider how computational methods could help to make sense of the vast data and support decision-making, we underline two data-centric aspects to consider: (i) what is the optimal number of candidates (and amount of information about them) to even consider in each case and (ii) how to analyze the data in a fair way that does not merely optimize for few attributes. Zhou et al., [58] have presented strategies for the decision-maker to be more mindful on when to stop searching, based on the mathematical concept of *optimal stopping*. As stopping early increases the risk of not finding a good applicant and stopping too late the risk of wasting resources, the optimum depends on the organizations' risk tolerance and case-specific criteria. On the question of how to analyze the data, algorithms that often aim to maximize performance have been found to develop unfair biases based on, for example, employee location or gender [14]. This calls for careful consideration on how much responsibility is given to technology and how to avoid such manifestations of *overfitting* in algorithmic solutions. Consequently, the current situation with the tools that are available to recruiters have been argued to be even worse than nothing [7].

5.2.6 Finding the Balance between Diversity and Similarity

The participants seemed to have a collective ideal about being mindful about diversity while making matching decisions. Previous research in the GROUP conference has addressed mainly gender diversity by proposing ways to design for inclusion at the team level [24]. At the same time, in many cases adding diversity is practically challenging and might result in a collision with the practices or culture of a team or the organization, therefore making it risky to pursue. Some organizations have started to consider nonconventional alternatives, such as people beyond retirement age and passive job-seekers, when trying to find people for hard-to-fill positions [38]. Identifying the similarities in the existing work community and seeing how they compare to the potential arrivals would be beneficial for the matchmakers, especially by helping them to explore in which qualities the community would benefit of increasing diversity. Our findings imply that the decision-makers would value a mechanism to recognize candidates who have a unique quality that is not yet present in the organization. Particularly, identifying qualities of candidates who could positively disrupt the existing community could be valuable in various knowledge work activities.

5.3 Methodological Limitations

Understanding the subjective experiences of matchmakers' calls for a rich qualitative account. Thus, the research objectives and practical limitations determined the choice to run an interview study. With a qualitative approach, we aimed at producing in-depth descriptive insights of individual cases and people's experiences of matching, and to identify relevant viewpoints and themes to study in more detail in future research.

However, our methodology choice has inherent limitations on generalizability. The participant sample represents a record of experiences from only one western country, which makes the data culture-specific. Moreover, this study approach did not allow revealing a vast spectrum of matching practices and challenges in decision-making across various kinds of organizations. Nevertheless, as this study did not aim at generalizable quantitative information or comparisons according to various background variables, we considered that the downsides are tolerable. It would be beneficial to run more quantitatively oriented follow-up studies (e.g., an online international survey) to assess the prevalence of our findings in various professional domains.

6 CONCLUSION

This paper contributes social matching as an emergent application area of IT, offering a qualitative account of the decision-making process and perceived challenges in recruiting. Our temporal framework suggests that making matching decisions in recruitment activities can be modeled as a sequential process that calls for deliberation at different stages. In practice, the decisions who to team or partner with were often found to be affected by cognitive limitations and human biases and be suboptimally supported by information technology. Based on interviews of 21 matchmakers, we reveal that many challenges revolve around balancing between a well-informed, thought-through and systematic process, and the practicalities regarding time, effort and availability of the alternatives. Based on the findings, we underline opportunities to support decision-making in this domain with various IT based solutions.

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PUBLICATION II

Understanding Matchmakers' Experiences, Principles and Practices of Assembling Innovation Teams

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Understanding Matchmakers' Experiences, Principles and Practices of Assembling Innovation Teams

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Abstract. The team composition of a project team is an essential determinant of the success of innovation projects that aim to produce novel solution ideas. Team assembly is essentially complex and sensitive decision-making, yet little supported by information technology (IT). In order to design appropriate digital tools for team assembly, and team formation more broadly, we call for profoundly understanding the practices and principles of matchmakers who manually assemble teams in specific contexts. This paper reports interviews with 13 expert matchmakers who are regularly assembling multidisciplinary innovation teams in various organizational environments in Finland. Based on qualitative analysis of their experiences, we provide insights into their established practices and principles in team assembly. We conceptualize and describe common tactical approaches on different typical levels of team assembly, including arranging approaches like "key-skills-first", "generalist-first" and "topic-interest-first", and balancing approaches like "equally-skilled-teams" and "high-expertise-teams". The reported empirical insights can help to design IT systems that support team assembly according to different tactics.

Key Words: Team assembly, Team formation, Matchmaking, Decision-making, Social matching, Innovation teams, Working life, Collaboration

1. Introduction

In knowledge work, organizations' success is increasingly dependent on team work, which, ideally, allows individuals to be more productive and creative than they could be on their own (Salas et al. 2018; Hall et al. 2018; Tebes and Thai 2018). An increasingly common approach to spur innovation capability is to assemble diverse teams that span organizational boundaries (Edmondson and Harvey 2018) and collaborate intensively in face-to-face settings. However, a perennial yet unsolved question is *how* to assemble teams with high chances of success – in particular, what kind of team compositions yield the best results (Bell et al. 2018). Prior research on team formation implies that the assembly phase fundamentally influences the team dynamics and processes that determine how teams achieve their objectives (Levine and Moreland 1990; Mathieu et al. 2014; Bell et al. 2018). While *team formation* more broadly refers to defining a team's purpose, tasks, and rules, according to Gómez-Zará et al. (2020), *team assembly* refers to "the process of searching for, identifying, and choosing members for a team".

Team assembly can be seen to represent one form of social matching (or 'matchmaking'), which as an application area of IT has been conceptualized as computer-aided identification and facilitation of new social connections between people (Terveen and McDonald 2005). In professional life, social matching looks into, for example, recruitment decisions and consideration of team compositions in work life, which both are characterized by high level of complexity and high cost of failure, especially when matching multiple actors (Olsson et al. 2019; Weller et al. 2019). While HCI and CSCW research has explored technological tools for facilitating team assembly (Gómez-Zará et al. 2019; Harris et al. 2019; Jahanbakhsh et al. 2017; Zhou et al. 2018), the important decision of *who should team up* is typically left to matchmaking experts like project managers, or HR specialists. Few digital tools have been adopted in day-to-day team assembly practice to support the identification of fruitful team compositions (Cappelli 2019). Even in research projects, the proposed solutions are often based on self-assembly (Harris et al. 2019; Lykourentzou et al. 2017), where people decide by themselves with whom to cooperate. To this end, this study focuses on experts who regularly assemble teams in various professional and organizational contexts. In this paper, they are referred to as *matchmakers*, even if in everyday life the term often refers to romantic matching.

Furthermore, we focus on the assembly of multidisciplinary innovation teams, which have been also named as "cross-boundary" (Edmondson and Harvey 2018), "cross-functional" (Love and Roper 2009) or "multifunctional teams" (Johnsson 2017). By definition, such teams aim to break boundaries associated with "differences in expertise and organization" in an attempt to solve problems or create new ideas (Edmondson and Harvey 2018). That is, individuals join newly assembled temporary groups with fluid membership, aiming to rapidly develop into high-performing units to take on unfamiliar projects (Edmondson and Harvey 2018). Activities that transcend organizational boundaries in order to share knowledge and create new ideas are often referred to as "open innovation" (Chesbrough and Schwartz 2007; Chatenier et al. 2010). Such cross-boundary innovation teams are relatively short-term (i.e., weeks or months, rather than years) and, hence, differ from long-term teams that are reasonably stable, functionally homogeneous, and typically bounded to one organization.

We consider the assembly of innovation teams particularly challenging and interesting in terms of social matching. First, such type of matchmaking is increasingly common, for example, in regional innovation ecosystem facilitation activities (Gryszkiewicz et al. 2016; Fecher et al. 2018). In this context, team assembly includes complex decisions, such as what features of individuals to consider in the team composition and how to balance the compositions across multiple teams. Assembling effective innovation teams across established organizational and disciplinary boundaries is notoriously challenging because of, e.g., possible conflicting interests among team members and the challenge to find time to co-create ideas with strangers (Rowe et al. 2008; Gryszkiewicz et al. 2016). Further, the context of innovation team assembly provides a sufficiently focused view on the broad topic of group formation that covers a variety of different organizational structures and organic groups (Harris et al. 2019). In contrast to virtual teams, for example, the question of team composition is arguably more central in the context of innovation teams that work intensively in face-to-face settings.

Our key premise is that assembling of innovation teams has become a common activity in certain organizational environments and that certain workers routinely conduct such activities (e.g., team coaches of innovation ecosystems or in higher education). Therefore, we assume that such expert matchmakers have formed certain practices —be they conscious and though-through processes and principles or intuitive habits —to reach effective team compositions (Harris et al. 2019). Considering the technical knowledge interest in CSCW and HCI, the endeavor to develop technology to support such practices calls for better understanding the matchmakers' experiences and practices in this activity context. To this end, our focus is on user research aiming to understand the *experiential* and *tactical* aspects rather than, for example, evaluation of specific technological tools the matchmakers use. Only a few attempts have been made to qualitatively study the decision-making processes (Kale et al. 2019) and the possible roles for information technology to support matchmakers in their decision-making (Koivunen et al. 2019). Thus, we set the following research questions: *(RQ1) How do matchmakers experience the assembly of innovation teams as professional matchmaking? (RQ2) What kind of practices have they established for this activity*?

To this end, we gathered qualitative insight with one-to-one, in-depth interviews of 13 matchmakers who regularly assemble innovation teams in various organizational contexts. We contribute a qualitative account of the matchmakers' experiences, principles and practices, thus shedding light on an emergent, yet understudied professional activity. To the best of our knowledge, empirical research on this topic is scarce, and there is little empirically grounded insight into research and development opportunities for IT supporting the studied activity.

2. Related Work

In the following, we first discuss the research on innovation teams and team assembly approaches, as well as position the activities that have been empirically studied in this conceptual landscape. We furthermore outline the research on computational support for team assembly, also underlining critical gaps between theory and practice.

2.1. Innovation Teams and Team Assembly Approaches

A team implies social interaction between two or more individuals who pursue shared goals or perform relevant organizational tasks (e.g., Kozlowski and Ilgen 2006). The individuals might have different roles and responsibilities and are interdependent regarding the workflow and outcomes of the teamwork. *Teamwork* can be defined as interdependent social interaction between individuals with shared goals and values (Salas et al. 2013). *The team composition* – "a configuration of team member attributes" (Bell et al. 2018) – then affects the behavioral processes, functioning and performance of a team. Prior work posits that in the heart of teamwork are the abilities to, for example, make use of complementary capabilities, monitor each other to reduce errors and shift workload (Salas et al. 2018). Different classifications of team types have been conceptualized based on criteria such as size and structure of the team, or its role, task and lifespan (Hollenbeck et al. 2012). The present work focuses on innovation teams (Johnsson 2017; Edmondson and Harvey 2018; Gryszkiewicz et al. 2016; Fecher et al. 2018) that involve individuals with different backgrounds brought together to innovate new products, services, processes, and systems in the form of cross-functional and cross-boundary projects.

2.1.1. Team Composition

While a body of research covers what constitutes cognitive selection processes (Sadler-Smith 2016), the subjective experiences of intuition-based and deliberate choices in organizational group assembly settings remain poorly understood. The decision-makers in complex and dynamic environments of organizations face a high level of uncertainty (Edmondson and Harvey 2018) due to the inconsistency of organizational structures. This can hinder developing unified strategies for team composition. We argue that the compositions of innovation teams are characterized by needs for considering the possibly different interests of the involved organizations and individuals, and the team's capability to perform and yield results relatively fast. Furthermore, the individuals who volunteer to apply to projects are typically rather early-career than experienced professionals, implying that their competences can be hard to articulate or compare.

In their seminal work, Mathieu et al. (2013) identified six types of team composition decisions (e.g., staffing a new team and simultaneously staffing multiple new teams). Relevant to our work, forming new teams can follow different principles when assembling a single team vs. multiple teams (adopted from Mathieu et al. 2013):

– *Single team formation* refers to forming a team with the optimal combination of all team members;
– *Multiple team formation* refers to forming multiple teams with the optimal combination of all team members;

– *Reconfiguration* refers to forming multiple teams by reassigning or assigning multiple team members. Within a team, the operations include simply an addition, a subtraction or a replacement of a single member.

Team composition has been empirically linked to innovation (Richter et al. 2012), and different approaches can be considered when assembling teams for innovation projects (Somech and Drach-Zahavy 2013). For instance, *aggregated individual creative personality* is a summative approach where people with the ability to generate many alternative solutions to an open-ended problem are teamed up. Another approach is to team up based on *functional heterogeneity* – matching people from different disciplines and functions who have domain expertise. Notably, Hackman and Katz (2010) suggested that aggregating individual attributes would not predict the team's characteristics.

Furthermore, approaches can be classified into *individual-based* and *team-based* approaches (Mathieu et al. 2014). While the first focuses on individual qualities with teamwork considerations (e.g., communication skills) and person-position fit, the latter is more holistic and aims at balancing distributional qualities of a team and complex mixing of individuals. Both strategies can utilize the traditional human resource *KSAO framework* – Knowledge, Skills, Abilities, and Other characteristics (Jayne and Dipboye 2004). In practice, team composition decisions usually consider both individual and team level KSAOs (Bell et al. 2018). In addition, a role-based approach called *Belbin team roles* has been developed to classify individual team members with specific work roles, such as coordinator, implementer and finisher. Such approach aims to help matchmakers to compose a group of people with complementary qualities (Belbin 2012).

A recent study investigated how team members are assigned to projects (Sankaran et al. 2019). Accordingly, on individual level, the importance of knowledge and skills is emphasized. Furthermore, interpersonal skills, capability of being a team player and ability to take leadership are considered even though they are hard to identify. A study by Sankaran et al. (2019) focused on long-term projects where new members are able to flexibly join and leave the project. In contrast, in our context of innovation teams, time-critical project teams are fully composed from the start with people who have applied to be part of the project. This is particularly important considering the way the teams are built, since talent often needs to be spread in a meaningful way across the teams.

Highly relevant to the present work, Hastings et al. (2018) used a team formation tool called CATME to compare criteria-based strategies with a random strategy. Surprisingly, they did not find differences in team performance or satisfaction under the tested conditions. The results contrasts with prior literature in terms of the relevance of team composition in the first place, and the authors discuss several possible explanations for this. First, the results might be influenced by an expectation effect caused by the students believing that all teams were created using the tool. The context was also acknowledged to differ from prior research (i.e., two computer science classroom courses). The tool stacks multiple criteria together, which means more complex compositions (8 or 13 criteria used to form teams, respectively). Alternatively, the CATME tool might have been ineffective; the authors found that the tool did not always match the instructors' mental models regarding how skills ought to be distributed across teams. All in all, while the results may seem to suggest random assignment as a valid strategy, the authors themselves draw rather cautious conclusions. More importantly, the result suggests that instructors should not be so concerned about fine-tuning the configurations of a team formation tool. In our context and study data, we did not find that similar tools would be used. Rather, our findings highlight several handwork based approaches when assigning applicants to teams. Furthermore, the study indicates gaps of knowledge in terms of authentic settings of team assembly, also beyond the context of classrooms. The context of innovation teams arguably differs from that of classrooms, calling for further exploratory empirical research.

2.1.2. The Role of Diversity in Team Assembly

The importance of heterogeneity of individuals' qualities is much discussed in literature. For example, the diversity of levels of expertise, skills and abilities can contribute to higher chances of knowledge breakthroughs and innovation (Baker 2015). Essential differences in human qualities include, for instance, *surface-level* (e.g., age, sex, ethnicity), *behavioral* and *cognitive* (e.g., personality traits, abilities, values and attitudes) differences (Haythorn 1953; Bell et al. 2018). According to the meta-analysis by Hülsheger et al. (2009), there seems to be a positive relationship between diversity in task-related attributes (e.g., profession, education, knowledge) and innovation. More specifically, composing individuals with dissimilar technological knowledge tends to improve creativity (Huo et al. 2019). It has been addressed that the individuals' innovation capability (Sun et al. 2017) and demographic diversity (Tshetshema and Chan 2020) drive the innovation team performance. However, prior research tends to omit the multifaceted nature of team composition, assuming that each team member possesses only a single quality or skill that contributes to the teamwork (Huo et al. 2019; Harrison and Klein 2007).

In summary, even though there is a large body of research regarding the effects of the diversity of individuals' attributes on team work functioning, the question of how to optimize the various personal qualities is less studied. This is for a good reason: the multitude and complexity of different qualities and actors in dynamic team work makes it very challenging to identify an optimum. While existing research tends to focus on relatively stable teams (Bell et al. 2018), the question of how the matchmakers deal with the optimization problem in the assembly of innovation teams remains understudied (Gryszkiewicz et al. 2016). Therefore, it is relevant to study experienced matchmakers' perceptions regarding this question.

2.2. Information Technology Assisting Team Assembly

We subscribe to Salas et al. (2018) who call to "address issues with technology to make further improvements in team assessment." They note together with Tebes and Thai (2018) that individuals should be involved in the research process to approach real-world problems and close the gap between theory and practice. In general, it seems that prior research on matchmaking for team assembly in workplace settings is limited—especially considering the context of innovation teams (Gryszkiewicz et al. 2016; Fecher et al. 2018) and generally the appropriateness of matchmakers' computational tools (Cappelli 2019).

In HCI and CSCW, computer-aided team assembly approaches have been classified as follows Jahanbakhsh et al. (2017) and Harris et al. (2019): *(i) Self-assembly*, meaning it is up to individuals to select cooperators (might include computational guidance or advice); *(ii) criteria-based*, that is, matching is automated by algorithms and performed according to fit of the individuals' qualities. A systematical review of the CSCW literature on team assembly (Harris et al. 2019) reveals that the majority of prior research on group assembly technology is focused on individual perspective where group membership comes with mobility and low cost. Recently, Gómez-Zará et al. (2020) proposed a taxonomy for existing team assembly systems based on user's agency and participation. The two dimensions manifest in four types of teams: self-assembled teams ("users assemble their own teams on the system"), staffed teams ("the user establishes the team formation criteria on the system"), optimized teams ("the system assembles teams based on defined criteria and the user's input") and augmented teams ("the system augments users' teammate choices"). For example, in staffed teams the user agency and participation are both high. Examples of such systems include TeamBuilder (Karduck 1994) and a sales team builder (Alkan et al. 2018). This article covers two important aspects that Harris et al. (2019) raised in their review: (i) how to deal with the imbalance of individual expertise in teams; (ii) how to consider the effects of technologies on team member attributes, group structures, task characteristics, and the context.

2.2.1. Self-assembly

Research in HCI and CSCW has focused on assembling teams online on digital platforms. For example, team assembly that happens in the context of Massive Open Online Courses (MOOCs) or virtual environments for distributed collaboration (Wen et al. 2017; Walton et al. 2015). Interestingly, a variety of studies have been conducted on compositions and effectiveness in the context of eSports (Alharthi et al. 2018; Kim et al. 2017; Freeman and Wohn 2019). The context of eSports is an example where team assembly is typically based on self-selection. Players search for a suitable group based on available information that includes data on (i) instrumental qualities (the competence) and (ii) cues about social skills that would increase the likelihood of team success (Freeman and Wohn 2019).

Furthermore, the self-assembly approach has been utilized, for instance, by Lykourentzou et al. (2017) who introduced the team-dating technique for ad hoc team assembly. The users had short dates to evaluate other users and data could be later used to automatically create more effective teams. In a similar vein, custom-tailored chatbots have been proposed to elicit in-depth information about a team member's personality in order to learn about individual preferences before teamwork (Xiao et al. 2019). Recent study on individual characteristics (Gómez-Zará et al. 2019) showed that especially bridging and bonding capital influences people in the selection of potential teammates, meaning that it is likely that an user invites someone that s/he is already familiar with.

2.2.2. Criteria-based Team Assembly

A variety of HCI research is focused on evaluation of existing criteria-based team assembly tools. For example, Jahanbakhsh et al. (2017) studied CATME – a Comprehensive Assessment for Team-Member Effectiveness, which can be used in university courses. The authors investigated perceived strengths and weaknesses of an automated team assembly tool from the perspectives of both the students and the instructors. The instructors were able to select a set of criteria based on what they believed were the most appropriate for their academic course (e.g., working style and demographics). They felt that the tool increased efficiency and leveled the playing field. Frequently a student's interpretation of what criteria should have been used did not match with what the instructor ended up using. As an idea for improvement, instructors called for better guidelines for configuring the criteria and a possibility to engage students in selecting which criteria are used in the tool. Furthermore, Hastings et al. (2018) showed that multi-criteria configurations in CATME do not achieve stacked benefits.

In contrast to the prior research with a system evaluation approach, we are interested to take a more user-centric approach and understand the matchmakers' team assembly practices and experiences. It seems that prior research has not been able to motivate the technology development with the matchmakers' actual needs or practices. Instead, the research motivation often comes from a general observation that effective teamwork is ever more important and, therefore, new tools for optimizing the selection are worth pursuing. We argue that this approach does not sufficiently consider if and how the tool offers an appropriate support in matchmaking. The present study aims to provide insight into what kind of qualities or criteria are typically sought to further understand the matchmaking process and enable design of next-generation matchmaking tools.

3. Methodology

We conducted altogether 13 in-depth, face-to-face interviews of professionals who regularly assemble innovation teams. The interviews were semi-structured by nature, featuring a broad array of open-ended questions. Twelve interviews were conducted at the workplace of the participant and one at university facilities.

3.1. Participants and Recruitment

The participants were recruited from different institutions in Finland, which is the cultural environment that the authors are most familiar with. Relevant candidates were identified based on their online profiles, such as LinkedIn, and further invited via email. Some of the participants helped us to find more potential interviewees by recommending people they knew in other organizations (i.e., snowball sampling). As an extra incentive, each participant was granted two movie tickets (worth 30EUR) after the interview. One interview was conducted in English with a native English speaker (P2), while the rest were conducted in Finnish.

Eleven participants were matchmakers at private sector organizations that look for voluntary people (primarily but not exclusively Master students) to join multidisciplinary innovation projects. One of the participants was developing technology to support team assembly, and another served as a coach for managerial people who assemble and work with organizational teams. The context of the matchmakers' work mainly relates to nationally well-known innovation platforms or innovation labs (*Demola Global*[1]*, Smart Campus Innovation Lab, Sitra*[2] *and Y-Kampus*[3]). The projects are generally set up to look for innovative solutions to loosely defined challenges, specified by local organizations in need of fresh ideas (Gryszkiewicz et al. 2016; Fecher et al. 2018). In practice, all the interviewees were involved in forming multidisciplinary and knowledge-intensive innovation teams.

In general, the participants have established a strong professional track record in relation to team assembly activities, as depicted in Table 1. The *experience* column refers to the number of years spent in the organization or around relevant activities or the number of projects the person has assembled. One participant did not disclose how much experience s/he had but it is safe to say that all the participants do the kind of work that is closely related to team assembly. A few of the participants were not actively assembling teams at the time of the interview yet they were still working closely with or for people who assemble teams on a regular basis.

Generally, assembling teams and related activities are key parts of the participants' duties. Their typical tasks include project topic specification, attracting and gathering a pool of potential team members, and the comparison and selection of the applicants. In this sample, the target size of a team typically varies from four to eight people. The nature of innovation projects often calls for recruiting people

[1] https://www.demola.net/
[2] https://www.sitra.fi/en/
[3] https://www.y-kampus.fi/en/

Table 1. Overview of the participants and their experience in matchmaking for innovation teams.

ID	Role regarding team assembly	Experience
1	CEO of a company developing an application that matches people into teams within an organization.	∼10 years
2	Innovation platform facilitator who assembles teams for higher education innovation projects.	1+ year, 8-9 innovation projects
3	Creative director. Responsible of the development of project teams on organizational level; involved in team assembly for higher education innovation projects.	7 years, 100-200 innovation projects
4	Director of digital development. Used to assemble teams himself for higher education innovation projects, and now consults others.	100-150 innovation projects.
5	Coach of team leaders and managers.	3 years
6	Innovation platform facilitator who assembles teams for higher education innovation projects.	1+ years, ∼20 projects
7	Vice president. Formerly a matchmaker in a company that organizes innovation projects for higher education students.	6 years, 200+ projects
8	Team coach. Coordinates innovation projects for higher education, also covering team assembly.	2+ years, 10 projects
9	Involved in team assembly of multiorganizational innovation teams that focus on societal challenges.	N/A
10	Team coach. Mainly guides innovation teams but also has assembled teams in the context of higher education.	9 years, 2 projects
11	Designer. Assembles and coaches higher education student teams.	10 years, 200-250 projects
12	Assembles and mentors higher education teams that, e.g., aim to organize an annual innovation event.	11 years, 20-30 projects
13	Facilitator who assembles teams for higher education innovation projects.	Less than 6 months, 3 projects

with technical, design, and business skills and, importantly, domain knowledge about the project topic. Typically, several project teams are set up at the same time. The applicants can apply to one or more projects but the matchmakers would typically consider all applicants for all projects. The projects typically last from two to four months and are part-time engagements for the team members.

3.2. Data Gathering and Analysis

After filling in the consent form, the interviews started by asking about the participants' activities related to team assembly and their experience in doing that. A central theme was their typical practices in team assembly. They were inquired, for instance, how the team assembly is predefined and what kind of criteria they use. To make the discussion well-grounded in real practices, we asked them to give concrete examples on typical team assembly processes. The interview structure also covered topics related to the information matchmakers use for matching, and how they obtain it. Other questions addressed how they assess the qualities of people and on what basis they match people together. The role of technology, the perceived challenges in the decision-making and subjective definition of a successful team or project were also addressed throughout the interview.

All the interviews were audio recorded and transcribed verbatim. The interviews conducted in Finnish were fully translated by the first author to English, however shortening some parts of the quotes for clarity and brevity. The average length of an interview was 74 minutes (min. 52 minutes and max. 113 minutes). With altogether 93,051 words of transcribed material, the interviews provided a rich textual data set that we analyzed using the Atlas.ti software. We employed a constructivist Grounded Theory oriented analysis. First, we recognized relevant team composition related themes and conducted initial open coding while reading through the data line-by-line. We then linked related themes producing large conceptual maps and networks of codes (i.e., axial coding). Finally, we used focused coding to synthesize data. We ended up with a set of codes with the most analytical power and organized them to our Findings. The coding was primarily conducted by the lead author using Atlas.ti, periodically being challenged and enriched by a senior scholar. The senior author participated in all stages of research except conducting and transcribing of the interviews. We organized meetings in every stage of the coding where we discussed individual codes, made clarifications to our categories and decided which would be the most interesting themes to report.

4. Findings

While conducting the interviews, it became quickly clear that the role of IT in the studied activity was rather minor, mainly confined to collecting the volunteering participants' resumés and communicating with them. This observation consolidated our decision to focus on team assembly as decision-making in terms of social matching, regardless of the IT tools in use, rather than analyzing the use of very conventional tools like Microsoft Excel. We organize the results according to three main themes: team assembly as a decision-making practice, team composition including different approaches, and relevant individuals' qualities in this type of teamwork.

4.1. Team Assembly Includes many Decision-Making Challenges

The participants perceived that a volunteer-based innovation project gives plenty of freedom in deciding who could work together, hence enabling collaboration also between people who normally would not collaborate. However, while most participants had pondered how to optimize the teams in different respects, in practice the selection process is naturally limited by the number of voluntary applicants. Also, the higher the freedom of choice is, the more challenging the comparison and decision-making becomes. Several participants recognized that they face challenges with the sheer amount of information that comes with the applications: one would ideally familiarize oneself with every application before making the final selection. At the same time, some matchmakers have to assemble the team from a small number of applicants and with straightforward selections without having time for a detailed comparison phase.

In addition to matching individuals with each other, also the project-applicant fit needs to be considered. The participants pointed out that they need to consider the applicants in relation to the project requirements from two perspectives. First, if it is practically possible, one considers the potential roles and responsibilities on the team-level. Second, one needs to match individuals' qualities also with the project's particularities. Typically, one would form an educated guess on what type of background or studies are needed in a particular case based on the topic of the project. At the same time, the participants were cautious not to fix an applicant to a certain role. Consequently, project-applicant fit is about balancing between making an educated guess in order to have predictability and giving participants room to surprise.

> "I do think about roles at some point but I do not think like "s/he is probably going to be the project manager" [...] I do not want to think that this person is the one who develops the most unique ideas or this person is the one who is able to create the first lines of code." (P13, speaking of a higher education innovation project)

4.1.1. Taking Risks to Reach an Unreachable Optimum

In order to maximize a team's innovation potential, the matchmakers pointed out their willingness to take what they perceived as bold risks. P4 explained that he had changed his team assembly approach from tightly drawn criteria regarding fulfilment of key skills to making as ambitious combinations of people as possible. In practice, the ambition manifested as high diversity of educational backgrounds, ages and cultural backgrounds. In such cases, the participant mentioned to be aiming at enabling radical innovations rather than incremental innovations. By making seemingly surprising choices, so-called wild cards, they could optimize for high potential for novel solutions.

> "I make quite a lot of provocative choices, so I dare to pick anything, provided that the team dynamics works and some very interesting avenues are opened. Even absurd combinations. This has almost turned to personal challenge seeking." (P4, speaking of assembling teams for higher education innovation projects)

In a few interviews, the matchmakers highlighted that they get pleasure from making risky choices that turn out to yield great results. The riskiness referred to, for example, combining people that do not have substance skills relevant to the project topic or being unsure if the applicants are motivated enough. It is noteworthy that the nature of innovation projects allows taking risks and more freedom from the fear of making mistakes, when compared to other forms of matching, such as recruitment. The most experienced matchmakers said to have developed self-confidence that allows them to try new compositions and make quick selections based on intuition. In other words, the matchmakers try to balance between maximizing innovation potential and making overly ambitious, i.e., practically dysfunctional team compositions.

> "There have been surprises. For example, in one case, we were a bit unsure of the motivation of a person. Would she shine or could she even quit at some point? We took a risk and selected her. She has proved to be marvellous regarding her attitude and is doing things with a big heart and enthusiasm." (P12, speaking of selecting somebody to a higher education team)

There is no ultimate answer regarding the perfect team composition. The optimum was regarded as a moving, even unattainable goal. The ambiguity of an optimum in team compositions is also explained by the dynamics within an innovation project. For instance, the success of one team member might depend on whether another team member will succeed. Over the life-cycle of a project, the team members might have different responsibilities at different stages of the project, which also changes the criteria for the optimal composition. Overall, this ambiguity led to expert matchmakers being able to justify almost any team composition based on some criteria, as demonstrated by the quote below.

> "You can assemble any kind of team and justify it by saying that it is what it is because of this and that [...] Basically we can make this type of decisions on any basis." (P4, speaking of the uncertainty related to team assembly)

4.1.2. Matchmakers' Awareness of their Selection Biases

Some rare occasions of matchmaking were said to be very straightforward, the matchmakers would use a score-sheet and give points to the applicants in different phases of the matching process. In this case, the phases typically include screening an application, face-to-face interviewing and group-based interviewing. The matchmaker gives points based on the perception of whether the applicant gives a positive or a negative impression at each phase. One participant pointed out that the key factor they try to spot in such situations is whether the applicants have negative attitudes or other potentially adverse factors on the team dynamics, that is, significant hindrances or barriers for the project success.

The straightforward approach to decision-making was, however, considered to come with the cost of biased decisions. Many matchmaking decisions and candidate evaluations were said to be largely based on intuition. The process resembles availability heuristics where sought features of people are recognized based on the matchmaker's previous experience in working with teams that aim for innovation.

Many of the participants said to be able to scan a profile of a person without reading every piece of information. In other words, rather than using a strict criterion, they tend to lean on expert intuition. In many cases, a quick scan meant glancing through demographic information and the motivation letter, which were typically requested from the applicants. While it was noted that experience in matchmaking creates trust to confidently make quick decisions, it was also seen to render the decisions hard to justify rationally. Notably, and in contrast to other matching activities, assembling multidisciplinary innovation teams is characterized by the possibility and often by the necessity to make quick decisions.

Especially familiarity between the matchmaker and a potential applicant divided opinions. For example, applicants who have shared connections with the matchmaker might have an advantage in the matchmaking process. On the positive side, matchmakers look for people who they can trust to become valuable team members. Sometimes there is an opportunity to select people who are known to be accomplished team workers, based on being familiar with the persons. On the other hand, familiarity introduces a bias to the selection, hence the matchmakers were often consciously trying to avoid favoring or discriminating anyone.

> "I have included someone in the team because I knew her/him only to be very disappointed by that [...] I try to put less weight on it (familiarity) than I have in the past [...] Every once in a while, they think: "oh, I know the instructor, I can just breeze through this." (P2, pondering on including a familiar person to a higher education innovation project)
>
> "Of course, I am a human and if I see that we have a mutual friend and I call her/him and ask how do you know her/him. What kind of a person is s/he? How did you meet?" (P7, speaking of the effect of having shared contacts)

4.2. Optimizing Team Composition in Practice

A recurring theme in the interviews was that there are various unpredictable and practical reasons why team members are unable to work well together. The practical reasons could include differences in language skills, challenges in matching schedules to work together, or physical distance between the team members. While such challenges are well known, it is hard for a matchmaker to prepare for them in the team assembly. On the other hand, matchmakers can have an influence on the team so that the members on average have the capabilities to complete the tasks. While some team members can contribute more than the others can, the matchmaker has to make sure that the work tasks can be balanced in a fair and meaningful way.

4.2.1. Principles in Relation to Heterogeneity

In most technology-oriented innovation projects, the matchmakers perceive that an optimal composition requires involving people from complementary fields or disciplines. The participants emphasized that while technical skills are very important, there should be enough diversity among team members, for instance, on the level of experience and values. Particularly, it was evident that there is a distinction between people who are capable of producing a prototype and people who are oriented towards producing user insight.

> "If we start from having six people, I would like to have maybe four who really have some skills regarding technology [...] There needs to be... architecture skills or something that enables to design the thing [...] If there are only technical skills, it easily becomes like a job gig." (P13, speaking of team composition in higher education innovation projects)
>
> "Let us say that we launch two projects and in one we need strong engineer skills and in the other we definitely need social science students. Still, we want people from social sciences to the engineering projects and engineers or people with technology skills to social science projects." (P3, speaking of diversifying higher education innovation projects)

Regarding an individual's readiness to work in heterogeneous teams, one matchmaker was concerned that the team could lose some of its innovation capability if it includes a person who has previously only worked in teams with similar backgrounds of the members. The ability to work in heterogeneous teams was thus considered a skill to investigate in the team assembly. Furthermore, an interviewee who had worked in cross-organizational innovation projects reflected on the manifestation of diversity beyond demographic differences. For instance, multisectoral cooperation and bridging is important, i.e., the inclusion of both government and municipal stakeholders and the private sector. In addition, it is possible to increase diversity of viewpoints by including people from different organizational levels in a hierarchical organization. Variance in terms of expertise or experience also has potential to increase diversity. Overall, innovation projects were seen to allow bringing together people who would not otherwise meet due to hierarchy and lack of flexibility and cooperation between institutions.

> "To be able to utilize multisectoral cooperation, you need people from governmental and municipal sectors [...] In addition of having different sectors represented, we try to find different people from the upper management, people from the middle management and workers." (P9, speaking of multiorganizational innovation teams that focus on societal challenges)

4.2.2. Approaches in Team Assembly

The participants elaborated on different approaches to assemble a team by giving various examples. A common way is to build the team around one seemingly very suitable applicant. In the case of student-based innovation projects, the only requirement the matchmakers could identify for team assembly is to include one or two people who are knowledgeable about the project topic. In a typical case, applicants are added to the team one by one where each addition provides a new angle to the project topic or complementary value in relation to the already selected team members. Some matchmakers had the opportunity to use a computer software that enables drag-and-drop type of team building.

> "The most common way is that we first check the whole list and if we find a gem that is a great match to the profile we are looking for, we take her/him and start to check other people around her/him. [...] In most cases, we start from a couple of people who have competence regarding the project topic or people who act as "glue" – meaning people who could work with anyone." (P4, speaking of arranging approaches in higher education innovation teams)
>
> "If a project has a technical aspect, (it is important to) make sure that there will be one or two people who can speak about it before making sure that the rest of the project team is filled." (P2, speaking of arranging approaches in higher education innovation teams)

For the most of our participants, several teams would be assembled at once, to work in parallel during a predefined project period. Here, team assembly can be seen as a zero-sum game where it is necessary to consider whether to aim at several equally skillful teams or a few great ones. To this end, one approach is to aim for balanced and equally competent teams. In this case, matchmakers would continuously look for balance across the teams by using their judgment and various criteria. The participants described their thinking in typical matchmaking situations:

> "I might (first) take all the business students, look at their motivations and distribute them across (groups), and then look at all the social sciences students and figure out how to distribute them. That way we could get well-rounded teams." (P2, speaking of balancing higher education innovation teams)
>
> "If we think from the viewpoint of the team, it might not be enough that you have every specialist of a certain topic in the same place. No, it is more about how they work together and how things like trust and empathy work... things

that relate to the interaction, they are much more important than how smart they are or how good they are in their work." (P5, a coach of team leaders and managers)

In contrast to the above-mentioned approaches, some matchmakers mentioned to have used an approach that could be considered the opposite, however less popular according to our data. That is, a matchmaker can prioritize some teams or projects over the others and create teams that have, in principle, higher potential to yield good results. However, the interaction among team members and the previously mentioned soft skills should still be considered.

"We also assemble teams that can be thought as, using interior design vocabulary... if we have six valuable pieces of furniture that cost 2000 per piece, they usually work together no matter what because they all are pieces of art. So (it is) a team of super people. Their communication might not be great as a team but they are able to produce something, because everyone is capable of doing something special." (P4, speaking of assembling higher education innovation teams)

Along the same lines, some projects and team assembly cases might be given more effort or better tools, for instance, because the project partner pays extra. In other words, the business model of the innovation platform could also set priorities to the matchmaking process. Such mechanisms set the teams in unequal positions from day one, whereas a common value in education is to provide more equal opportunities across the population.

"When there is a student who would fit to every project, we have to think from the perspective of the client. If we have a client who has bought a package of four projects [...] compared to if we have a small company that is doing their first experimental project or has had the opportunity of a free project (with us). For the big, older clients, we prefer these "safe options" (people who are the most likely to succeed)." (P3, speaking of higher education innovation projects)

A risk for an approach where team dynamics are not that much in the focus is that the people might not be able to effectively work together. It is easy to agree on that in the short-term, there is no room for conflicts between team members. The interviewees pointed out that strong-minded people sometimes clash in teamwork. However, it was also noted that it is very challenging to identify such individuals or combinations in the selection phase. One way to identify determined people could be to check whether the applicant has been really active in the past.

"I personally think that it does not work if everyone is really eager and wants to be the leader. Moreover, if everyone is really determined, it does not work either. There needs to be a balance." (P6, speaking of leadership qualities in higher education innovation projects)

4.3. Principles Regarding Individual Qualities

Identifying and describing one's skills and strengths can be challenging for anyone, let alone students who are only building their professional identity. Hence, the applications often remain on a very general level, often not helping the matchmaker to consider the combinations. This also brings forward the challenges related to impression management and the role of the technology between the matchmaker and the applicant. Currently, electronic applications for the projects typically favor the applicants who are good at expressing their skills and qualities in written form. After all, other forms of communication, such as speech and video, are typically not supported.

> "In theory, it is not even required to know what your [the applicant's] skill levels are.[...] A skill can be very limited. The clearer and more concrete it is the better. It is a bit of an art form and it easily becomes nonsense. It is an advantage if the skill is potentially usable in other projects as well." (P1, a CEO whose company is developing an app that matches people into teams within an organization)

4.3.1. Social Interaction Style Typically Matters the Most

When asked about the applicants' most important qualities, many matchmakers highlighted the abilities related to communication and self-expression. All project members need to be ready for close-knit teamwork and brainstorming. Therefore, they need to be not only capable of discussing the project topic but also willing to share something about themselves in order to build trust. The team members are also expected to be able to provide constructive feedback to each other and give a chance for others to explain themselves. The ability to communicate was stressed especially in relation to the beginning of the project when the team needs to map out the current level of understanding in the team. However, and more importantly, such qualities were said to be very challenging to identify and compare based on the applicants' resumés or even based on a group interview. According to the interviewees, focusing on the hard skills and motivation letters hinder making well-informed matching decisions but they had few ideas on how to mitigate this dilemma.

Regarding the working and interaction styles, the matchmakers reported a few differences that could be used to categorize individuals. For instance, an applicant might like to work on complex tasks that consider the big picture, while another prefers dividing the work into smaller and more concrete and attainable tasks. One might get excited by problem solving and brainstorming in the beginning of the project, while others might prefer grinding and doing more profound research. Matchmakers noted that the applicants differ in how much time they spend pondering, however, this might not predict success. Nevertheless, similar to the communication abilities, the matchmakers emphasized that they struggle to derive any insight on the way of working and interaction styles from the applications.

> "For some, the grinding phase is very suitable but they would need something more for the beginning. If there is an unclear problem-solving task in the beginning, they might get frustrated. On the other hand, some people might be like "we will do this and that" and the others can continue from there." (P10, a team coach who guides higher education teams)
>
> "Some people quickly volunteer information [...] whereas others sit, ruminate about it for a bit, think about it and only after they get a concrete idea, they put it out like "should we do this?" and that is usually the best option." (P2, speaking of individual differences regarding interaction styles in higher education innovation projects)

One matchmaker explained her thinking regarding the mismatch between the educational background of an applicant and the project topic. In such cases, there is typically some other reason, such as hobbyism, explaining why the applicant wants to join that specific project. Therefore, it is often perceived as a sign of creativity and courage if one applies for a project with which their skills or interests do not directly match. Especially if one is able to argue why their skills are relevant to the case, it indicates skills relevant to innovation projects.

> "If a geo-engineer wants to look at software, I have no idea why. But if they really want to do it, there must be a reason. Let us find it out. To me that is fascinating, I love the notion of apparent misfits." (P2, speaking of multidisciplinarity in higher education innovation projects)

4.3.2. Using Third-Party Tools to Model Behavior

During the interviews, the participants elaborated on using some third-party services to help their work. Particularly, the participants had mixed opinions about the so-called Belbin team role test (Belbin 2012). Measuring of personality or other individual qualities was seen as ethically questionable and potentially limiting a team member's thinking about their role. If such tests are conducted, it is important to consider how the results are communicated and to whom. On the positive side, profiling personality could help to identify what would be an ideal environment for an individual, and the team role test could also be used to verbalize the differences within a team.

> "We do not apply it [Belbin test], because the interpretation of the results is difficult and how can you tell the person the results in a way that it is useful and not harmful? Whatever measures you are using to classify people and put them into boxes, it easily becomes like "you are always like that" and "you are always in the corner". Alternatively, people get behind it like "well, I am always like this, I do not have to learn." (P5, a coach of team leaders and managers)

> "I think Belbin is good, because it gives vocabulary to the students to talk about the differences, different ways to work in a team." (P11, speaking of higher education innovation projects)

While the need for more detailed profiling of the applicants was evident, many participants felt that the matchmaking process should not be made too heavy by, for example, adding personality tests. This introduces an interesting contradiction and a need for making trade-offs between comprehensively analyzing the suitability of an applicant and keeping the application process light and the matchmakers' decision-making practically manageable.

5. Discussion

This study asked how matchmakers experience the assembly of innovation teams as professional matchmaking and what kind of practices they have established for this activity. In sum, the interview study highlighted many considerations in this challenging matchmaking activity—ranging from alternative approaches to selection and team heterogeneity to various soft skills and selection biases—and indicated that IT indeed plays an insignificant role in it. The decision-making in selecting candidates to teams and thinking about the compositions seems to include much ambiguity, and it is hard to establish clear optimums to aim at. The matchmakers want to avoid biased decisions and try to make deliberate decisions, yet, at the same time, they also noted that rationalizing whether a decision was good or bad is very complex. While they were tempted to generalize their opinion based on the background or other attributes of the applicants, they might even overcompensate in fear of making biased selections. Furthermore, achieving optimal team composition was not seen as an attainable objective by the most of the matchmakers, at least with current tools and processes. As the projects are often loosely defined and the requirements for the outcome of the team-work are flexible, it seems relatively easy to find positive aspects and consider a project successful.

The context of innovation seems to condition matchmaking in different ways than other types of professional life matchmaking processes, such as recruiting or team assembly within an organization (Koivunen et al. 2019; Holm and Haahr 2019). For example, the interviewed matchmakers generally seemed less limited by predefined selection criteria or decision-making processes. Hence, they were able to try to maximize innovation potential by courageously composing diverse teams. At the same time, they tried to ensure the functionality of the team by including team members who seemed likely to quickly be able to work together, for example, by examining the educational backgrounds of applicants. The matching decisions on innovation platforms inherently face high levels of uncertainty that prevent completely unified and consistent approaches to team assembly. For example, it is hard to predict what kind of applicants will apply and, consequently, to foresee the possibilities for optimizing the compositions. Taken together, it seems that team assembly in this context has unique challenges, which implies that it is indeed meaningful to differentiate between different types of team assembly according to the context of operation and the purpose of the team.

Despite the apparent lack of suitable IT tools, the participants were generally optimistic that technology could have a bigger role and help partly automate and scale up the decision-making. IT could arguably support decision-making especially considering inexperienced matchmakers, also not forgetting the chance to reduce the amount of manual labor and cognitive load that is required especially when there are several teams to assemble at once. While the studied matchmakers used information technology relatively little, we recognize its potential in increasing objectivity in matchmaking, as will be further discussed later in this section.

5.1. Tactics in Innovation Team Assembly

A specific opportunity that we identified for formalizing the qualitative findings relates to the different tactical approaches that the matchmakers had established over time. Even if not necessarily discussed explicitly, the participants seemed to stress certain mindsets or priorities when discussing how team assembly can be approached. As shown in Figure 1, we identified different *arranging* and *balancing* approaches (here termed as *tactics*) that the matchmakers followed on three levels of decision-making. Mathieu et al. (2013) provide a good outline of the various team composition decisions, which we extend with empirical understanding of concrete tactical approaches in context of assembling innovation teams.

The levels refer to variance in terms of what entities the matchmaker is primarily considering and optimizing the compositions for: one individual, one team, or multiple teams to be working in the same organizational context. As our study implies that matchmakers often need to assemble multiple projects at the same time, the question of alternative tactics becomes particularly salient. This practice is common in the so-called innovation platforms with an open enrollment process where a matchmaker assigns or recruits people to teams from a large pool of people (Gryszkiewicz et al. 2016). Furthermore, the matchmakers often followed the so-called sequenced selection strategy (Mathieu et al. 2014). It seems that there is often a critical function in a team and matchmakers seek to fill that role first with a key skill person or a generalist. A person with substance knowledge about the topic of the project or one who can serve as social glue is a desirable candidate around whom to start building the team. After this, it was found common to try to find people with complementary skills in relation to the previous selection(s). In practice, this tends to become a sequential process where the matchmaker adds one person at a time to the team, typically considering the suitability of an applicant only in comparison to previous choices.

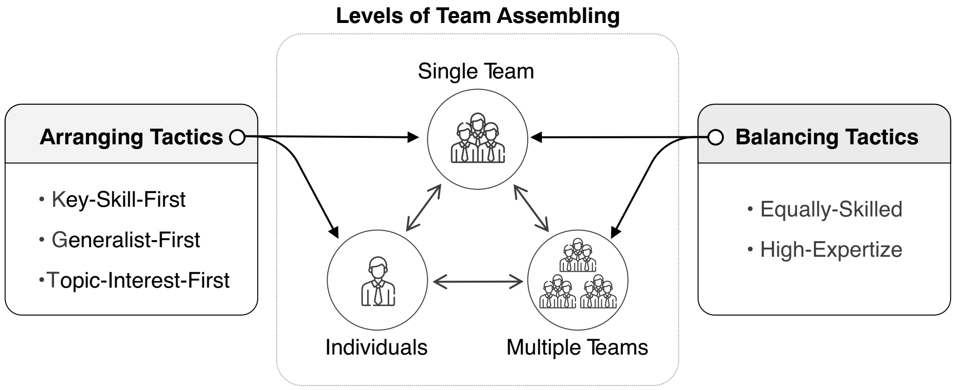

Figure 1. Different levels of team assembling and tactics. The level of decision-making defines which tactics may be applied.

Arranging tactics are typically present at the levels of selecting individuals and assembling a single team. Here, a matchmaker can start building a team by following the *key-skill-first* tactic, prioritizing individuals with key substance attributes, such as domain knowledge or crucial skills needed in the project, in the selection. The *generalist-first* tactic refers to selecting a teamwork player or social glue person who is, for example, likely to ensure effective teamwork due to their broad general knowledge. Finally, a matchmaker might prioritize applicants who have specified topics of interests that match the subject of the project (*topic-interest-first* tactic).

Balancing tactics come into play when assembling multiple teams simultaneously. *Equally-skilled* teams tactic aims to balance the multiple teams regarding their chances of high performance and good group dynamics, spreading the available skills equally across all teams. This tactic was often present in contexts with educational motives, attempting to provide equal chances for the participants. In contrast, the *high-expertise* tactic is used for bringing together very talented individuals in few teams, thus ensuring that at least those teams will succeed in producing innovative outcomes for the project. This tactic seemed to be more common in contexts where multiple teams work on the same topic and the best outcome from several projects would be selected for follow-up work.

The importance of diversity was highlighted by all the interviewees and it is a salient theme in the data. However, a diversity-based approach did not seem to comprise a specific tactic in team assembly. Rather, diversity seems to be an overall perspective that affects the choices with all the tactics. For example, when a matchmaker is balancing the teams (in the case of equally-skilled-teams), they might consider diversity as one metric of equality. The findings provide support that it is important to consider functional heterogeneity in team assembly (Somech and Drach-Zahavy 2013). In addition to diversity regarding disciplines and functions, the participants emphasized that there should also be diversity regarding the level of experience and organizational level. At the same time, diversity is not usually a tactical starting point when considering arranging tactics but becomes evident when bringing applicants with a different profile to the team after the first selection(s).

All in all, understanding this variance of tactics helps to formalize different approaches to team assembly and, hence, to support them with IT applications, such as decision-support systems. Acknowledging the alternative tactics in the very design of digital tools opens an interesting design space of potentially very impactful IT, as further discussed in the next subsections. Additionally, we expect that further alternative tactics might emerge in the future as the use of cross-boundary innovation teams increases in various contexts. This study provides a solid starting point for further empirical research on matchmaking tactics in this regard.

5.2. Limitations

There are certain methodological limitations that limit the generalizability and applicability of the findings. First, the sample is limited to one country with a relatively homogeneous organizational culture and having several participants from one prominent organization that facilitates innovation projects. We encourage further empirical research in other cultural and organizational contexts. Second, as this study focuses on innovation teams, the findings might not generalize to other team assembly contexts. That said, we believe that the assembly of project teams in, for example, consultancies or production teams in creative industries could benefit from these findings. Third, because team assembly is still an emergent and relatively unestablished activity in many organizations, it might be affected by many aspects that this qualitative study failed to identify. We call for further research on not only other matchmakers' experiences but also how the selected project members perceive the teams that have been assembled according to certain tactics.

5.3. Future Work and Design Considerations

In the light of this analysis, we argue that there is much room for introducing IT that helps matchmakers select more optimal team compositions. We call for courageous conceptualization of next-generation systems that could actively react to the matchmaker's tactics, offer deeper insights into the candidate team members' profiles, and offer interactive visualizations that help plan the team assembly as a whole. We plan to devise prototypes that manifest tactics or help the matchmaker to consider them. In particular, we believe that design efforts could focus on service features that assist matchmakers in multi-dimensional analyses of the individuals' qualities and support comparison, as explained in the following list.

- *Enhancing user modeling.* The decisions on team compositions are unavoidably influenced by the matchmaker's understanding of the individuals' qualities. Considering the breadth of potentially relevant qualities, likely many of them remain latent, that is, unacknowledged in the personal resumés and underutilized in matchmaking. Computationally assisting this issue necessitates more comprehensive and multi-dimensional user models. As current automatic profiling methods are typically intended to produce generally applicable representations of the actors (Sateli et al. 2017; Bastian et al. 2014; Horne et al. 2019), the models remain narrow in terms of ontological comprehensiveness. Hence, we call for new methods for deriving more nuanced insight about the applicants, for example based on the publicly available Big Social Data (Olshannikova et al. 2017) they have produced. This could mean traces of social interactions online, individuals' participation in public discourses on topic of interests, or peer support activities in question-and-answer communities (e.g., Quora, Stack Overflow). While utilizing such data introduces dilemmas of data ethics and necessitates careful data management, it might also help to reduce the effects of intuition-based biases and to consider qualities that otherwise would remain unnoticed.
- *Offering interactive views to help team assembly on different levels.* After the pool of applicants has been assembled, a view for each decision-making level (individual, single team and multiple teams) could support grasping a holistic picture of the team assembly complexity at hand as well as enable comparing teams. In the single team and the multiple team views, matchmakers should be able to see key information about qualities that they use to compare applicants (e.g., education, substance knowledge and skills) to further apply different prioritization tactics. Furthermore, the interface should allow the matchmaker to compare multiple applicants at once, place them effortlessly into teams, and contrast them with already selected team members;
- *Identifying potential team members.* In the single team view, a system could highlight individuals with interest towards a particular project topic, people who match with the matchmaker's preset preferences, and people who posses qualities that are significantly different in comparison to other applicants (e.g., a rare skill or rare education background) or a direct match to the project description requirements. While such features would allow quicker selection, they could also decrease the high cognitive load in cases where there is a large applicant pool and multiple teams to be assembled.

6. Conclusions

We interviewed 13 expert matchmakers who are regularly assembling multidisciplinary innovation teams, particularly in higher education. Based on a qualitative analysis of their experiences and practices, we found that the activity largely leans on personal decision-making and assessment, with digital tools playing an insignificant role. The selection of candidates to teams includes much ambiguity, and it was seen hard to establish clear optimums to aim at. According to the participants, the decision-making often features contradictions: wishing to avoid biased decisions and to make rational decisions but, on the other hand, also noting that judging the quality of a decision is complicated. As a highlight of the qualitative account, we identify and define three arranging tactics ("key-skills-first", "generalist-first", "topic-interest-first") and two balancing tactics ("equally-skilled-teams" and "high-expertise-teams") as alternative approaches to this complex activity. Based on the results, we discuss how IT could better support the decision-making process and call for more comprehensive user modeling methods. All in all, the study helps to design IT systems for decision-making based on different team assembly tactics.

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Publisher's Note

PUBLICATION III

The March of Chatbots into Recruitment: Recruiters' Experiences, Expectations, and Design Opportunities

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The March of Chatbots into Recruitment: Recruiters' Experiences, Expectations, and Design Opportunities

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Abstract. Organizations' hiring processes are increasingly shaped by various digital tools and e-recruitment systems. However, there is little understanding of the recruiters' needs for and expectations towards new systems. This paper investigates recruitment chatbots as an emergent form of e-recruitment, offering a low-threshold channel for recruiter-applicant interaction. The rapid spread of chatbots and the casual nature of their user interfaces raise questions about the perceived benefits, risks, and suitable roles in this sensitive application area. To this end, we conducted 13 semi-structured interviews, including 11 interviews with people who are utilizing recruitment chatbots and two people from companies that are developing recruitment chatbots. The findings provide a qualitative account of their expectations and motivations, early experiences, and perceived opportunities regarding the current and future use of chatbots in recruitment. While chatbots answer the need for attracting new candidates, they have also introduced new challenges and work tasks for the recruiters. The paper offers considerations that can help to redesign recruitment bots from the recruiter's viewpoint.

Keywords: Recruitment bot, Chatbot, Talent acquisition, Recruitment, E-recruitment, Human resource management, Expert interviews, User experience

1 Introduction

The trends on the global job market set new requirements for organizations' recruitment of workforce and human resource management practices. For example, the global competition of workforce (Ashton and Morton 2005; Stahl *et al*. 2012), passive job seeking (Trusty *et al*. 2019), and decline in employee tenure (Hollister 2011) add to the dynamics and degree of difficulty in hiring. The mismatch of demand and supply of skills on the job market (Cappelli 2015) can cause large numbers of job applications, yet few relevant candidates. The so-called "war for talent" between organizations (Michaels *et al*. 2001) and the job seekers' demand of good candidate experience may reverse the traditional recruiter-job seeker power relationship (Claus 2019). Such trends have led to the introduction of various digital services in recruitment (Holm 2012; Wirtky *et al.* 2016; Thite 2019). *E-recruitment* refers to the use of corporate web sites, social media, and various other information systems (Chapman and Gödöllei 2017; Holm and Haahr 2019) in workforce hiring. Despite the growing general interest towards e-recruitment activities (Holm 2012; Koivunen *et al.* 2019), there is relatively little empirical research on how e-recruitment is utilized in practice and how the various systems are experienced by recruiters who represent the employing organization.

A key goal of e-recruitment is to attract and encourage potential applicants to send job applications (Eveleth *et al.* 2015). To this end, this paper focuses on a specific emergent e-recruitment technology: recruitment chatbots (henceforth, *recruitment bots*). Following the conceptualization of chatbots by Grudin and Jacques (2019), recruitment bots refer to web-based, publicly available, and task-focused chatbots that communicate with potential applicants to gather information about them and to help the recruiter handle queries.

While various task-focused chatbots are already vast in number, scholars call for more HCI research regarding the purposefulness of chatbots, since user needs and motivations are often poorly understood (Følstad and Brandtzaeg 2017; Brandtzaeg and Følstad 2018). Furthermore, user research around e-recruitment is scarce and lagging behind industry adoption (Chapman and Gödöllei 2017; Johnson *et al.* 2017). The applicant perspective has been studied to some extent (McCarthy *et al.* 2017), for example, in relation to website usability effects on potential applicants' intentions (Eveleth *et al.* 2015). At the same time, considering the perspective of a recruiter, there is little academic research on the utilization of chatbots for this particular organizational need. We identify a need to study if and how recruitment bots address real needs in recruitment and the benefits they are expected to provide.

This research aims to support the development of next-generation chatbot-based e-recruitment systems by providing user- and activity-centric understanding of chatbots in recruitment from the viewpoint of the recruiter. Recruiters, are here defined as HRM professionals whose job tasks include coordinating recruitment processes and serving as the applicants' interface to the organization, hence representing a central user group for e-recruitment systems (Connerley 2014). Given the early phase of technology diffusion in this area, we ask: "What are recruiters' initial experiences of and the expectations towards recruitment bots?" To this end, we conducted qualitative interviews with 11 recruiters whose organizations have either recently deployed a recruitment bot or are intending to do so in the near future. To enrich the data, we also ran two interviews with software experts who are involved in developing recruitment bots and have extensive domain knowledge in recruitment. They represent a relevant stakeholder group that can give insight how recruitment bots have been across organizations and what kind of new features can realistically be envisioned from the next-generation recruitment bots. Regarding recruiters, to narrow down the broad spectrum of possible user experiences and subjective opinions, the study focuses on the chatbots' practical role in the organizations' recruitment process, how they relate to other e-recruitment systems, and users' expectations towards this technology. Studying domain experts' expectations help to understand how an emerging technology could be further developed to serve in the recruitment process and in what kind of recruitment tasks it could be particularly helpful. In other words, we focus on discussing and unpacking the *experiential and systemic aspects* of this emergent social technology, rather than, for example, usability evaluation of specific recruitment bot user interfaces. The systemic aspects include interviewees' considerations on chatbots' impact in recruitment processes.

The findings highlight several important themes to consider by both the technology developers and the organizations adopting recruitment bots in the hiring processes. While lowering the threshold to applying for certain positions was generally considered beneficial, a significant flip side was a larger pool of applicants to examine in detail. The recruiters felt burdened by unexpected tasks that they had little experience in, such as planning predefined scripts for the chatbots. In this sample, the recruitment bots were used rather separately from other recruitment channels and information systems, which added to the need for configurations by the recruiters.

To the best of our knowledge, this is one of the first qualitative studies on the user experiences and expectations considering recruitment bots from the perspective of recruiters. The job seekers' perspective has attracted more research interest, which has recently resulted in a call for research on the recruiters' perspective (Wheeler and Dillahunt 2018; Lu and Dillahunt 2021). We contribute to this emerging thread of research and provide valuable insights into the possible roles and uses of chatbots in recruitment. We offer considerations for the uses of, interactions with, and design of next-generation recruitment bots and explore opportunities for the future use of recruitment bots.

2 Theoretical framework and related work

The following first outlines e-recruitment as a context of applying chatbots, followed by an overview of chatbots and related taxonomies, along with a classification of currently typical categories of recruitment bots. The last subsection defines user expectations and trust in technology as a theoretical and conceptual lens for the empirical study.

2.1 The research context of e-recruitment

Organizational success is argued to depend on the social composition of employees (Breaugh 2013). In the broader context of Human Resource Management, the target of recruitment is to find the right person for the right job at the right time (Ashton and Morton 2005). Acquisition of new human resources typically takes place through external recruitment (Keller 2018). It refers to organizational activities like bringing a job opening to the attention of potential applicants, influencing them to stay in the applicant pool, and affecting the decision of accepting a job offer (Breaugh 2008; Lievens and Slaughter 2016). The recruitment process, if done with deliberation, tends to follow a linear decision-making process with multiple stages (Keller 2018; Holm and Haahr 2019; Koivunen *et al*. 2019), which include establishing requirements, identifying and attracting alternatives, comparing alternatives and selecting the most suitable match (Holm and Haahr 2019; Koivunen *et al*. 2019). Common challenges in this process are settling the requirements and deciding the recruitment channels (Holm and Haahr 2019; Koivunen *et al*. 2019). Further, according to market research surveys, organizations' top priorities in recruitment include acquiring candidates, engaging them during the recruitment process, and developing the employment brand (Bullhorn 2022).

The first electronic forms of recruitment included company websites, social networking sites, and job boards (Chapman and Gödöllei 2017). More recently, specific e-recruitment software (e.g., applicant tracking systems) have emerged for finding, attracting, and communicating with the applicants (Chapman and Gödöllei 2017; Holm and Haahr 2019). The benefits of e-recruitment include managing talent pool, potentially reaching new applicants, and branding (Chapman and Gödöllei 2017). However, empirical research on the effectiveness and appropriateness of various e-recruitment tools is scarce (Chapman and Gödöllei 2017) and the existing tools have been strongly criticized (Cappelli 2019). According to a critical view by Cappelli (Cappelli 2019), companies are generally obsessed to decrease the enormous costs of hiring and the market is full of vendors that offer new technology. At the same time, it remains unclear whether the various e-recruitment tools result in better hires or not (McCarthy *et al*. 2017; Woods *et al*. 2020).

Organizations' websites and web-based job boards are commonly used to attract potential applicants to apply (Eveleth *et al*. 2015; Chapman and Gödöllei 2017; Holm and Haahr 2019). Here, often the first touchpoints for applicants are standardized online forms (online applications) which provide personal and job-specific information (Woods *et al*. 2020). To this end, the much-studied website qualities like usability, visual design, and content of the website have been found to influence potential applicants' intention to submit an application (Braddy *et al*. 2006; De Goede *et al*. 2011; Eveleth *et al*. 2015). Especially the importance of website's aesthetic features, navigability, and interactivity in terms of two-way communication are emphasized (Chapman and Gödöllei 2017; Holm and Haahr

2019). Further considering conventional web applications' usability, while job seekers use mobile devices to search for jobs, it seems that many organizations do not often have mobile-optimized or even mobile-compatible websites (Chapman and Gödöllei 2017). Overall, the introduction and exploration of new technologies has been rapid despite the unsolved issues in the previous generations of e-recruitment technology.

While e-recruitment tools facilitate contacting and communication between job seekers and recruiters, this kind of sociotechnical systems remain relatively little studied in CSCW and HCI. Two key threads of research can be identified in this emerging area of literature. The first thread has focused on designing, implementing, and evaluating new tools (e.g., to support low-resource job seekers (Dillahunt *et al*. 2018; Dillahunt and Lu 2019). The second has focused on methods for gathering information about job seekers and employers (Wheeler and Dillahunt 2018; Lu and Dillahunt 2021). For example, Lu and Dillahunt (2021) conducted interviews with employers of low-wage workers in the U. S, providing insight into employers' use of social media in low-wage labor market. While their research context differs from ours, the research marked an important first step to study recruiters' perspective that had been called for in prior research (Wheeler and Dillahunt 2018).

Recently, management research has explored the opportunities and pitfalls in utilizing information systems in HRM, particularly looking at artificial intelligence (AI) solutions (Albert 2019; Allal-Chérif *et al*. 2021; Vrontis *et al*. 2021). Such studies imply that while AI tools can increase efficiency and fairness (Charlwood and Guenole 2022), HR's context-specific challenges for adopting AI include small data sets, accountability related to fairness, possible adverse employee reactions, and other ethical and legal constraints (Tambe *et al*. 2019). The research has specifically criticized whether e-recruitment tools clearly help organizations to attract large and diverse pool of applicants (Stone *et al*. 2015). To this end, recruitment bots address the issue of e-recruitment tools' traditionally static communication processes that merely provide information without the possibility to ask questions (Stone *et al*. 2015).

Furthermore, Charlwood and Guenole (2022) show that while there are over 100 published papers on technical aspects of applying AI in HR, there is little empirical research on the use and consequences of such systems in practice. It appears that much of the research investigates responses to hypothetical scenarios (Langer and Landers 2021; Charlwood and Guenole 2022), probably due to limited deployment of such systems in organizations (Benbya *et al*. 2020).

2.2 **Positioning recruitment bots in the family tree of chatbots**

In general, chatbots have entered a broad spectrum of application areas. Most often they are used in various forms of customer service (Zamora 2017; Følstad and Skjuve 2019) but also in specific areas like therapy services (Fitzpatrick *et al*.

2017), news (Jain *et al*. 2018), gaming (Jain *et al*. 2018), and education (Smutny and Schreiberova 2020). Also, conversational bots have been studied in the context of stimulating discussion on social media platforms (Nichols *et al*. 2013; Savage *et al*. 2016). In the workplace context, chatbots have been introduced, e.g., to support an individual's detachment and reattachment process (Williams *et al*. 2018).

The deployment of chatbots is often justified by improved efficiency and performance, delay-free and always-available service, and by making the end-user's life easier by supporting simple practical tasks (Zamora 2017; Brandtzaeg and Følstad 2018; Følstad and Skjuve 2019). Internet-based customer service has shifted from personal and dialogue-based interaction towards automated interaction and self-service, and chatbots represent a potential means for automating customer service (Følstad *et al*. 2018). Considering interaction design, chatbot's human-like behavior may have a positive effect on relationship building between the organization and individuals (Araujo 2018). In addition, the interactivity can facilitate a feeling of interacting with other people (i.e., social presence) (Liao *et al*. 2018; Go and Sundar 2019), which may induce greater involvement with the content provided by the website and even lead to more positive attitudes, especially when it minimizes the navigational load (Sundar *et al*. 2003; Sundar and Kim 2005). In turn, work by Zabel and Otto (2021) examined the existence of algorithmic biases when designing chatbot dialogues. They found similarity-attraction of gender, meaning that there was a more positive affect when a person reading, and the designer of dialogue had the same gender. Similarly, Feine *et al*. (2019) showed that gender-spesific cues are commonly used in the design of chatbots.

Prior literature offers classifications of the various manifestations of chatbots, which helps to position recruitment bots in a broader technological landscape. Smutny and Schreiberova (2020) propose a classification based on the input and messaging channel of the chatbot, covering button-based, keyword recognition-based, contextual, and voice-based inputs. Messaging channels may manifest as a standalone application (mobile or desktop), a web-based service, or are integrated into other services (instant messaging apps or collaboration platforms). The taxonomy by Grudin and Jacques (2019) is based on the conversation focus. In task-focused chatbots the focus is narrow, and a typical session has 3-7 exchanges, whereas intelligent assistants (e.g., Apple's Siri, Amazon's Alexa) have a broader focus and typically 1-2 exchanges, and virtual companions (e.g., Eliza and Tay) have the broadest focus and up to 100 exchanges per session.

2.3 **Preliminary taxonomy and prior research of recruitment bots**

Building on the aforementioned classifications, we interpret current recruitment bots as task-focused chatbots that utilize button-based or textual inputs. In practice, they are typically integrated into a web-based service such as company website or Facebook Messenger. To complement the existing taxonomies, Table 1 presents different types of chatbots used to support recruitment activities, based on the authors' review and analysis of their functionalities.

The categorization was produced through extensive search of examples and recruitment bots' offering, as well as analyzing them with respect to purpose of use (from the recruiter's viewpoint) and forms of applicant interaction. Before the interviews, we found several examples of attraction bots and customer service bots in use at websites of several Finnish companies. While we did not find functioning examples of interview bots, they had already been presented and discussed in several research papers. During our search, we identified a few vendors that were developing attraction and customer service bots for Finnish companies. Notably, vendors also typically produce various chatbot solutions for purposes that are also beyond recruitment. The chatbots' purposes and forms of interaction were further clarified during the study interviews (Figure 1).

First, attraction bots are meant to be an easily approachable way to send one's contact information and a few basic details to a potential employer in a matter of minutes. They serve as an additional channel for an applicant to indicate their interest: the bots provide an opportunistic and a low-threshold way to send contact information compared to conventional application channels, such as a phone call, an email, or web forms. Basic questions that the chatbot could ask include the amount of work experience and level of education, for example. Commercial solutions include, e.g., Mya,[1] XOR.AI,[2] and Leadoo.[3] Second, customer service bots can help the potential applicant to find relevant information concerning a specific position, the recruitment process, and the hiring organization. Such chatbots aim to automatize the repetitive work that a recruiter would traditionally carry out via emails and phone calls and offer a low-threshold way for the applicants to ask questions. The main motivation to automate customer service is to reduce costs (Følstad and Skjuve 2019). In practice, they can provide information and instructions on, for example, how to log in to a recruitment system, what the current open positions are, what the key qualifications for a specific position are, or what the salary level is. Alternatively, in large corporations with plenty of HR staff, a customer service bot may be implemented as an internal tool to provide easily accessible recruitment information for the staff. The third category, interview bots, refers to technologically more sophisticated chatbots that can conduct a virtual interview and, thus, help to screen applicants. While these currently seem to be little used, a few research prototypes and product visions have been created (e.g., (Xiao *et al*. 2019, 2020)). For example, Juji chatbots are promoted

[1] https://www.mya.com/
[2] https://www.xor.ai/
[3] https://leadoo.com/

Table 1 Identified categories of recruitment bots.

Type of chatbot	Main purpose	Interaction with user
Attraction bot	To collect basic information about the applicants. Offers an interactive alternative to online application forms.	Asks pre-scripted questions. User input is often based on clicking predefined answer options.
Customer service bot	To answer questions about recruitment and the organization. Helps candidate to find the right information and can reduce the recruiters' workload.	Analysis of user's textual answers and the intents therein based on natural language processing.
Interview bot	To elicit rich information and make interpretations of the candidate's personality and competences through a virtual job interview.	Understands natural language, is context-aware, and can react to the user's input by asking questions.

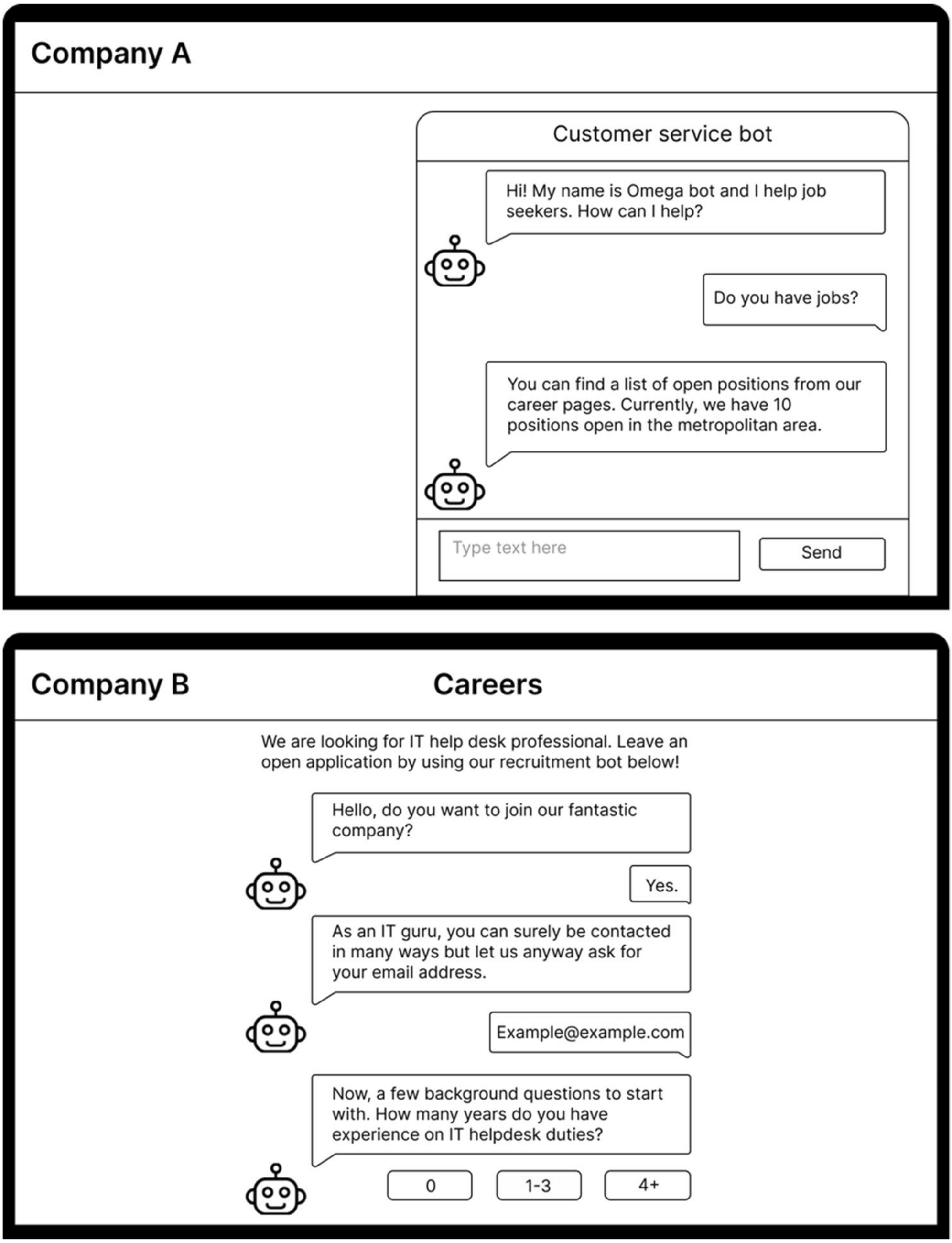

Figure 1 Illustration of two types of recruitment bots. Above (Company **A**) is a customer service bot that is typically realized as a pop-up window that opens from the bottom right corner when visiting the organization's web site. A candidate can ask a recruitment-related question by writing it to the text box and pressing the send-button. Below (Company **B**) is an attraction bot that, in addition to a pop-up window, can be more integrated to a specific web page. A candidate can type simple answers or choose from predefined answer options.

as a scalable, standardized, and potentially information-rich solution to infer applicant's characteristics, such as personality traits (Zhou *et al.* 2019).

There is some prior research on the use of customer service bots but, in contrast to our study, they have focused on the applicant's perspective. Notably, the abovementioned Juji that is able to conduct personality assessment interview has recently been used in several academic studies (Li *et al.* 2017; Xiao *et al.* 2019, 2020; Zhou *et al.* 2019). For instance, Li *et al.* (2017) used Juji as an virtual interviewer to screen candidates. They concluded that the chatbot can make the interview process more efficient as it was able to shortlist 12 candidates from 316 candidates that completed the interview. The job seekers were seen to act authentically in the virtual interview. Later, Xiao *et al.* (2020) found that it is technically and practically feasible to build an interview chatbot with a capability to actively listen, comprehend and respond properly to different kinds of open answers from job seekers. Zhou *et al.* (2019) highlighted that chatbot interviewer's personality influence job seekers' behavior and it seems that in a high-stakes situation like job interview, a more assertive agent is preferred. Overall, recruitment bots have emerged as a new e-recruitment tool and there are inspiring examples of the potential benefits from the applicants' perspective. However, we identify a need for qualitative research to better understand the experiences of utilizing chatbots in recruitment from the organizational perspective.

Overall, considering the level of automation, recruitment bots can be said to interact independently with the candidate but their role in recruitment seems to vary. For example, attraction bots support the recruiters' interests by attracting additional candidates but usually do not take a stance regarding the suitability of an applicant.

3 Methods

To understand recruiters' subjective experiences and expectations, we conducted 13 in-depth, semi-structured expert interviews with people from different types of organizations. We deliberately had a range of participants with different viewpoints in order to develop a rich qualitative understanding of this emergent socio-technical topic. Eight interviews were conducted at the participant's workplace, three remotely using a teleconferencing software, one at university facilities, and one in a meeting room at a public library.

We initially created an interview outline for three different groups of participants that we identified as relevant interviewees: 1) people with first-hand experience of using different kinds of recruitment bots, 2) people who are about to pilot a recruitment bot in the near future, 3) people who develop recruitment bot technology, having certain value propositions and benefits in mind. However, practical challenges in participant recruitment led us to focus on the first group and enriching their experiences with the perspectives of the second and third group. It is noteworthy that most of the actual user experiences in this sample of participants related to the use of attraction bots. However, in the interviews we deliberately asked about the expectations towards all the identified categories (see Table 1) as this was supposed to shed light on the perceived risks and opportunities in technologically supporting the recruitment process.

In the beginning of each interview, we asked the participant to describe their work, their job tasks and how recruitment bots are relevant considering their work. The participants described how the recruitment bot in question (either in use or about to be deployed) works, and what kind of concrete experiences the participant had with it. We explicitly encouraged participants to focus on the parts of interview they felt comfortable to discuss based on their expertise. According to that, we selected one of the interview structures to follow and refined its questions. The interview was further structured according to three key stages: before deployment, present use, and future use. The first stage covered questions such as why recruitment bots were deployed, what the expected benefits, risks and other implications were, and what the internal and external attitudes before deployment were. The second part inquired about, e.g., the role of recruitment bots in recruitment, the information on applicants that is collected or cannot be collected, perceived concerns (e.g., equality and privacy), perceptions of trust, effects on recruiters' work tasks, and how various expectations have been met. The third part covered themes like which direction the development of bots should be aimed to and the perceived future risks and opportunities. With the second participant group, we naturally focused on the expectations. With the developers, we also inquired about the expected benefits from the perspectives of their businesses as well as their clients' expectations.

3.1 **Participants and their recruitment**

We identified relevant organizations that have used recruitment bots through online searches, which led us, for instance, to relevant news articles or blog posts. Typically, we used "chatbot" and a recruitment related word, such as "recruitment" as search terms (in Finnish). In addition, we created a LinkedIn advertisement that targeted people with experience or interest in using recruitment bots. However, the advertisement resulted in only one interview, which convinced us to rather rely on online searches. Furthermore, after each interview, we inquired whether the participant knew other relevant interviewees (i.e., snowball sampling).

Overall, nine of the 13 participants had experience in using a recruitment bot, two were planning to deploy one in the near future (P12 and P13), and two were working at a company that develops recruitment bots (P6 and P10). All the participants represented different organizations from Finland. The participants' professional roles and other background information are presented in Table 2. It is noteworthy, that most of them had a considerable amount of experience in

Table 2 Participant information (experience refers to years in the current role).

ID	Professional role	Experience with chatbots	Experience in years
P1	Recruitment manager in construction sector.	Tested a live recruitment chat in the previous company and is planning to deploy an attraction bot in the current company.	~4
P2	HR manager. In charge of recruitment in a company that provides billing and financial management services.	Actively using an attraction bot to reach customer service and knowledge work professionals.	3-4
P3	Head of HR department. Worked in a company that provides IT services.	Tested various chatbots to automate HR activities.	7-8
P4	Head of HR Digitalization and AI project in a multinational company of ~100,000 employees.	Deployed an internal customer service bot for HR.	5
P5	HR software development manager in an employment agency (~250 employees) that helps to recruit 6000-8000 people annually.	Deployed a customer service bot for job seekers.	3
P6	CEO in a company that develops chatbots.	The company develops attraction bots for several clients. Also uses a recruitment bot to hire new people to their company.	1.5
P7	HR manager in restaurant business. Oversees the recruitment process.	Has experimented an attraction bot.	~20
P8	Product manager and HR/recruitment specialist for a public sector job board.	Tested AI-powered chatbots to match job seekers and job openings.	7+
P9	Director of recruitment department in a company offering a job board.	Offers two different attraction bots to companies that are placing job ads.	3.5
P10	Chief marketing officer and co-owner in a company that develops recruitment software.	The company is developing a recruitment bot that matches information provided by candidates to job ads.	3.5
P11	Responsible for communication and recruitment marketing in an employment agency that specializes in construction workers.	Oversees the use of attraction bots by, e.g., creating chatbot scripts.	10+
P12	Project manager. Manages a network of people in a company that promotes a better working life for the youth.	The company has recently received offers from chatbot vendors but has not yet deployed a recruitment bot.	~2
P13	Head of a production unit in a confectionery. Decides what kind of talent is needed.	Interested in testing recruitment bots in the near future.	7-8

conducting or overseeing recruitment processes even before their current work role. In addition, while such experts tend to have multiple work roles, they are all in significant roles in their organizations' recruitment activities (or are developing recruitment tools).

In the end, we had a few participants from both food and technology industries and several from organizations that provide personnel services. Organizations were mostly medium- or large-sized companies. Notably, the two people who were working with recruitment bot solutions (P6 and P10) were from small-sized companies. Most of the organizations were from the private sector.

All the participants were Finnish, and the interviews were held in Finnish. Considering generalizability of findings in this cultural context, we regard the Finnish job market to represent a typical Nordic system with relatively extensive regulation by the government, and labor unions having central roles in defining wages and contracts. While workforce mobility and general dynamics on the job market have been steadily increasing, they can be said to be lower than in North America, for example. According to the Finnish ministry of economic affairs and employment of Finland, other general characteristics of Finnish work culture include high level of participation, appreciation of equality, generally high skill levels and low hierarchy.[4]

3.2 **Data analysis**

All the interviews were audio recorded and then transcribed using a professional service or by one of the authors. The average length of an interview was 59 min (min. 39 min and max. 85 min). The total word count of the transcribed data was 95,447. We conducted a bottom-up data analysis with the help of Atlas.ti. We employed constructivist Grounded Theory oriented analysis as described by Charmaz and Bryant (Bryant 2017; Bryant and Charmaz 2019). The constructivists approach notably highlights multiplicity of perspectives, and that outcomes are provisional social constructs. It contrasts with traditional objectivist approach to Grounded Theory where investigation and observation are independent of a specific researcher and context-free generalizations are aimed for (Bryant 2017). The coding process started with descriptive initial coding by reading the data line-by-line (Bryant and Charmaz 2019). This was done separately by two of the authors. We then categorized codes that had the seemed to have the most analytic power using two seemingly potential lenses, the recruitment process and the expectations. Within the categories, we identified most promising themes and used focused coding to further identify the most interesting codes by relating them to other codes and themes. Finally, we arrived to set of codes and themes that captured a number of initial codes. We then organized them to form

[4] https://tem.fi/en/working-life

a narrative for the Results. The analysis was collaborative, multidisciplinary and iterative by nature. The coding process was conducted by the first two authors and was periodically challenged and enriched by the research team. In practice, we organized several meetings where we made clarifications on our categories and discussed the most promising themes and codes.

Finally, we express our findings through an analytical narrative that attempts to be abstract enough to show the theorization process, yet a contextually-rich description of recruitment bots (Bryant and Charmaz 2019). During the analysis, the storyline on early experiences and expectations started to seem evident and coherent across participants, and we are confident that the findings we raise stay true to all accounts and more broadly in our cultural context. We use quotes to illustrate the abstract concepts and to ground the storyline. Additionally, we deliberately avoid quantifying the findings as a concept has relevance because of what it brings to the theory qualitatively, regardless of how frequently it may have appeared quantitatively (Bryant and Charmaz 2019).

4 Results

We first focus on the motivations behind the development or utilization of recruitment bots, then follows an analysis of their practical effects on the activities and experiences of the recruiting experts' work. Finally, we analyze the experts' optimistic expectations towards the long-term future use of recruitment bots. In general, while there likely is variation across specific professions or industries in terms of the presented themes, the findings aim to raise general considerations that are relevant in most professional domains.

4.1 Practical motivations to deploy recruitment bots

The recruiters stressed that the key motivation to try recruitment bots is the general interest to increase both the quantity and quality of the applicants. To this end, attraction bots and customer service bots were expected to provide a new channel but with a distinct approach. In addition, the easy-to-approach UI was expected to provide benefits regarding accessibility. Here, we discuss how these three factors practically motivated deploying recruitment bots.

4.1.1 Attraction bots reach candidates that other e-recruitment channels fail to reach

Attraction bots were expected to reach candidates that other e-recruitment channels and marketing cannot reach. As a light-weight way for potential applicants to be in contact with an organization, such chatbots were seen especially suitable for attracting initial applications from passive job seekers. For instance, P2's organization had recruited an employee from a competitor with the help of an attraction bot on their career web page. Similarly, P7 consolidated that the recruitment bots can indeed attract candidates that do not realize that a certain organization could be their potential employer.

> *"This way we can reach a larger talent network. […] They (passive job seekers) might not exactly know what this (chatbot) is but when they try, it can lead to successes."* (P7, HR manager, representing knowledge work organization in commerce sector)

Many participants felt that the trends in the job market motivate them to try new application channels, such as attraction bots. First, P9 stressed that, in knowledge industries, the competition for talented personnel has led to headhunting, i.e., proactive searching and attraction of workforce, which partly explains why the potential candidates might not actively send their applications. Second, a CEO whose company develops attraction bots (P6) confirmed that one major motivation of their clients is their dissatisfaction with the results in conventional recruitment. Third, referring to the trend of skills mismatch in labor market (i.e., a discrepancy between the skills that are sought by organizations and the skills that are possessed by individuals), P1 told how their company receives large numbers of applications but not from people who meet the criteria.

> *"Getting more qualified applicants was the primary (expected benefit). Second, we received a lot of applications, but they were not the right kind of applicants at that time."* (P1, referring to a situation in a construction sector company)

4.1.2 Customer service bots could attract high-quality applicants by proactively helping candidates

Another expected benefit was increased general interest towards the company. For this type of brand image building and communication of company values or mission, a few participants had either deployed or tested a customer service bot that advices a web site visitor. For instance, P4 believed that the proactive chatbot offers a chance to opportunistically approach web site visitors and offer customer service that might, indirectly, result in high-quality open applications. This consolidates our classification in Table 1 that a customer service bot serves not only HR activities but also marketing and other external communication. Some participants highlighted that chat interface can be a great way to approach young job seekers. This was reasoned both by companies' target groups and the younger generations' assumed familiarity with chatbots.

"They (recruitment bots) could be more for engaging, they could ask whether you are like this or that […] It would motivate (the visitor) to later create an application." (P4, Head of HR Digitalization)

4.1.3 **Chatbot UI improves accessibility and lowers application threshold**

The interviewees felt that attraction and customer service bots could be more accessible and approachable than other e-recruitment channels and, therefore, lower the threshold to send an application**.** Recruiters acknowledged that job seeking can be stressing, laborious, and unrewarding. For example, it is hard to estimate how much time it takes to prepare the various position-specific documents. The participants further acknowledged that the typical experience of sending an application often tends to appear complicated, and the presence of various information systems during the process might hamper the overall applicant experience. For instance, despite the popularity of mobile browsing, online application forms are rarely mobile-friendly, while chatbots were seen to fit well with responsive web design and, therefore, can be smoothly used in both desktop and mobile. However, the quotes from P1 and P6 reveal a contradiction: the desire and need for responsive UIs based on website traffic (P1) and the assumption that applicants' wish to craft their job applications with care (P6). It seems, however, that mobile-friendly UIs tend not to cater for creating detailed and fine-tuned applications. Other perceived potential benefits of mobile UI included faster task completion time and easy to use speech-to-text functionality. The interviewees felt that attraction and customer service bots are more accessible and approachable than other e-recruitment channels and, therefore, lower the threshold to send an application**.**

"People are terribly stressed about how their CV looks and nobody wants to be rejected […] Especially if they have put in a lot of effort." (P6, CEO, both develops and utilizes attraction bots)

"It is much easier to type the answer using a mobile device. I noticed that two thirds of the visitors on our career pages were on mobile but job applications are almost always sent on desktop." (P1, Recruitment manager)

4.2 **Early experiences and implications to recruiters' practices**

At the time of the study, the early adopter participants had used recruitment bots for several months or even years already. The early adopters' trials could be publicly witnessed on organizations' web sites, and the examples were recognized to have created positive expectations and encouraged piloting also in other organizations. At the same time, the adoption of chatbots was found to have introduced interesting new challenges and needs for compromising, which we will focus on in this subsection.

4.2.1 **The new channel has brought new applications and new tasks**

According to participants with experience of using attraction bots, the expectation of increased quantity and quality of applications has been surprisingly well met. The number of applications has concretely increased, and while it is hard to measure the quality of applications, for example, P11 believed that their attraction bots result in as good applications as the online job application forms they use. P11 is working in a company that searches construction workers for other companies and, as an organization, they are striving to make the application process for the job seekers as easy as possible. After experimenting with an attraction bot, they realized that they only need to inquire a few key details about the applicant. The recruiter can then make the decision whether to contact the applicant or not simply based on the chatbot conversation log.

> *"We get approx. 10 000 applications per year, 2500 of them come through lead bots, nowadays […] I think the share is surprisingly big […] Based on discussion with our recruiters, at least (the quality) does not significantly differ from what we get to our (recruitment) system.* (P11, Oversees the use of recruitment bots)

At the same time, a central change that chatbots have brought relates to the recruiters' new tasks in managing them. If a company has deployed an attraction bot, it is typically the recruiter's job to create the chatbot script and to supervise that it produces relevant answers. For example, in P2's organization, recruiters both tailor unique attraction bots for individual job openings and manage a more permanent attraction bot for open applications. In a typical case, the attraction bot first checks the contact information and the applicant's professional suitability for the targeted work task. Next, the recruiter contacts the candidate for further details and, if the candidate is interesting enough, the recruiter books an interview with a hiring manager.

> *"It takes maybe 15 to 60 minutes to create and test (an attraction bot)—depends on whether I can copy an old bot script or if I need to create a new one with new questions […] I usually take one day per week when I am anyway reading the open applications we receive through email. Then I also check the bot applications and possibly contact people."* (P2, HR manager)

While it is relatively fast to create a recruitment bot for an individual job opening, this brings the challenge for a recruiter to present the questions in a way that optimally attracts job seekers. P9 pointed out that recruiters and other HR professionals are used to creating traditional job descriptions, which, as a form of communication, is far from creating a sequential script for a chatbot.

"People are used to creating bullet points but not a recruitment bot." (P9, Director of recruitment department)

In contrast, it seemed that a customer service bot did not require as active role by the recruiters. As its purpose is to automatize answering frequently asked questions, it decreases repetitive work. P5 told that their customer service bot is updated based on the asked questions, and this information also helps to update the company website. Interestingly, in that particular case, the customer service bot was able to provide information that was not available from the website:

> *"It takes maybe 15 to 60 minutes to create and test (an attraction bot)—depends on whether I can copy an old bot script or if I need to create a new one with new questions […] I usually take one day per week when I am anyway reading the open applications we receive through email. Then I also check the bot applications and possibly contact people."* (P2, HR manager)
> *For sure there can be found some unique information (by using the customer service bot). Also, we have a lot of information available on our web pages. The chatbot can help to find the correct (desired) information (from the web pages*). (P5, HR software development manager in an employment agency)

4.2.2 **Recruitment bots as a potential fast lane for applicants**

A recurring theme in the interviews was that attraction bots are a complementary technology in relation to the conventional applicant tracking systems or other recruitment channels. Notably, at least in the current phase of emerging, recruitment bots are typically developed outside the company by a vendor. Therefore, they were not yet connected to the existing e-recruitment systems. P11 highlighted that in their organization the recruiters get an email notification when they receive a new application from an attraction bot. In contrast, applications from traditional recruitment channels end up to an applicant tracking system in which case the recruiters need to open the software to see the application. Also, in the applicant tracking system, the application presented just as another line among other applications. In other words, an attraction bot application can offer a fast lane for a job seeker to get the recruiter's attention. While this might put some applicants in unequal position, P11 justified this by the need for faster ways to react to the applications in order to succeed in the competition for talented workforce.

> *"(In the past) either people have called, or we have received (the applications) to our recruitment system […] Now, we receive fast email leads and we call back. It has made contacting faster […] We need to contact people as fast as possible […] Because otherwise they have already accepted another job offer."* (P11, representing a field with fierce competition of workforce)

4.2.3 **Chatbot can be an option to replace a human-operated chat**

P1 did not have experiences about chatbots but they had worked in a construction company that, a few years before the interview, had tested a chat where a human customer service professional collects initial applications in a similar manner as an attraction bot. Interestingly, it seemed that the conversations in human chat do not remarkably differ from those with current recruitment bots. Typically, a human customer service person would start a conversation and ask questions about work experience or educational background. While human conversations would allow asking much more creative or personalized questions, in practice, the customer service professionals might have up to ten chat conversations simultaneously open, and, to boost their performance, they frequently resort to predefined questions. The participant speculated that in the future, a chatbot could accompany a human chat by automating most of the conversation and giving space for the human operator to come up with follow-up questions. Finally, P1 emphasized the drastic change in work tasks that resulted from deploying the chat:

> *"It (the deployment of a chat service) actually made me a salesperson overnight […] After I started to receive contacts from outstanding candidates every five minutes, all my time went into making follow-up phone calls […] 80 percent of my working time transformed. We needed to immediately hire more recruiting professionals who continued the conversations with the candidates."* (P1, Recruitment manager)

4.2.4 **Balancing between acquiring details and easy application process**

The participants reported that, in some cases, an attraction bot would be offered as one channel to apply even for positions in which the applicants would conventionally need to show creativity and unique skills to be selected. This necessitates open-ended textual answers rather than closed-ended questions; the combination of short conversations with simple answering options inevitably results in applications that are quite similar to each other. At the same time, it was often assumed that the chatbot conversation should be short in order to keep the potential applicants interested, especially the passive job seekers. P6, whose company develops attraction bots, argued that if open text fields were used instead of multiple-choice questions, their clients would receive even 80% less applications through the chatbot, which would be considered suboptimal:

> *We have already noticed from our chatbots that, if an open text field is used, you can say goodbye to 80 percent of your chatbot conversations (that have been started) […] Right after you start asking (in the attraction bot) that*

could you write down your life story by typing on your mobile, then the response is an immediate "bye bye". (P6, CEO in a company that develops chatbots)

Moreover, while applying through a chatbot might require less effort from the applicant, several recruiters (e.g., P7 in the quote below) told that a shorter application often means more work: the application might be missing key details that need to be inquired later via other communication channels. Consequently, when using attraction bots it is necessary to balance between brevity and high level of detail, and chatbots might not provide the applicants with the best ways to stand out.

"We have to balance between having an easy application process and gathering enough information for a recruiter (to make an informed decision). However, at least currently (our) recruiters think that there is enough information." (P11, Oversees the use of recruitment bots at an employment agency that recruit construction workers)
"It is more laborious than receiving a complete application that has tremendous amount of information and a CV attached. Here we get only the lead and a little bit information on what kind of job they are searching and if they have any work experience." (P7, HR manager)

4.2.5 Indirect recruiter–applicant interaction affects the candidate experience and sense of privacy

From the recruiter's perspective, all recruitment bots are autonomous agents that interact directly with the applicant. Especially customer service bots tend to reduce the conventional recruiter–applicant interaction. As a result, the interviewees pointed out that the candidate's communication with the recruiting organization might feel a bit distant. This was seen particularly worrisome for organizations that aim to create a pleasurable candidate experience or convey certain company culture through their communications. This highlights that, considering user experience design, a customer service bot might not influence the organization's recruitment process as much as it influences the candidate experience. Also, it underlines the importance of piloting the chatbots before extensive use, which was also much discussed in the interviews.

"We wanted to be certain, that it really works and that we are allowed to talk with other organizations who have also implemented it. We just wanted to be sure that it does not risk anything in current processes or impair the candidate process." (P3, Worked recently in a company where they oversaw HR technology and tested various chatbots to automate HR activities)

Several participants brought up challenges regarding potential privacy issues and data protection. Interestingly, such challenges arose because of the job seeker trusting the technology too much: even if private information is not asked, one might be tempted to provide this information to ensure that they are seen as a genuine applicant.

> *"A chatbot user may write anything, for example, about personal data (that makes them identifiable) […] That information is stored in our system, which then forms a person register. That is a challenge."* (P5, Developer, in charge of developing HR software)

On the other hand, if the job seeker is concerned of privacy issues, they might also not like to use chatbot interface to share private information. For example, a passive job seeker might not want that information on their job seeking activities spreads beyond the target company's recruiter.

In addition, attraction bots that simplify the application process might not be attractive to all active job seekers. P9 speculated that the first-generation attraction bots with simple UI might not be considered as a serious application channel among active job seekers. The participant elaborated that a high-quality user interface of a recruitment bot probably affects the job seekers feeling of authenticity and encourages to start a conversation.

> *"If it looks like it is blinking and looks a bit shady in general, it will raise a suspicion, where does it (recruiting bot) come from, from this website or somewhere else?"* (P9, Director of recruitment department)

4.3 **Expectations towards future recruitment bots**

Some of the discussion in the interviews revolved around rather optimistic expectations towards the next generation of recruitment chatbots, which we will cover in what follows.

4.3.1 **New behavioral data and insights into the job market**

The participants were hopeful that, in the long run, chatbots could provide them with insightful new data that could support other human resource management needs. For instance, a few participants raised the idea about the so-called *talent pool* in which the applicant could be added to serve as ad-hoc workforce when the need arises. This could be a secondary option if the attraction bot or recruiter recognizes that the candidate does not match with current recruitment needs. P12 underlined the organizations' benefit: a large talent pool would help them to quickly search for a suitable candidate when a recruitment need arises. Another line of thought was to conduct a lightweight yet broad skill survey with the help of a chatbot, which was raised by P8 when considering the future of public sector job boards. This could give interesting statistical insight about the job market in general and help the public sector to inform the private sector about what kind of skills are available and to what extent. Similarly, data analytics based on web-based customer service bots could offer valuable information to the organization on which seem to be most interesting open positions or what might be unclear in the recruitment process based on the most frequently asked questions. Especially if hiring volumes are high, like in the case of employment agencies or large enterprises, customer service bots or attraction bots could allow gathering valuable data about the intentions of the job seekers.

> *"(Trend information) could give statistically relevant information on what kind of competence needs there will be. For example, where should we target training and coaching."* (P8)

4.3.2 Needs for chatbots beyond candidate attraction and applying

While different types of recruitment bots serve different purposes, they are typically utilized to support the early stages of the recruitment process and to enable instantaneous interactions around a specific job opening. Hence, many interviewees speculated whether a chatbot could be useful also in later stages of recruitment, for example, by increasing two-way interaction between a job seeker and an organization. There seems to be a need for actively engaging in information exchange also during the recruitment process, particularly when the recruitment is a deliberate process with multiple, inevitably time-consuming stages. Additionally, P4 saw an opportunity to implement an internal customer service bot to support a newly hired employee when they is onboarded to the company and large amounts of practical information is presented in a short time. While offering such support would typically not be a recruiter's responsibility, for the applicant the first days at work form a continuation of the candidate experience and influence the employer image.

5 Discussion

The following summarizes the findings from the perspective of the recruiters' practical activities throughout the recruitment process and the systemic effects that chatbots could bring to recruitment activities. Hence, we contribute to the emerging research thread in HCI that focuses on the understudied recruiters' perspective (Lu and Dillahunt 2021). Furthermore, we raise design considerations that can help designers and organizations to identify more sensible uses of, interactions with, and designs of chatbots in recruitment.

5.1 Towards next-generation recruitment bots

5.1.1 Support for careful planning of the chatbot script

The ongoing march of chatbots into recruitment seems to have introduced interesting new tasks, risks, and dynamics, some of which can be regarded as unexpected consequences from the recruiter's viewpoint. Important downsides include ending up with larger masses or seemingly unsuitable applicants as well as additional tasks for the recruiters. While the bots might seem autonomous in terms of interacting with the job seekers, recruiters actually need to pay much attention to predefining and coordinating their actions. This efficiency paradox seemed to have caught the recruiters by surprise and forced them to redesign their work practices. Amongst the participants who had deployed an attraction bot, a fundamentally new task was to create the chatbot scripts. The sequential and pre-scripted attraction bot conversations arguably present a challenge of optimizing what information is given and inquired in the conversation.

However, there seems to be little guidance for recruiters on how to prepare high-quality scripts in practice. For example, the order of the questions, the answering options, the conversation flow, potential dead ends in the conversation, and the tone of voice can make a significant difference in terms of effectiveness. The underlying challenge is to turn relatively abstract and diverse recruitment criteria into short and engaging questions. Because task-focused attraction bot conversations typically do not offer many exchanges, the recruiter is forced to think what the essential aspects are that should, at a minimum, be covered.

This opens an interesting design space for chatbot interaction design (or *conversation design*) for the HCI community. For example, digital assistance in defining the questions could help with the general flow of questions: e.g., easy ones first (for ease and flexibility) and more specific questions later (for detailed applicant information). In addition, a chatbot script could include weighted answer options and the most potential combinations of answers could be automatically detected. The chatbot conversation should also be encouraging and polite in case the candidate does not have a realistic chance. In the long run, rather than following a tight script of inquiry, the chatbot interaction design could follow a mental model of guiding the applicant through the application process (Sands *et al*. 2020). To this end, Sands *et al*. (2020) interestingly encouraged the development of service-oriented chatbots to draw on learnings from the theatrical domain. Particularly, they encouraged to develop a dramatic script for service managers including considerations on how to relate with customer's experience, their physical environment, and the narrative context of the experience.

5.1.2 **Chatbots support low-threshold interaction but are also part of external communications**

The lack of communication between a recruiter and an applicant is a general challenge in recruitment (Koivunen *et al*. 2019). To keep the connection between a recruiter and an applicant alive, there exists commercial chatbot solutions, such as Mya, that can be used to interact with applicants during a recruitment process via a mobile application. Such messaging channel combined with a conversational UI seems like a promising way to communicate with the applicants but would of course require the job seekers to find and download the application. In this sense, web-based chatbot interfaces have a natural advantage.

At the same time, especially when deployed on a public website, recruitment bots represent the recruiting organization and form a connection to the organization's brand. The significant role in organizations' external communication could explain why the perceived risks of recruitment bots relate to possible negative candidate experiences. This necessitates careful planning of how the chatbot represents the organization. For example, the chatbot's tone of voice was found to have been modified to better represent the organization but this is hardly the only way to tailor the communication style. More broadly, instead of seeing recruitment bots as information systems for human resource management, they could be regarded (and marketed) as marketing tools.

Another practical opportunity identified in the study is that customer service bots could help applicants to easily follow the situation in the recruitment process on general level (i.e., as a tracking system), without needing to bother the recruiters. However, web-based chatbots are not an optimal way to exchange personal information as a personalized service would require identification; if such a feature was implemented, the general approachability of the chatbot could decrease as the benefits of anonymous interaction and a low-threshold service would be lost.

5.1.3 Attraction bots can benefit most when targeted at specific job seeker profiles

The key opportunity and expected benefit in the use of recruitment bots seems to be reaching new candidates. The findings imply that the target audiences should be thoroughly considered when defining requirements for a particular job opening. It seems that recruitment bots are used rather opportunistically, and while some participants had a specific target audience in mind, they had not developed established practices to match the benefits of recruitment chatbot technology and job seeker profiles. For example, attraction bots could be a way to attract candidates who (i) primarily use mobile devices, (ii) are not likely to have their up-to-date CV or other traditional documents at hand, (iii) are opportunistically browsing for jobs while being employed (i.e., passive job seekers), or (iv) are highly accustomed to interacting through chatbots or an asynchronous chat interface in general. On the other hand, it was questioned whether the chat UI would attract serious job seekers. Therefore, it seems unlikely that an attraction bot would be used as the only way to apply for job openings in job sectors where it is vital to provide an extensive application. With these opportunities, we call for more targeted use of recruitment bots to complement the way of using them as general recruiter–candidate interaction channels for all. This opens an interesting design space for more contextualized instances of this generic technology, necessitating new designs with respect to the interaction scripts as well as administrative interfaces for the recruiter.

5.2 Limitations

We acknowledge that the methodological choice to run an interview study in a specific cultural context has inherent limitations on generalizability. In addition, given the relatively early stage of diffusion of this technology in the target context, the study was challenged by practical issues like availability of eligible participants. First, while not weakening the contribution, the participant sample represented experiences from one country and from a limited number of organizations, rendering the data possibly specific to culture and/or certain professional domains. At the same time, it was clear from the beginning that there were not many people who could attend as a participant with experience in using recruitment bots. Hence, our participants had different levels of knowledge and perspective to the topic, which is both a limitation considering generalizability and an advantage considering diversity of the qualitative dataset. That said, we are confident that the qualitative findings help to understand the ongoing march of chatbots into recruitment and their systemic effects, as well as to identify relevant design challenges for follow-up HCI research to address. Second, it is inevitable that voluntary-based participation is likely to attract interviewees with an optimistic viewpoint to the topic. Should recruitment bots become more popular, it would be beneficial to run more quantitatively oriented follow-up studies.

We notice that in our findings, experiences and practical implications mainly focus on attraction bots, whereas the expectations and motivations also include other recruitment bot types. While expectations are arguably more speculative compared to actual experiences, we felt that adding the perspective gave a valuable opportunity to look at this topic more broadly covering different needs and functions in recruitment.

5.3 Future work

Our approach was explorative and as such it provides several directions for future research. We encourage other scholars to continue exploring this area from different viewpoints, for example by focusing on a certain type of recruitment bot or by more systematically analyzing the possibilities and limits of recruitment bots in the context of specific professional domains or cultural contexts. This has already been done to some extent with Juji interview bots (Xiao *et al*. 2019; Zhou *et al*. 2019) but customer service bots and attraction bots remain understudied to this end. Importantly, as recruitment bots are becoming more prevalent, job seekers' perceptions would warrant more extensive research, preferably by focusing on a specific type of recruitment bot.

6 Conclusions

Various types of chatbots used in recruitment represent an emerging form of e-recruitment systems that can help recruiters to attract potential applicants, partly automate the communication with them, and gather basic applicant information. The activity context, i.e., the inherently delicate, dynamic, and high-stakes recruitment process, contrasts with the use of chatbots in many other application areas and questions the effectiveness and appropriateness of conventional chatbots in this area. Prior HCI research has highlighted the need to study chatbot solutions in different contexts, especially focusing on the unheeded perspective of the recruiter. In order to understand the related motivations, needs, expectations, and early experiences, we conducted 13 expert interviews with people who are already using, developing, or planning to deploy recruitment bots in the near future. The initial experiences revealed interesting new dynamics and tasks related to the design of recruitment chatbots and the scripted conversations. Especially attraction bots that collect application information should be considered in relation to other e-recruitment channels in order to reach the most suitable target audience and, hence, yield most value considering the general interests of recruitment. As one the first qualitative studies on the utilization of recruitment bots, the study offers timely insights for both the designers of chatbots and the organizations intending to deploy such in e-recruitment activities.

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Declarations

Conflicts of interests/Competing interests The authors have no conflicts of interest to declare that are relevant to the content of this article.

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PUBLICATION IV

Pitfalls and Tensions in Digitalizing Talent Acquisition: An Analysis of HRM Professionals' Considerations Related to Digital Ethics

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Pitfalls and Tensions in Digitalizing Talent Acquisition: An Analysis of HRM Professionals' Considerations Related to Digital Ethics

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Abstract

The practices of organizational talent acquisition are rapidly transforming as a result of the proliferation of information systems that support decision-making, ranging from applicant tracking systems to recruitment chatbots. As part of human resource management (HRM), talent acquisition covers recruitment and team-assembly activities and is allegedly in dire need for digital aid. We analyze the pitfalls and tensions of digitalization in this area through a lens that builds on the interdisciplinary literature related to digital ethics. Using three relevant landmark papers, we analyzed qualitative data from 47 interviews of HRM professionals in Finland, including team-assembly facilitators and recruitment experts. The analysis highlights 14 potential tensions and pitfalls, such as the tension between requesting detailed data versus respecting privacy and the pitfall of unequal treatment across application channels. We identify that the values of autonomy, fairness and utility are often especially at risk of being compromised. We discuss the tendency of the binary considerations related to human and automated decision making, and the reasons for the incompatibility between current digital systems and organizations' needs for talent acquisition.

RESEARCH HIGHLIGHTS:

- Several ethical tensions and pitfalls relate to the ongoing digitalization of talent acquisition.
- We identified upper-level categories of values, such as fairness and autonomy, that relate to the described tensions and pitfalls.
- The described tensions and pitfalls imply new perspectives to consider in the design and development of new information systems to support decision making in talent acquisition.

Keywords: *sustainability*; *digital ethics*; *collaboration*; *team assembly*; *recruitment*; *talent acquisition*

1. INTRODUCTION

This paper focuses on the digitalization of *talent acquisition* (Ployhart *et al.,* 2018; Breaugh, 2021), which represents a high-risk area of decision-making related to an organization acquiring human capital (i.e. employees). In practice, *talent acquisition* is here understood to cover the organizational activities of recruitment and team assembly. Namely, talent acquisition aims to find *the right person for the right job at the right time* (Cappelli and Keller, 2014; Ployhart *et al.,* 2018), and it is the critical first step in effective talent management (Breaugh, 2021). The practices and successfulness of an organization's talent acquisition bear significantly on their productivity, employee well-being and long-term economic competitiveness (Breaugh, 2013; Weller *et al.,* 2019). Recently, the phenomenon called *the Great Reshuffle* (i.e. *the Great Resignation*, a term coined by Anthony Klotz, 2022)—wherein workers change jobs to increase purpose, flexibility, and empathy—can be seen to have highlighted the importance of efficient talent acquisition (Cook, 2021). In regulation, talent acquisition has been recognized as a high-risk area wherein digital systems can significantly impact on future career prospects and livelihoods (see, e.g., GDPR and the Artificial Intelligence [AI] Act of the European Union).

To these ends, various information systems and digital tools have been actively developed, typically reflecting intentions to improve the efficiency of labor-intensive human resource management (HRM) tasks or to support human decision-making (Albert, 2019; Black and van Esch, 2021). The HRM (Boxall and Purcell, 2022) in organizations is increasingly supported by information technology (IT), covering systems for payroll, productivity, compliance and onboarding measurements, as well as for recruitment and team assembly (Albert, 2019; Fuller *et al.,* 2021). The introduction of digital systems inevitably creates the need to weigh up different goals, values, practical possibilities and tool suitability, often leading to tensions and trade-offs between these. As advanced systems are increasingly introduced in talent acquisition (Statista, 2017; Albert, 2019; Fuller *et al.,* 2021), academics have investigated human resources (HR) professionals' practical experiences of utilizing such tools (Koivunen *et al.,* 2019; Laurim *et al.,* 2021; Li *et al.,* 2021). Nevertheless, research in this area is still underdeveloped and lagging behind industrial

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adoption, particularly in the aspects of digital ethics and the social sustainability of the introduced systems (Raghavan *et al.,* 2020; Sánchez-Monedero *et al.,* 2020). In fact, we are witnessing a mushrooming of literature on the detrimental societal and cultural effects of digitalization at the general level, highlighting issues related to unfairness and discrimination (Eubanks, 2018), data ethics and privacy in the surveillance economy (Zuboff, 2019) and considerations about AI ethics, including those related to accountability, transparency, and human control (Fjeld *et al.,* 2020). Together, such viewpoints form an interdisciplinary area of research often termed *digital ethics* (or *IT ethics*) (Moor, 2006). These developments introduce an intriguing research gap that demands interdisciplinary, sociotechnical analysis of the ongoing digitalization of talent acquisition. The general principles and viewpoints in such literature call for critical analysis of the more specific challenges and pitfalls encountered in the digitalization of specific areas.

Using a 3-fold framework, we conducted a secondary analysis of 47 interviews that we carried out within a 3-year period with HRM professionals. The interviews focused on activities related to recruitment and assembling creative teams, uncovering the HRM professionals' practices and challenges in relation to digital systems, as well as their expectations regarding next-generation digital systems. To develop our novel analytical framework, we identified three landmark papers that offer intertwining and complementary perspectives on digital ethics in talent acquisition. Together they enabled us (i) to identify relevant ethical values, tensions between those values and general pitfalls encountered in the digitalization of talent acquisition; and (ii) to analyze how the interviewees understood and responded to the identified issues. First, Royakkers *et al.* (2018) posited that the emerging forms of technology have put pressure on public values, such as human dignity, the balance of power, privacy and autonomy. Highlighting areas of ethical concern in digital transformation, the article provided us with evaluative lenses (i.e. *values*) through which the interview material could be analyzed. Second, Whittlestone *et al.* (2019) called for focusing on the tensions that arise when ethical principles for AI are interpreted and applied in practical contexts. This article guided us toward identifying *tensions* and *trade-offs* that emerged within the interviewees' situated practical realities—for example, due to business needs, pressures, and technical constraints—thereby allowing us to better contextualize the research material. Third, Selbst *et al.* (2019) described 'abstraction traps' that can undermine or misguide the pursuit of public values, such as fairness, in dynamic sociotechnical contexts. Keeping these traps in mind, we were able to highlight common tendencies pertaining to the interviewees' ethical reasoning.

In sum, the three articles thus provided us with a conceptual framework applicable for analyzing both (i) what public values are at stake and (ii) how the pursuit of these values might be successful or unsuccessful in the context of digital talent acquisition. To these ends, we ask: *What kind of pitfalls and tensions relate to the development and use of IT in HRM experts' decision-making?* This explorative paper contributes practically relevant considerations for designing and developing ethical IT to support talent acquisition. Digital ethics and particularly fairness and autonomy have received increasing attention in HCI (Holstein *et al.,* 2019; Mulligan *et al.,* 2019). We further describe what public values HRM experts perceived as central in digital talent acquisition and why they considered this to be the case and which stakeholders are affected by the identified value conflicts and pitfalls. Overall, our work contributes to designing ethically aware talent acquisition activities for complex sociotechnical systems and presents new avenues for research in this area. Being able to develop such ethically aware guidelines is an important topic for HCI, and research to this end has been called for in the IwC journal also (Abascal and Nicolle, 2005).

2. THEORETICAL BACKGROUND AND RELATED WORK

2.1. Talent acquisition as an application area of IT

We focus on market-based talent acquisition where interested *candidates* are invited to apply (typically from outside an organization); if they apply, they are regarded as *applicants* (Keller, 2018). Organizations typically rely on external human capital (i.e. new talent) when seeking to build new competences (Cappelli, 2010; Cappelli and Keller, 2014), motivated by the facts that employee tenure is declining and that employment stability has decreased both in the private and the public sectors (Hollister, 2011). These trends result in increasing numbers of talent acquisition decisions and, hence, also increase the offering of new digital systems. Overall, scholars advocate for having systematic practices for talent acquisition (Collings and Mellahi, 2009). However, it seems that organizations' and decision-makers' motives are often less rational than is commonly assumed or desired (Rivera, 2012, 2020). For example, human decision-making can be influenced by greed, overconfidence, prejudice or fatigue (Kausel *et al.,* 2016; Lepri *et al.,* 2018).

While 'talent' is sometimes considered as a rarity, in reference to high-potential workers (Lumme-Tuomala, 2019), research shows that a more inclusive approach includes, for example, inconsequential forms of work (Breaugh, 2021). Talent acquisition offers a strategic perspective on activities that are not limited to external recruitment (Breaugh, 2021). Therefore, our analysis includes team assembly, which refers to 'the process of searching for, identifying and choosing members for a team' (Gómez-Zará *et al.,* 2020). After all, work teams are ingrained in organizations (Salas *et al.,* 2017), and organizations' success is increasingly dependent on teamwork (Hall *et al.,* 2018; Salas *et al.,* 2018; Tebes and Thai, 2018). While much of the existing research on teams tend to focus on relatively intact teams and generally what makes teams effective after they are assembled (Bell *et al.,* 2018), the interviews in this study cover particularly the assembly phase of diverse innovation teams that span organizational boundaries explicitly before the teamwork processes begin (Edmondson and Harvey, 2018; Fecher *et al.,* 2020).

The talent acquisition process tends to follow a linear decision-making process with multiple stages, including (i) establishing requirements, (ii) identifying and attracting alternatives, (iii) comparing alternatives and (iv) selecting the most suitable match (Holm and Haahr, 2019; Koivunen *et al.,* 2019). Practical tasks throughout the stages include, for example, writing job advertisements, deciding on the channels for attracting candidates or proactively searching for candidates, and comparing applications (Holm and Haahr, 2019; Koivunen *et al.,* 2019). Later in this paper, we utilize this four-stage framework to structure the findings and to highlight the strategic decisions at different stages, such as *bringing a job opening to the attention of potential job candidates* and *encouraging a candidate to apply for a job opening* (Breaugh, 2021).

Typically, the idea behind digitalizing and automating such labor-intensive tasks is to reduce costs and save time by reducing administrative work, increasing processing speed, and enhancing decision making (Parry and Tyson, 2011; Suen *et al.,* 2019). To this end, organizations conventionally utilize e-recruitment technologies (like websites, social media and job portals) to attract or to find applicants ('sourcing'). for example, Microsoft's LinkedIn. Further, applicant tracking systems (ATS) are used to manage the workflows and tasks, such as reviewing applications ('screening') and communicating with the applicants.

Systems based on AI are increasingly utilized through, for example, robotic process automation, chatbots and predictive technology (Albert, 2019; Black and van Esch, 2021). Most common use cases include searching for candidates on online networking sites, such as LinkedIn or Indeed Resume. Furthermore, according to market research, numerous vendors develop AI systems to find, filter and assess applicants (Statista, 2017; Bersin, 2021; IndustryARC, 2021). One potential purpose of AI is to identify and mitigate patterns of bias and discrimination in the decision-making process (Raghavan *et al.,* 2020; Sánchez-Monedero *et al.,* 2020; Wilson *et al.,* 2021). However, in studies where participants have been asked to choose between an algorithmic or human decision, there is growing evidence that algorithmic decisions are perceived as less fair and perceived to evoke more negative emotion and skepticism (Lee, 2018; Kaibel *et al.,* 2019). In addition, Wilson *et al.* (2021) reminded us that, while discrimination that is driven by human biases is a long-standing and widespread issue in talent acquisition, we should not assume that algorithms aiming to remove biases are neutral or bias free. Tambe *et al.* (2019) summarized in their study that AI faces challenges in the HRM context because of the complexity of the HR phenomena, constraints regarding small data sets, fairness and other ethical and legal constraints, and possible adverse employee reactions to algorithm decisions.

Literature is increasingly investigating the use of IT in talent acquisition. The applicant perspective was very recently introduced in IwC (Dillahunt *et al.,* 2021) with the existing research generally tending to focus on that perspective (McCarthy *et al.,* 2017). By contrast, the research on HR professionals' perspective seems to be scarce with a few notable exceptions. For example, Li *et al.* (2021) interviewed 15 HR professionals who used AI-enabled software for sourcing or assessments. They found that socio-organizational contexts, including professionals' individual motivation and organizational practices, shape how AI systems are used. They provide suggestions for how sourcing and assessment systems could be more equitable by reconsidering the HR professionals' role versus technology's role in assessment. In addition, van den Broek *et al.* (2019), van den Broek *et al.* (2021) conducted a rigorous ethnographic field study wherein they collected data from both machine learning (ML) developers (who develop software based on ML algorithms that utilize training data to make predictions) and the HR professionals using the developed ML service. In the first paper, the authors empirically illustrated how fairness ideals can fail to account for the contextual, temporal and contestable nature of fairness (i.e. the formalism trap; Selbst *et al.,* 2019), and highlighting the crucial role of ethical values in the use and development of digital solutions (van den Broek *et al.,* 2019). In the second paper, the authors described the hybrid practice that formed through mutual learning between ML developers and domain experts (van den Broek *et al.,* 2021). All in all, empirical research on the HR experts' perspectives seems to be gaining HCI scholars' attention as the community develops an understanding of the problematic aspects of IT in terms of decision-making transparency, accountability, and the societal impact of digitally mediated HR processes.

2.2. Developing an analytical framework for ethical considerations in talent acquisition systems

The ethical and social sustainability of various information systems have been extensively discussed over the past decade across research communities. In what follows, rather than outlining this vast and multidisciplinary area of literature, we focus on the central question of how digitalization comes to be at odds with public values and individual rights (such as the rights of privacy, human autonomy and fairness; Royakkers *et al.,* 2018) specifically in the context of talent acquisition. We present the conceptual framework that we used in the analysis, building on the above-mentioned three articles on the ethical considerations of IT that we deemed particularly relevant and complementary.

As the talent acquisition process conditions applicants' opportunities and may have repercussions for both companies and applicants, digital ethics offer a crucial analytical lens. Not only do employers' choices influence social inequalities by contributing to employment disparities (and thus play an important role in individuals' economic chances; Rivera, 2020), but also do companies' reputations, in terms of ethicality plausibly, affect their attractiveness from the perspective of candidates and applicants. A common expectation is that digital systems can help in devising fairer, less biased processes. For example, systems might increase procedural justice through structured approaches and standardized definitions, as well as decrease the likelihood of making political decisions (Dries, 2013). However, the legal and ethical risks in talent acquisition are intricate and perhaps increasingly more so due to digitalization. This underlines the need for a sociotechnical perspective that is seemingly missing in the initial wave of guidelines and codes of conduct that aim to set ethical boundaries for the development and use of emerging technologies (Jobin *et al.,* 2019). A dire need for more practical approaches to digital ethics that suit practitioners' contextual needs persists (Holstein *et al.,* 2019; Selbst *et al.,* 2019; van den Broek *et al.,* 2019; Whittlestone *et al.,* 2019).

Our conceptual frame synthesizes the insights from three papers related to digital ethics (Royakkers *et al.,* 2018; Selbst *et al.,* 2019; Whittlestone *et al.,* 2019). The different viewpoints are expected to help identify critical perspectives through our analysis process. We particularly chose these papers due to the insights they offer for research on ethics in sociotechnical systems: They emphasize the plurality of the values and interests at play in digitalization and datafication, the contextual tensions that arise and the complexity of interactions between social and technical systems. This 3-fold frame enables us to analyze HRM professionals' situated perspectives while maintaining the critical distance necessary for identifying pitfalls and tensions in regard to how their perspectives address public and societal values and concerns.

The first paper contributing to the framework, by Royakkers *et al.* (2018), identifies privacy, security, human autonomy, human dignity, the balance of power and justice as areas of ethical concern in digitalization and digital transformation. The paper also discusses specific concerns related to filtering and categorization (including questions regarding power in terms of who gets to define the standards for filtering and categorization), servitization, unfair competition and monopolization. In the analysis of the research data, we located connections between participants' comments, both specific and broad, and the themes introduced by this article; we also sought to identify how the participants position themselves as agents in relation to the normative requirements posed by different ethical values.

Second, noting that values and ethical principles lend themselves to contested interpretations of the concrete requirements they impose on agents, Whittlestone *et al.* (2019) argued that a focus on tensions between values should be taken as the starting point. There is a need to understand the stakeholders' goals and (interpretations of) values, the constraints that practitioners face in reasoning, and trade-offs that arise given those goals and constraints. Fairness, for example, is a contextual and highly contested concept (Holstein *et al.,* 2019;Lee *et al.,* 2019 ; Whittlestone *et al.,* 2019), and domain-specific resources, metrics, processes and tools are in demand by practitioners for navigating challenges related to fairness that are unique to their domains (Lee *et al.,* 2019; Whittlestone *et al.,* 2019). Existing interview studies show that ML practitioners need cheap and effective strategies for addressing fairness issues and for helping in anticipating trade-offs between fairness (and other) desiderata for ML systems (Veale *et al.,* 2018; Holstein *et al.,* 2019). The focus on tensions helps to highlight ambiguities and gaps in agents' understanding of how the use of technology is impacting on society in ethically relevant ways and to contextualize their needs regarding the pursuit of ethical sustainability.

Third, the focus on interpretative flexibility and practical challenges is also emphasized by Selbst *et al.* (2019). Taking a sociotechnical lens to ethical design, the authors present five 'abstraction traps' into which agents may fall when designing, implementing or evaluating technological solutions. They argue that *over-abstraction*—here, a failure to model the social context into which sociotechnical systems are deployed and how that context interacts with the implemented technology, producing ripple effects—can misguide design and lead to harmful outcomes. *Solutionism* can obscure the fact that technology cannot always provide the best solutions to business problems or social issues. Solutionism is especially a paramount issue as AI software is designed for smooth *portability* across contexts, even though decision makers and affected individuals can in fact have differently situated needs and interests. We analyzed the interview data through these notions of over-abstraction, solutionism and portability aspirations. We aimed to identify the levels of abstraction in which HRM professionals operate when considering the digitalization of talent acquisition and whether non-technological factors and social implications figured into their considerations (and, if so, to what extent they did so).

On a conceptual note, we specifically use the term *pitfall* to describe how HRM professionals might fail to account for ethically meaningful factors due to, for example, an excessive focus on other factors (e.g. business needs) or because of practical constraints (e.g. a lack of relevant information). The term *tension* is used to describe situations where the ethical and practical requirements faced by HRM professionals come into conflict. These include *genuine trade-offs*, where there are necessarily conflicting ethical duties; *practical trade-offs,* where conflicts between duties arise due to contingent, practical circumstances; and *false dilemmas*, where agents fail to recognize available options that would resolve tensions (Whittlestone *et al.,* 2019). This distinction does not imply that practical trade-offs are less 'genuine' in terms of their concrete consequences for ethical decision making. Rather, the distinction serves to highlight that practical circumstances may necessitate trading off desirable aspects in talent acquisition, even if those aspects are compatible in theory.

Together, this conceptual frame allowed us to draw conclusions about what HRM professionals need in digital talent acquisition, what factors were accounted for, how these factors were accounted for and what kinds of critical tensions, trade-offs and pitfalls occurred.

3. METHODS

The present study is a secondary analysis (Heaton, 2008; Ruggiano and Perry, 2019) based on empirical, qualitative data from three qualitative interview studies conducted by the authors. Before this study, each of the studies has resulted in a published research paper in HCI and CSCW outlets (Koivunen *et al.,* 2019, 2021, 2022). Altogether 47 interviews were conducted (21 + 13 + 13). All the interviews were semi-structured by nature, and afterwards, they were transcribed word for word using a professional service or by one of the authors. The large majority of the interviews were conducted face-to-face as the studies took place before the COVID-19 pandemic. Almost all the face-to-face interviews were conducted at the participant's workplace.

In all interviews, we inquired about the HRM professionals' practices and the perceived challenges in relation to digital systems in talent acquisition activities, and we typically asked them to give concrete examples. In the first study, we interviewed HR specialists and headhunters, inquiring about their practices and focusing particularly on various challenges and risks they perceive in the recruitment context (Koivunen *et al.,* 2019). In the second study, we interviewed people who regularly assemble innovation teams, inquiring about their practices, for example, in relation to how they obtain and process information received from applicants and on what basis they match people to teams (Koivunen *et al.,* 2021). In the third study, we inquired about recruiters' early experiences and expectations regarding a specific, emerging form of e-recruitment technology: recruitment chatbots (henceforth, *recruitment bots*) (Koivunen *et al.,* 2022).

As this paper utilizes the secondary analysis method, it is necessary to address methodological rigor. In the following, we provide our reflection that is particularly based on the findings and the recommendations by Ruggiano and Perry (2019) who studied the topic. The findings reported in the earlier papers have not been utilized in the analysis and are not republished here. To ensure the rigor of our secondary analysis of the qualitative data we (i) utilized uncoded, clean transcripts from the parent studies that, importantly, provided settings that met the requirements of the present study (Sherif, 2018); (ii) applied a novel analytic approach where we purposefully read the transcripts from a new perspective; (iii) included new researchers with relevant expertise considering the new perspective; and (iv) used a constructivist-grounded theory-oriented approach that helped us to be critical and reflective when coding the data. Notably, constructivist grounded theory approach has been utilized in secondary analysis (Whiteside *et al.,* 2012).

This paper significantly differs from the parent studies in two respects. First, whereas the parent studies concerned concrete practices, and user expectations and experiences in digital talent acquisition, here we center on digital ethics as a novel perspective and set of challenges in that context. Second, we take a more abstract approach to the discussion of recruitment and team assembly by considering both as forms of talent acquisition.

3.1. Participants and their recruitment

As all three studies were conducted in Finland, this research focuses on the Finnish cultural environment, which is also the most familiar cultural environment to the authors. In terms of professional life, Finnish culture is typically considered a Nordic culture with democratic decision-making practices, high worker autonomy and work ethics, and an advanced level of digitalization throughout society.

The participants were invited to participate either by identifying relevant candidates from both public and private organizations in Finland and then contacting them directly or with the help of snowball sampling and LinkedIn advertising. The participants' professional roles are presented in Table 1. The way the participants reported their professional role varied slightly between the parent studies, consequently there are more details about some participants than others. One participant was interviewed twice in separate studies; therefore, the total number of interviews was 47. To summarize, the participants represent a variety of job roles, including HR managers, HR consultants, HR department leaders, HR software development managers, team coaches, facilitators of innovation teams and CEOs of companies that develop relevant digital tools. Almost all the participants were working in the knowledge work industry. All of them had a strong professional track record in either talent acquisition or the development of systems for talent acquisition. A diverse range of work roles was considered crucial in order to develop a rich qualitative account of this space. While HR professionals have gained much attention in talent acquisition literature, e-HRM studies have shown that digitalization has also transferred to line managers (Myllymäki, 2021). In the Results section, we refer to the participants collectively as *HRM experts*.

3.2. Data analysis

The 47 interviews were reanalyzed following a bottom-up analysis procedure; however, we used the presented conceptual framework as an interpretative lens. We used constructivist-grounded theory-oriented analysis (as described by Charmaz and Bryant; Bryant, 2017; Bryant and Charmaz, 2019) while being mindful of the framework throughout the process. The average length of the interviews per study was 73, 74 and 59 minutes, resulting in 335,378 words of transcribed text. Before initiating the analysis, two of the authors had several discussions in order to identify a suitably complementary viewpoint and scope for the secondary analysis.

The first author conducted the initial descriptive coding that produced 836 codes. This was followed by discussions with another author familiar with the framework who commented on the individual codes. To ensure that a focus on aspects of digital ethics was maintained, two authors checked all the codes with respect to their relevance and added interpretations as annotations. This process of selecting the codes with most analytical power and relevance resulted in a narrower set of 382 codes, which was then utilized in the following analysis process. At this point, a decision-making process with four stages (Koivunen *et al.,* 2019) was found to be a useful framework with which to organize the findings. We categorized the codes according to the stages and initiated focused coding where the abstraction level was raised and codes were synthesized. Further, we highlighted interesting codes or code groups relevant to highlighting tensions or pitfalls.

Because the analysis produced more tensions and pitfalls than could be practically reported in one article, three of the authors refined them and narrowed down the list to the most interesting ones. The analysis was conducted in Finnish, and the quotes presented in the Results section have been translated by the authors. We deliberately avoid quantifying the findings as concepts have relevance in virtue of what they bring to the framework qualitatively, regardless of how frequently they may have appeared quantitatively (Bryant and Charmaz, 2019).

4. RESULTS AND REFLECTIONS

We report our findings through an analytical narrative that attempts to offer a contextually rich description, supported by user quotes at places. Related to each temporal stage in talent acquisition (Koivunen *et al.,* 2019), we structure the findings according to the identified tensions and pitfalls and we describe them in the light of the interview data and potential design considerations for future development of digital HRM tools.

4.1. Establishing requirements

This stage relates to the identification of the kinds of qualities that are sought, as well as to specification of the application process and the most suitable tools to support it.

4.1.1. *Tension: Short- vs. long-term planning*

New tools constantly flood into the market with promises to streamline the talent acquisition process (Cappelli, 2019). Spending on the latest tools and expertise on using them can be a major investment for an organization. The interviewees rightly reminded that new tools also introduce new tasks and demand skills to learn in order to utilize the benefits. For example, when a new recruitment bot is deployed, the HRM experts need to learn how to write chatbot scripts. Furthermore, the systems tend to require configuration work; they might not be updated regularly and, in general, they can be short-lived. One participant told that their organization had started to develop a system to collect application information and to make suggestions on who could work together. However, as demonstrated in the quote below, they emphasized that creating such functionality has proven to be challenging, and the system still requires a lot of development in order to create value. In other words, fulfilling what was envisioned to be the tool's expected potential seemed challenging.

'It requires honing to make it work perfectly or even just enough to get it work properly. At the moment, it is maybe more like a databank for us and, in practice, a lot is done by our own personnel.' (Study 1, ID in the participant table: 16. Project manager, discussing the development of their system).

As Royakkers *et al.* (2018) point out, IT service providers are increasingly using the software-as-a-service pricing model, meaning that they are always-active services with continuous expenses. However, needs for talent acquisition are irregular and tend to accumulate according to the economic situation. Moreover, in the labor market, there can be many suitable applicants available at one moment, while none at another. Organizations therefore need to consider whether to conduct the process internally and invest in new systems and the required expertise to use them or to outsource talent acquisition to external service providers.

In sum, the interviews implied that there is a risk that companies lean on reactive short-term thinking and quick technological fixes, rather than improving their decision-making processes, which reflects techno-optimistic and tool-centric solutionism trap, as described by Selbst *et al.* (2019). The first stage of creating requirements greatly impacts the following stages (Koivunen *et al.,* 2019; Breaugh, 2021), hinting that a better approach is to increase the time spent in carefully designing the job advertisements and considering strategic actions of talent acquisition such as what competences would be truly beneficial.

4.1.2. *Tension: Abstract vs. detailed job descriptions*

The established requirements for talent need to be clearly reflected by the job description shown to candidates. However, throughout the process of creating the description, the

TABLE 1. Professional roles of the participants, listed in the order they appear in the parent publications

ID	Professional Role
1	Startup CEO, developing recruiting apps
2	Startup CEO, developing recruiting apps
3	Startup CEO, analyzing social media
4	Organizer of a student job fair
5	HR consultant, a job fair organizer
6	Project manager, event organizer
7	Strategic resourcing and recruiting expert
8	Head of recruitment and employer branding
9	HR manager
10	Recruitment consultant
11	HR consultant
12	Recruitment team leader
13	Sales and recruitment team leader
14	Journalist, team leader (responsible of hiring team members)
15	Director of digital environment. Used to assemble teams for higher education innovation projects
16	Project manager in a mentoring program
17	Account manager, consultant
18	People development consultant
19	User experience team leader
20	Community manager, career counseling
21	Social media recruitment trainer
22	CEO of a company developing an application that matches people into teams within an organization
23	Innovation platform facilitator who assembles teams for higher education innovation projects
24	Creative director. Responsible of the development of project teams, involved in team assembly for higher education innovation projects
25	Coach of team leaders and managers
26	Innovation platform facilitator who assembles teams for higher education innovation projects
27	Vice president. Formerly a matchmaker in a company that organizes innovation projects for higher education students
28	Team coach. Coordinates innovation projects for higher education, also covering team assembly
29	Involved in team assembly of multiorganizational innovation teams that focus on societal challenges
30	Team coach. Mainly guides innovation teams but also has assembled teams in the context of higher education
31	Designer. Assembles and coaches higher education student teams
32	Assembles and mentors higher education teams that, e.g., aim to organize an annual innovation event
33	Facilitator who assembles teams for higher education innovation projects
34	Recruitment manager in construction sector who has tested a live recruitment chat, and is planning to deploy a chatbot in their current company
35	HR manager. In charge of recruitment in a company that provides billing and financial management services. Is actively using a chatbot to reach customer service and knowledge work professionals
36	Head of HR department. Worked in a company that provides IT services. Has tested various chatbots to automate HR activities
37	Head of HR digitalization and AI project in a multinational company of ∼100 000 employees. Has deployed an internal chatbot for HR
38	HR software development manager in an employment agency that helps to recruit 6000–8000 people annually. Has deployed a customer service chatbot for job seekers
39	CEO in a company that develops chatbots for several clients. Also uses a chatbot to hire new people to their company
40	HR manager in restaurant business. Oversees the recruitment process. Has experimented a chatbot for recruitment.
41	Product manager and HR/recruitment specialist for a public sector job board. Has tested AI-powered chatbots to match job seekers and job openings
42	Director of a recruitment department. Their company offers chatbot solutions to companies that are placing job ads to their job board.
43	Chief marketing officer and co-owner in a company that develops recruitment software. The company is developing a chatbot that matches information provided by candidates to job ads
44	Responsible for communication and recruitment marketing in an employment agency that specializes in construction workers. Oversees the use of chatbots by, for example, creating chatbot scripts
45	Project manager. Manages a network of people in a company that promotes a better working life for the youth. The company has recently received offers from chatbot vendors but has not yet deployed a chatbot
46	Head of a production unit in a confectionery. Decides what kind of talent is needed. Interested in testing recruitment chatbots in the near future

requirements tend to become more abstract for the sake of keeping the job advertisement text relatively short and attractive. In other words, a tension between abstraction and detail emerges. Organizations increasingly compete for attention on online job boards (e.g. Indeed) or in social media (e.g. LinkedIn) where a well-designed job advertisement can overshadow others, while also noting that targeted advertisements on these online websites certainly influence what job opportunities are visible to the candidates. Many participants underlined that, in practice, attracting relevant applicants often means balancing between abstract descriptions with loose requirements and detailed descriptions with more restrictive specifications. In addition, both our interviewees and recent industry reports (Deloitte., 2021; LinkedIn, 2022) highlight the need to focus on the perks, cultural match and additional benefits of the position to make the description stand out in a positive light.

If the job description text is optimized for search engines, the texts tend to be further simplified and generalized, which can result in many non-ideal applicants. Conversely, more detailed and tailored advertisements can increase the accuracy of the process, possibly with the cost of excluding certain (groups of) candidates. Prior research has underlined that communicating the requirements realistically has numerous benefits, including reduced turnover rate of new hires (Baur *et al.,* 2014), even when doing so practically reduces the number of applications. Conveying realistic picture in the acquisition process is also considered to be an 'ethical imperative' for the HRM experts (Buckley *et al.,* 1997). Echoing findings of emergent trade-offs between accuracy and fairness targets (Whittlestone *et al.,* 2019), this suggests group fairness and recommendation relevance can be in conflict, for example, when learning algorithms are used for generating recommendation lists for headhunters. The interviewees emphasized that considerations in these respects need to be especially thorough when the specified applicant attributes might be discriminatory (e.g. language requirements).

All in all, we identified this tension as a form of challenging choices at the level of external communications, which could be better supported by IT systems. An interesting AI tool to this end is Textio[1], which argues to help optimizing job descriptions in terms of applicant reach and checking that the language is, for example, gender neutral (Yarger *et al.,* 2019). According to market reports, another seemingly promising approach is to include video content that feature a recruiter (VideoMyJob, 2021). This may again increase complexity in terms of work tasks for HRM experts but also introduce possibilities to better reach candidates who prefer visual rather than textual job descriptions.

4.1.3. *Tension: Ease and speed of applying vs. detailed information*

The interviewees presumed that many candidates would not read long, textual job descriptions because they are considered boring, or because they lack the time, tools or skills to complete a full-scale application. Hence, emerging digital systems attempting to lower the threshold to apply tend to be proactive and clearly guide the applicant through the process, and they do not require attachments, such as external CVs. In fact, many participants believed that oftentimes the candidates wish to be able to quickly scan through new opportunities without initiating any kind of process or going through the questions one by one, which is, for example, the default in recruitment bots. Based on the data many of our interviewees' organizations had collected, it was evident that initial questions that appear troublesome, irrelevant or too personal can cause the applicant to flee, hence further motivating to use low-threshold application channels.

'It has been widely discussed that we should be able to contact a person interested to work for us as fast as possible, because otherwise they have already run to the next employer.' (Study 3, ID:44, responsible for communication and recruitment marketing in an employment agency that specializes in construction workers).

In a speedy process, the initial applications tend to be highly structured and simplified, addressing relatively few core questions. This can improve the consistency and comparability of the applications, helping the recruiter to quickly scan through the applications and identify key differences. However, simplicity also means that individual applicants lack the opportunity to present themselves in detail, hence making it harder for them to stand out. Moreover, a recruiter or team leader might end up with many similar applications, rendering a well-informed and fair choice nearly impossible.

A speedy process can be particularly alienating to experienced applicants, especially in knowledge work sectors where the decision makers often appreciate an application with personal style and the merits of the candidates are expected to weight in the choice. Compared to experienced candidates, it seems that inexperienced candidates are typically less influenced by the issue-relevant content of a job advertisement (Walker *et al.,* 2008). Therefore, utilizing large digital job boards and application channels that support conveying relatively simple messages (e.g. recruitment bots) seems to make sense especially for entry-level positions where broad attractiveness and, hence, large numbers of applicants is desirable. Here, a playful approach can work, while in the case of seeking to fill a specialist position, there are likely expectations of following a standard format with a considerable level of detail.

Overall, this tension between speed and ease, on the one hand, and detail and accuracy, on the other, introduces a need for additional support in selecting the most suitable strategy for applicant attraction: does the organization want to opportunistically explore the alternatives on the market by lowering the threshold or, do they prefer a predefined and relatively inflexible application process with a narrower focus?

4.1.4. *Tension: Uncertainty vs. inclusion*

While gathering and specifying requirements for a talent acquisition case, digital systems could support the involvement of different stakeholders, such as senior executives, hiring managers, team members, project clients and different HRM experts. Several participants generally agreed with the benefits of an inclusive process, mentioning, for example, cases of involving other team members in the decision-making. Certainly, a democratic approach could decrease uncertainty in requirement specification. However, the participants shared their concerns that having high number of voices can delay the process, increase complexity in terms of coordination, require compromising when there is a variety of opinions, and demand more time altogether—which is typical in democratic governance. In an inclusive process, finding a common ground and shared principles can be challenging, as different people join with various levels of understanding regarding, for example, project details, what the relevant substance skills are and how to best describe them. Furthermore, they can have different views on what kind of approach to utilize regarding application channels and application analysis, as highlighted in the quote below.

'The teams are by no means homogeneous, nor are the projects. They vary very much in their level of abstraction and technical requirements. This means that if we have a highly technical project that is not necessarily abstract, then at that point someone (of the stakeholders) may not understand at all what it is all about' (Study 1, ID:15. Director of digital development, discussing how much variation innovation teams have).

Several HRM experts mentioned that their software for talent acquisition includes mechanisms for reaching agreement, for example, by enabling discussion and editing of job descriptions among relevant stakeholders within the organization. From an ethical perspective, software features that support this kind of inclusion promote transparency and equalization of power among stakeholders. However, HRM experts' discretion with respect to specifying talent acquisition requirements could be diminished, thus affecting their perceived autonomy. Moreover, issues related

[1] https://textio.com/

to fairness in this process may become salient in case stakeholders have different expectations about the extent to which they ought to be able to influence those specifications.

In sum, ideally the tools spark and enhance data-based discussion among stakeholders regarding the job requirements, the potential applicant profiles, and combinations of people or teams that would help the organization to consider broader positive impacts than filling an emerging need.

4.2. Identifying and attracting alternatives

This stage covers the identification of potential applicants who would meet the requirements as well as the selection of the means of attracting their attention and encouraging them to apply.

4.2.1. *Tension: Requesting detailed data vs. respecting privacy*

Complex tensions concerning business needs and utility, privacy, transparency, and fairness are particularly salient in this context (Whittlestone *et al.,* 2019). HRM experts request and can gain access to applicants' private personal information in order to make well-informed decisions. Therefore, they need to balance between persuading applicants to share relevant work-related information and avoiding issues with privacy and confidentiality—especially concerning information that should not influence the talent acquisition decisions. Participants discussed that CVs often have very little or no relevance to the applied position, but they nevertheless tend to reveal information related to protected attributes, such as race, gender or age. A participant developing a recruitment application emphasized that they intend to respect applicants' privacy by avoiding gathering extra information and supporting user control:

'In a way the trust is based on the fact that the user controls all the data they enter at all times. They can delete their information and account at any time. They control whether they want to meet someone. No intermediaries, we are not in between, but the user is directly in contact with the company [. . .] if the applicant has such a feeling that when he has decided to give these things there, he can feel that they are used with respect.' (Study 1, ID:1. Startup CEO developing recruiting apps, discussing what creates trust to the vendor's brand).

An interviewee working on a public sector job board said that applicants are increasingly creating anonymous profiles in their website for employers to find, demonstrating a way to reduce discrimination. While initial research evidence shows that such anonymization can prevent discrimination in the early stages, there is a risk that it only postpones discrimination to later stages, or that the prejudices of other unmasked cues are enhanced (Rinne, 2018). Moreover, Foley and Williamson (2018) interviewed managers in Australia and found that even when applicants' names and identities are anonymized, managers use implicit signals and cues to infer the gender identity. This calls for piloting anonymization before large-scale use and consideration that the discrimination might move into another stage and that other cues might be weighed differently.

Transparency, candidates' privacy, and control over data and interactions with the recruiter were considered desirable from an ethical perspective. This echoes the notion that privacy, transparency, and meaningful control are essential for human autonomy in sociotechnical contexts (Laitinen and Sahlgren, 2021).

4.2.2. *Tension: Candidates' data rights vs. tracking their interactions*

Closely related to respecting privacy of the application data, the participants also considered whether it is acceptable that candidates' behavior is tracked implicitly. Having an interactive application channel (e.g. chatbots) creates an opportunity to collect data on the applicants' micro actions *en masse* and to optimize the application experience accordingly. For example, it could be analyzed how long it takes to answer certain questions or where an applicant might leave the application form or cease interaction with a chatbot.

Targeted job descriptions (e.g. in the form of advertisements) based on the user's browsing history have emerged (e.g. on LinkedIn; Kenthapadi *et al.,* 2017) as an attempt to grab the attention of seemingly relevant individuals. A participant who was working on a job board within a large media group speculated that it would be possible to analyze what kind of news the applicant reads and, based on the information, to recommend a suitable job description. Another participant explained how LinkedIn data can be connected to other services that, for example, track how much time potential applicants spend on other websites. If the applicant is aware of how the browsing behavior affects, for example, what kind of positions are recommended, it is possible that they appreciate relevant recommendations, and even customize their behavior or the settings of the tool.

At the same time, one participant reminded that a digital footprint on the platforms can be deceiving and typically tell little about the availability of the person. The seemingly most qualified and active individuals might look like good candidates, but the recognized activity might be part of their current job, or they might simply lack the interest to apply.

Together with the previous section, this introduces a classical challenge of data ethics concerning if and how the tracking activities can be justified through the logic of utilitarian consequentialism (i.e. the ends of recommending an interesting opening justifying the means of gathering data about them). While this is a common challenge in recommender systems in general, the context of talent acquisition can demand very detailed data gathering and user modeling for the system to be able to recommend anything meaningful. Further, while the benefit to an applicant is conditional, the hiring organization might benefit in any case by gaining insights about the job market and useful information about their application process.

4.2.3. *Pitfall: Unequal treatment of applicants across application channels*

While the interviewees agreed that different application channels are necessary to reach different audiences, the value of treating all applicants equally regardless of the used channel was evident as well. However, in practice, it seems that applicants applying via certain channels can get an unfair advantage when the channels result in different forms of applications. For example, the channels can vary regarding the maximum length of the answers, in which case the UI can imply or encourage to send short or long answers. They can also involve different numbers of questions and requests for external documents. Compared to a web form or an open application, a recruitment bot application contains significantly less information, and can include predefined answer options rather than open fields. Furthermore, the language support can vary in application channels and, thus, direct some applicants to use suboptimal channels.

While introducing a low-threshold and easy-to-access channel can increase equality in terms of reaching busy applicants or those who do not have the ability or skills to prepare detailed external documents, it can also favor those that are good at expressing themselves in a concise manner. The participants figured that specialists might find it easier to talk about specific themes and competences rather than answering questions on their personality or values, while more generalist type of applicants can give a positive impression by giving abstract but convincing answers. For example, whereas one software programmer might seek to impress by listing the coding languages and tools they master, another might do that by writing generally about coding paradigms.

Both Royakkers *et al.* (2018) and Whittlestone *et al.,* 2019 point out the issue of equal treatment in digital environments: groups of people, such as linguistic minorities, may be disproportionately disadvantaged when efficiency or convenience are prioritized. Here, it seems to be important to be aware of subtle UI level or accessibility differences of application channels, particularly when new channels are introduced. Disclosing optional channels in the job description, and ensuring that there are opportunities for all applicants to express themselves are also practical ways to increase transparency.

4.2.4. *Pitfall: Counterproductive UIs with unfair advantages*

Based on HRM experts' perceptions, applicants typically have strong expectations regarding information security and a clean and user-friendly UI in the used systems, as well as a certain formality of the application procedure as a whole. For example, the proactive and fast-paced interaction style of pop-up chatbots can cause a feeling of hurry, which stands in tension with the intention to encourage potential applicants. Chatbots can surprise the candidate in an unpleasant way by producing a feeling of having to engage in a conversation. Furthermore, several participants said that the impressions and user experiences of chatbots in other contexts influence how they are perceived and emphasized that the impression is not often favorable, in part because of their perceived limits in interaction capabilities. In the long term, the applicant experience is compromised if the experiences of the application channels do not match the applicant's expectations.

While this issue primarily relates to user experience, we also recognize an ethical component to it. The perceived proactivity (up to aggressively requesting interaction) of the tool can decrease the applicant's sense of autonomy and control. Furthermore, concerns regarding fairness arise as novel forms of UIs and the media for applicant-recruiter interaction can be difficult to use for those who are unexperienced or unfamiliar with the underlying interaction metaphors. People who have used similar tools before might get an unfair advantage even if such technical skills were not relevant to the position in question.

While the issue of accessibility advantage due to technical competences has been identified in the literature (Truxillo *et al.,* 2004), the introduction of increasingly diverse technologies tends to increase the digital divide. In HCI, this issue of power asymmetry among the applicants or between applicants and HRM experts has been discussed in the context of low-wage or low-resourced job seekers (Wheeler and Dillahunt, 2018; Lu and Dillahunt, 2021). Lu and Dillahunt (2021) demonstrated how employers utilize online employment groups in social media to reach low-wage workers and how they pay attention to information that signals job readiness, finding that there remains an unaddressed power imbalance between employers and job seekers. For example, while Facebook seems to be a popular platform in low-wage recruitment, it is designed to support personal rather than professional impression management. Consequently, researchers found that this unintentionally resulted in lack of activity by job seekers.

4.3. Comparing alternatives

At this stage, the alternatives are iteratively screened, filtered and compared against each other.

4.3.1. *Tension: Utilizing existing data vs. initiating a new process*

Applicants tend to update their profiles and applications only when deliberately seeking for a position, while they may develop new and improve their existing skills at any time. At the same time, in urgent needs for talent, organizations may utilize the information accumulated over time in their ATS, talent pools, or online work profiles. Therefore, the stored applicant data can be outdated in a matter of months. Moreover, applications and online profiles typically focus on recent developments, and they might not be able to highlight the most relevant information. A participant gave an example where someone had applied to an aviation themed project team without disclosing that they used to be a pilot and, therefore, had very relevant subject knowledge that resulted into an immediate selection. In this case, the information was found during a phone interview but, more broadly, systems and platforms that convey information, such as LinkedIn, tend to be organized according to latest information. At the same time, several participants argued that some of the most qualified workers do not have time to update their information.

This issue of operating with out-of-date information pertains particularly to the so-called talent pools, that is, databases where organizations or job board websites maintain lists of potential candidates accumulated over time. While talent pools can help to quickly identify seemingly relevant applicants, the accuracy of the information is often questionable. This introduces uncertainty to the organization seeking talent, as well as the problem of excluding potential candidates who ack awareness of the talent pool. Thus, introducing a fairness issue of inevitably not giving equal chance to succeed.

Furthermore, storing applicant information introduces ethical risks that the data will be used in ways that the applicant is not aware of, which is not only morally questionable but also against general data protection regulations. However, due to power asymmetries and opportunistic behavior, there is, for example, typically no way to know how the application data is analyzed. A participant working in a company that collects online data emphasized that people are not aware how their data is used, whether it is for positive or negative purposes:

'A lot of data about people is publicly available and can be exploited in ways that may not be clear or obvious to the person who has publicly shared their data [...] It may not be obvious to everyone that it is a threat, and it may indeed be the case that it will have some effect in the future or in the present.' (Study 1, ID:3. Startup CEO, analyzing social media, discussing risks in utilizing AI systems).

This dynamic relates to the privacy issues identified by Royakkers *et al.* (2018) and the tension between efficiency and privacy noted by Whittlestone *et al.* (2019). In response to these issues, recent regulative efforts have aimed to increase transparency that highlight talent acquisition as a high-risk context where systems may impact future career prospects and livelihoods (e.g. in 2021 EU proposed law on artificial intelligence).

4.3.2. *Tension: Efficiency vs. quality and fairness of the assessment*

Many participants realized that the numbers of applications have generally risen as a result of introducing chatbots and other channels that lower the threshold of applying. High numbers of applications are generally desired by HRM experts, and the high quantities are further strengthened by many organizations' explorative and open mindsets while seeking new staff and following the supply in the job market. However, some participants were surprised to have noticed a flipside of this aim for quantity: increased share of low-quality applications. The interviewees gave examples of applications where applicants confessed that they are not applying seriously or where applicants lacked the minimum required skills for the job. These trends tend to decrease the time and attention given to any individual application, which naturally makes the comparison challenging and prone to arbitrary choices.

Consequently, HRM experts might need to filter out much of the applicants, which can practically mean that ATS is used to filter out dozens or even hundreds of applicants. While efficient in some sense, this leads to a risk of decisions being based on insufficient or surface-level information. Indeed, ATS tends to highlight only a few of each applicant's qualities, such as the name, job title, age, or a photo. While using names as IDs, for example, can make the comparison easier and help to remember who is who, there is an apparent risk of the much-discussed racial, gender and age biases. Further, due to heavy workloads, details in the applications might not be read carefully or the applicants might be quickly filtered out based on minor negative signs in the application. For instance, one participant elaborated that a recent or a long unemployment period typically creates a negative impression and may end up being filtered out before the applicant has a chance to explain themselves.

A related issue that stood out is that variation in HRM experts' interpretation of applications can result in disagreement among multiple assessors and further risks for bias. Acquiring an experienced professional typically involves several people from the organization in order to ensure the applicants' cultural fit, for example. While digital tools can support such democratic processes by providing easy ways to review and comment on the applications, involving several evaluators can counter-intuitively make talent acquisition more susceptible of subjective preferences. For example, a participant overseeing facilitators who assemble innovation teams explained that they might alternatively be very impressed by a detailed list of coding skills while a more detailed textual description might impress a senior facilitator more. (As noted above, applicants can also actively seek to manage these impressions.) In addition, another participant even questioned many stakeholders' ability to appropriately assess the applicants:

'First of all, less frequently recruiting supervisors might not have the skills or experience to conduct good job interviews, other than assessing whether the applicant is a nice person or not, that is, technical tests [...] Sometimes the kind of stuff happens, related to the similarity, that too similar persons are being looked for. I have seen many cases where people seek exact clones.' (Study 1, ID:21. Social media recruitment trainer, discussing how to target companies' brand message to applicants).

These responses highlight a notion increasingly emphasized also in fair ML literature: that the human-user component should not be abstracted away when considering digital ethics (Selbst *et al.,* 2019). It seems that application channels should not only produce useful and relevant information through a fair process, but there should be also safeguards in place to ensure application data is also interpreted fairly in the talent acquisition pipeline.

4.3.3. *Pitfall: Video interviews may introduce unpredictable conditions*

One area of concern related to the technology-mediated interaction is the recording and analysis of video interviews. Asynchronous video interview (AVI) software allows the applicants to record answers to pre-defined questions with their personal camera and may provide the organization with automatic analysis of the applicants' skills in oral expression and body language, for example. However, the use of personal videorecording devices is quite a lot asked from an applicant and places them in a position that can appear even more asymmetrical than typically in talent acquisition. Several of our participants utilized AVI, and mentioned using software such as RecRight[2]. Another notable example is HireVue[3], which claims to reduce hiring bias and increase diversity and fairness.

When analyzing the videos, a practical risk is that decision-makers' attention turns to irrelevant things, such as the technical quality of the applicant's recording, the lighting in the room, or what is going on in the background. In our interviews conducted in 2019–2020, facial expression analysis was seen as a rising and concerning trend. In fact, HireVue recently removed a controversial feature that used algorithms to assign traits and qualities based on applicant's facial expressions, which involved obvious ethical concerns regarding privacy (and potentially transparency) (Kahn, 2021). Our participants further noted that adding a video interview can benefit applicants with technical skills even if such skills were not relevant to the sought job. There is also a salient pitfall in automating interactions with the applicant—namely, applicants may have fewer opportunities to ask counterquestions and clarifications.

On a positive note, however, asynchronous interviews give the applicant an opportunity to carefully answer specific questions, which can be especially valuable to those who are not at their best in live situations. Furthermore, asynchronous alternatives provide applicants with flexibility regarding when to participate, and they have several opportunities to record an answer. Both the questions and responses can be more thought-through compared to face-to-face situations where, as one participant exemplified, applicants' religious views or plans to build a family are often inquired more or less directly.

Recently, research on video interviews in HRM has become an increasingly popular topic in research, partly due to the increased potential the tools have presented during the COVID-19 pandemic (McColl and Michelotti, 2019; Suen *et al.,* 2019; Basch and Melchers, 2021; Mirowska and Mesnet, 2021; Dunlop *et al.,* 2022). For example, Mirowska and Mesnet (2021) interviewed professionals who raised justice issues with these tools, whereas Basch and Melchers (2021) found that recruiters tend to view these tools skeptically, and face-to-face settings are perceived to be fairer than conducting technology-mediated interviews (particularly AVIs). Notably, prior research generally tends to focus on applicant perceptions, thus, neglecting organizations' point of view (Basch and Melchers, 2021).

[2] https://new.recright.com/
[3] https://www.hirevue.com/

4.4. Selecting the Most suitable match

This stage represents the temporally short, yet strategically crucial moment of making the final selection among the top applicants.

4.4.1. *Pitfall: Under- or overestimating the value of human decision-making*

Human values such as kindness and empathy were considered values that are endangered by increasing digitalization. When attracting talent, organizations often seem to emphasize the human dimension of decision-making. In practice, this can mean promising potential applicants that human decision-makers are in control of (and responsible for) evaluating and selecting, as is required by the GDPR. Some participants further emphasized that it is their personal goal and a value to provide feedback and consider applicants for other positions than the ones they applied to. For example, during the process, the HRM expert can see potential combinations of people, or several suitable applicants that should be selected. Allowing deviations from the standard process and established criteria can thus enable the HRM expert to create unexpected opportunities. For an unselected applicant, the human dimension of being transparent about what kind of opportunities the decision-maker saw based on the application can be very valuable.

HRM experts thus recognized a tension between the benefits of digitalization and respect for human dignity and autonomy: transparency was perceived as important to candidates' autonomous choices and control over the process for those of the decision-maker. More generally, these comments echo concerns raised by Royakkers *et al.* (2018) who consider that digitalization might instrumentalize persons, consequently leading even to dehumanization, and loss of social competences.

According to our interviewees, comparisons between technologies and humans are made with respect to further aspects of talent acquisition. Curiously, algorithms are expected to produce similar results that a human would, even though our participants simultaneously questioned whether human decision-making is optimal or provides an appropriate yardstick for a fair procedure. Kuncel (2017) provides examples of several oversimplifications and decision errors where the final selection depends on the characteristics of other people in the list of top applicants. For example, 'decoys tend to attract attention to other candidates who fully dominate them on all characteristics'. One participant further questioned whether legal security issues are appropriately considered in AI-assisted or even in manual decision-making:

'Probably the legal security issues of that specific individual come to mind. But are they more reliably secured even in manual recruitment, then?' (Study 1, ID:11. HR Consultant, discussing potential weaknesses of AI systems).

Overall, the participants' comments suggest that the introduction of digital tools can create a type of 'ripple effect' where the insertion of technology changes behaviors and embedded values of pre-existing systems (Selbst *et al.,* 2019). In the present context, such an effect is seen in how insertion triggers reflective comparisons between the benefits and downsides of human decision-makers and technology, respectively.

4.4.2. *Tension: Selecting quickly vs. slowly*

The thoroughness of the selection process affects applicants' perceptions of procedural fairness (Gilliland, 1993). Practical reasons, such as time constraints or outstanding, positive first impressions of certain applicants, can simplify the process, however. A tension between procedural fairness and utility in terms of process speed and convenience might emerge, respectively. For example, in the case of assembling innovation teams, having some experience and substance skills might get the applicant very close to being selected, despite the existence of other applicants and rich application information. In another example, a participant said that they do not want to overly complicate the process and explained that they would be ready to name the top three applications based on a quick scan of dozens of applications. Indeed, it seems that digital systems (such as ATS) can encourage collecting and comparing a pool of candidates, whereas managers and company leaders often aim for quick solutions. One participant noticed that going through the digitally assisted process can seem slow especially when there is a chance to present suitable candidates to managers within the day. It seems that LinkedIn, in particular, can amplify the risk by providing or presenting alternatives in an attractive way that encourages skipping steps.

It seems that shortening the process is of the main selling points for many of the tools. Quick processes can be appropriate in other forms than external market-based talent acquisition, like in proactive headhunting (or sourcing) and when serendipitous encounters are looked for. Nevertheless, the challenge remains that, for example, ATS tools can be used in unexpected ways (e.g. cutting corners in the talent acquisition process). This relates to the 'framing trap' discussed by Selbst *et al.* (2019), who note that even value-sensitive digital tools (e.g. recommendation tools with fairness guarantees) can be used inappropriately in ways that compromise the adherence to the values in question (e.g. practitioners might act on tools' recommendations inconsistently). Adding to this issue, there are numerous other reasons why practitioners might not use staffing tools as intended, for example, 'because they perceive it as going against tradition, sapping their autonomy, being terribly confusing, requiring too much work, or simply saying "that doesn't look like what good workers do"' (Kuncel, 2017).

4.4.3. *Pitfall: Portability trap in copying metaphors*

When discussing future developments of talent acquisition systems, it seemed typical to regard talent acquisition as a simplified choice of the right person to the right job, benefitting from a list of recommendations based on a scoring system. This highlights the nature of talent acquisition as a professional social matching activity (Olsson *et al.,* 2020). It appears that popular examples of matching apps from the dating context (e.g. Tinder) may set the standard and expectations how matching of people is generally regarded. In fact, one participant had conducted a project on the topic of creating matching apps, finding that on the user interface level the swiping gesture specifically seems to be exclusively reserved for the dating context. Starting one-to-one conversations with someone on shared interests by using a mobile application can disturbingly resemble the logic of dating apps:

'The application (the project members created) was about learning science. Team members discussed the way of communication, how the other person (within the app) would know that you now want to learn. There was feeling of being like in a dating app. You pick a person because s/he looks interesting, or s/he would like to talk about an interesting topic. It is very hard to get rid of the feeling.' (Study 2, ID:31. A participant who assembles and coaches higher education student teams, 10 years of experience).

Reflecting the previous section (4.4.2), copying metaphors from the dating context can also encourage making quick decisions in situations where all candidates or applicants should be evaluated fairly. Skipping phases can compromise procedural fairness in a similar vein as in Section 4.1.3 where other aspects of speedy approach were discussed.

These issues with copying metaphors resembles the portability trap, as described by Selbst *et al.* (2019): 'solutions designed for one social context may be misleading, inaccurate, or otherwise do harm when applied to a different context'. Some of our participants emphasized how the professional working context should be strictly separate from other forms of connections. Therefore, while designers are often taught to aim for portability (Selbst *et al.,* 2019) and while copying established matching design solutions seems tempting, it should be questioned and preferably consulted with HRM experts in which situations metaphors from other types of social matching maybe utilized. Based on the findings, we can confidently recommend avoiding swiping gestures as mechanisms of selection in talent acquisition.

5. DISCUSSION AND CONCLUSIONS

We sought to empirically understand practical constraints that arise in HRM experts' work, thus responding to the criticism that research on digital ethics tends to abstract away from specific social contexts (Selbst *et al.,* 2019; Whittlestone *et al.,* 2019). Our analysis implies that digitalization, while improving gathering and conveying of data, has introduced or amplified several tensions between business and ethical values across the decision-making process of talent acquisition. Notably, these tensions in part arise due to common pitfalls in digitalizing such delicate and human-centered processes. In what follows, we first reflect on the general values and considerations that we observed across the result categories.

5.1. Reflections

5.1.1. *Values and value tensions*

Recalling the categorization of trade-offs mentioned in Section 2.2, we note that genuine trade-offs are rare. Rather, most tensions arise due to epistemic uncertainty, constraints of practical circumstances, conflicts of interests between stakeholders, and other contingent factors. Accordingly, HRM experts do not typically face strict moral trade-offs where one set of values would have to be prioritized over another (Whittlestone *et al.,* 2019). Practical constraints often include the availability of digital tools or workforce, high costs, and administrative demands, such as need for a speedy acquisition process.

The following four upper-level categories of values were implicated in the interviewees' discussions about digital talent acquisition:

- *Utility,* understood as the satisfaction of business needs (e.g. needs for efficiency, convenience, ease, and speed) and the aims of digital talent acquisition
- *Autonomy,* understood as (the capacity for) self-determination, to which privacy and transparency are considered instrumentally valuable (Laitinen and Sahlgren, 2021)
- *Fairness,* understood as a legal norm and a socially desirable goal requiring that candidates or applicants be treated without unacceptable bias
- *Balanced power,* understood as an ideal situation wherein relevant parties are symmetrically positioned with respect to epistemic resources and leverage in negotiating terms of agreement

Table 2 categorizes the findings of our study according to the used 3-fold conceptual framework and also to reflect the study's core aims. The purpose here is to bridge the gap between abstract values and concrete cases. To the best of our knowledge, this is the first attempt to recognize values and stakeholders at this level of granularity in this context. By explicitly recognizing key values and value conflicts, on the one hand, and the stakeholders affected therein, on the other, we can begin to develop guidelines and standards that are not only ethically aware but rigorous and practically relevant (Whittlestone *et al.,* 2019).

5.1.2. *Binary considerations regarding digital ethics*

The first tendency that stands out from the material relates to patterns in HRM experts' moral reasoning. When considering whether to digitalize specific aspects of talent acquisition, HRM experts' considerations tended to sustain a binary divide between human and automated decision-making. This pattern was most salient in discussions concerning digital systems and their risks and benefits, with human decisions typically constituting the baseline for HRM experts' comparisons in these respects (as noted in Section 4.4.1). Reflections on transparency, privacy and fairness in this technological context often involved comparisons with how the values are currently met when humans conduct or are involved in the relevant tasks. Similarly, the 'human element' of the talent acquisition process was perceived as valuable, highlighted at times by participants who emphasized user control and treating applicants with dignity. This tendency suggests that, in our cultural context, HRM experts' expectations and ethical considerations regarding digital talent acquisition are grounded in applicants' and candidates' practical and situated needs—our interviewees seemed quite sensitive to their normative expectations concerning talent acquisition and how the implementation of digital tools might change things for them.

From the perspective of moral reasoning, however, it would seem that comparisons that maintain binaries can also restrict or misguide ethical considerations (as opposed to facilitating ethical decision-making). On the one hand, both human and technological actors inevitably have their respective upsides and downsides. Digital tools can, for example, structure a given part of the process and improve its ease and speed, but human decision-makers can provide lenience and flexibility by deviating from the customary way of doing things when appropriate. On the other hand, it may be the case that humans and digital tools do not always introduce trade-offs between different values (e.g. consistency, utility and individualized consideration) but, rather, comprise different mechanisms through which an ethical issue arises.

Comparisons between the benefits and risks of digital systems, on the one hand, and human decision-makers, on the other, can inform decisions concerning the use of specific digital tools at a given stage of the talent acquisition process. However, there is a risk that the tendency to revert to the immediate vicinity of the binary poles (namely, digital systems and humans) in ethical consideration may actually preclude the identification of appropriate risk management measures that could be implemented (i) throughout the process and (ii) at the level of the sociotechnical system. A processual, sociotechnical systems perspective on ethics in digital talent acquisition would focus not only on individual stages and digital tools but also on how technological and human elements interact, underlining the importance of introducing incremental control through redundancy and 'layered' ethical safeguards. For example, to mitigate issues with bias, an appropriate approach could involve measures to mitigate related risks at a processual and systemic level. In practice, this might involve, for example, combining technical measures (e.g. UI design

TABLE 2. Tensions and Pitfalls in relation to upper-level value categories, related to specific stakeholders (in parenthesis). The roman numerals refer to the stage of the process. When necessary, the table indicates the relevant stakeholders using an initial: candidate (C), applicant (A) and HRM expert (H). Also, there are sometimes tensions between values—for example, in the case of pitfalls—and these are marked with '–'.

	Tensions and pitfalls	The value(s) in question
I	Short-term vs. long-term planning	**Short-term utility – long-term utility:** *Solutionism can lead to a practical trade-off between short- and long-term benefits*
	Abstract vs. detailed job descriptions	**Utility – fairness (C):** *Attracting suitable candidates versus fairness in terms of providing equal opportunities*
	Ease and speed of applying vs. detailed information	**Tension between types of utility:** *A lower threshold vs. comprehensive information*
	Uncertainty vs. inclusion	**Balancing power (H), autonomy (H), fairness (H) and utility:** *These result from common pitfalls of group decision-making*
II	Requesting detailed data vs. respecting privacy	**Utility, fairness (C) and autonomy (C)**: *Detailed data is necessary for making accurate decisions but can lead to bias and privacy violations*
	Candidates' data rights vs. tracking their interactions	**Utility – autonomy (C):** *Ensuring transparency and privacy is necessary for autonomy, but tracking has business benefits*
	Unequal treatment of applicants across application channels	**Unfairness (A)**: *A practical trade-off: additional channels increase the reach but can result in inequal treatment*
	Counterproductive UIs with unfair advantages	**Unfairness (C), lack of utility (H) and diminished autonomy (C)**: *Solutionist aspirations in UI design may lead to issues with accessibility and respect for autonomy*
III	Utilizing existing data vs. initiating a new process	**Autonomy (C) – utility (H):** *Reanalyzing existing data on candidates versus collecting new data involve distinct risks for privacy and utility, respectively*
	Efficiency vs. quality and fairness of the assessment	**Utility – fairness (A):** *The pursuit of efficiency may lead to unfair treatment if the actual human-user is not considered*
	Video interviews may introduce unpredictable conditions	**Utility – respect for autonomy (A) and fairness (A):** *This serves convenience but introduces risks for privacy violations and possible bias*
IV	Under- or overestimating the value of human decision-making	**Autonomy (H):** *There is difficulty in recognizing the benefits and shortcomings of humans and/or technology*
	Selecting quickly vs. slowly	**(Procedural) fairness (A) – utility**: *Results from the framing trap and practical/human constraints including lack of motivation or skills*
	Portability trap in copying metaphors	**Fairness toward applicants – utility**: *Portability aspirations lead to failures in understanding contextual values and needs*

and fairness constraints), operational safeguards (e.g. algorithmic audits (Wilson *et al.,* 2021) and diverse teams of people assessing applications), feedback channels (e.g. feedback for and from the applicants), and access to remedies (e.g. the right to contest decisions).

From this perspective, neither the benefits nor the downsides of technical tools and humans are viewed as absolute benefits or inevitable downsides that are 'locked in' at a single point of the talent acquisition process. Rather, they become relational and interacting aspects of a broader sociotechnical process that can complement (or run counter to) one another, with each aspect configuring the process as a whole.

5.1.3. *Technology and codification of standards make immediate ethical concerns in talent acquisition more visible*

Talent acquisition is a delicate process involving many stakeholders, expectations and behaviors. For example, applicants have different expectations regarding the process and exhibit different behaviors when applying for a job (e.g. impression management). Meanwhile, HRM experts differ in what they search for in applicants. Digital systems, however, tend to codify standardized structures into tasks taking place at different stages of talent acquisition, ranging from writing job descriptions to assessing applicants. Standardization clearly has its merits in terms of improving efficiency, consistency and comparability. For example, standardizing application forms across channels would allow for equal treatment of potential applicants (and thereby resolve the tension identified in Section 4.2.3). However, digitalization—especially in relation to its standardizing tendency—raises many ethical questions, such as power imbalances between stakeholders (e.g. applicants and HRM experts) and within each stakeholder group (e.g. between experts and generalists among applicants, and between programmers and team assemblers in organizations). The structure codified by a given tool as the operative standard will have different consequences for different stakeholders and will empower some but disadvantage others. A pattern we observed was that ethical questions became increasingly salient, especially in relation to the issue of standardization. For example, consequences for fairness in treatment of the applicants and for decision makers' access to information during the process were somewhat frequently discussed in relation to the issue of standardization. In this sense, the HRM experts were quite sensitive to the issues introduced by technology, particularly in terms of its tendency to codify practices and values.

5.1.4. *Solutionism drives the market, but tends to backfire for organizations*

The set of challenges that we identified pertains to incompatibilities between available digital systems and organizations' needs regarding talent acquisition. Business needs, and organizational pressures and constraints seem to lead organizations and HRM experts to favor data sources that are continuously 'on tap' (e.g. LinkedIn) and systems or designs (e.g. swiping logic) that are easily implemented and portable. This, in turn, incentivizes them to procure established technologies for talent acquisition from vendors providing tools that are designed for portability, but which address only narrow tasks in the talent acquisition pipeline. Meanwhile, specific needs regarding digital systems inevitably vary depending both on how organizations conduct talent acquisition and on external factors (e.g. overall labor market conditions).

We observe that such dependency on established technologies gives rise to various undesirable outcomes. First, it may simply be that organizations do not get what they need from a given system. The adapted digital tools can be counterproductive (e.g. design features and UIs might repel potential applicants), and their limitations can even prevent HRM experts from gaining relevant information (e.g. application forms lack open text answers). The prevalent software-as-a-service model can also be uncomfortable for organizations whose needs for talent fluctuate unpredictably, while organizations searching actively and continuously for talent through talent pools may fail to reach potential applicants due to their exclusivity.

Second, the dependency on 'monolithic vendors' that offer to digitalize various talent acquisition tasks (e.g. applicant tracking systems) can create 'ripple effects' that undermine the pursuit of efficiency and ease that motivate the adoption of digital tools in the first place. This pitfall is apparent in cases where the procurement or adoption of a tool poses, for instance, the need to restructure HRM practices around the employed system, or to build additional systems in order to reap the benefits of the original system. In other words, seemingly portable digital tools combined with solutionist aspirations can backfire due to mismatches between available digital systems and organizations' specific needs, and due to the extra effort and implementation that costs incur.

Third, dependency on 'monolithic vendors' can also be problematic from the perspective of ethically conscious procurement. As our findings suggest, HRM experts are mindful of compliance and the ethical issues encountered in the context of digitalization, but the current market for digital tools is likely to be less sensitive in these respects. Especially in the case of reliance on third-party platforms, HRM experts had to weigh possible benefits (e.g. increased reach and effectiveness) against the ethical risks and costs to which they would be committing. For example, while the possibilities offered by LinkedIn and video interview software were recognized, so were some of the issues related to privacy or bias associated with the with LinkedIn and video interview software. From the perspective of HRM experts and their respective organizations, the market for tools for digital talent acquisition remains focused on business values—perhaps it is even characterized by the Silicon Valley mentality of 'moving fast and breaking things'—rendering ethically conscious procurement difficult. This issue also underlines the broader issue that the conditions for ethical digitalization are dependent on the technology market, its incentive structures, and the power that different agents hold therein.

5.2. Future work

Our approach was exploratory, which offers several potential directions for future research. Even though extant literature on digital ethics is already thorough, we argue that more empirical research is needed in order to expand the topic and gain more understanding of the possible ethical tensions found in the digitalization of specific sociotechnical contexts. While still remarkably understudied, digital ethics in talent acquisition has recently started to gain attention among HCI researchers (Marks, 2022), focusing particularly on the issues involved in algorithmic decision-making (Raghavan *et al.,* 2020; Sánchez-Monedero *et al.,* 2020). Methodologically, especially promising approaches include ethnographical studies where HRM experts are observed that are in a similar vein to the study by van den Broek *et al.* (2021).

Our Findings section introduced several tensions and pitfalls that should be further studied. Digital tools could be studied in terms of considering the pertinent ethical values, particularly with the aim of practically guiding the trade-off choices. Some tasks (e.g. conducting video interviews) have been studied in HRM research; however, we emphasize the need to consider the task's connection to the overall process (i.e. how it affects the choices made in the following tasks).

So far, the research has mostly focused on applicant perceptions (McCarthy *et al.,* 2017). Therefore, in line with recent research (e.g. Lu and Dillahunt, 2021), we call for more research from the perspective of HR professionals. According to our analysis, various stakeholders—such as line managers, HR department leaders, company leaders, and people who are developing digital solutions for HR—seem to be fruitful sources of subjective insights and experiences.

5.3. Limitations and closing remarks

We first note that the data is collected in one Nordic country and most likely represents Scandinavian work culture and values. Therefore, the findings are not generalizable for all cultures and talent acquisition practices. Second, the interviews did not systematically consider organizational differences across, for example, fields of business, size, or organizational culture. Public and private organizations might have different requirements regarding the talent acquisition process and the values to consider. As for the analysis, it is evident that the identified aspects are, first, formed through subjective interpretation and, second, limited by the concepts and viewpoints of the specified conceptual framework.

Furthermore, as Ruggiano and Perry (2019) recommend, when utilizing qualitative secondary analysis, the involvement of researches in the parent studies and the present studies should be reported. In our case, two of the authors were involved in all the parent interview studies where their responsibilities covered data collection, data analysis, and writing the publications.

All in all, talent acquisition in organizations includes complex decision-making, strategic and organizational activities, and repetitive routine tasks that could all, in principle, be supported by IT. However, the expected benefits do not come without ethical risks that require navigation among pitfalls, tensions, and trade-offs. This study is an attempt to identify such concerns from a rich empirical data set and with the help of a conceptually thorough framework. This serves as a basis for raising practical considerations for both the developers and users of talent acquisition systems. We particularly encourage further research on the pitfalls involved in digitalizing these kinds of sociotechnical contexts that feature a breadth of requirements and principles to follow, and complex decision-making that significantly influence both the involved organizations and individuals.

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DATA AVAILABILITY

As the present work was a secondary analysis, no new data were generated in support of this research. Due to ethical concerns of privacy and deanonymisation, the original qualitative raw data cannot be made available. However, kindly note that we present carefully selected extracts from the raw data in the 'Results and Reflections' section.

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