

## Considerations on Human-AI Collaboration in Knowledge Work – Recruitment Experts’ Needs and Expectations

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### Abstract

*Organizations’ decision-making processes are increasingly supported by novel AI applications. While intelligent systems appear promising for enhancing various professional tasks, domain experts’ perceptions of the adoption and use of AI remain understudied. Following a human-centered design approach, this qualitative interview study (N=15) explores the potential of AI applications from recruitment experts’ perspectives. The results of the study emphasize the collaborative nature of AI: recruitment experts anticipate AI to augment their expertise positioning as a complementary information source. Domain experts would then evaluate and justify this outcome according to certain recruitment situations and combined with recruitment experts’ tacit knowledge. Novel AI applications are expected to align with underlying social and societal factors that guide the domain experts’ work practices. The results provide qualitative understanding into domain experts’ user experience and human-AI collaboration in knowledge work, offering insight into human-centered AI design and development.*

**Keywords:** Artificial Intelligence, Human-AI Collaboration, Knowledge Work, Recruitment

### 1. Introduction

Across disciplines, applications of Artificial Intelligence (AI) are anticipated to cause fundamental changes to work-life, automating different tasks and augmenting human capabilities (Brynjolfsson & McAfee, 2012; Brynjolfsson & McAfee, 2017; Jarrahi, 2018). In recruitment, AI applications are anticipated to, for instance, automate candidate communication, mitigate biases in recruitment decisions, or make sense of the hiring data (Black & van Esch, 2020; Albert, 2019; Laurim et al. 2021; Lee, 2018). There are also emerging concerns regarding AI systems in

recruitment context, relating to the social and societal consequences, risks and pitfalls, such as the autonomy of recruitment experts, and justice in terms of candidates’ fair treatment (Koivunen et al., 2023). Overall, the new wave of digitization is considered to put pressure on public values, underlining a need to ensure that societal values and fundamental rights are safeguarded in AI-era (Royakkers et al. 2018). To this end, novel AI systems can be considered as sociotechnical artifacts, which refers to a mutual constitution and interdependency of social and technological elements. These systems do not function in technical isolation but are embedded in societal, institutional, or organizational contexts with their own mechanisms and roles (Sawyer & Jarrahi, 2014; Araujo et al., 2020.) Sociotechnical system design acknowledges the human values and the needs of the employee (Mumford, 2000) and collaboration of social and technical to accomplish tasks (Appelbaum, 1997).

In this study, we aim to understand the domain experts’ needs and expectations towards novel AI applications in their work, and the expert-AI interaction and collaboration in the recruitment context. Expectations can reveal how people conceptualize novel technology (Hiltunen et al., 2002; de Vries et al., 2003). Understanding users’ expectations might help to interpret the product characteristics that contribute to the user experience (Olsson, 2014; Yogasara et al. 2011) and the circumstances and factors encouraging or discouraging the system adoption (Raj & Seamans, 2019). In this study, we refer to AI as a collaborative system: machines and humans cooperate to achieve a common goal and engage to some extent in complex problem-solving processes (Seeber et al., 2020). Although the “machine as a teammate” perspective has also gained criticism due to unnecessary anthropomorphism (e.g., Schneiderman, 2020), there is an ongoing discussion if human and machines can

have complementary strengths in organizational decision-making processes (Jarrahi, 2018; 2022), and what skills and competencies end-users need to develop in AI-driven organizations (Budhwar et al., 2022). In addition, domain expert users' user experience with novel AI systems in their work remain understudied, even though recent research has found that domain expert users perceive AI systems differently in comparison to non-expert users (Brynjolfsson et al., 2023).

Considering the increasing development of novel AI applications to support work life, we argue that understanding domain experts' perspective is essential in designing and developing AI applications that provide means to enhance and support domain experts in their work. Human-centered AI design approach underlines the augmentative nature of AI systems: rather than replacing humans, AI systems can extend human capabilities resulting as safer and more manageable future (Crowley et al., 2019; Shneiderman, 2020, 2022; Jarrahi, 2018; Preece et al., 2019). Consequently, human-centered design approach necessitates the identification of user needs, emphasizing the humanistic perspective instead of technological, and focuses on human values such as justice and dignity in the design (Auernhammer, 2020; Xu, 2019). It is noteworthy that research on AI design and development comprises two distinct philosophical perspectives: rational and empirical approaches, in which rationalists favor laboratory research and empiricists real-world observations (Shneiderman, 2022; Auernhammer, 2020). Currently, most AI research focuses on rationalistic perspective although it might not be able to capture the complexity of a real-world contexts (ibid). Our research follows an empirical approach, underlying the importance of recognizing the complex and socially constructed nature of knowledge work that novel AI-tools aim to support.

In our study, we use empirical methods to explore recruitment experts' perceptions of using AI in their work, and to gain insight on human-AI collaboration in practice. To this end, we ran a qualitative study to answer the following research questions:

**RQ1.** *What kind of needs and expectations do recruitment experts have towards AI in their work?*

**RQ2.** *How is human-AI collaboration expected to unfold in practice in the context of workforce recruitment?*

To answer these questions, we conducted semi-structured interviews with 15 domain experts based on Finland. The study creates an empirical understanding of human-AI interaction and collaboration in

recruitment and provides insight into domain expert users' user experience.

## 2. Related work

The following discusses the concepts of human-AI collaboration and domain expertise and describes the sociotechnical context of recruitment as AI application area.

### 2.1. From human-computer interaction to human-AI collaboration

Emerging novel AI applications are challenging the current design paradigms in human-computer interaction. Iterative development and learning abilities, utilization of big data and the "black box" nature of AI (i.e., lack of explainability and transparency) can make AI applications unpredictable when used in real-life context. Due to their adaptive nature, AI applications can respond differently to the same text input over or behave differently from one user to other (Amershi et al., 2019). In addition, AI systems can learn to perform tasks autonomously, even without existing instructions: like humans, AI systems might gather tacit knowledge (Brynjolfsson and Mitchell, 2017; Jarrahi et al., 2022). Human users are then needed to supervise and "make sense" of the system outcomes. For instance, AI systems do not know what is or isn't biased and cannot determine if it is learning one (Black & van Esch, 2020). Therefore, users should decide when to defer to or override the system's recommendation (Burton et al., 2020; Zhang et al. 2022).

For AI system to be considered collaborative, it will need to engage in at least some of the steps in a complex problem-solving process (Seeber et al., 2020). Previous research suggests that AI and humans have their own strengths in organizational decision-making: AI can extend humans' cognition by providing computational and analytical insight whereas humans' holistic approach outperforms AI in uncertain and ambiguous situations (Jarrahi, 2018; 2022). In this "augmentation work" (Baer et al., 2022) humans can have different roles, for instance, in training and supervising the algorithm, controlling it, and explaining its results (Grønsund & Aanestad, 2020; Teodorescu et al., 2021). Knowledge sharing within an organization is considered to facilitate effective collaboration between AI systems and human employees. These strategies are likely to change depending on the context and purpose of use, but they might include codification (storing the knowledge in a database) and personalization (person-

person communication of knowledge) (Chowdhury et al. 2022). Depending on the application domain, human's holistic perspective, tacit knowledge and intuitive analysis might affect the decision-making situation (Jarrahi, 2022; Brynjolfsson & McAfee, 2014). Recent research underlines the notion of complementary expertise, referring to a situation in which human and AI have complementary strengths, resulting as enhanced expert performance and human-AI cooperation (Zhang, 2022; Bansal et al. 2020).

## 2.2. Domain experts as technology users

In various domains, individuals holding expert titles are characterized by their specialized skills, distinct attributes, and extensive knowledge acquired through substantial experience within specific subdomains. In comparison to their less skilled peers, experts demonstrate superior performance in precise and dependable judgment in challenging situations (Ericsson, 2012; Hoffmann, 1998). Expertise in our study follows a relative approach, assuming that expertise is a level of proficiency that novices can achieve (Chi, 2012). Therefore, becoming an expert requires 'deliberate practice': engaging in repetitive activities with a clear goal and gradual improvement process supported by immediate feedback. With increasing experience, decision-making becomes less effortful and more intuitive (Ericsson, 2014).

In software development, domain expert users are experts in a specific domain who use computer environments to perform their daily tasks (Costabile et al., 2003). Recent research on AI and expertise has been focusing mainly on comparison between algorithmic outcomes and expert decisions, and if people rely more on human experts' advice or algorithmic outcomes. Findings divide between algorithmic appreciation (reliance on algorithms rather than humans) and algorithmic aversion (reliance on humans rather than algorithms). For instance, Logg et al. (2019), Thurman et al. (2019) and Araujo (2020) found that people adhere more to algorithmic advice than human advice, even when the process is opaque or when the advice comes from human experts. Algorithmic aversion is more likely to occur if users have incorrect expectations, they experience a lack of decision control, or AI suggestions counteract the user's intuition (Burton et al., 2020). The preference for human vs. AI advice depends on the decision domain and the task type the AI is performing in (Castelo et al., 2019). For instance, humans might be perceived more morally trustworthy than their AI equivalent (Tolmeijer et al., 2022). Similarly, in recruitment decisions human experts are considered fairer than AI similar decision (Newman et al. 2020).

## 2.3. Recruitment as AI application area

Recruitment and selection are one of the Human Resource Management (HRM) activities (Shen & Edwards, 2006), referring to a multi-staged decision-making process including setting the criteria and requirements, attracting, and identifying potential employees (sourcing), comparing candidates, and making the final selection (Barber, 1998; Connerley, 2014). In recruitment, AI applications are seen as promising way to fasten the recruitment process and to produce new and objective knowledge by either automating or augmenting recruitment processes (Black & van Esch, 2020). For example, AI tools can automate repetitive tasks, screen candidate CV's and applications, clarify and produce job descriptions, gather relevant candidate information, and to increase the reliability of the decision-making (Albert, 2019; Laurim et al., 2021; Lee, 2018; van den Broek et al., 2021). Especially in high-volume recruitment processes, novel AI systems have proved to increase efficiency (Boak & Niehueser, 2020). In addition, algorithmic systems are argued to potentially mitigate human biases as they lack the influence of emotional factors (Black & van Esch, 2020), and thus, might even increase diversity (Houser, 2019) and enhance the quality of HR decisions (Vrontis et al., 2022). On the contrary, algorithmic systems can carry human biases and confirm humans' biased intuition replicating and duplicating existing inequalities (Raisch, & Krakowski, 2020; Lee, 2018; Sartori, et al. 2022).

The successful use of AI in the recruitment context is considered to depend largely on the recruiters' acceptance (Boak & Niehueser, 2020). Recent studies have examined recruitment experts' perspectives on using AI in their work. Boak & Niehueser (2020) explored the employees' (N=7) attitudes towards AI on high-volume recruitment and found three main factors that support the AI adoption: increase in efficiency, demonstrable performance and quality of the technology, and ease of use of the technology. The findings also uncover concerns, such as technology's ability to conduct the given task, and hiring managers' and candidates' resistance and doubt towards AI. Li et al. (2021) studied recruiters and HR professionals (N=15) perspectives on algorithmic sourcing and assessment, and the individual and organizational dynamics regarding the use of AI-enabled tools. Their findings underline socio-organizational factors, such as new assessment processes and implementations and recruiter's social capital influencing the use and adoption of AI systems.

Laurim et al. (2021) studied recruitment experts, managers, and candidates (N=15) expectations and attitudes towards AI in recruitment, and the personal and contextual factors influencing the acceptance of AI-based recruitment technologies. Transparency, trialability, and a sense of control were found to be the key components increasing the user's acceptance of AI tools whereas successful adoption was based on understandability of the algorithms' internal operation and its reasoning. van den Broek et al. (2021) studied the development of a machine-learning system for hiring and the tensions between developers and domain experts. Based on the findings, domain experts should be able to define, evaluate, and complement machine inputs and outputs whereas developers should help experts to discover previously unknown insights from data. This process created a new hiring practice combining machine-learning and domain expertise, labeled as human-ML hybrid practice. While these studies offer contextual understanding of user acceptance, adoption and social dynamics in recruitment, the research concerning human-AI collaboration in recruitment remain largely unexplored, especially on the future of augmentation (Budhwar et al., 2022; Dutta et al. 2022).

### 3. Method

#### 3.1. Study design

Semi-structured expert interviews were seen as useful to gather information about the end-users' perceptions and experiences (Blandford et al., 2016). The study participants represent both public and private organizations and different professional positions as indicated in Table 1. This study focused on similarities to be able to understand recruitment expertise in depth. All participants were living in Finland at the time of the interview, and they represent the Finnish work culture.

Altogether 15 one-to-one expert interviews were conducted by the first author between December 2020 and February 2021. The interviewees were recruited from recruitment-focused online communities on LinkedIn and Facebook. The call for participants was targeted at recruitment experts and introduced AI as a potential collaborative technology. We did not require the participants to have previous experience in AI or algorithmic systems.

After each interview, we took advantage of snowball sampling. Interviews were conducted via virtual communication platforms Microsoft Teams and Zoom. The average length of an interview was 78 minutes. Before the interviews, the participants were asked to fill out a background survey that inquired

their organizational work environment and recruitment practices, their experience in recruitment activities, and preliminary expectations regarding the use of AI in recruitment.

#### 3.2. Interview themes and procedure

The semi-structured interviews comprised three thematic parts: 1) current recruitment decision-making process, practices, and the systems, 2) expectations and needs towards AI in their work, 3) envisioning the use of AI in recruitment. The follow-up questions aimed for a deeper understanding of the issues that emerged during the interviews. All interviews were recorded after asking the participant's consent.

**Table 1.** Study participants

| ID  | Work experience in recruitment | Title and field  | Main tasks   | Experience on AI/algorithmic systems in recruitment  |
|-----|--------------------------------|--|--|--|
| P1  | 8 years                        | Recruiter, IT  | Talent acquisition, recruitment support  | LinkedIn Recruiter   |
| P2  | 15 years                       | Talent acquisition director, IT                            | Leads international recruitment team   | -  |
| P3  | 15 years                       | Recruitment director, IT                                   | Leads recruitment team, strategic recruitment  | -  |
| P4  | 10 years                       | Talent acquisition partner, HR                             | Strategic recruitment, recruitment process development and coordination                                | Implementing AI-based talent platform for data analysis  |
| P5  | 12 years                       | Head of talent acquisition, banking industry               | Leads international recruitment team, sourcing   | Robotic process automation for background check, implementing facial recognition for screening |
| P6  | 15 years                       | Recruitment and management consultant, business management | Strategic recruitment, recruitment process development and coordination, psychological assessment      | Tested IBM Watson for psychological assessment   |
| P7  | 15 years                       | CEO, recruitment   | Sourcing   | Tested robotic process automation for sourcing   |
| P8  | 10 years                       | Executive talent agent, IT                                 | Talent acquisition, recruitment support  | LinkedIn Recruiter   |
| P9  | 4 years                        | Head of training and recruitment partner, IT               | Recruitment process development and coordination, recruitment training, sourcing                       | LinkedIn Recruiter   |
| P10 | 22 years                       | Growth manager and product developer, recruitment          | Recruitment system development and marketing   | -  |
| P11 | unknown                        | CEO and data scientist, software development               | Recruitment training, recruitment system development   | Developing AI system for candidate matching  |
| P12 | 8 years                        | Recruitment specialist, municipal sector                   | Strategic recruitment, recruitment process development and coordination, recruitment system management | -  |
| P13 | 20 years                       | Growth manager, municipal sector                           | Management of business and employer services, entrepreneurship support                                 | -  |
| P14 | 14 years                       | Service manager, municipal sector                          | Business and employer service support, entrepreneurship support, recruitment                           | -  |
| P15 | 13 years                       | HR partner, higher education                               | Strategic recruitment, recruitment process development and coordination                                | -  |

#### 3.3. Data analysis

Thematic analysis was conducted to identify, examine, and record patterns of experiences and explain the phenomena (Cairns & Cox, 2008). 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 categorized into 47 themes from which we identified 3 main themes: 1) the core expertise of recruitment experts, 2) the appropriate use of AI systems in

recruitment, and 3) the human-AI collaboration in recruitment. The analysis was conducted utilizing Atlas.ti software by the first author and iteratively discussed, challenged, and refined by the co-authors, including early-, mid-, and late-career researchers. This research follows a constructivist-interpretive paradigm in which coding refers to an inductive interpretation (McDonald et al. 2019; Blandford et al., 2016).

## 4. Results

We structure the results according to three key themes: 1) domain experts' role and responsibilities in the recruitment process, 2) identified needs, and expectations towards novel AI application in recruitment, and 3) considerations related to human-AI collaboration in practice.

### 4.1. The roles and responsibilities of domain experts in the recruitment process

The interviews indicated that the recruitment experts' typical role is to work between the candidates and hiring managers, aiming to serve both parties in different steps during the recruitment process. Recruitment experts' responsibilities include a) external and internal communication, b) supporting candidate selection, e.g., participating in the interviews, c) educating managers in recruitment decision-making, e.g., to identify biases, and d) analyzing market trends and identifying organizational needs. The more experienced the manager is in conducting recruitment activities, the less likely they need support from the recruitment experts, as P5 highlighted: *"The manager's experience on recruitment affects our [recruiters] participation. For instance, how actively we participate in the process and what kind of support we provide to them."* One of the main tasks for recruitment experts is internal and external communication. This might include, for instance, defining the candidate requirements, sending personalized messages to potential candidates, or informing hiring managers or candidates about the recruitment process. The participants acknowledge communication to be one of the most time-savvy tasks in the recruitment process. Nevertheless, it is considered important both from the perspective of employer brand and candidate experience.

The recruitment expert's tacit information about surrounding cultural context and candidate's previous work experience was seen as an important part of recruitment decision-making. This kind of knowledge was emphasized when recruitment was conducted in a

familiar cultural environment: several participants perceived it helpful in evaluating the candidates' cultural fit into an organization. Recruitment experts articulated to have tacit knowledge about organizational similarity, job positions, titles, salaries, and geographical differences. In addition to evaluating the candidate's cultural fit into an organization, the recruitment experts aim to provide information for candidates about the hiring organization's culture, underlining the reciprocal nature of recruitment and the social match between the candidates and the organization. On the other hand, many participants were aware of the various hidden biases in recruitment decision-making and, therefore, recognized that avoiding them completely is immensely hard. The participants said to mitigate biases by openly discussing with the managers during the recruitment process and participating in the interview situations with an aim to challenge hiring managers' perceptions and assumptions about the candidate. Still, human biases were seen as an inevitable part of the recruitment process.

While there are no formal educational requirements for recruitment in Finland, there seems to be commonly shared ethical principles among study participants. Especially values related to equality and inclusion were acknowledged among several participants. These values guide the overall recruitment process and implementing these values in the process is mainly the recruiter's responsibility. In addition, six participants underlined the importance of empathy. P1 underlines the recruitment process should not be too discouraging or tiring for the candidates, underlining the societal function of recruitment: *"It is societally important that candidates remain capable of applying for jobs"*. However, there might be discrepancies depending on the recruitment experts' role in the organization. For instance, if a participant was employed within the organization (in comparison to recruitment being outsourced), they had more practical opportunities to implement values into practices. P4 had shifted their position from external recruitment consultant to internal recruitment expert and perceived that it improved the opportunities to develop the practices in accordance with their professional ethics. In contrast, if the recruitment functions are outsourced, or consulting services are used, the recruitment expert's main task is to fulfil their clients' needs, as P9s' exemplified: *"Recruitment experts deliver what is asked, and we try to make it fairer, but we cannot fix the system from this position."*

## 4.2. The use of AI systems in recruitment process and decision-making

Several study participants stressed the need to either gain support for the recruitment decision-making process or challenge it with analytical and objective insight. Algorithmic systems were considered potential to fulfil this need, as P8 defines: *“The [recruitment] decisions are made with intuition and AI could bring more transparency into this. This is essential if we want to make good recruitment decisions”*. Algorithmic systems were perceived more capable to focus on relevant factors than humans which was expected to enhance the quality of the overall recruitment process especially in situations that might be affected by human biases, such as recruitment interviews. P5’s organization is planning to implement facial recognition system into high-volume recruitment to help recruiters in candidate screening. In addition to efficiency, they aim for objectivity, as P5 explains: *“Timesaving, but also comparability and neutrality. Although we educate our recruitment team about biases and how to be neutral, it is hard. I think humans are not made to be neutral in all circumstances.”*. P1 visualizes that recruitment interviews could be recorded and analyzed by an AI application, and both the interviewee and candidate could then evaluate and either agree or disagree with this analysis. This kind of semantic analysis was assumed to increase the transparency of the hiring process by deducing biased assumptions and hasty conclusions based on the interview situation. Similarly, P9 suggests that AI could also question the recruitment decision if it identifies e.g., discriminative decision-making: *“AI could display 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.”*

In addition to objectivity, study participants identified several opportunities to make sense and provide insight regarding the organizational data. For instance, AI could be used to predict upcoming recruitment needs based on general trends on the job market, help organizations to identify weak signals and global trends, and to identify existing in-house expertise. In addition, AI was considered potential in supporting candidates in the recruitment process, for instance, helping them to find potential job positions, analyzing the candidates’ previous work experiences and helping them to recognize their unidentified skills or talent. From the perspective of recruiting organizations, this would result in a larger candidate pool and more diverse job applicants. Some participants were also curious to use algorithmic systems in creative problem-solving, as P14

articulates: *“we could give it a challenging task to solve and then with open mind listen what solution AI would offer”*.

In addition to augmentation, AI’s potential to automatize routine and repetitive recruitment tasks and decisions was visible in the research interviews. AI was seen suitable to automate tasks that do not necessarily require specific recruitment knowledge, such as finding and recommending candidates, e.g., from existing talent pool, improving communication, or helping in administrative tasks. Automated systems were particularly emphasized in high-volume recruitment with well-defined and straightforward job positions, 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.”* (P12: Recruiter, public sector). However, four participants underline that using AI in candidate screening might exclude “unexpected but positive hires” if these candidates do not proceed in the recruitment process due to predefined requirements and automated decision-making. For instance, P1 mentioned a person who used to work as a butcher but later appeared to be *“one of the best salespersons in the organization”*. (P1: Recruiter, IT).

Automated systems were anticipated to increase the efficiency of the recruitment process, which was seen to benefit the recruiting organization but especially the candidates as P7 exemplifies; *“the faster the process, the better the candidate experience”* (P7: CEO, recruitment). In addition, many participants underlined the importance of good candidate communication in recruitment. Eight participants admitted that the recruitment process might not be transparent to candidates and identified a need to enhance the candidate's experience by finding new ways to improve communication. AI as automation was seen as useful, for instance, in sending automated updates about the recruitment process and providing recruitment feedback for the candidate. Automated processes were emphasized in larger organizations and in high-volume recruitment.

## 4.3. Considerations on human-AI collaboration in recruitment

To be able to justify the recruitment decision and to remain responsible and accountable for the overall recruitment process, several participants underlined the need to understand the technology, either from the process perspective; what the AI does and why, or from the product perspective; how the algorithm has

been built. Three participants acknowledge that the systems' performance would be compared to other recruitment tools and systems. For instance, P4 compared AI applications to a talent assessment tool where recruitment experts 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 the 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). The participants stated that they should have the possibility, for instance, for an AI audit, evaluation, and validation, or trial the AI system. As an outcome, they stressed the need to develop new skills in an increasingly digitalized recruitment environment. They identified educational needs to learn the practicalities in the use of AI, for instance, technical understanding and analytical skills. Also, responsive attitude towards new technologies was perceived important among few participants. Some participants considered that uncertainty and even fear might prevent the use and deployment of novel AI applications, as P12 demonstrates: *"That 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)

For most of the participants the role division between humans and AI seemed to be clear. "Human-in-the-loop" perspective (i.e., human users supervising the AI system) was underlined, and participants seemed to be receptive towards AI if humans remain in control. P3 visualizes their ideal human-AI interaction and collaboration: *"We should use AI to support recruitment but not to make decisions. AI could give hints and suggestions that we could process further. Collaboration with humans would be the most fruitful"*. Similar observation was made by P13: *"I wouldn't let the technology decide: it cannot think through. But maybe it could bring to the surface those issues that we have been blind to"*. Many participants underline that AI can't understand ethical perspectives, social connections and empathy that recruiters consider essential in recruitment. Nevertheless, few participants acknowledge that AI can be more reliable than their human counterpart questioning the human "idealization" in comparison to AI, as P10 comments: *"machine can be more systematic and therefore more reliable than human"*. Some participants underline that the decision outcomes might not be immediate and therefore, the quality of the overall recruitment process and

decisions are monitored in long-term performance: such as if the selected person appears to be a good fit for the organization. It is noteworthy that uncertainty is an essential characteristic of the recruitment process.

Several participants indicated a critical attitude regarding the imagined challenge that AI applications aim to solve. They necessitated a need to understand recruitment as an AI application area and emphasized the need to consider critically if the technology is the right solution for an identified problem. P15 calls for understanding domain experts' perspective: *"It would be nice if you could see if from recruitment experts' perspective. What we do and what could be done, what is a good way to proceed in each step"*. Collaborative design practices were considered essential when developing algorithmic systems to support recruitment experts' decision-making. Few participants questioned the AI developer's competence to identify and solve recruitment-specific challenges without having domain expertise, as P6 exemplifies: *"Those who have not worked a single day in recruitment, are supposedly identifying a problem and building a solution for that."* (P6: Recruitment and management consulting). Interestingly, cautious attitudes towards technology providers' domain expertise focused mainly on external providers. P2's and P5's organizations can develop technological recruitment solutions internally and declare that having this knowledge of organizations' recruitment practices is helpful in developing useful and usable systems.

## 5. Discussion

The aim of this research was to explore recruitment experts' needs and expectations towards AI in their work, and human-AI interaction and collaboration in knowledge work. The findings of our study reflect general discourse around AI risks and pitfalls, such as erroneous machine learning or lack of human control, emphasizing a need for collaborative design practices (van der Broek et al. 2021). The findings underline the complementary nature of AI: recruitment experts anticipate AI to enhance their expertise and decision-making by providing objective insight which would then be evaluated according to certain recruitment situations and combined with recruitment experts' tacit knowledge. Although our study focuses on recruitment domain, the findings offer generalizable considerations on human-AI interaction and collaboration in knowledge work. These considerations include a) *value-based expert role*, b) *augmented expertise*, c) *domain experts' user*

*experience*. We will discuss these considerations below, followed with future work and limitations.

*Value-based expert role* refers to the underlying motivational and societal factors that are embedded in the domain experts' work practices. Although the organizational goal of recruitment is "to find the right person in the right position at the right time" (Breugh, 2013; Koivunen et al., 2019), our findings suggest that the domain experts' work are driven by social and societal factors and values, such as inclusion, equality, and candidates' well-being. These values guide their work practices and reflect also in their perceptions regarding AI. It is noteworthy that although the participants did not specify the origin of these values, none of them mention such requirements emerging from their organization. Instead, these underlying values seem to be more an individual or professional preference, also reflecting the cultural context in which the study was conducted in. According to Li et al. (2021), societal factors (e.g., diversity), can cause shifts in the employer's hiring focus. As digitization might pressure public values (Royackers et al., 2018), these societal values should be acknowledged in the design and development of novel AI applications and safeguarded accordingly as they can also be considered to increase the meaningfulness of the work.

The participants in our study underline a need for AI augmentation: recruitment experts aim for the best possible decision with available information, and AI systems could position as one additional information source. This is what we define as *augmented expertise*. Recruitment decision-making is a collective decision-making process in which AI-provided information can amplify but the outcomes are coordinated and evaluated by domain experts. AI application might have agency and these systems might trigger the decision-making process (van den Broek et al. 2021), but AI-outcomes are not expected to override domain experts' judgment: rather these systems offer a reflection that is not possible for humans to achieve in interpersonal communication. This refers to augmentation work, in which the user of algorithmic systems audits and assesses the algorithmic output against the ground truth (Grønsund & Aanestad, 2020). It is noteworthy that achieving the ground truth might be difficult in recruitment as recruitment decisions are very situational, and only time reveals if the selected person was the right decision for the position. Recruitment experts' tacit knowledge might be an essential part of the recruitment processes and also a relevant factor when considering knowledge sharing in organization, and e.g., the codification (storing knowledge on database) (Chowdhury et al. 2022).

When considering the *domain experts' user experience*, our findings align with previous research. AI systems are expected to be understandable and transparent, and using these systems might require domain experts' de-/reskilling, for instance, regarding their technical capabilities and proper training (Laurim et al., 2021; Boak & Niehueser, 2020). Boak & Niehueser (2020) underline that different learning strategies should be considered during the technology implementation, and thorough briefing and training are also needed for other stakeholders, such as candidates and hiring managers. There seems to be an interesting paradox regarding human-AI collaboration in expert work: AI is expected to exceed human capabilities by providing objective insight while simultaneously AI systems are expected to be thoroughly explainable and transparent. It remains to be seen how this challenge can be tackled. On a more practical level, there is a concern that current design paradigms are not suitable when designing AI systems into expert work. For instance, Li et al. (2021) stress that 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. On the contrary, Boak & Niehueser (2020) found that ease of use and intuitiveness of the AI system in high-volume recruitment is a key factor in recruitment employees' AI adoption. Overall, novel systems in knowledge work should be designed in a way that allows either following the algorithmic outcome or acting oppositely with confidence, and this is not only a technical but also an educational issue.

As future work, we will continue exploring the social and technical factors in expert-AI interaction in knowledge work. For instance, further research is needed regarding the development of expertise in the AI era and the terms in which expertise can be transferred to AI systems. Also, domain expert users' user experience requires more exploration, for instance, in drafting design practices that can both support ease of use and evoke critical thinking and user autonomy. In addition, it is important to re-investigate factors that support users' acceptance towards novel AI technologies, including candidates' and hiring managers' needs and expectations.

This study has certain limitations. Focusing mainly on expectations, it might reflect idealistic visions of AI systems capabilities in recruitment. With an emphasis on a human-centered perspective, this study excludes the materiality the technology holds. Also, fear of being replaced by AI might lead to biased

answers and emphasis on AI augmentation (although this fear was not visible in our study). It is noteworthy that research was conducted in an environment that follows the EU General Data Protection Regulation (GDPR) causing legislative limitations in AI implementation in recruitment. Overall, it is important to acknowledge the cultural context the study was conducted in, and how different demographic and societal values might affect the interpretation of the study findings.

## 6. Conclusion

The aim of this study was to examine the recruitment experts' needs and expectations toward AI systems in their work, and the human-AI collaboration in knowledge work. The findings of the study emphasize domain experts' need and willingness to augment their existing expertise with novel AI systems and reveal interesting insight on domain expert users' user experience. The study results underline professional and individual values that are expected to be supported by AI systems, stressing the need for collaborative design methods. Implementing AI into knowledge work is not only a decision to design and use technology to achieve organizational goals but also a decision that reflects societal values, and it should be approached with that respect. The study contributes qualitative understanding regarding the domain experts' perceptions towards AI in their work and provides empirical insight into human-AI collaboration in complex and socially constructed knowledge work.

## 7. References

- Amershi, S., Weld, D., Vorvoreanu, M., Fournery, A., Nushi, B., Collisson, P., Suh, J., Iqbal, S., Bennett, P. N., Inkpen, K., Teevan, J., Kikin-Gil, R., & Horvitz, E. Guidelines for human-AI interaction. *Conference on Human Factors in Computing Systems - Proceedings*. (2019).
- Araujo, T., Helberger, N., Kruikemeier, S., & de Vreese, C. H. In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI and Society*, 35(3), 611–623. (2020).
- Appelbaum, S.H. "Socio-technical systems theory: an intervention strategy for organizational development", *Management Decision*, Vol. 35 No. 6, pp. 452-463. <https://doi.org/10.1108/00251749710173823>. (1997).
- Auernhammer, J. Human-centered AI: The role of Human-centered Design Research in the development of AI. *DRS2020: Synergy*, 1(August). (2020).
- Baer, I., Waardenburg, L., Huysman, M., & Waardenburg, L. Association for Information Systems What Are We Augmenting? A Multidisciplinary Analysis of AI-based Augmentation for the Future of Work. *Completed Re.* 0–17. (2022).
- Bansal, G., Wu, T., & Zhou, J. Does the whole exceed its parts? The effect of ai explanations on complementary team performance. In *Conference on Human Factors in Computing Systems - Proceedings*. Association for Computing Machinery. (2021).
- Barber, A. *Recruiting employees: Individual and organizational perspectives*. Vol. 8. Sage Publications. (1998).
- Budhwar, P., Malik, A., De Silva, M. T. T., & Thevisuthan, P. Artificial intelligence – challenges and opportunities for international HRM: a review and research agenda. *The International Journal of Human Resource Management*, 33(6), 1065–1097. (2022).
- Burton, J. W., Stein, M. K., & Jensen, T. B. A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making*, 33(2), 220–239. (2020).
- Black, J. S., & van Esch, P. AI-enabled recruiting: What is it and how should a manager use it? *Business Horizons*, 63(2), 215–226. (2020).
- Blandford, A., Furniss, D., & Makri, S. Qualitative HCI Research: Going Behind the Scenes. *Synthesis Lectures on Human-Centered Informatics*, 9(1), 1–115. (2016).
- Breaugh, J. A. Employee Recruitment. *Annual Review of Psychology*, 64(1), 389–416. (2013).
- Brynjolfsson, E., & McAfee, A. Winning the race with ever-smarter machines. *MIT Sloan Management Review*, 53(2), 53–60. (2012).
- Brynjolfsson, E., & McAfee, A. The Business of Artificial Intelligence: what it can and cannot do for your organization. *Harvard Business Review Digital Articles*, 1–20. (2017).
- Brynjolfsson, E., Li, D., & Raymond, L. Generative AI at Work. Retrieved from <http://arxiv.org/abs/2304.11771>. (2023)
- Cairns, P., & Cox, A. L. (2008). *Research methods for human-computer interaction*. Cambridge University Press.
- Castelo, N., W Bos, M., Lehmann, D.R., (2019). Task-dependent algorithm aversion. *Journal of Marketing Research* 56, 5, 809–825. (2019)
- Connerley, M. Recruiter effects and recruitment outcomes. *The Oxford handbook of recruitment*. (2014).
- Costabile, M., Fogli, D., & Letondal, C. Domain-Expert Users and their Needs of Software Development. In *Proceedings Session on End-User Development* (pp. 6–10).
- Chi, M. T. H. Two Approaches to the Study of Experts' Characteristics. In *The Cambridge Handbook of Expertise and Expert Performance* (pp. 21–30). Cambridge University Press. (2012).
- Chowdhury, S., Budhwar, P., Dey, P.K., Joel-Edgar, S., & Abadie, A. AI-employee collaboration and business performance: Integrating knowledge-based view, socio-technical systems and organisational socialisation framework. *Journal of Business Research*. (2022)
- Dutta, D., Mishra, S. K., & Tyagi, D. Augmented employee voice and employee engagement using artificial

- intelligence-enabled chatbots: a field study. *International Journal of Human Resource Management*. (2022).
- Ericsson, K. A. Expertise. *Current Biology*. Cell Press. (2014).
- Ericsson, K.A., Charness, N., Feltovich, P., & Hoffman, R. R. *Cambridge handbook of expertise and expert performance*. Cambridge, UK: Cambridge University Press. (2006).
- Grønsund, T., & Aanestad, M. Augmenting the algorithm: Emerging human-in-the-loop work configurations. *Journal of Strategic Information Systems*, 29(2), 101614. (2020).
- Hoffman, R. R. How can expertise be defined?: Implications of research from cognitive psychology. In R. Williams, W. Faulkner, & J. Fleck (Eds.), *Exploring expertise* (pp. 81–100). New York: Macmillan. (1998).
- Houser, K. Can AI solve the diversity problem in the tech industry? Mitigating noise and bias in employment decision-making. *Stanford Technology Law Review* 22. (2019).
- Jarrahi, M. H. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586. (2018).
- Jarrahi, M. H., Lutz, C., & Newlands, G. *Artificial intelligence, human intelligence and hybrid intelligence based on mutual augmentation*. Big Data and Society. SAGE Publications Ltd. (2022).
- Koivunen, S., Olsson, T., Olshannikova, E., & Lindberg, A. Understanding decision-making in recruitment: Opportunities and challenges for information technology. *Proceedings of the ACM on Human-Computer Interaction*, 3(GROUP). (2019).
- Koivunen, S., Sahlgren, O., Ala-Luopa, S., & Olsson, T. (in press). Pitfalls and Tensions in Digitalizing Talent Acquisition: An Analysis of HRM Professionals' Considerations Related to Digital Ethics. *Interacting with Computers*. (2023)
- Laurim, V., Arpacı, S., Prommegger, B., & Kremer, H. Computer, whom should I hire? - Acceptance criteria for artificial intelligence in the recruitment process. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 2020-January (February), 5495–5504. (2021).
- Lee, M. K. Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data and Society*, 5(1), 1–16. (2018).
- Li, L., Lassiter, T., Oh, J., & Lee, M. K. Algorithmic Hiring in Practice: Recruiter and HR Professional's Perspectives on AI Use in Hiring. *AIES 2021 - Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*, 1(1), 166–176. (2021).
- Mumford, E. A Socio-Technical Approach to Systems Design. *Requirements Eng* 5, 125–133. <https://doi.org/10.1007/PL00010345>. (2000).
- Newman, D.T., Fast, N., Harmon, D. (2020). When eliminating bias isn't fair: Algorithmic reductionism and procedural justice in human resource decisions. *Organizational Behavior and Human Decision Processes* 160 (2020), 149–167.
- Niehueser, W. and Boak, G. "Introducing artificial intelligence into a human resources function", *Industrial and Commercial Training*, Vol. 52 No. 2, pp. 121-130. <https://doi.org/10.1108/ICT-10-2019-0097>. (2020)
- Preece, A., Cerutti, F., Braines, D., & Pham, T. Explainable AI for intelligence augmentation in multi-domain operations. *ArXiv*. (2019).
- Raisch, S., & Krakowski, S. *Artificial Intelligence and Management: The Automation-Augmentation Paradox*. *Academy of Management Review*, 1–48. (2020).
- Raj, M., & Seamans, R. Primer on artificial intelligence and robotics. *Journal of Organization Design*, 8(1). (2019).
- Royakkers, L., Timmer, J., Kool, L., & van Est, R. Societal and ethical issues of digitization. *Ethics and Information Technology*, 20(2), 127–142. (2018).
- Sawyer, S., & Jarrahi, M. *Sociotechnical approaches to the study of Information Systems*. *Computing Handbook*, Third Edition: Information Systems and Information Technology. (2014).
- Shneiderman, B. Human-Centered Artificial Intelligence: Reliable, Safe & Trustworthy. *International Journal of Human-Computer Interaction* 36, 6: 495–504. (2020).
- Shen, J., and Edwards, V. *International HRM in Chinese MNEs*, London and New York: Routledge. (2006).
- Thurman, N., Moeller, J., Helberger, N., Trilling, D. My friends, editors, algorithms, and I: Examining audience attitudes to news selection. *Digital Journalism* 7, 4 (2019), 447–469. (2019).
- van den Broek, E., Sergeeva, A., & Huysman, M. When the machine meets the expert: An ethnography of developing ai for hiring. *MIS Quarterly: Management Information Systems*, 45(3), 1557–1580. (2021).
- van Esch, P., Black, S. J., & Ferolie, J. Marketing AI recruitment: The next phase in job application and selection. *Computers in Human Behavior*, 90, 215e222. (2019).
- Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review. *International Journal of Human Resource Management*, 33(6), 1237–1266. (2022).
- Zhang, Q., Lee, M. L., & Carter, S. (2022). You Complete Me: Human-AI Teams and Complementary Expertise. In *Conference on Human Factors in Computing Systems - Proceedings*. Association for Computing Machinery.
- Xu, W. Toward Human-Centered AI: A Perspective from Human-Computer Interaction. *Acm*, 1072–5520. (2019).