Trusting AI: Recruitment Experts' Expectations Towards AI-assisted recruitment

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Abstract

Applications of artificial intelligence (AI) are increasingly deployed to support complex expert work, such as the recruitment of workforce to organizations. Amidst the push of new e-recruitment systems by technology providers, there is little research on recruitment experts' views on trusting AI in their work, particularly concerning user needs, opportunities for employing AI, and considerations regarding trust in AI. To understand recruitment experts' perceptions of the future use of AI in their work, we conducted an interview study with Finnish recruitment experts (N=15). The findings underline the need for AI as augmentation: AI could offer analytical competencies that complement or challenge the recruitment experts' analysis and deliberation. This may help recruiters to reach and justify decisions in this challenging decision-making sphere. Trusting AI in this situation necessitates the domain experts' ability to evaluate and supervise the AI-provided outcomes in a real-life context, which challenges current design paradigms in human-computer interaction. These insights emphasize the sociotechnical nature of the human-AI interaction in expert work and inform present-day human-centered AI design endeavors.

Keywords: trust; artificial intelligence; human-AI collaboration; expectations; recruitment; human-centered AI; sociotechnical systems

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Introduction

Across disciplines, applications of Artificial Intelligence (AI) are anticipated to cause fundamental changes to work-life, automating different types of tasks and augmenting human capabilities (Brynjolfsson & McAfee, 2011, 2017; Jarrahi, 2018). Recruitment is not exception of this. To find the right person for the right job at the right time, organizations have established a decision-making process that has multiple stages from setting the requirements to the final selection (Breaugh 2013; Koivunen et al., 2019). Novel AI applications has been regarded as promising area to support the multi-phased nature of recruitment, for instance, by automating candidate communication, mitigating biases in recruitment decisions, or making sense of the hiring data (Albert, 2019; Laurim et al., 2021; Li et al., 2021; Black & van Esch, 2020). Mindful of the diverse definitions of AI, in this article we consider AI broadly as information technology applications that feature seemingly intelligent qualities, such as advanced data analysis, recommendations based on machine learning, and autonomous decision-making.

Research in management sciences focusing on recruitment has generally concluded that the success of an organization is closely tied to its success in employee recruitment (Breaugh, 2013; Ployhart et al., 2017). However, recruitment has also a societal impact concerning, for instance, general well-being. Therefore, the use of AI in recruitment has raised discussion about the AI-specific risks and ethical concerns such as applicant privacy, autonomy of HR experts, and justice in terms of fair treatment of the candidate (Royakkers (2018), Selbst et al. (2019). In fact, the European Union has recently listed recruitment as a high-risk application area for AI[1] This tension underlines a need for a user-centric

[1] https://www.eipa.eu/publications/briefing/the-artificial-intelligence-act-proposal-and-its-implications-for-member-states/

understanding of the opportunities of utilizing AI in recruitment, for instance, what kind of AI-infused solutions are considered acceptable and usable from the recruitment experts' perspective. While there is an emerging research strand focusing on studying AI in recruitment from the recruitment experts' viewpoint (Laurim et al., 2021; Li et al., 2021), we extend this research by exploring the phenomenon from the perspective of AI trust formation. By taking trust for our main analytical lens, we aim to provide insight on human-centered AI design and development.

It is well established that trust in technology is a key element influencing the user uptake and acceptance of technologies, as well as creating positive experience (Kassim et al. 2012; McKnight et al. 2011; de Visser et al. 2018; Siau & Wang 2018). While trust in technology, in general, has been extensively studied in Information Systems (IS) and Human-Computer Interaction (HCI) research, much less is known about trust in AI concerning the domain expert users' perspective. Our aim is to gain insight on the user needs, opportunities for AI, and consideration on trust in the recruitment context. Few current studies have attempted to study domain expert users' trust in AI empirically (Bedué & Fritzsche, 2022, Saßmannshausen et al., 2021, Lockey et al. 2021). The findings of these studies reveal fundamental differences for building trust in AI compared to more traditional technologies and emphasize the importance of understanding the contextual and environment factors.

This findings on this article contribute to the design and development of human-centered AI. The aim of human-centered AI (HCAI) is to develop AI applications that increase human performance and support human self-efficacy, mastery, creativity, and responsibility (Shneiderman, 2020). According to human-centered perspective in AI design and development, novel AI applications should be designed with social responsibility, such as fairness and accountability, and with awareness of a larger surrounding system, including all the stakeholders (Riedl, 2019). To design human-centered and useful AI applications for the expert work, we must have a thorough understanding of the user needs (Xu, 2019). Building on Mumford, (2000) and Sawyer & Jarrahi, (2014), we emphasize that use of AI in recruitment constitutes a sociotechnical system where social and technological factors intermingle and mutually shape the users' and stakeholders' experiences and expectations. We believe that adopting a sociotechnical and human-centric perspective on AI design and development is necessary concerning the socially sustainable use and deployment of AI, especially in the context of expert work.

Against this backdrop, this study explores trust in AI by studying recruitment experts' expectations towards the use of AI in recruitment. We ran a qualitative study to answer the following research questions:

RQ1. *What needs and opportunities do recruitment experts identify for using AI in their work?*

RQ2. *What contributes to the recruitment experts' trust in AI in their work?*

To gain empirical insight on the topics, we conducted semi-structured interviews of 15 domain experts based in Finland. This study contributes to a qualitative understanding regarding the possibilities of human-AI interaction in a specific AI application domain and provides insight into the design and development of socially sustainable and acceptable AI applications for the future of work. The study reveals a need to support the objective and transparent recruitment process with novel AI applications, with an emphasis on AI as augmentation. This also challenges the current design paradigm in human-computer interaction. The findings of this empirical study can inform the design and development of human-centric AI systems and tools for recruitment.

Literature review

The following introduces a conceptualization of trust in AI and describes the sociotechnical nature of trust considering the domain expert as a technology user.

2.1 Conceptualizing trust in technology

Trust is a ubiquitous and dynamic phenomenon affecting all kinds of social relationships, including those in work life. Research on technology use has recognized trust as an important factor also in product-user relations, influencing user uptake and acceptance of technologies (McKnight et al., 2011; Gefen et al., 2003; Pavlou & Gefen, 2004). The importance of trust is emphasized under conditions of risk and requires a willingness to be vulnerable in an uncertain situation: the defining characteristic of trust is the trustor's inability to control the trustee (Mayer, Davis, & Schoorman; 1995). Therefore, trust is based on positive expectations regarding the behaviors or outcomes: the extent to which these expectations are fulfilled defines the degree of continuous trust (Lee and See, 2004). More generally, expectations may reveal how people conceptualize novel technology and help to interpret the product characteristics that contribute to the user experience (Hiltunen et al., 2002; de Vries et al., 2003; Olsson et al., 2014; Yogasara et al., 2011).

Trust in technology has been widely studied both in Information Systems and Human-Computer Interaction, concluding relatively coherent theoretical background. Trust in technology typically considers beliefs about technology's functionality, reliability, predictability, and helpfulness (McKnight et al. 2011, Muir, 1994; Wang & Benbasat, 2005). If a technological application has human-like characteristics (e.g., recommendation agent), also human-like trust characteristics may become relevant, such as competence, benevolence, and integrity (Lankton et al. 2005; Wang & Benbasat, 2005). Trust in automation considers performance, process and purpose as key factors influencing users' trust (Lee & Moray, 1992). Thus, the factors that influence trust in technology might vary according to the technology.

Prior research on trust in automation provides interesting insights into trust formation when considering new technologies that display high levels of agency and proactivity. For instance, the flawed partnerships between automation and users, known as misuse (overreliance on technology) and disuse (rejection of the automations' capabilities) (Parasuraman & Riley, 1997; Lee & See, 2004) might be relevant also in human-AI interaction. Appropriate calibration of trust has been regarded as a solution for the flawed partnership, referring to the correspondence between human's trust and the automations' capabilities (Muir 1987; Lee & Moray, 1994; de Visser et al. 2018;). Similar topic is discussed also in current research regarding trust in AI, referred as 'incorrect' levels of trust. The goal of calibrating trust is to help people correctly distinguish situations to trust or distrust an AI (Jacovi et al. 2020). So far there is little research on trust calibration or the concept of appropriate trust in the context of AI systems.

The loss of human control has emerged as a common concern in the use of AI as automation. To mitigate this risk, human-centred AI calls for proper oversight mechanisms. Augmentation, or 'human-in-the-loop' approach, aims to extend human capabilities, such as human cognition and decision-making, rather than replacing them (Jarrahi 2018; Preece et. al. 2019). In augmented decision-making, the human user semi-supervises the algorithm by having opportunities to intervene, provide input, and have the final say on AI outcomes (Dietvorst, 2016). Human-centered AI considers AI augmentation more acceptable than AI automation as it could lead to a safer, more understandable, and more manageable future (Crowley et al., 2019; Shneiderman, 2020). Currently, there is not a lot of research regarding trust in AI as augmentation.

2.2. Empirical perspective on trust in AI

Trust in AI is an emerging research field that has gained a lot of academic interest lately. Although there are different approaches to trust in AI (e.g., technical, sociological, psychological), the common element is linked to previous research of trust in technology: trust is essential in the use and acceptance of novel technologies, and a certain amount of risk and vulnerability are defining element of trust relationships. To define trust in this study, we follow the definition by Lee & See (2004), who perceive trust as "an attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability." This definition of trust has also been used to study trust in AI (e.g., Ashoori & Weisz, 2019; Lee, 2018).

In this study, we explore trust from a qualitative, empirical perspective with an emphasis on domain expert users' expectations. Thus, our focus is on trust prior AI interaction. Similar approach has been taken by Bedué & Fritzsche (2022) and Saßmannshausen et al. (2021). Bedué & Fritzsche (2022) conducted an interview study (N=12) with industry decision-makers to explore trust as a moderator of perceived benefits and risks concerning AI in the early stages of technology development. Their findings suggest that trust in AI is fundamentally different when compared to trust in traditional technology. In addition to the technology's actual operation, trust in technology is always shaped by environmental factors and the public discourse. They conclude that access to knowledge, transparency, explainability, certification, as well as self-imposed standards and guidelines, are important factors in trust in AI. Saßmannshausen et al. (2021) explored the antecedent variables on trust in AI within production management. Their mixed-method study assigns the antecedents of trust into three groups: the trustor (human), the trustee (AI), and the context/environment. According to their findings, the antecedents of trust in AI are perceived ability (ability, performance, and competence) and perceived comprehensibility (quality, plausibility, and conclusiveness). For humans, the antecedents of trust are expert status (competence, skills, and experience) and digital affinity (interest in technology). Based on their findings, they present three recommendations to design socially sustainable human-AI interaction. Firstly, AI designers should make the AI appear capable. For instance, the decisions of the AI should be verified by a second system or a human to avoid errors and to increase the perceived ability. Secondly, they recommend subjectively better explanations or more expectable decision-making behavior to foster trust in AI. Thirdly, they advise introducing AI to digitally competent employees as the familiarity with technology leads to higher trust.

In their review of empirical trust in AI, Lockey et al. (2021) identify key vulnerabilities affecting trust in AI from the domain experts' perspective. To trust AI, domain experts need to be able to understand, explain and justify AI decisions to other stakeholders. They need to remain accountable for the accuracy and fairness of AI output, and for privacy and data usage. Therefore, transparency and explainability of AI are associated with domain experts' ability to provide human oversight in the use of AI. The findings suggest that AI automation might cause professional over-reliance and deskilling, loss of expert oversight and professional identity, an even loss of work. Trust in AI from the domain experts' perspectives include also reputational and legal risks, for instance, from biased results, or inappropriate data use. The findings reveal interesting insight into domain expert users' user experience regarding AI in their work.

All the presented studies emphasize the importance of contextual and user-centered factors in assessing trust in AI in the early phase of AI deployment. This is a central motivator of the present study, too: we expect to elicit new insights by empirically focusing on a specific user group and context of use.

2.3. Recruitment as AI application area

Research in management sciences focusing on recruitment has generally concluded that the success of an organization is closely tied to its recruitment (Breaugh, 2013; Ployhart et al., 2017). Employee recruitment typically refers to the process of attracting, appointing, and managing suitable candidates for jobs within an organization, also covering the so-called third-party head-hunting activities (Breaugh, 2013). To find the right person for the right job at the right time, organizations have typically established a decision-making process that has multiple stages from setting the requirements to the final selection (Breaugh 2013; Koivunen et al., 2019).

AI-based applications in the recruitment context can be regarded as tools that enhance human capabilities to process and make sense hiring data (Black & van Esch, 2020). These tools can, for instance, help recruiters by automating recruitment tasks, clarify and produce job descriptions, gather relevant information about the candidates, or help mitigate biases in decision-making (Albert, 2019; Laurim et al., 2021; Li et al., 2021). The AI applications potential to increase objectivity in recruitment is especially interesting because recruitment is susceptible to intuitive decision-making (Miles & Sadler-Smith, 2014). Although intuitive decision-making might be one of the human strengths in recruitment decisions (ibid.), algorithms are argued to be more objective than humans in their decision-making due to the lack of emotional factors (Lee, 2018).

A few recent studies have examined the use of AI in recruitment focusing especially on the recruiters' perspective. Li et al. (2021) studied algorithmic hiring practices (sourcing and assessment), and the individual and organizational dynamics in the use of AI-enabled tools. By interviewing 15 recruiters and HR professionals, they found that socio-organizational contexts shape how AI systems are used, and the practice in algorithmic hiring varies a lot depending on the situation. These contextual factors shaping the use of AI include, for instance, recruiter's social capital and performance evaluation metrics, assessment implementations and its impact on HR professionals' job content, and new assessment process and its influence on candidate-employer relationship. Trust in this study is discussed through evaluation of the output of AI-infused applications: for instance, how much trust do participants place on the results generated by AI.

Similar study was conducted by Laurim et al. (2021) who studied the recruitment experts, managers, and candidates' (N=15) expectations and attitudes towards AI in recruitment. Interestingly, their aim was to identify personal and contextual factors that influence the acceptance of AI-based recruitment technologies. However, they could not observe any effects of participants' individual characteristics (including gender and age) on their perceptions and therefore also this study emphasized the contextual factors. Laurim et al. (2021 suggest that transparency, complementary features of the AI tools, and a sense of control play key roles in the acceptance of AI-based recruitment technology. Technology Acceptance Model (TAM) by Davis (Davis, 1989; Davis et al., 1989) complemented by Technology Readiness Index by Parasuraman and Colby (2001) were used to investigate the reasons for acceptance or rejection of AI in recruitment. Trust in this study is defined as the secureness of technology and its ability to work properly (ibid.).

van den Broek et al. (2021) offer another perspective on the AI in recruitment. In their two-year ethnographic study, they explored AI development in hiring, focusing on the tension between independence (producing knowledge without domain experts) and relevance (producing useful knowledge to the domain). They argue AI systems should not be distanced from the domain experts and the wider social context in which these tools are embedded. The findings of this study suggest that developers manage the tension of independence and relevance through a mutual learning process between developers and domain experts. For instance, domain experts should be able to define, evaluate, and complement machine inputs and outputs whereas developers help experts to discover previously unknown insights from data.

Method

3.1 Research design

The aim of this research was to study recruitment experts' expectations and trust formation towards AI in their work and produce a new, empirical understanding of the topic. Considering the qualitative research questions, semi-structured expert interviews were seen as a meaningful way to gather research data on people's perceptions and experiences. Interview studies are typically used to approach such multi-faceted and subjective topics as they allow a certain level of systematism and consistency across different research subjects as well as personalization in terms of to what extent various sub-themes are covered (Blandford et al., 2016). The interviewees were recruited with an open call from recruitment-related communities on LinkedIn and Facebook. The call for participants underlined recruitment expertise and introduced AI as a collaborative technology emphasizing the ideal role of AI in recruitment, the human-centered nature of recruitment and trust formation in AI.

Altogether 15 one-to-one recruitment expert interviews were conducted by the first author between December 2020 and February 2021. After each interview, we took advantage of snowball sampling. Due to the COVID-19 pandemic, interviews were organized on virtual communication platforms Microsoft Teams and Zoom. The average length of an interview was 78 minutes (min. 58 minutes and max. 92 minutes). The participants were asked to fill a background survey in advance concerning their work environment and recruitment practices, their experience on recruitment, and preliminary expectations in the use of AI. This information was aimed to provide a researcher with preliminary information regarding the study participants and their versatility, and to help the participants to orientate to the research interview.

3.2 Participants

The 15 recruitment experts in our sample represent a variety of organizations and professional positions, as indicated in Table 1. Representing both public and private sectors and different organizations and recruitment roles, participants reflect the similarities and differences in the recruitment sector. This study focused on similarities to be able to understand recruitment expertise in depth. All the participants lived in Finland at the time of the interview and were considered to represent the Finnish work culture. In terms of professional life, Finland is typically considered as a Scandinavian culture with established democratic decision-making practices, high worker autonomy and work ethics, and an advanced level of digitalization throughout society.

Table 1. Study participants

ID	Recruitment experience	Main recruitment role and industry
1	8 years	Recruiter: searching talent and supporting recruitment in IT industry
2	15 years	Talent acquisition director: working in international recruitment in IT industry
3	15 years	Recruitment director: working in international recruitment in IT industry
4	10 years	Talent acquisition and HR partner: Supports strategic recruitment in HR/ITC industry
5	12 years	Head of talent acquisition: working in international recruitment in banking industry
6	15 years	Recruitment and management consulting: working in strategic recruitment
7	15 years	CEO, recruitment: working in strategic development and customer acquisition in recruitment and sourcing industry
8	10 years	Executive talent agent: sourcing in IT recruitment industry
9	4 years	Head of training, tech recruiter, and partner: recruitment consulting, sourcing in IT industry
10	22 years	Growth manager, recruitment product developer: working in recruitment solutions development and sales
11	unknown	CEO, data scientist: develops an AI solution for recruitment, participates in recruitment and recruitment education
12	8 years	Recruiter: supporting recruitment, administration and development of recruitment software, recruitment education in public sector
13	20 years	Growth manager: supporting entrepreneurship, management of business and employer services in public sector

14	14 years	Service manager: supporting entrepreneurship, working in employer and business services and recruitment in public sector
15	13 years	HR partner: supporting recruitment and recruitment process in research and education in public sector

3.4 Interview themes and procedure

The interviews comprised three thematic parts. Firstly, participants introduced themselves and their organizational context, including current recruitment practices and tools. Secondly, participants were asked to describe their expectations towards AI in recruitment, for instance, what is the identified need and motives to deploy AI, and what do they consider as possible risks or trade-offs in the use of AI. Follow-up questions aimed for a deeper understanding of the emerging issues. Also, the notion of expertise was discussed among these topics. Thirdly, we discussed trust in technology. Participants were asked to define their trust in technology which was followed by more detailed questions regarding the factors that increased or decreased their perceived trust in AI. The themes of human-AI collaboration in the recruitment context were discussed at the end of the interviews covering issues such as responsibility and control. It is noteworthy that the interviews focused mainly on individual recruiting rather than high-volume recruiting. All the interviews were recorded after asking for participants' consent.

3.5 Analysis

All the interviews were transcribed by the first author. The study utilized an abductive thematic analysis method. Thematic analysis was conducted to identify patterns of experiences regarding the processes and related attitudes (Cairns & Cox, 2018). Firstly, all the transcriptions were carefully read and re-read, followed by descriptive, sentence-level open coding. This resulted in 258 initial codes.

These codes were summarized into 47 categories from which we identified 6 emerging themes: recruiters' role in recruitment, recruitment goals and challenges, factors that format trust in technology, risks in the use of AI, possibilities in the use of AI, and the participants' organizational environment. All the analysis work was conducted in Atlas.ti. The analysis was collaborative and iterative by nature: the coding process was conducted by the first author and was periodically discussed and challenged by two senior scholars. The following description of results purposefully narrows down the focus on themes that we perceived most insightful and novel in the light of prior work.

Results

We structure the results according to three key themes: (1) the recruitment experts' role and responsibilities in the context of utilizing AI, (2) domain experts' needs and the perceived opportunities of AI in recruitment, and (3) the domain expert's considerations on their trust in AI.

4.1 The roles and responsibilities of recruitment experts in the recruitment process

We first offer contextual background regarding the tasks and processes where AI could be employed by characterizing the nature of recruitment experts' work and outlining their core expertise. These themes explicate certain organizational conventions and underlying values that ought to be thoroughly considered in human-centered design of AI, and we will refer to these characteristics in the upcoming sections.

4.1.1 Recruitment experts focus on coordination rather than decision-making

The interviews consolidated the recruitment experts' typical role between the candidates and decision-makers, aiming to serve both parties. Rather than making the final selection decisions, their main task is to support the overall recruitment activities and decision-making of HR executives, such as line managers or hiring managers (henceforth, *decision-makers*). They may educate the decision-makers to identify possible biases in their thinking (P3, P4, P5), help with candidate communication (P12, P15, P4), offer support or conduct applicant interviews (P4, P5, P15) or plan the strategic direction of recruiting together with decision-makers (P5, P6). The more experience the decision-makers have on recruitment, the less likely it is that they need support from the recruitment experts, as P5 highlighted:

> "Their [decision-makers] recruitment experience affects our [recruiters] participation. For instance, how actively we participate in the process and what kind of support we provide to them." (P5: Head of talent acquisition, banking industry)

While there are no formal educational requirements for professional recruitment in Finland, there seems to be commonly shared ethical principles that are reflected in the recruitment practices. Especially values regarding equality and inclusion were acknowledged among participants (P12, P15, P1, P9, P14, P5). In addition to such organizational values, the individuals can have ethical principles that guide their work: for instance, P13 had previously worked in the private sector where they aimed to always give feedback to the candidates although it was not required by the organization.

4.1.2 The importance of candidate communication in recruitment

Many participants (P12, P7, P15, P1, P9, P14) underlined the importance of candidate communication in recruitment. For instance, public job announcements can be used to reach potential candidates. Recruitment experts can also utilize so-called sourcing, where the recruitment expert contacts the potential candidates directly. In addition of choosing the advertisement channels, recruiters can help to identify the candidate requirements, such as necessary skills or knowledge needed for a job position. Participants (P1, P8, P9, P12, P13, P15) admitted that the recruitment process might not be transparent to the candidates, and therefore identified a need to enhance the candidate experience by finding new ways to improve the communication. Especially the IT sector and other competitive job sectors seem to utilize sourcing where it is vital to try to convince the candidate to take the job offer, or the offer to apply for a job. This was seen to resemble marketing. According to P1, P7, and P9, sending personalized messages to candidates is an important part of successful sourcing.

> "It is quite close to selling – if a candidate has a good situation in their current job, I need to be able to read the situation in order to emphasize the right things when I am communicating the offered position" (P7: CEO in recruitment and sourcing industry)

Notably, the recruitment is more regulated in the public sector in comparison to the private sector. Thus, the public sector has stricter requirements regarding transparency of the recruitment process. For instance, all formal requirements in the public job advertisement should be fulfilled when making the final selection. This is useful if the excluded candidates question the recruitment decision and request justification for their rejection. P12 had recently changed their workplace from the private sector to the public sector, and admitted that while the requirement for transparency ensures the fairness of the recruitment process, it can be challenging to communicate:

> "We cannot tell the candidate that "we got bad vibes from you." Communicating the [decision] justification is sometimes very tricky and brings a lot of extra work." (P12: Recruiter, public sector)

4.1.3 Tacit knowledge is part of recruitment expertise

The candidates' cultural fit into an organization was considered very important among the participants (P2, P9, P1, P12, P6). To this end, the recruitment experts have a lot of non-verbalized information that can support a successful recruitment decision. The participants stressed that understanding the surrounding cultural context is part of their role as a recruiter. For instance, they had tacit knowledge in relation to similar organizations (P7, P9, P10, P5), job positions, titles, or salaries (P7, P6, P1), and geographical differences (P3, P8, P2). This kind of knowledge is particularly relevant when the recruitment is conducted in a familiar cultural environment, as P9 states:

"I need to pay more attention to it [international recruitment]. I need to aim for a better understanding of the candidates' competence and expertise because I might not identify the companies listed in CV." (P9: Head of training, IT industry)

In addition to evaluating the candidate's cultural fit into an organization, the recruitment experts wish to provide information for the candidates regarding the hiring organization's cultural context. The goal to avoid unsuccessful hires is reciprocal, and thus the social match between the candidates and the organization is emphasized in the final recruitment decision.

4.2. Needs and opportunities for AI in recruitment

Building on the contextualization above, this subsection focuses on the recruitment experts' identified needs and opportunities for the use of AI in their work. Findings focus on those tasks that recruitment experts consider acceptable to either automate, augment, or assist with AI.

4.2.1 AI as augmentation: enhancing recruitment process with objective information

The recruitment experts were aware of the various hidden biases in recruitment decision-making and, therefore, recognized that avoiding them completely is immensely hard (P6, P1, P15, P9, P4, P14, P5). The interviewees said to mitigate biases by openly discussing with the decision-makers regarding their perceptions and assumptions during the recruitment process. However, hidden biases were seen as an inevitable part of human decision-making. This emphasized the need to increase the objectivity and transparency of the recruitment decision-making (P12, P6, P10, P8, P9, P3, P14). AI was expected to increase the transparency of recruitment decisions, as P8 defines:

"The [recruitment] decisions are made with intuition. AI could bring more transparency into this intuition. This is essential if we want to make good recruitment decisions" (P8: IT recruitment industry)

Few participants (P1, P14, P6) emphasized the opportunity to include AI in the recruitment process as an objective actor. For instance, P1visualized that recruitment interviews could be recorded, and then analyzed by an AI application. This could provide insight into the discussed topics in the interview and its conclusions. Both the interviewee and the candidate could then evaluate this summary and either agree or disagree with the analysis. P1 claimed that this could increase the transparency of the hiring process and decrease the impact of human biases in the recruitment decision. P6 presented a similar idea of AI providing recommendations during the interview with an aim of guiding the situation to be more equal or fair. It seems that they expected that AI could have more capacity to focus on relevant factors in interview situations than humans. The participants expected that AI could provide analytical information that supports the final recruitment decision (P8, P9, P14). For instance, P9 suggest that AI application could question the recruitment decision if it identifies e.g., discriminative decision making:

> "AI could express that "now you are making decisions based on these factors, are you sure you want to proceed?" This could increase the equality of recruitment decisions" (P9: Head of training, IT industry)

The participants stressed the need to either gain support for the recruitment decision-making process or challenge it with analytical and objective insight. Furthermore, AI was expected to be able to provide creative insight and perspectives regarding the organizational data (P5, P14, P13, P6), as P13 demonstrates:

> "We could let AI solve a specific task and approach this solution with open mind to hear what AI's suggestion to the situation would be" (P13: management of business and employer services in public sector)

Overall, participants identified several opportunities to analyze data by utilizing AI both within and outside the organization, especially in the often unstructured, and constantly developing context of recruitment. For instance, AI could be used to predict upcoming recruitment needs based on general trends on the job market (P12, P3, P14) and to identify existing in-house expertise (P3, P4). Also, AI could help organizations to identify weak signals and global trends (P3, P10, P13), and with this information, predict customer needs (P3, P12).

In addition, it was perceived that new AI solutions could find and recommend potential candidates to the recruitment experts (P12, P3, P6, P1, P14). For instance, AI could proactively explore LinkedIn data, generate a list of potential candidates according to the details gathered from the previous hires (P12, P10, P2), or provide hiring suggestions regarding the most suitable candidate during the recruitment process (P1, P14, P12). Although the participants underlined that AI could support recruitment in many ways, it should not free recruitment experts from the process, as P3 demonstrates:

> "AI could provide suggestions and hints that we could advance further. In my opinion that would be ideal." (P3: Recruitment director in IT industry)

The participants of the study emphasize the use of AI as an augmentation to increase the objectivity and transparency of recruitment. They were optimistic that AI applications could enhance the quality of the overall recruitment process, especially in a situation that might be affected by human biases, such as recruitment interviews.

4.2.2 AI as automation: removing repetitive routine tasks and increasing efficiency

The AI's potential to automatize routine and repetitive recruitment tasks was visible in the research interviews. Participants perceived mundane tasks as time-consuming and not very tempting professionally (P12, P7, P15, P5). The potential of AI as automation seems to be particularly emphasized in high-volume recruitment where AI could, for instance, conduct candidate screening (P12, P1, P5). AI as automation was expected to increase the speed of recruitment process which was perceived beneficial both to the candidates and recruiting organization (P7, P12, P15, P9, P13). For instance, AI could support the candidate communication by providing timely reminders to the candidates about the ongoing recruitment process (P12, P15, P8, P9). It seems that AI as automation was perceived acceptable and useful, especially in well-defined job positions that require specific certifications or licenses, as P12 exemplifies:

> ”We have several job openings that require certain certifications or licenses – those would probably be difficult to misinterpret and easy to recognize automatically from a CV. If a certain license or certification is mentioned [in a CV], these applications could be automatically accepted to proceed in the recruitment process.” (P12: Recruiter, public sector)

4.2.3 AI as assistance: improving candidate experience

The importance of a good candidate experience was emphasized among participants (P1, P3, P6, P12, P15, P14, P2, P8, P9, P4). They recognized a need to provide better feedback for the candidate (P15, P14), and to find ways to make the recruitment process more efficient, easier, and tempting for the candidates (P2, P3, P6, P8, P9, P5). P2 argues that the candidate experience should be prioritized in the recruitment process:

> “Communication and the whole [recruitment] process should focus on the candidate and not the recruiting organization” (P2: international recruitment in IT industry)

It is noteworthy that candidate experience might be emphasized especially in competitive fields and in sourcing where the job opportunities are offered for the most potential candidates. Nevertheless, AI was considered potential in supporting candidates also in the traditional recruitment process, for instance, via tools developed for applying for jobs. These tools could help the candidates to find potential job positions (P3, P2, P13), or analyze the candidates' previous work experiences and help them to recognize the unidentified skills or talent (P1, P14). From the perspective of recruiting organizations, this would result in a larger candidate pool and more diverse job applicants. Therefore, enhancing the candidate experience was also beneficial for the recruiting organization.

4.3. Considerations on trust in AI-based recruitment systems

The third results section focuses on the factors that were recognized to contribute to trust (or the lack of it) in AI at early stages of technology adoption. The findings emphasize contextual factors in domain experts' trust in AI.

4.3.1 Trust in AI necessitates reliability and predictability

The participants considered trusting AI if it was perceived to conduct a given task in reliable manner. This indicates the expected benefit of AI in recruitment experts' work practices: participants insisted that AI should meet their identified needs, for instance, by reducing workload, or otherwise operating according to expectations (P12, P14, P11, P8, P14). AI was seen as useful if it added value to the work practices, as P13 stated, further underlining the importance of continuous reliability:

> "Trust is formatted when you notice that using a system or a solution, your job becomes easier. And of course, that it does not fail you under any circumstances." (P12: Recruiter, public sector)

The participants emphasized a need to understand the technology, for instance, what the system does and why (P1, P12, P7, P11, P13, P4, P5). This was crucial to be able to justify the recruitment decision and to remain responsible and accountable for the overall process. Therefore, the same requirement regarding the transparency of the overall recruitment process, also covers AI applications, as P1 states:

> "There needs to be transparency regarding the decisions AI has made. And there should be a possibility to test AI; what has been left out during the process and why" (P1: recruitment in IT industry)

Some participants expected full transparency regarding the technical details and internal operations of the algorithm (P3, P6, P10, P15, P9). This depended on the personal characteristic and interest in technology, as P9 demonstrates:

> "I'm a technical person, I want to know what the system does. Especially, if I can decide about its deployment. I need to know, how it works and what value it produces. (P9: Head of training, IT industry)

Similarly, AI's potential unpredictability was seen as the main concern in the use and implementation of AI. Participants were worried about the erroneous learning process and lack of control in the use of AI (P15, P10, P12, P11). P12 visualizes their ideal interaction with AI underlining the human-in-the-loop decision-making:

> "I wouldn't leave any aspect of the recruitment completely to the responsibility of AI or automation although I wish to include AI in the process. But humans must be able to monitor and intervene AI all the time." (P12: Recruiter, public sector)

The unintended consequences AI might cause for the overall recruitment process were considered as its main vulnerability. For instance, participants were concerned that unrecognized AI errors might lead to biased decisions or discrimination (P9, P15, P12), or to poor candidate communication (P9, P12, P15). Interestingly, the necessity of predictability and understandability was applied also to possible AI errors. For instance, P6 believed that systematic errors could be acceptable because these would be easy to identify and therefore, prevent. Uncertainty was considered to decrease trust in AI, as P15 states:

> "Trust in AI would be decreased if the system creates a report which has uncertainty, or if it is not clear what attributes it has included into the process" (P15: recruitment in research and education in public sector)

In addition to the potential unpredictability of AI, the participants were concerned about data quality and how data acquisition is done (P12, P7, P13). Privacy and security were the main concerns among the participants due to the amount of personal data in the recruitment process (P7, P11, P9, P13, P2).

4.3.2 Understanding and evaluating AI demands time and dedication

The participants underlined that recruitment decisions' quality is evaluated in long term, for instance, if the selected person appears as a good employee for the organization. Similarly, AI's performance was evaluated according to its impact on long-term recruitment (P6, P8, P4, P14). This necessitated the possibility to evaluate and validate AI, further underlining the requirement for AI's transparency (P15, P1, P4, P15, P5). Few participants stressed the need to compare AI applications and traditional recruitment technology or a tool (P4, P6, P5). For instance, P4 compared AI applications to a talent assessment tool where recruitment expert must understand how the tool arrives at a certain conclusion and then, according to their own judgment, choose if they should rely on this outcome:

> "I do not make decisions or recommendations based on it [assessment tool]. The same principle would probably apply in the use of AI." (P4: Talent acquisition and HR partner: Supports strategic recruitment in HR/ITC industry)

It seems that trusting AI would require observed benefits and improvements in comparison to man-made decisions. For instance, P7, who had a sourcing business, had made AI experiments with an aim to increase automation in their sourcing practices. In the end, they were not able to use the developed tool because they did not consider it sufficiently reliable:

> "In the end, the results were not 100% reliable and we could not trust it [the tool]. We had to anyway go through all applicants manually." (P7: CEO in recruitment and sourcing industry)

Interestingly, the participants stressed the need for develop new skills in increasingly digitalized recruitment environment (P5, P2, P13, P15). They identified educational needs to learn the practicalities in the use of AI (P15, P1, P5, P4), for instance, technical understanding (P9) and analytical skills (P13). In addition, a positive and responsive attitude towards new technologies was perceived important (P8, P13, P14). Uncertainty and even fear were considered to prevent the use and deployment of novel AI applications (P5, P12, P15), as P12 demonstrates:

> "It is what I am afraid of. That if we were implementing AI now... my expertise is not yet on that level; I certainly would not be able to consider everything." (P12: Recruiter, public sector)

It seems, that the recruitment experts' accountability and responsibility for the overall recruitment process also cover the use of AI. This set requirements both for the development of AI applications and domain experts' user experience.

4.3.3 Social factors in trust formation

Participants acknowledged that before trusting the AI, they evaluate the trustworthiness of the developing company (P6, P10, P4, P5). Before having prior experience on AI, technology developers' competence and capability to identify and solve recruitment-specific challenges are carefully assessed, as P4 exemplifies:

> "I do trust in technology and AI. But the question is whether I trust the people who designed and developed the technology? Have they understood the task correctly, and have they considered all the necessary aspects in the AI development?" (P4: strategic recruitment in HR/ITC industry)

The cautious attitude towards technology providers' domain expertise focused mainly on external vendors. For instance, P2's and P5's organizations are capable to develop recruitment solutions internally. They admitted that the internal developers' understanding of the organization's specific recruitment practices has helped them to develop useful and usable systems. The findings emphasize a need to understand the contextual of use in AI deployment. This might also affect the overall acceptance of novel AI applications. For instance, P6 indicated a slightly irritated attitude towards technology providers solving recruitment problems without having a first-hand experience on recruitment:

> " Those who have not worked a single day in recruitment, are supposedly identifying a problem and then building a solution to it." (P6: Recruitment and management consulting)

In addition to the overall evaluation of the technology developer's competence to understand the nuances in the recruitment context, well-known technology providers were seen more trustworthy than smaller providers. They were expected to have established control mechanisms, and the best competence to ensure the quality of the product (P6, P5). In addition, well-known technology providers were perceived to have a better reputation and thus they were seen able to provide references from other users, which was also considered as a relevant factor in trust formation (P5, P2). According to the EU, recruitment is considered as high-risk AI application area. This might explain the emphasis on social factors in trust formation.

Discussion

The following summarizes the main observations and insights into the recruitment experts' expectations towards AI in recruitment (RQ1) and into trust formation in AI (RQ2). We highlight key theoretical implications for the use of AI-based recruitment technology, trust formation, and domain expert user experience.

5.1. Recruitment experts' needs and opportunities in AI reflect societal and personal values

In this study, we conducted an interview study of 15 recruitment experts in Finland to explore their needs and opportunities in AI in their work. The findings of the study underline the variety and complexity of the organizations' recruitment practices. From the organizational perspective, the main goal of recruitment is to find a right person to a right place at the right time (Breaugh 2013; Koivunen et al., 2019). However, from the recruitment experts' perspective, the recruitment process includes a variety of organizational conventions and underlying values. The findings of this study suggest that recruitment experts aim to oversee the overall objectivity, transparency, and fairness of the recruitment, for instance, by educating the recruitment decision-makers to recognize their possible hidden biases. Despite this, they are aware that biases cannot be completely removed from the recruitment process. This might explain the emphasis on AI as augmentation in our study. Li et al. (2021) suggests that societal factors, such as diversity, can cause shifts in employer's hiring focus. This observation might be relevant also in our study and underline the studied cultural context of Finland. Participants did not specify the origin of the emphasis on certain values in recruitment, but none of them mention such requirements emerging from the hiring organizations.

Using AI as augmentation underlines a perspective of human-centered AI design and development where AI is expected to enhance human capability rather than replace them (Shneiderman, 2020; Riedl, 2019). AI is expected to provide objective information and insight that is beyond human capacity – it is expected to complement possible human flaws in the recruitment process. It is noteworthy, however, that the emphasis on AI as augmentation might be explained also with the fear of losing jobs to AI, and therefore, the domain experts rather focus on AI as augmentation. This observation underlines the need to include domain experts in the design and development of AI, especially if AI is aimed to support domain experts' work. In their ethnographic study of developing AI in hiring, van der Broek et al. (2021) underlined at a new hybrid practice that relied on a combination of ML and domain expertise. Our findings support this observation. However, the collaboratory design process might not be enough to generate human-centric AI applications because all the domain experts might not have the digital competence to participate such process. Saβmannshausen et al. (2021) suggest that AI applications should be introduced to digitally competent employees, further underlining the social factors in the deployment of AI in certain context.

5.2. Domain experts' trust in AI challenges the current design paradigms in human-computer interaction

The findings of our study partly consolidate previous research on trust in AI: expectations and requirements on reliability, predictability, transparency, and understandability of AI were identified (Lockey et al., 2021; Bedué & Fritzsche, 2022; Saßmannshausen et al., 2021). AI is considered reliable if it performs as expected, fulfils the aims of the user, and does not increase the recruiters' workload. These factors are identified also in previous studies on trust in technology, such as McKnight et al. (2011). It seems that the general requirements of reliability and predictability of the technology are relatively similar in novel AI applications. The fundamental difference in trust in AI and trust in traditional IT underlines the aim of the objectivity and transparency of the application. Interestingly, the similar requirement seems to consider the overall recruitment process. This might reflect the entanglement of AI into the underlying personal or organizational values.

Recruitment is a complex AI application area as there might not be one right solution or decision. Trusting AI in this context necessitates the ability to evaluate the AI outcome, for instance, by comparison with traditional tools and systems. This finding aligns with Li et al. (2021) who suggest that the ability compare sorted recruitment results alongside manual search results would increase recruiters' trust in the tool. However, if AI is considered as objective actor that provides analytical information and insight into the recruitment process, the AI-provided outcome might not correct for the certain situation. Therefore, the domain experts need to remain critical towards AI-provided outcomes. The findings of the study suggest that 'design for trust' in AI might not be preferable design goal, especially in expert domain. Rather, the design and development of AI applications should aim for appropriate trust, or even distrust, to maintain human control over AI applications. Li et al. (2021) express a concern regarding the domain experts' user experience: tools used for finding candidates follow similar design paradigms as those that are built for everyday enjoyment, and thus, the decisions could be made too hastily without reflecting the possible consequences. To remain accountable of the overall process, the domain experts should have both technical knowledge regarding the AI applications internal operations and confidence to rely on their own rationale. This reflects a new paradigm in human-computer interaction: there is a need to design usable AI applications that support the domain experts in their varied recruitment practices but keep "human-in-the loop". In addition, there is a need to empower domain experts to override the AI-provided outcomes, if necessary. This is not only a design challenge but also an educational and attitudinal challenge. These observations underline a need to design human-centered AI applications that are both useful and usable but enhance human control and cognition.

Conclusion

The aim of this study was to examine the domain experts' needs and opportunities in AI, and their consideration on trust in AI. The results of this study emphasize AI as augmentation, supporting and complementing the recruitment experts' expertise. Therefore, the findings align with human-centered AI design and development with an aim to enhance and augment human capabilities. AI as augmentation necessitates the recruitment experts' ability to evaluate the technology and justify its use while being accountable for the overall recruitment process. Recruitment experts must be able to supervise and even intervene the AI-provided outcomes, if necessary. This observation questions the need to design AI applications that foster trust in AI: instead, AI application in the context of expert work, should aim to create appropriate trust, or even distrust, to remain domain expert users' critical towards AI decisions and recommendations. Taken together, these results suggest that understanding the contextual factors in the use of AI in recruitment, and the participation of the domain experts in the design process, is crucial when designing and developing AI for expert work. The findings in this study provide a new understanding of human-AI collaboration in the recruitment context, underline the perspective of domain expert user expertise, and contribute to the design and development of human-centered AI. Implementing AI into work-life is not only a decision to design and use a certain technology but also a decision that reflects societal and organizational values, and it must be approached with that respect.

Limitations and future research directions

We acknowledge that the study has its methodological limitations: as it focuses on expectations, it might reflect idealistic expectations of AI's capabilities. Further research is needed to study real-life experiences in AI in expert work, the underlying dynamics in the AI use, and the domain expert user experience. In addition, the study was limited to recruitment experts in a particular cultural environment excluding, for instance, the job candidates' perspective. More information on the cultural context of recruitment and other stakeholders of the AI-based systems would help to establish a greater degree of accuracy on this matter. In addition, trust formation in AI as augmentation calls for theorization and a profound exploration of the domain experts' continuous trust in the decision-making in case of possible disagreement with AI. The broad and multidisciplinary concept of trust provides an intriguing perspective to study trust in AI considering different notions of expertise in a relation to, for instance, required education and decision-making process.

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