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Artificial intelligence in talent acquisition: exploring organisational and operational dimensions

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Abstract

Purpose – With the recent proliferation of AI, organisations are transforming not only their organisational design but also the input and output operational processes of the hiring process. The purpose of this paper is to explore the organisational and operational dimensions resulting from the deployment of AI during talent acquisition process.

Design/methodology/approach – The authors conducted semi-structured interviews and meetings with human resources (HRs) professionals, recruiters and AI hiring platform providers in Sweden. Using an inductive data analysis rooted in the principles of grounded theory, the study uncovered four aggregate dimensions critical to understanding the role of AI in talent acquisition.

Findings – With insights from algorithmic management and ambidexterity theory, the study presents a comprehensive theoretical framework that highlights four aggregate dimensions describing AI's transformative role in talent recruitment. The results provide a cautionary perspective, advising against an excessive emphasis on operational performance driven solely by algorithmic management.

Research limitations/implications – The study is limited in scope and subject to several constraints. Firstly, the sample size and diversity are restricted, as the findings are based on a limited number of semi-structured interviews and meetings with HRs professionals, recruiters, and AI hiring platform providers. Secondly, the rapid evolution of AI technologies means that the study's findings may quickly become outdated as new advancements and applications emerge.

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Data availability statement: In addition to the data presented in the paper, more data supporting the findings of this study are available upon request from the corresponding author. The data are not publicly available because they contain information that could compromise the privacy of the company where the interviews were conducted.

Practical implications – The results provide managers with actionable information that can lead to more precise and strategic management practices, ultimately contributing to improved organizational performance and outcomes. Plus, enhancing their ability to make informed decisions, optimize processes and address challenges effectively.

Social implications – The results signal both positive and negative impacts on employment opportunities. On the positive side, AI can streamline recruitment processes, making it easier for qualified candidates to be identified and hired quickly. However, AI systems can also perpetuate existing biases present in the data they are trained on, leading to unfair hiring practices where certain groups are systematically disadvantaged.

Originality/value – By examining the balance between transactional efficiency and relational engagement, the research addresses a crucial trade-off that organizations face when implementing AI in recruitment. The originality lies in its critique of the prevailing emphasis on e-recruiting.

Keywords Organizational design, Human resource management, Artificial intelligence, Operations

Paper type Research paper

1. Introduction

Digital recruitment, particularly through the use of artificial intelligence (AI), offers a significant advantage by increasing the number of job applications received and broadening the diversity of the applicant pool (Wilson and Daugherty, 2018). This expansion, however, does not necessarily equate to a rise in the quality of candidates (Stone *et al.*, 2015). Additionally, what is seen in practice is that AI in talent acquisition presents a nuanced balance between transactional efficiency and relational (human-to-human) engagement. The trade-off between transactional efficiency and relational engagement creates an impact in the organisational design and operational dimensions. The purpose of this paper is to explore the organisational and operational dimensions as a result of deploying AI in the talent acquisition process. We explore how the integration of AI, play a role in the talent acquisition process. We argue that the recent proliferation of AI within organisations (Meijerink *et al.*, 2021) is transforming not only organisational design but also the operational processes of the hiring process (Meijerink and Bondarouk, 2023). As a consequence, we question the incorporation of AI in talent acquisition which raises a debate; on one hand, it could be argued that relying on AI diminishes the importance of human-to-human relational interactions during the hiring process. On the other hand, AI enhances the capacity to perform transactional tasks, thereby leading to greater operational efficiency. This duality presents a complex trade-off for organisations aiming to leverage AI in their hiring processes, necessitating a deeper investigation into how AI tools like chatbots can be deployed effectively without compromising the essential human elements of talent acquisition and biases. One of the commonly used components of AI is the chatbot, which is simplified as a software application that allows for text- and voice-based communications. Chatbots are AI tools that handle text and voice chats. They have been used for years to quickly answer customer questions and provide information, based on past conversations. Undoubtedly, with text- and voice-based communications, chatbots transform organisational routines with automated capabilities by removing human-human integration during the recruitment process, but to what extent does it compromise the economies of human-to-human interactions? Previous research on the recruitment process may be viewed from the transactional and relational perspective (Stone *et al.*, 2015), where the former is associated with the administrative process, and the latter deals with the people aspect. The point of departure in this paper is that within the field of human resources (HR) research, both transactional and relational aspects play vital roles. Transactional efficiency fueled by automation in administrative tasks like document screening leads to cost savings and less waiting time. Simultaneously, there is a trade-off whereby the relational dimension is sidelined. We observe that although this approach improves the candidate experience and allows for more in-depth assessments, it may still raise questions about whether it enhances talent attraction and retention, which is a crucial topic in HR research.

To explore the intricate balance between relational and transactional competencies during talent acquisition, we adopt the algorithmic management literature and ambidexterity theory. Firstly, in the broader literature, advances in algorithmic management (Meijerink and Bondarouk, 2023; Parent-Rocheleau and Parker, 2022) primarily focus on AI with human interactions. This body of work argues that algorithms designated by managers or HRs departments play a pivotal role in organisational processes (Cheng and Hackett, 2021; Duggan *et al.*, 2020; Leicht-Deobald *et al.*, 2019). In the context of managerial function in an organisation, the algorithm is supported through an interconnected system surrounding organisational devices called algorithm management (Lee *et al.*, 2015). However, there is still a lack of clarity due to the emerging nature of research and rapid AI advancements in HRs, especially in talent acquisition (Cheng and Hackett, 2021). Secondly, our study incorporates insights from ambidexterity theory, which describes the organisation's capacity to balance the exploration and exploitation routines (O'Reilly and Tushman, 2021; Van Looy, 2022). We use ambidexterity as a lens to refer to a company's capacity to enhance the efficiency of existing business operations through exploitation while concurrently exploring new opportunities and pursuing radical innovations (Raisch *et al.*, 2009). As such, this paper identifies several dimensions where the balance of relational and transactional competences converges when organisations aim to enhance efficiency, especially using AI in talent acquisition.

Integrating insights from algorithmic management literature and ambidexterity theory, this paper aims to provide an explanation of the use of AI such as chatbots in talent acquisition, with a particular focus on the interplay between transactional and relational competences. As such, the purpose of our study is to explore the organisational and operational dimensions from the potential use of AI in the recruitment process. We are specifically interested in understanding how the transactional (task-oriented) and relational (people-oriented) aspects of AI impact these organisational structures and operational workflows. To explore this, we pose the research question:

RQ1. How do the transactional and relational aspects of AI influence both the organisational and operational facets within the talent acquisition process?

Through a qualitative study, we conducted interviews and meetings with HR professionals, recruiters, and AI provider. Our results show a cautionary perspective, advising against an excessive emphasis on operational performance driven solely by algorithmic management. Such a narrow focus may inadvertently neglect the significance of relational aspects, which encompass competencies acquired through human-to-human interactions in the workplace, such as communication, values and integration (Wieland and Marcus Wallenburg, 2013).

Apart from the introduction, the rest of the paper is structured into four sections. Section 2 provides a comprehensive overview of the talent acquisition literature, including an exploration of the transactional approach and insights from Algorithmic Management and Ambidexterity Theory. Section 3 outlines our chosen methodology, which uses an inductive approach. In Section 4, we present the findings of our study, and Section 5 discusses our results, future research and conclusions.

2. Algorithmic management within the hiring process in organizations

2.1 The organisational recruitment processes

Digital recruitment presents a significant advantage by increasing the number of job applications received and widening the applicant pool (Wilson and Daugherty, 2018).

This expansion, however, does not necessarily equate to a rise in the quality of candidates (Stone *et al.*, 2015). The ease of e-recruitment brings forth a challenge for organisations: navigating through a vast array of applications to pinpoint top talent. This process can potentially hinder a fair assessment of individual compatibility for the job. Talent acquisition, whether using AI or not, is a crucial aspect of HR development and management. This function needs to strike a balance between being strategic and adaptable to implement cost-efficient methods effectively (Lepak and Snell, 1998). In understanding HR strategies, it is essential to view them through an operational – systemic lens, considering input, process and output elements. HR management typically revolves around two strategic focal points: competency and behaviour (Wright and Snell, 1991). However, talent shortages can obstruct business growth prospects (Chambers *et al.*, 1998). To address this challenge, talent acquisition, adopts a strategic approach to recruit individuals with the right competencies and cultural fit (Anita, 2019). This approach taps into a pool of competitive applicants who might otherwise go unnoticed (Kumar, 2013). Ultimately, the primary HR objective remains the same: to successfully place the most qualified candidates, as determined by the selection process (Walford-Wright and Scott-Jackson, 2018). Traditionally, HR goals encompass cost-effectiveness, enhancing service delivery for internal customers and aligning with the organisation's strategic objectives (Parry and Tyson, 2011).

Within the context of this article, recruitment is defined as a timely basis process that covers the entire process of attracting, shortlisting and appointing qualified applicants for available jobs in an organisation in a cost-effective and timely manner (O'Meara and Petzall, 2013). There are four main stages in recruitment which start from job advertising, screening, selection and completion of selection (Hmoud and Laszlo, 2019; Ordanini and Silvestri, 2008).

The first stage is the job posting also known as sourcing, as the first phase of the recruitment process to start searching and attracting applicants to apply for a job (Hmoud and Laszlo, 2019) through the use of job advertisements posted in numerous channels such as newspaper ads, Internet job boards, company's websites, employee referrals, job fairs (Holm, 2010) and social media (Gupta *et al.*, 2018). Secondly, after job seekers apply to the job vacancy, the stage moves on to the document screening (e.g. resumes, certificates, etc.). Submissions by applicants are received by the recruiters and are managed in database management (Ordanini and Silvestri, 2008). It involves a screening process to filter and eliminate job applicants who do not fulfil the minimum requirement, matching the skills required by analyzing candidates' resumes, and shortlist the best candidates (Singh *et al.*, 2010). In this stage, recruiters are accountable for reviewing the incoming resumes and applications and setting phone interviews to shortlist qualified candidates to be invited for onsite interviews (Leong, 2018). The third stage is the selection phase which can be composed of assessment tests and interviews (Ordanini and Silvestri, 2008). The selection stage is the process to identify the best-qualified person for a specific job or position (Louw, 2013) in which the procedures are varied among companies, ranging from the use of curriculum vitae (CV), interviews and selection tests such as aptitude test, personality test and assessment centres (Branine, 2008; Schmidt and Hunter, 1998). The variety approach of selection can be distinguished with multilevel fit such as person-job fit, person-team fit and person-organisation fit (Anderson *et al.*, 2004). Finally, the final qualified candidates move on to the hiring decision and offering stage.

2.2 Operational efficiency

The recruitment process exemplifies a business process that is defined as "a series of continuous or intermittent cross-functional activities that are naturally connected with work flowing through these activities for a particular outcome/purpose" (Bititci *et al.*, 2011, p. 12). Several processes are involved and transformed into specific and valuable output for the customers or market (Hammer and Champy, 2009). Due to the diverse multidiscipline context, the business process serves different purposes, such as customer-facing operational process and administrative support (Bititci *et al.*, 2011) . *Both* are operational for the primary business process. Still, the latter is not customer-facing (Bititci *et al.*, 2011). The business process is divided into core (primary) and supportive (secondary) (Aguilar-Savén, 2004), where human resource management (HRM) as the umbrella division of recruitment is regarded as the support process (Bititci *et al.*, 2011). Technology utilization such as AI in electronic HRM (e-HRM) is proven to improve efficiency, service delivery, standardization and organisational image, to empower managers and HR to focus on more static activities (Parry and Tyson, 2011). The emphasis on the transactional approach is reasonable considering unfavourable operational performances in the recruitment process. According to Murray (1999), it takes at least 15 days to respond to a resume after the office receives it, and the first interview should be scheduled, which takes several weeks in the future. This is possibly due to some administrative tasks such as matching job description, competency mapping and CV sourcing that occupy the longest time of the entire recruitment cycle time at approximately 15 days (45%) out of 33 days (Singh *et al.*, 2010). Additionally, initial HR screening and debriefing sessions to make final decisions require a minimum of 2 days (6%) out of 33 days (Singh *et al.*, 2010). Failing to address this problem would potentially lead the firm in losing more qualified candidates.

The tendency to prioritize operational performance driven by algorithmic management may, however, overlook the importance of human-to-human relationships. Relational competencies can include interactions that rely on communication, cooperation and integration (Wieland and Marcus Wallenburg, 2013). Additionally, relational competencies can be represented in the capabilities of coordination, cooperation, capability and connection (Lado *et al.*, 2011). Relational aspects have been discussed in the literature as having less physical distance between applicants and HR managers. The consequences of relational aspects have also been acknowledged, such as "improved communication, cooperation, relationships and HR service improvements" (Bondarouk *et al.*, 2017). The preferred approach between both depends on how firms view their recruitment process, whether transactional, relational or balanced (Rousseau, 1995). However, despite some prior research confirming the importance of operational and relational capabilities as the key drivers for customer satisfaction, Zhao and Stank (2003) observed that trade-off between both is inevitable to achieve a strategic fit, balancing operational and relational aspects necessarily true.

2.3 Artificial intelligence in recruitment

The chatbot is one of the AI applications that has been used for talent acquisition to automate 80% of the total of "Top of Funnel" recruiting activities as it helps automate time-consuming tasks such as sourcing, screening and messaging (Balachandar and Kulkarni, 2018). It helps screening candidates, qualifying candidates, scheduling the interview, answering FAQs, assessing experience feedback and responding to unsuccessful candidates (Nawaz and Gomes, 2020). It is reasonable that it has been widely adopted to automate resume screening process (Raviprolu, 2017) and as the front-end communication channel to build engagement with candidates through the Web, mobile platforms and social media in the form of messages or dialogue box (Upadhyay and Khandelwal, 2018).

AI can be defined from a process perspective as input-process-output as the amalgamation of theory and practice of system development (Paschen *et al.*, 2019, 2020) and operations management (Slack and Brandon-Jones, 2018). Input refers to the data received (structured and unstructured); process refers to pre-process, which encompasses any activity before the central processing such as cleaning, transformation and selection as well as problem-solving, reasoning and machine learning; and output refers to information that can be helpful for human decision-making or the input into another information system (Paschen *et al.*, 2019; Paschen *et al.*, 2020). In the relational perspective for AI, it can be viewed from the discipline of human-computer communication, where AI is viewed as a communicator and about "how people understand AI to themselves and themselves to AI" (Guzman and Lewis, 2020). In other words, it is related to how humans perceive AI as their communication counterparts. Similarly, it can be seen as communicative robots that are defined as "autonomously operating systems designed for quasi-communication with human beings to enable further algorithmic-based functionalities" (Hepp, 2020). There are considerable benefits perceived with the use of AI in recruitment. The first benefit is operational efficiency for both companies and candidates (Upadhyay and Khandelwal, 2018). AI enables HR managers and leaders to efficiently attract, retain and inspire talented HRs, which are beneficial for the company's success (Raviprolu, 2017) and replace repetitive tasks traditionally performed by human recruiters (Upadhyay and Khandelwal, 2018). It potentially results in a firm's savings due to improved hiring-process efficiencies through employee turnover and reduced staffing costs (Buckley *et al.*, 2004). The second benefit is linked to the leveraged cultural fit and diversity due to the minimal involvement of humans' unconscious bias (Altemeyer, 2019) hence allowing for fair assessment. AI can help removing unconscious bias such as names, schools attended, gender, age and race (Upadhyay and Khandelwal, 2018) from the manual selection and evaluation to acquire the best candidates (Walford-Wright and Scott-Jackson, 2018). Thirdly, there are benefits associated with candidate engagement. Potential job candidates might withdraw from the recruitment process because they do not hear back from the recruiters. After all, the screening process may take more than one week to start (Upadhyay and Khandelwal, 2018). With AI, the screening can be started immediately and confirmed within 24 h (ibid). In other words, AI in recruiting helps employers to engage with the candidates immediately and not to lose the potential candidates. It shows the positive pre-employment relationship behaviour due to technology factors on its aesthetics, ease of use, playfulness, service excellence and usefulness (van Esch *et al.*, 2019).

2.4 Insights from algorithmic management and ambidexterity theory

Algorithm management, as described by Lee *et al.* (2015), encompasses an interconnected system that supports organisational devices, facilitating a structured approach to manage these algorithmic functions. The burgeoning literature on algorithmic management may explain the transformative role algorithms play in various organisational functions, including talent acquisition. As defined by Meijerink and Bondarouk (2023), an algorithm is a computational formula that autonomously makes decisions based on statistical models or decision rules, operating without explicit human intervention. This capability to autonomously process and learn from vast amounts of data marks a significant shift in how organisations approach decision-making, particularly in human resources and managerial functions (Beer, 2017; Kellogg *et al.*, 2020).

In organisations, algorithms are typically deployed by managers or HR departments to perform a range of functions, from data processing to decision-making (Cheng and Hackett, 2021; Duggan *et al.*, 2020; Leicht-Deobald *et al.*, 2019). Algorithmic management uses descriptive, predictive and prescriptive algorithms to support organisational decisions (Meijerink and Bondarouk, 2023; Parent-Rocheleau and Parker, 2022). Descriptive algorithms process and sort data to assist in observing metrics such as performance and personality traits; predictive algorithms forecast potential outcomes, aiding in recruitment and selection; and prescriptive algorithms propose actions based on simulations and scenario analysis (Leicht-Deobald *et al.*, 2019).

These algorithmic functions are instrumental in performing essential HRM activities, including monitoring employee data, setting goals, managing performance, scheduling, calculating compensation and even terminating employment (Parent-Rocheleau and Parker, 2022). The influence of these algorithms extends to work design, impacting task characteristics, knowledge requirements, social dynamics and job demands, with outcomes potentially affecting motivation, well-being and performance.

Research highlights the categorization of algorithmic management based on its control spectrum, ranging from monitoring and controlling employee behaviour to enabling and augmenting employee decision-making (Noponen *et al.*, 2023). This framework emphasizes the balance between human and machine interaction, advocating for a synergistic approach that leverages the strengths of both. Concerns have arisen regarding the opacity of algorithmic management and the potential for algorithm aversion, where individuals may hesitate to rely on algorithmic outcomes, particularly in cases where the algorithm's accuracy is perceived to be flawed (Dietvorst *et al.*, 2018; Prahl and Van Swol, 2017). This highlights the need for developing algorithmic competencies that foster a mutual relationship between workers and algorithms, encompassing both human-assisting and machine-assisting roles (Jarrahi *et al.*, 2021).

In the context of talent acquisition, algorithmic management facilitates a nuanced approach to hiring. Descriptive algorithms assist in analyzing candidate data, predictive algorithms forecast job fit and performance potential, and prescriptive algorithms automate resume screening and candidate selection (Meijerink and Bondarouk, 2023). However, perceptions vary regarding the fairness and trustworthiness of decisions made by humans versus algorithms, especially for tasks requiring nuanced human skills versus those that are more mechanical in nature.

In sum, the intersection of algorithmic management and AI in the hiring process represents a complex spectrum of human-AI interaction, ranging from minimal to full automation. This spectrum underscores the evolving nature of talent acquisition, where the integration of AI and algorithmic management offers both opportunities and challenges for organisations striving to optimize their hiring processes while maintaining fairness, trust and engagement with candidates.

2.5 Insights from ambidexterity theory

In examining the deployment of AI in talent acquisition and the trade-off between transactional efficiency and relational engagement, we use the ambidexterity theory as a theoretical lens. This theory describes the organisational capacity to navigate the complexities of balancing exploration and exploitation routines, a concept highlighted by O'Reilly and Tushman (2021). Ambidexterity, in this context, refers to the ability of an organisation to refine and use existing knowledge (exploitation) while concurrently creating new knowledge to address deficiencies or gaps identified during work execution (exploration) as defined by Turner *et al.* (2013).

Within talent acquisition, firms engage in exploitation by optimizing and refining existing recruitment processes, leveraging AI to enhance efficiency and accuracy in tasks such as document screening and candidate assessments. This reflects the continuous improvement through incremental changes, aiming at addressing market needs with minor modifications to existing routines and technologies, thereby sustaining established practices with increased resource efficiency and cost savings (Clauss *et al.*, 2021). Conversely, exploration strategies involve the adoption of AI for uncovering new methodologies in recruitment, such as the use of chatbots for engaging with candidates in a more dynamic and personalized manner. This aspect aligns with the pursuit of disruptive innovations in practices, anticipating potential desires and generating new demand by exploring emerging market opportunities and understanding customer needs (Clauss *et al.*, 2021).

The ambidexterity theory, therefore, offers a valuable perspective in understanding how organisations can harness AI in talent acquisition to achieve operational ambidexterity. This balance enhances organisational agility and enables firms to maintain a competitive edge by efficiently managing their current operations while exploring innovative recruitment practices. This theoretical framework has been instrumental in exploring the connection between technology and organisational processes across various domains, including the impact of humanoid robots on employee productivity (Del Giudice *et al.*, 2022), employee attitudes towards intelligent robots (Van Looy, 2022) and the implications of ambidextrous organisations for automation and relational stability (Hiebl and Pielsticker, 2023). Within this literature, Van Looy (2022) served as a pivotal reference in developing a conceptual framework that encapsulates the exploitation and exploration of AI and human elements within HR management, particularly in recruitment and selection. This framework underscores the significance of operational ambidexterity as a means to enhance organisational agility, through which companies can simultaneously achieve transactional efficiency and foster relational engagement in the talent acquisition process.

3. Method and data

To explore the organisational and operational dimensions from the potential use of AI in the talent acquisition process, this research used an inductive approach through exploratory study and adopted Corley and Gioia (2004) in building a data structure. These approaches allowed a deep examination of the focal phenomenon within the specific context of organisational processes. Following an inductive research design, our study adopted a naturalistic inquiry approach, aiming to derive insights through interpretive means, as outlined by Lincoln and Guba (1985). These choices aligned with our research objectives and were consistent with prior studies that had investigated the dynamic interplay within firms' recruitment and selection processes, especially concerning the balance between human-to-human interactions and transactional aspects facilitated by AI.

3.1 Data collection

For data collection, there were mainly two sources that were used. As outlined in Table 1, the first set of data sources were derived from interviews with 11 HR Professionals/ recruiters and the second set of data source was acquired by meetings with AI provider.

No.	Data source	Industrial sectors
1	Interviews	• Fintech • Hospitality • Energy • Insurance • Industrial technology and manufacturing • Furniture • Media
2	Meetings	• Kick-off meetings • Discussion on technical and practical use of AI. • Interview guide discussion • Finding's discussion on substantive topics • Discussion on technical and practical use of AI. • Internal presentations and discussions on future developments

Source: Compiled by authors'

Table 1. Source of data collection

The first data set was obtained mainly from the semi-structured interviews. The interview guide was constructed and divided into three main topics: general information, overview of existing recruitment practices, and potential of AI use in recruitment process. In addition, we posed follow-up questions to interpret interviewees' responses better. As the research progressed, the interview guide was regularly checked and modified to fit with the findings and research objectives. As the context of this study was the recruitment process, the target group for the sample was professionals from the HRs and recruitment field who worked at the companies. The companies interviewed were based in Stockholm and Uppsala, Sweden, for ease of access and to limit the scope. All interviews were audio-recorded as verbally agreed by the participants. According to participants' consent, the identity and companies of participants are anonymized in the report.

The second data set was acquired from consistent consultation with the legitimate AI provider. These data were used to describe AI applications in the hiring process and justify the findings obtained from other data sources. Several meetings were conducted and followed by a session to present the findings and results. As a startup that extensively works on AI, the meetings allowed information exchange and valuable insights helpful to validate the findings and assist the author's analysis. In addition, several communication forms in both face-to-face meetings and online meetings were conducted to gain understanding of AI, especially the technical aspects and its practical use for talent acquisition. The method used was field notes (Bryman and Bell, 2011) by briefly jotting down notes from the meeting.

3.2 Data analysis

During data analysis, we mainly conducted a three-stage analysis. The method of analysis was rooted in the principles of grounded theory, especially the systematic processes of open and axial coding (Corbin and Strauss, 2014). We started with open coding, which enabled us to distill the raw data into open codes that directly reflected the language and perspectives of our informants. This initial stage involved meticulously breaking down the information gathered from interviews with HR professionals and interactions with AI recruitment platforms, paving the way for a granular understanding of the data. Following the open coding, we engaged in the second phase of our analysis: axial coding. As this step, we aimed at refining the broad categories identified during the open coding into more specific themes and patterns, facilitating an in-depth exploration of the relationships between these categories and their subcategories. For example, by examining the link between "operational efficiency" and "quality of hire", we gained valuable insights into how AI tools' speed and efficiency could influence the overall recruitment process's quality. This phase was instrumental in uncovering the core phenomena under study and illustrated the spectrum of AI's impact on recruitment, from enhancing operational efficiencies to highlighting the challenges in maintaining quality human interactions. This approach was further informed by data analysis principles as explained by Corley and Gioia (2004) and Gioia *et al.* (2013), which advocates for an analysis that centres on informants' interpretations to discover new concepts rather than confirming pre-existing ones. This approach emphasizes the role of researchers as knowledgeable agents capable of identifying patterns and generating concepts and theories from the data. We prioritized the use of informants' terminology in our notes and ensured immediate transcription of interviews to maintain a close connection with the data. This ongoing engagement with the data through constant comparative analysis allowed for a dynamic interaction between data collection and analysis, where codes, themes and findings were continuously compared and refined. For trustworthiness of our analysis, we integrated six critical steps of thematic analysis outlined by Braun and Clarke (2006) and Nowell *et al.* (2017) into four main stages. Initially, we immersed ourselves in the collected data to identify patterns of meaning from transcripts, field notes and interviews. This deep familiarization facilitated the generation of initial codes, which were then organised into relevant themes and aggregate dimensions through a rigorous process of connection and interpretation. Authors regularly met to review and define these themes and dimensions, ensuring a rich contextual understanding through thick descriptions. Our analytical process incorporated a systematic review of our data against the backdrop of scientific literature and HR reports. This allowed us to select pertinent quotes that exemplified first-order concepts and second-order themes, which were then grouped to form aggregate dimensions. These methodological steps, highlighted in Table 2, demonstrate clustered assigned quotes with their corresponding first-order concepts, second-order themes and aggregate dimensions.

4. A conceptual framework of organisational and operational dimensions

From our results, we found that the roles of AI in talent acquisition encompass several organisational and operational shifts. Through inductive analysis, we present a comprehensive theoretical framework that highlights four aggregate dimensions that describe AI's transformative role in talent recruitment. As illustrated in Figure 1, these dimensions are Speed and Efficiency, Quality, Dependability and Relational. Collectively, these dimensions encapsulate the nuanced impact of AI on organisational routines and operational efficiency thereby distinguishing transactional and relational dimensions. Table 2 shows the transparency from our raw data to the aggregate dimensions.

Our study uncovered four aggregate dimensions critical to understanding the role of AI in talent acquisition. Within our framework, speed and efficiency emerges as a key dimension, shaped by *scalability, time efficiency and work redesign*. This dimension underscores how AI can adapt to varying demands and expedite recruitment tasks. Quality is another dimension highlighted in our study, focusing on the outputs of AI in the recruitment process. It is influenced by validity and *accuracy,* ensuring the *validity and accuracy* of AI-generated results, alongside *functionality* and *inputs quality*. Dependability of the recruitment process forms a crucial dimension, characterized by consistent and reliable *service delivery* and the capacity for *objective assessment*. This dimension speaks to the reliability of AI tools in delivering consistent outcomes and their ability to evaluate candidates impartially and free from human biases. Finally, the relational dimension addresses the human aspects of recruitment, influenced by *candidate experience* and the value or the loss of *rapport* from both parties. It highlights the challenge to leverage on unwritten, experiential insights for improved decision-making in talent acquisition. The first three dimensions represent the transactional aspect while the last dimension covers the relational part. In the next section, we describe each of the components and explore their interrelationships.

4.1 Speed and efficiency

Drawing on operations management literature, our analysis yields speed and efficiency to view the talent acquisition process as an input-transformation-output process. Large organisations typically receive large number of applications hence the process with high speed and efficiency is crucial. Our results show that speed and efficiency is characterized by three attributes; *scalability, time efficiency and work design.*

(1) *Scalability:* It refers to the capability to streamline a large amount of application by employing more efficient work methods. In the case of recruitment, the large number of received documents can be screened faster by initially providing short assessments, knockout questions or automated screening tool. According to

Table 2.
Data supporting interpretations

Themes	Representative quotes
Aggregate dimension 1: speed and efficiency	
Scalability	"Since we use a screening tool to simplify the screening, we have taken out some of the problems when it comes to higher volume, that's usually bottleneck that could be automated even further. *(Interviewee 4)*
	"Sometimes, we have some questions in the application form that you need to answer. So we can do a better screening. That's very good when you have many candidates. In that case, you don't need to read every single application; you can focus on candidates that answer yes to this" *(Interviewee 5)*
	"That's why it is essential to have simple tools. We have an ancient recruitment system; we change to a more modern solution. Now managers have a lot less to do when it comes to recruitment. If you have 100 applications and the tools is difficult, then it will add more time". *(Interviewee 4)*
Time efficiency	"You made several phone calls, emails, contacts, also you need the time to do to look at to all applications that are the biggest challenge to find the time". *(Interviewee 5)*
	"Since we talk about AI, we could have opportunity to make AI any other simple tool, automatically reject those, reduce some of the time needed for screening". (Interviewee 4)
Work redesign	"We used to need more people working manually, and now we need fewer people working manually, especially in screening". (Interviewee 1)
	"Do the screening ongoing because we don't want to lose the candidates". (Interviewee 6)
	"I think it is partially (AI implementation) where we can be more effective because we are human we can put our energy and skill where we add value or use AI where AI can add value. So, the success is the right mix of AI and HR". (Interviewee 8)
Aggregate dimension 2: quality	
Validity and accuracy	"We use competency-based question for position to increase validity the of recruitment to be able to compare between candidates which are the most suitable for the position" *(Interviewee 7)*
	"When we'd say we will use AI in recruiting, we want to have 100% on matches. 100% matches is not possible yet; it is 95%, it is 2% when it talks to companies that using or providing with AI, they always give you 95% maximum, in the 5% you may be missing top candidates, so when we use AI in recruitment, maybe we should 99.9%". *(Interviewee 10)*
	"Is there 100% accurate CV parsing in the world? In all languages? That's my question. If that exists, then I will give that to a chatbot. My CV is in Swedish, Danish, Norwegian, and that CV is going structured. And the program is going to structure to understand the experience, background. I think that it's human to do that. If AI can do that, then we can do that" (Interviewee 8)
Inputs quality	"[. . .] the biggest challenge is that for recruitment is difficult in terms of getting the CV as a base on taking a decision who of these 100 or 20 applications would do the job the best. The CV is a quite bad measurement for future performance". (Interviewee 2)
	"Also challenge with some candidates, their CV is not good. They are not writing about the period; it is very little about how are they doing and why they want this job. It is difficult to understand the candidate's experience". (Interviewee 5)
	"I think the main challenges that the candidates don't express the experience in the right way in the CV, so you get the wrong idea about the right person, or we as the recruiters misunderstand the CV, misinterpret. Candidates interpret their experience into the CV; we interpret the CV into the experience. [. . .] Misinterpretation from both sides". (Interviewee 8)

(*continued*)

Table 2.

Themes	Representative quotes
Functionality	"We want the process to be easier for our internally and managers. We have managers who are active partners in recruitment we want to provide excellent experience in terms of using systems and tools, and we want to support our decision with the right information". *(Interviewee 1)* "But it has the same function as the knock-out question. It looks cooler, it looks more modern. It could be nice candidate experience for the screening question". *(Interviewee 8)* "At this point, I wouldn't trust that we would take in a robot instead of the process we have now. Fine-tuning on the AI, for example, reading a CV, is supposed to pick up the name. The robot is working, pick up the wrong things, then I still have to change it. It needs to be more stable for us to use it externally". *(Interviewee 2)*
Aggregate dimension 3: dependability	
Service delivery	"We also have recruitment education for the managers who are doing the recruitment process themselves because the recruiters like me are helping about 15% of all recruitment process. Because of that, we will educate the managers to handle this by themselves. In that application, we try to get them don't have too long processes like eight weeks is what we want them to do". *(Interviewee 5)* "It takes a lot of time, and we have the challenge to wrap it up, so we take it six weeks if you are good in 4–5 weeks. But that needs good collaboration and good project plan with the hiring managers". *(Interviewee 3)*
Objective assessment	"You have to be very unbiased, very objective, and to make sure that you have an excellent argument behind the reason why not to proceeding with the rest of candidates". *(Interviewee 1)* "We aware of bias, reducing them, when we get away from CVs, then that will help a lot. Awareness of bias the first step we have to work with" (Interviewee 3) "To focus objective, focus on the requirement profile, and work strictly competency-based based, in the best-case scenario you have job profile where you can use screens to ask questions" *(Interviewee 8)*
Aggregate dimension 4: relational	
Candidate experience	After the candidates doing an interview here at the office, it is super essential to take the time to give a call and give feedback, and not just send an email, because they have invested their time and they deserve to have personal feedback. *(Interviewee 3)* "Interaction is important because we need continuous update where they are in the process. Also, we try to at least give as much feedback as possible when they are not moving forward with the process [. . .] You have to see that the candidates applying in *(company name)* are also the customers. If they have the best possible experience, even if they don't move on in certain roles, they still will go on buy with us and see *(company name)* as a partner, instead of, we don't want people to feel that we are not interacting with them". *(Interviewee 10)* "You have to be fast in your process. You have to be put in the candidate's interest first rather than the companies". (Interviewee 11)
Rapport	"Most people into knowing the people that they will meet at work. What are you expecting as a manager, and what my expectation on you. Better to do in person". (Interviewee 2) "Recruitment is also building trust, building relationship that you want to come and work for us". (Interviewee 2) "It is hard to describe culture with the words. It is in the walls. And when we are meeting with the people". (Interviewee 3)

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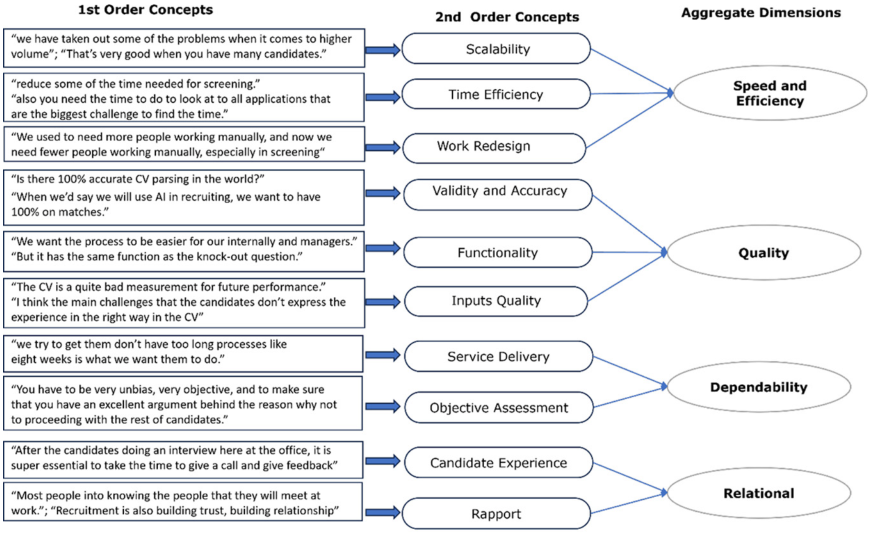

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Figure 1.
Data structure

interviewees, providing assessment is considered to ease recruiters' job as "you don't need to read every single application, you can focus on candidates that answer yes to this" or by using a screening tool, "Since we use a screening tool to simplify the screening, we have taken out some of the problems when it comes to higher volume."

(2) *Time efficiency:* It is related to the reduced time needed in the recruitment process, which is inferred from eight interviewees who emphasize the bottleneck in talent acquisition because of the time-consuming process and/or a large number of applications. Speed is related to the time needed in each recruitment process and the entire time-to-hire. Most companies agree that speed is crucial to ensure that they will not lose the best candidates over the competitors, "Do the screening ongoing because we do not want to lose the candidates."

(3) *Work redesign:* It refers to the potential use of AI to release staff from manual and administrative tasks as cited from Interviewee 1, "We used to need more people working manually, now we need fewer people working manually especially in screening". It leads to the opportunities of redesigning work to adapt to the change as mentioned by Interviewee 8, "we can put our energy and skill where we add value or use AI where AI can add value". Hence, having AI to support administrative tasks may enable recruiters to focus on more strategic roles.

4.2 Quality

Quality is manifested in each stage of input-transformation-output process. Ensuring high quality in input (e.g., CV) and transformation (e.g., AI quality) is crucial to achieve high quality of the output (e.g., qualified candidates). We observe that quality is characterized by the following attributes:

- *Validity and accuracy:* The recruitment and selection are performed by matching the competencies required for specific jobs with the candidates' qualification. Therefore, it is crucial that AI should have high accuracy to provide a valid assessment and ultimately recruiting the right candidates for a specific position as mentioned by Interviewee 10:

> When we'd say we will use AI in recruiting, we want to have 100% on matches. 100% matches are not possible yet, and it is 95%, it is 2% when it talks to companies that using or providing with AI, they always give you 95% maximum, in the 5% you may be missing top candidates, so when we use AI in recruitment, maybe we should 99.9%.

- *Functionality:* It refers to how well the product fulfil its designed job (Slack and Brandon-Jones, 2018). It means that the AI tool is expected to achieve outcomes that are traditionally performed by human recruiters, including reading CVs (versus AI CV parsing) and interview (chatbot interview). "It has the exact same function as the knock-out question. It looks cooler, it looks more modern. It could be a nice candidate experience for the screening question."
- *Input quality*: To ensure that the recruitment outcomes is dependable, the inputs should have the sufficient quality to be properly evaluated by either humans' recruiters or automated screening tool. "The biggest challenge is that for recruitment is really difficult in terms of getting the CV as a base on taking a decision", which is possibly driven by the limited amount of information in the CV that acts as the barrier for the documents to objectively reviewed. This can also result from individuals' inability to showcase their competencies in their resumes as "I think the main challenges that the candidates do not express the experience in the right way in the CV".

4.3 Dependability

The dependability of AI and chatbots in talent acquisition hinges on their ability to streamline and enhance the recruitment process. Our results shows that the effectiveness of such process is contingent on the integration with existing systems, and adherence to ethical and privacy standards. While AI can predict candidate success and learn over time, challenges still remain with human emotions. Our results show that dependability of such process and maximizing their potential in talent acquisition is described by the following attributes:

- *Service delivery:* Improving service delivery is analogous with the dependability as the operations' performance objective. With the support of established systems that are user-friendly, it enables the improvement of service delivery in the context of talent acquisition. As stated by Interviewee 3:

> It takes a lot of time, and we have the challenge to wrap it up, so we take it six weeks, if you are good then it is 4-5 weeks. But that needs good collaboration and good project plan with the hiring managers.

- *Objective assessment:* From our data, we found that AI and chatbots enhance talent acquisition by automating routine tasks and providing consistent, unbiased evaluations, thereby supporting objective assessment. They efficiently screen candidates based on quantifiable criteria, reducing human bias and enabling data-driven hiring decisions. However, their effectiveness depends on unbiased training data and integration with human judgment to address nuances. It is emphasized that the assessment should be objective and "[...] that you have a very solid argument behind the reason why not to proceeding with the rest of the candidates". The tendency of unconscious human bias, however, hinders objective assessment, especially when there is a large number of applications that can result in inconsistent objective evaluation. Ensuring transparency and ethical use of AI is crucial for maintaining fairness in the recruitment process.

4.4 Relational

We found that AI technologies can significantly influence the dynamics of human interactions in settings like job interviews or performance reviews. Most importantly, many of our respondents suggested that the lack of human-to-human interaction in AI-driven processes can lead to impersonal connection and low trust. We find that relational is described by the following dimensions:

- *Candidate Experience* refers to the degree of personal involvement in the recruitment process. Generally, AI is perceived as rigid or impersonal as:

> There is a risk may be too clinical if you use AI in the screening process, it could be unhuman. [...] The personal communication is very important to do the evaluation of the candidates:

Besides, AI is perceived to be one-sided communication as it works like questionnaires instead of the communication partner. Therefore, the human touch is highly preferred by the majority of interviewees. Based on the data collection, the importance of personalized feedback is emphasized as:

> [...] after the candidates doing an interview here at the office, it is super important to take the time to give a call and give feedback, and not just send an email, because they have invested their time and they deserve to have personal feedback.

> Engagement with candidates should be carried out throughout the entire recruitment process to ensure that the employer remains in candidates' primary concern. Otherwise, it may lead to the risk of losing talented candidates over other companies.

- *Rapport* refers to the importance of person-to-person interactions to establish harmonious relationship. "You do need to meet the person in some stages" because it enhances the candidates' evaluation through personal communication as "the personal communication is very important to do the evaluation of the candidates". The personal touch is emphasized in the context of recruitment and selection because "Recruitment is also building trust, building relationship that you want to come and work for us." Therefore, the majority of interviewees incline to conduct face-to-face interviews.

4.5 Conventional organisational elements in recruitment process versus artificial intelligence recruitment

From the interviews with HR professionals and/or recruiters, we also derived the general flow of the recruitment process which can be categorized into three main steps: (1) Pre-screening stage; (2) screening process; (3) decision on the shortlisted candidates to proceed for the interview stage. As illustrated in Figure 2, candidates first go through the pre-screening stage, which encounters some scenarios such as submitting the documents and/or completing the pre-screening assessments as the pre-requisites to proceed further. In the following stages, documents are reviewed and followed up by recruiters, either to proceed with phone screening interview or directly proceed to the decision of shortlisted candidates for a face-to-face interview.

On the other hand, we found that AI in recruiting can augment the conventional recruitment as seen in Figure 3. This insight was derived from the discussions and meetings with an AI provider that work extensively with AI for recruitment, especially with chatbots as its core product.

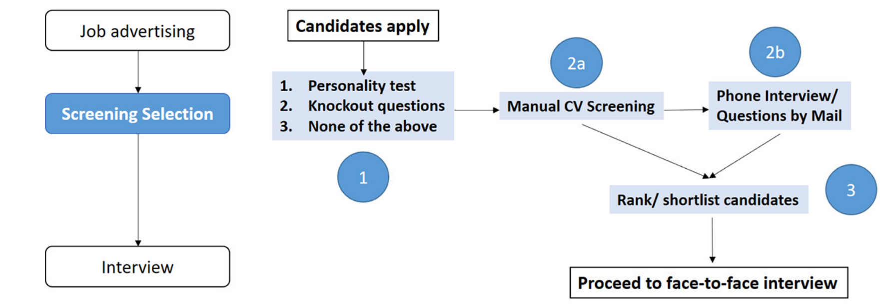

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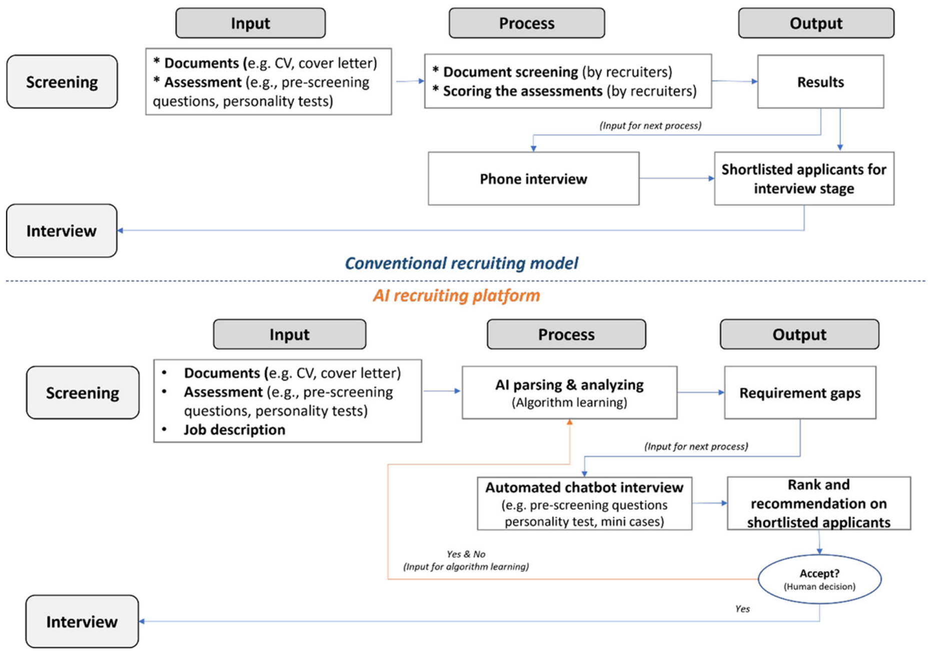
Figure 2.
Findings in recruitment process based on interviews



Source: Authors' elaboration

Figure 3.
Process flows of (1) Conventional recruiting model, and (2) AI recruiting platform

Firstly, it starts with parsing documents (i.e. CV and cover letter) that are submitted by applicants and extracting the information about education, experience, skills, training and other needed variables. The candidates have chances to review and supplement any missing information that was not automatically extracted. The data retrieved from these documents are compared and matched to the job description; thus, the gaps can be identified accordingly. Secondly, such systems use chatbots to perform an automatic short job interview that allows candidates to add information and fill the gaps identified in the CV analysis. The chatbots can also ask candidates to solve mini cases to assess candidates' domain knowledge. Furthermore, assessment tests such as personality or logical tests can be included and are automatically administered and analysed. Finally, the automatic systems assess eligibility and rank the candidates based on the qualifications needed by employers. Recruiters can use the results retrieved as the basis of decision-making to decide whether the selected candidates can proceed to the next recruitment stage.

5. Discussion, conclusion and future research

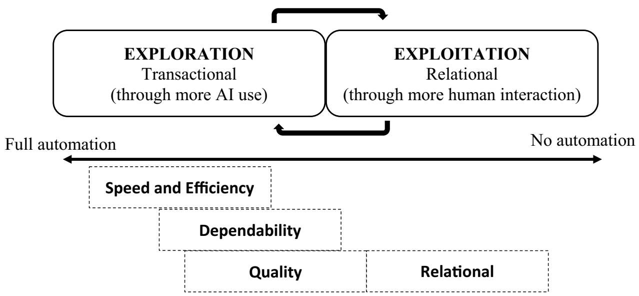
We started this paper with the purpose of exploring the organisational and operational dimensions that emerge from deploying AI in the talent acquisition process. Through our investigation, we aimed to understand the nuanced impacts of AI, particularly focusing on the balance between transactional efficiencies and relational dynamics. Our findings reveal an important implication for both of these aspects when introducing AI tools, such as chatbots, into the recruitment framework. Additionally, our results show that there is a minimum relational approach during the screening stage, even in conventional recruitment, unless the phone interview is performed. It indicates that the screening stage is mainly transactional, which is reasonable because it is mainly administrative and analytical tasks. However, the relational aspect can be viewed from the perspective of AI as a communicator (Hepp, 2020; Guzman and Lewis, 2020), in which the chatbot acts as a communication extension from the company to the job candidates. In addition, AI in recruiting takes lesser human involvement both in administrative and analytical tasks. Therefore, apart from improvement in operational performance, the absence of humans in assessment minimizes the possibility of humans' prejudice towards job candidates. It is indicated as fairness in which the decision-making process owns similar treatment to all individuals, both in favourable and unfavourable groups (Farnadi *et al.*, 2018).

Our findings hold implications for organisations using AI in talent acquisition, as seen in the final conceptual model in Figure 4. Through ambidexterity theory, the model delineates the interconnection between AI recruitment and the spectrum of human-AI interaction. It demonstrates crucial trade-offs between relational and transactional competences in the recruitment process (Stone *et al.*, 2015). Previous research in this area recognizes that points of convergence are paramount for a comprehensive understanding of this dynamic (Meijerink *et al.*, 2021). In this study, however, we demonstrate that both relational and transactional competences complement each other in the employee recruitment process. Our research has pointed to the mechanistic nature of talent acquisition, where operational aspects tend to outweigh relational factors. As discussed in e-HRM studies, the prevailing definition often leans towards its transactional function (Lengnick-Hall and Moritz, 2003) or its role as administrative support (Voermans and van Veldhoven, 2007) through internet technology. Specifically, e-recruiting typically strives for improved operational performance, such as enhancing applicant quality (McManus and Ferguson, 2003), shortening the hiring cycle (Cappelli, 2001) and achieving cost savings (Buckley *et al.*, 2004). However, this predominant focus on transactional aspects has overshadowed the importance of relational aspects within e-recruitment. It highlights the limitations of recruiting through internet technology when it comes to effective communication and interaction (Stone *et al.*, 2015).

Our results unequivocally demonstrate that both transactional and relational aspects of AI in recruitment carry equal importance in delivering effective recruitment services. The integration of technology has a profound impact on enhancing the overall quality of recruitment services. Building on existing research, Bondarouk and Brewster (2016) have suggested that studies in e-HRM should evolve in three primary areas: context, multiple stakeholders and long-term outcomes. Our data collection underscores the importance of considering various contextual factors when exploring the synergy between transactional and relational aspects in AI recruitment. In conclusion, our research underscores the intricate interplay between transactional and relational competences in AI-based recruitment. Recognizing their significance and understanding how contextual factors shape their synergy is pivotal for organisations aiming to leverage technology for effective talent acquisition.

To conclude, from a transactional perspective, our analysis underscores two primary enhancements attributed to AI integration. Firstly, the automation of administrative tasks, such as document screening and initial applicant assessments, marks a significant shift from traditional methods. In conventional recruitment processes, the review of incoming documents like CVs and cover letters demands considerable time and effort from recruiters, serving as a bottleneck that slows down the hiring cycle. AI's capability to automate these tasks not only streamlines the process but also ensures a level of accuracy and consistency that manual screening might not achieve. Secondly, we observed an intelligent automation in the assessment phase, where AI technologies, including chatbots, play a pivotal role. These AI tools transcend traditional screening methods by conducting an automated initial interviews or assessments. This automation extends to the communication phase, where chatbots interact with candidates to clarify discrepancies or gather additional information. Such interactions, while automated, are designed to mimic the relational aspect of recruitment, aiming to maintain a degree of personal touch in the process.

Our investigations discovered that knockout questions have traditionally played a crucial role in recruitment practices, often appreciated by interviewees for their straightforward nature. However, the advent of chatbots in the recruitment process can introduce a significant enhancement to this approach by incorporating open-ended



Source: Authors' elaboration

Figure 4. A conceptual framework of organizational and operational dimensions

questions. This shift allows for a deeper exploration of a candidate's experience and qualifications, particularly beneficial when applicants narrowly miss the minimum requirements for work experience or educational qualifications. By asking open-ended questions, chatbots can gather more nuanced information, reducing the risk of overlooking potentially suitable candidates due to rigid screening criteria. For example, when applicants fall short of the minimum years of work experience or educational qualifications, chatbots can ask open-ended questions to gain more context and clarity. This approach minimizes the risk of prematurely dismissing potentially qualified candidates.

However, the potential transition to AI-driven processes raises questions about the relational trade-offs involved. While chatbots and automated systems can enhance efficiency and reduce the administrative burden on recruiters, the potential impact on the candidate experience and the quality of interpersonal interactions warrants careful consideration. The challenge lies in balancing the operational gains with the need to preserve a human-centric approach in recruitment, ensuring that the introduction of AI will support rather than supplant the relational dynamics.

5.1 Future research and implications for practice

The future research in the area of digital recruitment, especially with the integration of AI, is poised to explore several key directions to address emerging challenges. In this paper we have focused more on organisational design and operational dynamics, future research could explore the resulting impact of bias and fairness in AI algorithms. This can be complemented by investigating the methods to detect, mitigate and prevent biases in AI recruitment tools. This includes developing more transparent algorithms that ensure fairness and diversity in candidate selection processes. Additionally, future research could explore long-term outcomes of AI-recruited employees by assessing their performance, retention and job satisfaction and compared to those who were selected via traditional methods. This research could provide insights into the effectiveness of AI in predicting job fit and success. Finally, given the increasing reliance on AI for talent acquisition, future research can explore how AI in recruitment operate with a global perspective, especially for multi-national firms. This is to examine how the use of AI in recruitment varies across different cultural and legal contexts, including the acceptance of AI tools and their impact on global talent acquisition strategies.

For practitioners, particularly HR professionals and technology developers, the paper underscores the importance of implementing balanced AI tools in recruitment processes. It offers a foundation for developing best practices in AI deployment, ensuring these technologies enhance, rather than compromise, fairness in talent acquisition. Companies can leverage these insights to improve their recruitment strategies, fostering diversity and inclusivity in their workforce.

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