Enablers and inhibitors of AI assimilation in hiring: mitigating the effects of inhibitors through human–AI collaboration

Maryam Hina, Nasreen Azad and Najmul Islam
Department of Software Engineering, LUT University, Lappeenranta, Finland

Received 14 July 2024
Revised 20 November 2024
Accepted 25 February 2025

Abstract

Purpose – Most prior studies have primarily investigated AI adoption, with less attention given to AI assimilation in human resource management (HRM). Additionally, prior studies often lack empirical verification of the extent to which human–AI collaboration might alleviate challenges and promote AI assimilation in the HRM context. Thus, this study aims to explore AI assimilation in recruitment with a balanced view that identifies both enabling and inhibiting factors while examining the role of human–AI collaboration in mitigating the effects of inhibiting factors.

Design/methodology/approach – We used a mixed-method approach. Using an open-ended survey questionnaire approach and collecting data from 26 HR professionals, we identified five factors, namely, AI competency, recruitment agility, AI opacity, AI empathy and human–AI collaboration, potentially impacting AI assimilation. Thereafter, drawing from the enabler–inhibitor perspective, we theorize that AI competency and recruitment agility are the enablers, whereas AI opacity and AI empathy are the inhibitors of an organization's efforts to assimilate AI in recruitment practices. We tested our proposed model by collecting data from 309 HR professionals.

Findings – The findings showed that both enablers, AI competency and recruitment agility, significantly influence AI assimilation; however, both inhibitors, AI opacity and AI empathy, are non-significant for AI assimilation. While looking into the reasons for these non-significant effects, we observed that the interaction term between AI empathy and human–AI-collaboration as well as between AI opacity and human–AI-collaboration both had significant effects on AI assimilation. These interaction effects suggest that human–AI collaboration mitigates the constraining impact of both inhibitors.

Originality/value – Drawing from the enabler–inhibitor perspective and by empirically testing our proposed model, this paper significantly contributes to the IS literature. Our study not only identifies factors that promote and inhibit AI assimilation in the context of HRM practices but also reveals how human–AI collaboration may mitigate the effects of inhibitors. Our findings suggest that organizations should have a collaborative recruitment environment where AI handles repetitive tasks, and humans focus on roles requiring emotional intelligence. This approach enhances the integration of AI-powered tools, addresses AI assimilation inhibitors and optimizes recruitment effectiveness.

Keywords Artificial intelligence, Assimilation, AI competency, Collaboration, Recruitment, Agility

Paper type Research paper

1. Introduction

Emerging technological trends such as automation, big data, and artificial intelligence (AI) are drastically altering how businesses structure their human resource management (HRM) operations. This shift affects several HRM areas including recruitment and selection, talent management, job design, training and development, performance management, and employee engagement. Especially the widespread adoption and use of AI in HRM practices is evident. For example, a recent Havard report highlighted that 99% of Fortune 500 companies use AI-powered applicant tracking systems in their hiring processes (Fuller *et al.*, 2021). Similarly, in

Information Technology & People
Vol. 38 No. 8, 2025
pp. 73-96
Emerald Publishing Limited
e-ISSN: 1758-5813
p-ISSN: 0959-3845
DOI 10.1108/ITP-06-2024-0808

2022, a survey conducted by the Society of Human Resource Management reported that 79% of companies are utilizing AI in recruitment (Friedman, 2023). Consequently, AI use in HRM has also drawn the attention of academic scholars (Maity, 2019; Van Esch *et al.*, 2019; Kim *et al.*, 2021; Malik *et al.*, 2021).

Despite recent scholarly contributions on the use of AI in automating HRM practices, a significant knowledge vacuum persists in a comprehensive understanding of AI in recruitment. We have identified three major gaps in prior literature that we tackle in this paper, in particular. First, most prior literature investigated AI adoption and only a few prior scholarly endeavors aimed at investigating AI-assimilation in HRM (e.g. Prikshat *et al.*, 2023a). AI assimilation is defined as the integration of AI into organizational practices (e.g. recruitment) and work processes (e.g. identifying, screening, and selecting candidates) as well as the subsequent routinization of AI in the activities associated with these practices and processes (Wamba, 2022).

Second, prior AI HRM literature suggests that AI-powered tools enable organizations to reduce costs by giving them affordable access to a large pool of candidates on professional and social media sites (Black and van Esch, 2020). These tools not only help expedite the hiring process but also identify the most suitable candidates by carefully examining resumes, skills, and job requirements, enhancing successful hiring and lowering employee turnover (Black and van Esch, 2020; Allal-Chérif *et al.*, 2021). While these potential benefits are considerable, some challenges still remain. For instance, the decision-making process of AI is often not transparent and difficult to understand for HR professionals (Oswald *et al.*, 2020). This, in turn, reduces users' trust in the system and fosters reluctance to adopt it. On the other hand, the AI deployers who decide the use of AI for various HRM activities deliberately trim the detailed information to increase AI system effectiveness (Langer and König, 2021), thereby intentionally keeping the system less transparent for other stakeholders. While this helps organizations to avoid hostile use of insights in AI based systems, they also hinder other stakeholders' ability to comprehend AI based processes and outputs. Moreover, AI systems exacerbate the difficulty in interpreting individual emotions, further complicating its assimilation in HRM. These crucial aspects have received limited attention in scholarly research on the use of AI in HRM. In fact, research studies that identify factors that promote and prohibit AI assimilation in the context of HRM practices are needed to provide a balanced view.

Finally, there are a wide variety of challenges that prohibit AI assimilation for HRM practices as we discussed earlier. Prior scholars have also noted the importance of human-AI collaboration to minimize such challenges (Chowdhury *et al.*, 2023). However, these studies lack empirical verification of the extent to which human-AI collaboration can mitigate the challenges and promote AI assimilation in the HRM context. In order to fill the above mentioned research gaps, we address the following two research questions in this paper.

RQ1. What are the enablers and inhibitors of AI assimilation in hiring?

RQ2. How does human-AI collaboration mitigate the effects of inhibitors on AI assimilation?

To answer the above questions, we conducted a mixed-method study on AI assimilation in HR recruitment. We conducted a survey with open-ended questions following the critical incident approach (CIT) (Flanagan, 1954) (i.e. study 1) and collected survey data (i.e. study 2) from the participants who had prior experience with AI technologies in HRM. In study 1, we collected data from 26 participants to learn about their experiences and perceptions about the use of AI in HR recruitment. We identified five major factors from our data analysis that can enable or inhibit AI assimilation. The factors include AI competency, recruitment agility, human-AI collaboration, AI opacity, and AI empathy. We adopted the enabler-inhibitor perspective (Cenfetelli, 2004) and developed a research model. Then, in study 2, we collected data from

309 individuals to analyze the relationship between enablers, inhibitors, and AI assimilation. We found that AI competency and recruitment agility enable AI assimilation. Regarding inhibitors, we observed that human-AI collaboration has the potential to mitigate the restraining impact of AI opacity and AI empathy on AI assimilation. Our study offers substantial contributions in two ways. First, it provides a nuanced understanding of AI assimilation in HR recruitment by determining its enablers and inhibitors and contributes to the literature that discusses the use of AI in HRM practices. Second, our study illustrates a viable mechanism for overcoming the hindrances of AI opacity and AI empathy through human-AI collaboration.

The rest of the study is structured as follows. Next, section 2 discusses prior literature findings on AI in HRM. In section 3 we conducted study one to identify and delineate the specific enablers and inhibitors of AI assimilation. The findings from study one helped us to develop a framework drawing from the enabler inhibitor perspective as discussed in section 4. Next, in section 5 we validated the study framework by collecting real-time data from HR managers. Sections 6 and 7 discuss the study findings with the following study implications. The last section concludes the study and highlights the future research directions.

2. Literature background

Prior literature discussed the adoption of AI in the HR life cycle, impacting recruitment, onboarding, training, performance management, retention, promotion, and benefits for employees (Tambe *et al.*, 2019; Wang *et al.*, 2024). While scholars have highlighted several factors driving AI adoption, including AI's ability to be more objective, its capacity to anticipate future behavior, and reduced likelihood to make mistakes (Giermindl *et al.*, 2022), critical issues persist such as ethical dilemmas, biases and AI system opacity (Langer *et al.*, 2021). Black and van Esch (2020) argued that AI performs better in hiring than human-centered methods by automating processes such as CV scanning and evaluation, resulting in a faster and more precise applicant selection process. Nonetheless, these merits are undermined by the challenges of AI discrimination, for example gender prejudice in AI-enabled job advertisements (Lambrecht and Tucker, 2019). These contradictions underpin the necessity of a balanced approach to integrating AI in HRM, specifically in recruitment.

Organizations are motivated to utilize AI in hiring due to its efficiency in quickly screening resumes, crafting job descriptions, and employing advanced video-based analysis to assess candidates' behavior in relation to job position criteria (Belhadi *et al.*, 2021). Additionally, previous findings suggest that AI systems used for monitoring can improve employee retention by analyzing social media data to predict employees' intentions to leave. These systems can also motivate employees by offering tailored compensation packages based on insights derived from their financial payment data (Gaur and Riaz, 2019). These studies recognized AI's effectiveness over conventional approaches in the recruitment process.

Despite the positive outcomes of using AI in HRM processes, AI systems have faced criticism for perpetuating inherent biases. Numerous prior scholars have raised concerns, including the possibility of biased, discriminatory, and opaque decision-making. For example, Langer *et al.* (2021) underscored the opaque nature of AI, which challenges the efficiency and quality of decision making in HRM. Although being superior to human HR managers in assessing job applicants (Campion *et al.*, 2016), AI-enabled job advertisements have been evidenced to reveal gender bias (Lambrecht and Tucker, 2019). Similarly, biases coupled with a lack of AI transparency and explainability makes it difficult for managers to trust the output of AI-based systems (Chowdhury *et al.*, 2022a). Moreover, adversarial behaviors occur in organizations when employees are unable to comprehend AI-based decisions and don't accept them (Tambe *et al.*, 2019). Several studies have indicated the ethical implications of AI highlighting concerns regarding data security and privacy along with AI's potential biases (Kellogg *et al.*, 2020). In an experimental study, Lee (2018) found that AI-based hiring decisions are often viewed as less trustworthy and unfair and elicit hostile feelings. This negative perception results in an unfavorable attitude of employees and may hinder the adoption and utilization of AI-based tools.

While the above studies have highlighted both positive and negative aspects of AI in hiring, these studies lack an understanding of how organizations can balance AI benefits with its ethical challenges. This gap necessitates the profound exploration of AI assimilation beyond its initial adoption. AI assimilation is defined as a sequential process that begins with the organization's preliminary assessment of AI systems during the pre-adoption stage progressing to its formal adoption, followed by its routine usage in HR practices and ultimately leading to its exploration of newer AI techniques (Prikshat *et al.*, 2023b). Recently, a few prior scholars have drawn attention to the different steps of AI assimilation, including diffusion, routinization, and extension (Prikshat *et al.*, 2023a). These steps reported the operational repercussions of AI assimilation in HRM, resulting in time and cost savings due to its efficiency and other macro-level benefits (e.g. reduced HR staffing, quicker procedures, and freedom from administrative responsibilities). Hence, AI offers considerable possibilities for strategic HR decision making and aligning HR plans with corporate objectives (Johnson *et al.*, 2020). Consequently, this study builds on this critical and nascent area of research to systematically investigate the perception of HR professionals toward AI assimilation.

3. Study 1: identifying the enablers and inhibitors of AI assimilation

The objective of study 1 was to identify a list of factors that enable or inhibit AI assimilation in the HRM context, particularly during hiring/recruitment.

3.1 Method

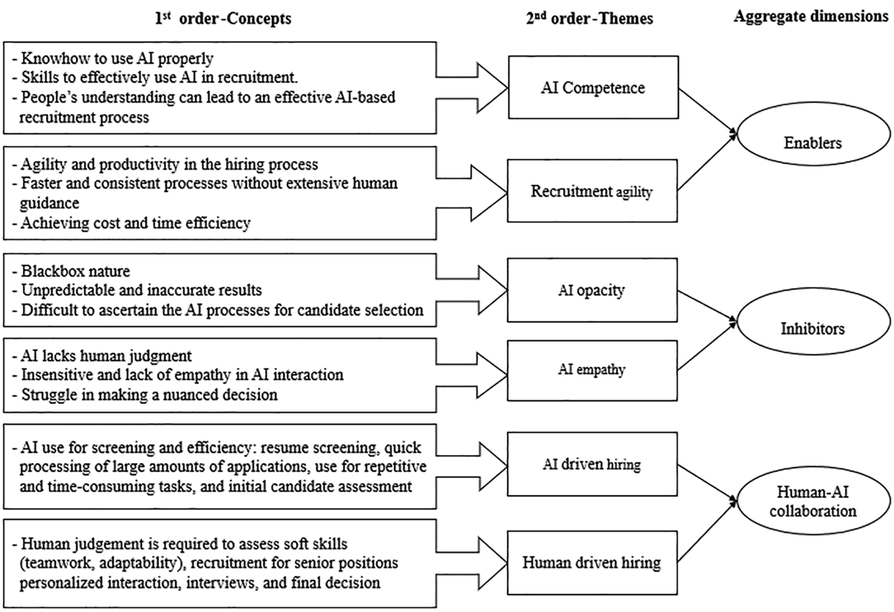
We have employed the CIT (Flanagan, 1954) approach in this study. CIT is a set of procedures for collecting self-reported stories of specific events viewed as incidents (Holloway and Beatty, 2008). CIT has been widely used in a wide range of fields, including marketing (Sirianni *et al.*, 2013), psychology (Tsai *et al.*, 2012), management (Lin and Loi, 2021), and information systems (Maier *et al.*, 2022). CIT has been found ideal in the context of exploratory research (Holloway and Beatty, 2008). As in study 1, our target was to conduct exploratory research to identify a list of factors that enable or inhibit AI assimilation in the HRM context, we employed the CIT technique. Next, we describe the data collection and analysis procedure.

3.1.1 Data collection and analysis. Prior research suggested employing open-ended survey questionnaires for collecting data when the target is to cover a large number of respondents (Schluter *et al.*, 2008). Following this, we designed an open-ended survey questionnaire and collected data from a market research company. We included a screening question indicating that respondents who have used AI-powered tools for hiring should respond. This enabled us to ensure data collection from relevant respondents. Prior scholars have held diverse opinions regarding the appropriate sample size for a qualitative study. For instance, the number of participants recommended for grounded theory studies ranges from 20 to 30, for case studies, only three to five (Creswell, 2007), four to 12 participants for homogeneous populations, and 12–30 participants for heterogeneous populations (Saunders, 2012). Generally, scholars advocate a sample size that is adequate to attain data saturation (Saunders and Townsend, 2016). Reflecting on these recommendations, in our study's context, we found that by engaging with 26 informants, data saturation was attained. Our respondents had experience of using AI for recruitment or hiring purposes in different industries such as IT, manufacturing, healthcare, education, and finance. In the questionnaire, we asked the respondents a few demographic questions. Furthermore, we asked about the possible benefits and risks of using AI for HRM purposes. After that, they were asked to report their satisfying and dissatisfying incidents using AI for hiring/recruitment purposes. The respondents were free to report their responses using the provided unlimited text area.

For data analysis, we adopted the Gioia method (Gioia *et al.*, 2013). The Gioia method brings qualitative rigor and creates a data structure to visualize the analysis process. Our analysis technique was iterative in nature; however, certain phases, as we describe next can be recognized. We started the first stage of data analysis with open coding (Strauss and Corbin, 1998); this involves reading the collected data and marking with first-order concepts to describe the content (Miles and Huberman, 1994). We used the objective of our study, specifically the identification of enablers and inhibitors related to AI assimilation (RQ1) to guide the coding process. Figure 1 shows the summary of the codes that are identified. During the second stage of data analysis, we merged the first-order codes by combining them based on similarity into second-order themes. At this stage, we came up with six categories of concepts describing the possible enablers, inhibitors of AI assimilation, and distinct categories of AI-driven and human-driven hiring in the context of HRM. During the third stage of the analysis process, we merged the second-order concepts to come up with three aggregate dimensions that represent either enablers or inhibitors of AI assimilation and human-AI collaboration in the HRM context.

3.2 Results

The respondents disclosed a mixed opinion towards AI assimilation. In their narratives, they were optimistic about using AI to perform some hiring tasks; however, they were skeptical about completely relying on AI. They found that AI is useful at the initial screening level of candidates due to its speed and accuracy, specifically when facing a high volume of applicants. On the other hand, they also indicated that AI is insensitive and unreliable for candidates'



Source(s): Authors' own work

Figure 1. Data structure of enablers and inhibitors of AI assimilation

personality assessments. Based on these general insights, we moved to eliciting insight from our data about specific enablers and inhibitors of AI assimilation in recruitment.

The analysis of the collected data allowed us to identify the explicit enablers and inhibitors of AI assimilation and human-AI collaboration as shown in Figure 1. We found two major enablers namely AI competency and recruitment agility, whereas the identified inhibitors were AI opacity and AI empathy. Furthermore, we found that human-AI collaboration could help overcome the challenges of AI assimilation, as shared by the respondents.

3.2.1 AI enablers: AI competence, recruitment agility. Many respondents reported optimistic views over the AI applications in HR recruitment. We identified two key enablers that we describe next. First, we found AI competence as a key enabler. AI competence is described as the ability of an organization to apply AI tools in HR recruitment practices and comprehend its results. The respondents underlined that AI is a novel technology for HR recruitment, and managers need to be knowledgeable about how to utilize AI-based hiring tools efficiently. For example, effective prompting is necessary for AI to provide quality output, and this calls for specialized knowledge. Moreover, there are no drawbacks to utilizing AI when humans are competent in its use; nonetheless, caution should be exercised when solely relying on AI. As one respondent reported:

> I personally believe that there are no drawbacks to using an AI as long as you know how to use it properly and do not leave everything to something that only uses algorithms. [P01, Manager, from Finance industry]

Second, we identified recruitment agility as the second enabler of AI assimilation. Recruitment agility refers to the degree to which an organization may shorten the hiring process duration, lower hiring costs, boost hiring productivity, and accelerate the hiring process by using AI. Most respondents highlighted that AI saves time in reducing an enormous list of applications to a reasonable quantity, which may lighten the workload of HR personnel, expedite the hiring process, and speed up repetitive administrative hiring activities, which can save costs. The responses also highlighted that the main benefit of AI is its ability to handle vast amounts of data, minimize bias, particularly during the initial selection process, improve data analysis for decision making, and improve recruiting quality overall. As one of the respondents highlighted:

> AI can quickly scan and evaluate a large volume of resumes, significantly reducing the time and effort required for initial screenings. This efficiency allows HR professionals to focus on more strategic and personalized aspects of recruitment. AI evaluates candidates based on predefined criteria, minimizing the risk of human bias in the initial stages of recruitment. This promotes fairness and diversity in hiring practices. AI provides valuable data and insights about the recruitment process. It tracks which qualifications and attributes are most important for successful hires, helping organizations make data-driven decisions about their hiring criteria and strategies. [P21, Manager from IT industry]

3.2.2 AI inhibitors: AI opacity, AI empathy. Respondents highlighted several benefits of AI-powered tools in HR recruitment, but they also voiced concerns about two significant factors: AI opacity and AI empathy. Managers become less inclined to integrate AI into HR recruitment when these inhibitors are not sufficiently handled. Next, we describe these two inhibitors.

First, several respondents highlighted AI opacity. This relates to an organization's challenge in understanding the internal operations of AI-powered tools in its HR recruitment practices. The respondents voiced concern over the possibility of misleading and unpredictable outcomes, even if the results could seem accurate at first glance. The basic reason for AI opacity lies in the less transparent mechanism of AI decision making. Since the managers are unaware of the processes by which AI arrived at a particular judgment, this opacity casts doubts on the authenticity of the outcome. As a respondent noted:

> Ai-based tools can result in a black box type situation, where it can be difficult for us to ascertain the processes which lead the AI to exclude or include certain candidates, especially at the later stages of the application process. [P24, Manager from Finance industry]

Second, we found that most organizations believe AI powered tools lack empathy since they cannot evaluate an individual's emotional responses. Many respondents mentioned that AI is more effective at measuring outcomes that don't require empathy or human emotions. However, it is less capable of understanding and analyzing an individual's behavior and emotional responses, such as how a candidate will perform in teams in various situations. The respondents opined that AI cannot perform the same as humans can to learn candidates' skills. Therefore, AI tools might not be the best choice when evaluating soft skills and cultural fit, which call for human judgment and intuition. One respondent stated:

> It's not very sensitive and probably it has to learn from humans and to properly interact with the candidates. It would feel very cold to talk with an AI tool during a recruitment process, without any empathy. [P10, Manager from the Education industry]

3.2.3 Human-AI collaboration. From the narratives of the respondents, it was clear that AI is most effective when it comes to screening a huge volume of applicants against a predetermined set of requirements during the early phases of hiring. Moreover, we found that human-AI collaboration is needed for the final outcomes that an organization intends to achieve. For example, since senior roles are sensitive positions, human involvement was deemed vital. As AI lacks empathy, humans need to be involved in the recruitment process to collaborate with the AI. Nonetheless, it was also noted that AI may be applied to recruit for jobs that do not require human sentiments or emotions. AI can be used, for example, to quickly scan resumes and find applicants who match requirements such as skills and qualifications. It can also conduct pre-screening interviews. However, when resumes are narrowed down, human recruiters may go over them to assess soft skills, cultural fit, and other qualities that are challenging for AI to analyze. Next, they can conduct an in-depth interview to assess a candidate's interpersonal skills and general appropriateness for the position as well as organization. As a respondent noted:

> Humans and AI can collaborate in recruiting by using AI for tasks like resume screening, initial candidate assessments, and data analysis. Human recruiters can then focus on more nuanced tasks, such as conducting interviews, assessing cultural fit, and making final hiring decisions, where human judgment and empathy are crucial. [P24, Manager, industry/age]

4. Theoretical framework and hypotheses development

4.1 Enabler inhibitor perspective

Prior scholars have underscored the choice of using or not using technology is influenced by the interaction of several factors called enablers and inhibitors, which are distinct rather than opposing factors (Cenfetelli and Schwarz, 2011). The enabler-inhibitor perspective (Cenfetelli, 2004; Kannabiran and Dharmalingam, 2012) has been considered in this study to provide insights into AI assimilation in HRM. The concept of "enabler" refers to the external belief on the structure and operation of a system that, depending on its valence, may enable or hinder usage (Cenfetelli, 2004). Similarly, "inhibitors" are user judgments about a system's features that impact the choice to utilize it and the consequent effect of discouraging usage (Cenfetelli, 2004). However, the key distinction between enablers and inhibitors of use is that the latter only dissuade usage. Given the understudied area of AI assimilation in HRM, and the need to investigate enablers and inhibitors in this setting guided our choice to consider the enabler-inhibitor perspective. Moreover, inhibitors can function independently of enablers and have a distinct impact on rejection or acceptance (Cenfetelli and Schwarz, 2011). This emphasizes how important it is to identify the factors that facilitate and impede AI assimilation. Thus, by examining the enablers and inhibitors in the same study, we can identify the mechanism that may be able to counteract or lessen the effects of inhibitors.

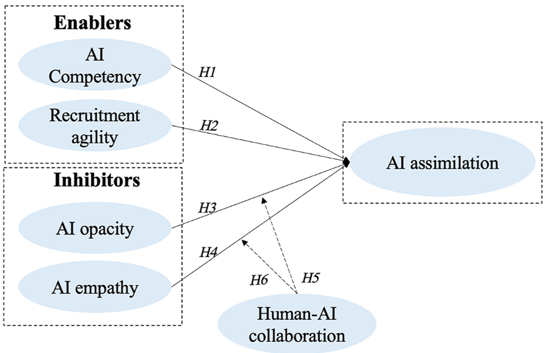
From study 1, we found AI competency and recruitment agility as the critical enablers of AI assimilation. Organizations are intrigued by AI assimilation in HRM due to strong AI competencies, as shown in Figure 1, know-how, skills, and understanding to use AI effectively. Moreover, the intricacies of HRM processes, specifically recruitment, encourage organizations to use AI tools to improve recruitment agility in terms of time efficiency, cost-effectiveness, and less dependence on human guidance leading to AI assimilation.

Conversely, study 1 also identified the significant inhibitors of AI assimilation in terms of AI opacity and AI empathy (Figure 1). AI empathy highlights that AI could not completely understand human factors (e.g. emotions, soft skills), thereby impeding AI assimilation. Prior scholars have characterized empathy as either an emotional response or a cognitive comprehension of the experiences and feelings of other individuals (Preston and De Waal, 2002; Wieseke *et al.*, 2012). The emotional component is considered to be a sentiment of care and concern for others (Pelau *et al.*, 2021). In contrast, cognitive empathy is the capacity to comprehend the feelings and thoughts of another individual (Pelau *et al.*, 2021), which can be called "perspective taking" (Weisz and Cikara, 2021). Furthermore, for AI assimilation in HRM to be effectively accepted, it appears that transparency is required, considering the viewpoint of all stakeholders (i.e. applicants and AI users) (Langer and König, 2023). However, when discussing AI models, the inability to comprehend the logic behind a certain outcome when that reasoning is hidden or not transparent is referred to as opacity (Stohl *et al.*, 2016). It could refer to models whose logic is unclear to humans throughout, hindering the acceptability of AI tools.

4.2 Hypotheses development

Drawing from the aforementioned discourse and theoretical foundation, we contend that enablers and inhibitors both are imperative for organizations to realize AI assimilation in HRM practically. The underlying enablers comprise AI competence and recruitment agility, whereas the inhibitors include AI opacity and AI empathy. Interestingly, based on the practical insights of HR managers, we assert that human-AI collaboration can lessen the impact of inhibitors on AI assimilation. The primary hypotheses and the direction of the relationship among study constructs are outlined in Figure 2.

4.2.1 Effect of enablers on AI assimilation. The recruitment environment has experienced profound changes since the proliferation of AI tools. Despite the inception of powerful AI tools, such as AI bots for candidate identification (Van Esch and Black, 2019), resume parsing for screening (Hunkenschroer and Luetge, 2022), and machine learning models for assessment (Polli *et al.*, 2019), the seamless assimilation of such AI tools throughout the recruiting process remains difficult. Limited scholarships have highlighted the crucial role of several factors, such as technological infrastructure, organizational readiness, and HR staff skills for



Source(s): Authors' own work

Figure 2. Theoretical framework

successful AI assimilation into HRM (Prikshat *et al.*, 2023b). These findings, together with well-known examples from industry as mentioned before show that AI assimilation can enable improved recruitment processes and selection practices (Tambe *et al.*, 2019). To support such an integration of AI in recruitment, it is crucial for organizations to build AI competencies. Building on these observations, it is becoming increasingly clear that managing innovative and harmonious AI applications requires a core organizational competency called AI competence (Mikalef *et al.*, 2023). Considering these, it is imperative to investigate that companies with greater levels of AI competency would have AI assimilation into their recruitment process. Thus, we propose the following hypothesis:

H1. AI competency positively affects AI assimilation.

Agility is defined as the organizational efficiency to quickly respond to ongoing change through persistent adaptation (Ulrich and Yeung, 2019) and has become a requirement for shaping organizational dynamics. Agile approaches can be found in innovative ways to recruitment, such as using new networking strategies, giving applicants homework during interviews (Heilmann *et al.*, 2020), and maximizing social media for recruitment marketing (Ranasinghe and Sangaradeniya, 2021). The constant evolution of recruitment emphasizes how crucial it is to match the right people with the company at the right time (Ranasinghe and Sangaradeniya, 2021). Notably, technology enabled HR systems may enable innovative practices in HRM, particularly in recruitment in conjunction with all other processes. Organizations that value recruitment agility and transitioning towards technology adoption would more rapidly embrace AI systems. Hence, we posit:

H2. Recruitment agility positively affects AI assimilation.

4.2.2 Effect of inhibitors on AI assimilation. Stakeholders, such as applicants and employees affected by personnel selection decisions, scheduling outcomes, or performance evaluation (Langer and König, 2023), for them, opacity is particularly related to decision processes and outputs of using AI-based systems in HRM, and they desire to know if choices made based on these processes and their results were equitable (Arrieta *et al.*, 2020; Myhill *et al.*, 2021). Several prior scholars have explored AI transparency and presented divergent findings for its solution. For example, AI algorithms may be recognized as transparent when they rigorously follow predetermined rules, guaranteeing fairness in decision making (Höddinghaus *et al.*, 2021). However, an opposing narrative also emerges, highlighting the limited explainability and transparency of AI system, which enhances system opacity, and its output response, which is a major inhibitor to achieving the expected benefits of reliably converting data-centric decisions into workable strategies (Chowdhury *et al.*, 2022b). For employees who lack awareness of the AI-based decision-making processes and results that shape their daily work experience, opacity may undermine their sense of control and autonomy at work (Kellogg *et al.*, 2020; Langer and König, 2023), hence increasing reluctance to integrate AI in HR recruitment. Overcoming opacity concerns related to AI algorithms' responses might increase managers' trust, thus exploring AI opacity for AI assimilation has become critical. Hence, we hypothesize:

H3. AI opacity negatively affects AI assimilation.

AI recruiting services claim to predict a candidate's emotions and other affective phenomena (Boyd and Andalibi, 2023), promising companies to enable them to predict and affect employment outcomes (Roemmich *et al.*, 2023). Prior literature highlighted how important it is for employers to consider the interviewer's emotional experiences when evaluating candidates (Rivera, 2015). The dynamic interpersonal exchange of emotions that occurs throughout the recruiting process shows that candidates may face consequences if they elicit unpleasant sentiments in interviewers, such as anger or boredom. In contrast, candidates can process their own interpretation of the emotional responses of interviewers and infer their performance in the interview process. However, AI tools cannot effectively identify and react to human emotions or exhibit human-like empathy (Chamorro-Premuzic and Ahmetoglu, 2016). When it comes to workers' demand for social connections, AI tools fall short of their human counterparts because they lack true human appreciation and empathy (Höddinghaus *et al.*, 2021). Therefore, these tools are viewed as being essentially neutral toward people since they lack empathy and are unable to recognize human emotion (Chamorro-Premuzic and Ahmetoglu, 2016). This raises a concern that AI assimilation in recruiting practices can be hindered due to AI's alleged lack of AI empathy. Thus, the following hypothesis posits:

H4. AI empathy negatively affects AI assimilation

4.2.3 Moderating effect of human-AI collaboration. Prior scholars have documented the positive role of human-AI collaboration in different contexts, such as employees' learning behavior (Chen *et al.*, 2023), and consumers' acceptance of AI, given that humans are better at feeling emotions than AI (Peng *et al.*, 2022). In the context of this study, a few prior scholars revealed that machines are more effective than humans at recruiting new employees (Hoffman *et al.*, 2018). However, it is widely believed that opacity makes it more difficult to develop sufficient trust in systems and their results (Wong *et al.*, 2024), which discourages users from adopting and integrating AI systems. Even if a system is transparent overall, but the detailed information and complete transparency may be detrimental (Lahuis *et al.*, 2003). Because there is no human involvement, this detailed information and transparency is unclear to applicants who could feel distanced from AI, raising concerns about hiring fairness (Yu *et al.*, 2023). In contrast, a prior study identified that when AI and humans work together, it leads to significant performance gains (Wilson and Daugherty, 2018). Interactive transparency is a means of regaining the human agency, which is lost when AI performs in isolation, so when the user and AI collaborate in the decision-making process then both user agency and AI agency together lead to better outcomes (Molina and Sundar, 2022). Therefore, by including human decision makers, AI-based processes can satisfy applicants' concerns of fairness and help them feel appreciated by the hiring organization (Mirowska and Mesnet, 2022). Additionally, human warmth and empathy of recruiters can provide a sense of social presence (Walter *et al.*, 2015), potentially enhancing applicants' responses to interviews that are heavily automated during the hiring process. Therefore, we propose the following hypothesis.

H5. Human-AI collaboration will moderate the relationship between AI opacity and AI assimilation such that the effect of AI opacity on AI assimilation will be positive when Human-AI collaboration is high.

H6. Human-AI collaboration will moderate the relationship between AI empathy and AI assimilation such that the effect of AI empathy on AI assimilation will be positive when Human-AI collaboration is high.

5. Study 2: testing the proposed model

5.1 Methodology

5.1.1 Survey development and administration. We used a multifaceted strategy to construct a questionnaire that was used for data collection. We adapted the survey items from prior validated scales to measure the study constructs, including two enablers, two inhibitors, human-AI collaboration, and AI assimilation. For example, the measures of AI competency consisted of four items adapted from Mikalef *et al.* (2023), whereas the measures of recruitment agility were six items adapted from Chuang (2020). Similarly, for the inhibitor, AI opacity measures consisted of three items adapted from Höddinghaus *et al.* (2021), and the measures of lack of empathy were four items adapted from Daniels *et al.* (2014). Finally, the measures of human-AI-collaboration included four items adapted from Li *et al.* (2022), whereas the scale for measuring AI assimilation consisted of three items adapted from (Wamba, 2022).

After designing the questionnaire, it was checked by three researchers to ensure clarity. Based on the feedback received, the wording of a few items was updated. Thereafter, to ensure the content and face validity of the instrument, we sent the questionnaire to 7 HR professionals who were experienced in using AI for recruitment purposes for further feedback. In this phase, we evaluated whether the items measured the expected outcomes, were easy to comprehend and pertinent to the study's setting. A few suggestions were made to improve the clarity of the questionnaire items at this stage. We revised the questionnaire based on the feedback we received. A five-point Likert scale, with 1 denoting strongly disagree and 5 denoting strongly agree was used to measure each item. Participants' confidentiality and anonymity were ensured, and we administered the survey in English. The final questionnaire of the measures is shown in Appendix.

5.1.2 Data collection. We collected data from a market research company. We employed a screening question to exclusively hire HR experts who have experience of using AI tools in HR recruitment processes. We collected data from HR professionals with AI experience since they are aware of the potential problems they may have encountered with AI tools. Consequently, a comprehensive understanding of such tools may direct their orientation toward AI assimilation. To ensure that participants consistently engage with the survey and mindfully respond, we included attention checks in the survey design. A total of 429 participants accessed this survey and 379 participants attempted to answer. Those participants who did not complete or failed these attention checks were subsequently eliminated for further analysis. After elimination, we ended up with data from 309 respondents from Europe who belonged to different industries including IT, education, manufacturing, finance, retail, consulting, healthcare, fitness, hospitality, legal, games, real estate, pharmaceuticals, energy, etc. The descriptive statistics are presented in Table 1.

5.2 Results

5.2.1 Measurement model. We employed the PLS technique using the software smartPLS 3.2 for analyzing the data. Before evaluating the structural model, we ensured the validity and reliability of the data. First, to ensure convergent validity, we checked the loadings of individual items, composite reliabilities (CRs), and average variance extracted (AVEs) values of the constructs (Table 2). According to Fornell and Larcker (1981), the loadings of the individual items must be above 0.7, CRs must be above 0.8, and AVEs must be above 0.5. As shown in Table 2, these criteria have been fulfilled. A few items (Agility4 and Agility5 in

Table 1. Demographic profile of respondents

Demographic measure	Category	Frequency	Percentage
Gender	Male	182	59%
	Female	124	40%
	Other	3	1%
Years of experience in recruiting	Less than 1 year	65	21%
	1–5 years	154	50%
	More than 5 years	90	29%
Industry	IT	55	17.8%
	Education	51	16.5%
	Retail and Manufacturing	45	14.6%
	Finance	39	12.6%
	Consulting	33	10.7%
	Healthcare	31	10%
	Hospitality	29	9.4%
	Others	26	8.4%

Source(s): Authors' own work

Table 2. The assessment of measurement model for constructs

Constructs	Cronbach's Alpha	Composite reliability (CR)	Average variance extracted (AVE)
AI competence	0.905	0.934	0.779
Assimilation	0.834	0.901	0.753
Human-AI collaboration	0.914	0.939	0.794
AI empathy	0.917	0.941	0.800
AI opacity	0.894	0.934	0.825
Recruitment agility	0.894	0.919	0.655

Source(s): Authors' own work

Appendix) did not meet the loading criteria of above 0.7; consequently, these items were removed.

Next, we looked at the values for ensuring discriminant validity. To ensure a sufficient level of discriminant validity, we followed three approaches. First, we examined the correlation matrix (and square roots of AVEs shown diagonally) in Table 3. From this table, we observed that the square roots of AVEs were consistently higher than the correlation values. Second, we looked at the loadings and cross-loadings and observed that the loadings were higher than the cross-loadings. Finally, we looked at the HTMT matrix (Table 4) and observed that the values are much lower than the suggested threshold of 0.85 set by Henseler *et al.* (2015). All these tests ensured that our data had a sufficient level of convergent and discriminant validity.

We further ensured that our data did not suffer from common method bias (CMB). To ensure this, we followed two approaches. First, we conducted Harman's single factor test and observed that no single factor explained the majority of the variance. Second, we conducted a common method factor test using the approach described by Liang *et al.* (2007).

Table 3. Correlation matrix (square roots of AVEs are presented diagonally)

	1	2	3	4	5	6
1. AI competence	0.883					
2. Assimilation	0.639	0.868				
3. Human-AI collaboration	0.551	0.646	0.891			
4. AI empathy	−0.389	−0.368	−0.349	0.894		
5. AI opacity	−0.420	−0.334	−0.294	0.097	0.908	
6. Recruitment agility	0.682	0.585	0.548	−0.541	−0.371	0.809

Source(s): Authors' own work

Table 4. HTMT matrix

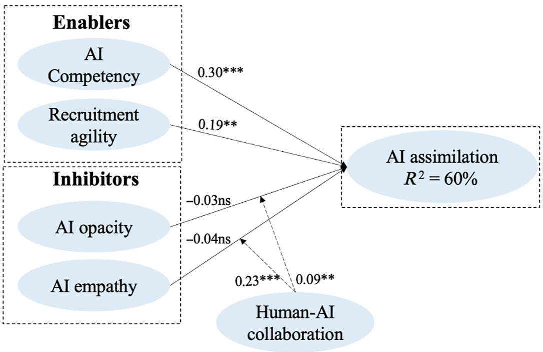
	1	2	3	4	5	6
1. AI competence						
2. Assimilation	0.729					
3. Human-AI collaboration	0.599	0.737				
4. AI empathy	0.418	0.418	0.380			
5. AI opacity	0.466	0.382	0.317	0.115		
6. Recruitment agility	0.756	0.675	0.606	0.596	0.408	

Source(s): Authors' own work

We observed that the method variance was very small compared to the substantive variance. A small variance ensured that CMB is not a major concern in our data.

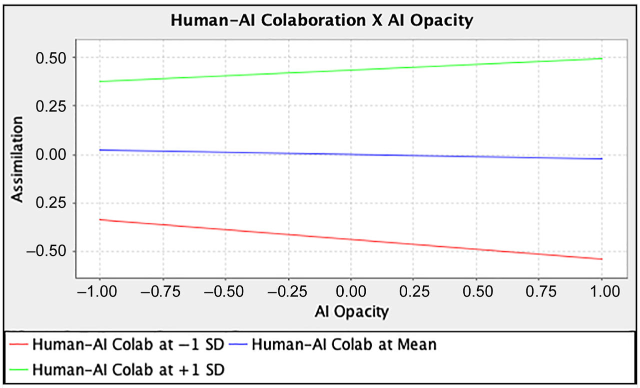
5.2.2 Structural model. After ensuring the validity and reliability of our collected data, we tested the proposed research model. The results are shown in Figure 3.

As hypothesized, AI competence ($\beta = 0.30$; $p < 0.001$) and recruitment agility ($\beta = 0.19$; $p < 0.01$) both had positive effects on AI assimilation. Thus, both H1 and H2 are supported. In contrast, H3 and H4 were not supported as both AI opacity ($\beta = -0.03$; $p > 0.05$) and AI empathy ($\beta = -0.04$; $p > 0.05$) had non-significant effects on AI assimilation. Finally, we observed that the interaction term between AI empathy and human-AI-collaboration ($\beta = 0.23$; $p < 0.001$) as well as between AI opacity and human-AI-collaboration ($\beta = 0.09$; $p < 0.01$) both had significant effects on AI assimilation. Thus, H5 and H6 were supported. These two effects are graphically shown in Figures 4 and 5. As shown in these figures, when human-AI-collaboration is +1 SD, the effect of both AI empathy and AI opacity turns positive, whereas at −1 SD, the effects are negative as we hypothesized. These results imply that higher levels of human-AI collaboration reduce the negative effects of both



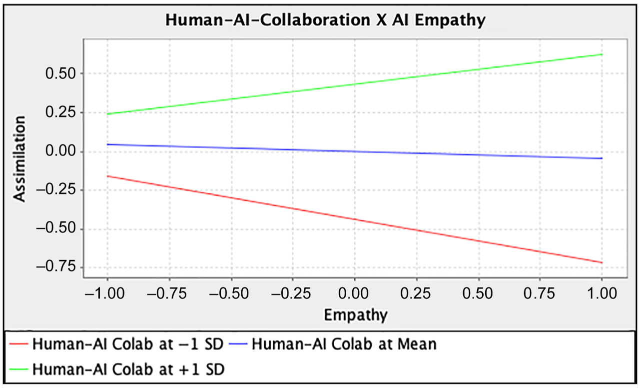
Note(s): *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$
Source(s): Authors' own work

Figure 3. Structural model results



Source(s): Authors' own work

Figure 4. Interaction effects between human-AI-Collaboration and AI Opacity



Source(s): Authors' own work

Figure 5. Interaction effects between human-AI-collaboration and empathy

inhibitors on AI assimilation. The control variables, gender and experience had no significant impact on AI assimilation. The model explained a 60% variance of AI assimilation.

6. Discussion

Our study findings illustrate how AI competence and recruitment agility considerably enable AI assimilation in HR recruitment, which confirms our proposition, implying that users' understanding, and skills are significant for AI assimilation. Aligning with prior AI-HRM literature, our results highlight the need for HR personnel to upgrade and refresh their skills to understand and integrate AI in HRM (Tambe *et al.*, 2019). The findings showed that recruitment agility significantly influences the extent of AI integration into HR recruitment. This aligns with the perspective of Saha *et al.* (2017), who considered recruitment agility as an approach highlighting speedy and dynamic hiring practices that necessitate organizational responsiveness to evolving technological infrastructure. Altogether, AI competence and recruitment agility both have emerged as important forces driving AI assimilation in HR recruitment. However, the effect of AI competency was observed to be higher than recruitment agility, suggesting AI competency is perhaps the most important driver for AI assimilation in HRM.

In contrast with prior literature (von Eschenbach, 2021; Langer and König, 2023), the employed inhibitors, AI opacity and AI empathy, have been found not to have a significant association with AI assimilation. Since prior literature contends that AI outcomes are opaque, people find it difficult to comprehend them, which makes them distrust the AI system and reluctant to employ it (von Eschenbach, 2021). Additionally, AI is unable to recognize subtle emotional indicators, in contrast to human recruiters who can relate to the prospects on an emotional level. Thus, a lack of AI empathy might cause AI to become disengaged with candidates and impede its integration into HR recruitment. Based on these prior findings, it is surprising that our results show that neither of the inhibitors had any influence on AI assimilation. There are two possible explanations for these surprising findings. First, it is possible that the enablers are stronger in predicting AI assimilation, and therefore the inhibitors have only negligible or no effects. In order to verify this, we removed the moderating factor, human-AI collaboration from the model and reran the model. We observed that both inhibitors had significant effects on AI assimilation. Therefore, we conclude that despite the enablers may hold greater predictive power, inhibitors have some effects. Second, there is a possibility that the effects of enablers are reduced due to the presence of human-AI collaboration as the moderator. Therefore, we continued our investigation and tried to identify if human-AI collaboration mitigates the negative impacts of these inhibitors. Our results show that indeed human-AI collaboration turned the effects of both inhibitors non-significant.

As discussed earlier, the findings of this study underscore the significance of human-AI collaboration in mitigating the constraining influence of AI opacity and AI empathy on AI assimilation. Our findings indicate that when human-AI collaboration is introduced, then the inhibitory effect of AI opacity is diminished. One plausible explanation lies in the notion that the involvement of human decision makers enhances trust in AI and mitigates the impeding effects associated with its opacity. The sensitization of collaborative efforts between humans and AI holds the potential to improve the understanding of AI outcomes among HR personnel, thereby alleviating associated concerns (Chowdhury *et al.*, 2023). Furthermore, the involvement of humans with AI in recruitment practices, wherein repetitive and administrative tasks are delegated to AI, while humans handle the hiring activities requiring emotional intelligence, serves as an effective strategy to foster AI assimilation in HR recruitment (Peng *et al.*, 2022; Chowdhury *et al.*, 2023). We contend that such collaborative approaches can ensure that decisions are made with due consideration of human empathy and judgment, enhancing the overall effectiveness of the decision-making process.

Altogether, the findings have underscored the importance of enablers and inhibitors, specifically the significant role of human-AI collaboration to alleviate the impact of inhibitors, which will promote the seamless integration of AI in HR recruitment.

7. Study implications

7.1 Theoretical implications

Our study has three major theoretical implications.

First, from a theoretical standpoint, this study aims to contribute to the ongoing discourse on AI in HRM, specifically AI assimilation in HR recruitment in organizations where AI is expected to disrupt HRM practices. The investigation of AI assimilation is relatively new, despite prior studies examining AI adoption (Pan *et al.*, 2022), and AI rejection (Park *et al.*, 2021). In contrast to prior scholarly endeavors, AI assimilation has emerged as a contemporary research construct in HRM literature (Prikshat *et al.*, 2023a). Considering the nascent research nature of AI assimilation, this study's findings are positioned as a groundbreaking attempt to understand its complexities fully.

Second, this study makes a noteworthy contribution to the prior AI literature by offering key insights into the key enablers that facilitate AI assimilation and differentiating them from inhibitors in HR recruitment. Prior AI scholars have explored various AI enablers including technical enablers – such as privacy and security, technical skills, system compatibility, data quality, and IT infrastructure – organizational enablers – such as top management support, organizational culture, and vision and strategy - and cultural enablers – such as data driven, autonomy, openness to change, and information sharing (Cadden *et al.*, 2022; Merhi and Harfouche, 2023). In contrast, this study has been positioned to identify explicit HRM enablers from practice, such as AI competence and recruitment agility for AI assimilation in HR recruitment. Furthermore, in order to provide a balanced view, we identified two key inhibitors namely AI opacity and AI empathy. Employing the theoretical lens of the enabler-inhibitor perspective, this study delves into the complex interplay of various factors influencing AI assimilation (Cenfetelli, 2004; Li *et al.*, 2022; Prikshat *et al.*, 2023a). By clearly delineating AI competence and recruitment agility as enablers and AI opacity and AI empathy as inhibitors, our study extends the prior theoretical landscape, particularly the enabler-inhibitor perspective.

Third, we found that both inhibitors of AI opacity and AI empathy had no effect. However, prior findings have confirmed that these hindrances, traditionally perceived as inhibitors to the integration of AI, manifest as real-world challenges during AI implementation (von Eschenbach, 2021; Langer and König, 2023). In this backdrop, through empirical confirmation, we provide insights into how these hindrances can be mitigated through human-AI collaboration. Hence, our study is one of the earlier studies introducing the theoretical concept of human-AI collaboration as an intervention in the relationship between AI opacity, AI empathy, and AI assimilation. This theoretical proposition aligns with contemporary perspectives on the pivotal role of collaborative efforts in overcoming barriers to AI assimilation (Seeber *et al.*, 2020). Unlike prior studies, which primarily focused on generic moderating factors, for example, demographics (Flavián *et al.*, 2022) and leadership support (Chatterjee *et al.*, 2021), our study provides a contextual intervention. This intervention sheds light on the nuanced integration efforts of AI in HRM, paving the way for a profound understanding of collaborative dynamics between humans and AI. In essence, our study not only extends the enabler-inhibitor framework by adding human-AI collaboration as a moderator but also contributes to a practical and context-specific intervention perspective, enriching the theoretical discourse in the field of AI assimilation in HRM.

7.2 Practical implications

Our study findings have three major practical implications.

First, this study offers implications for organizations prosecuting AI assimilation in HR recruitment. We believe that the proposed framework can assist HR professionals and managers in developing an understanding of the enablers and inhibitors of AI assimilation within an organizational recruitment process. Our results show the necessity of acquiring relevant AI competencies as the foundation for integrating AI-powered tools in HRM. Thus, we suggest organizations offer training and development programs specifically designed to enhance AI competence among HR personnel. We also emphasize the importance of continuous skill enhancement for HR professionals to facilitate the effective integration and utilization of AI tools in HR recruitment practices.

Second, the study underscores the significance of recruitment agility in realizing the benefits of AI tools and assimilating them into recruitment processes. Organizations may use AI-powered tools to prioritize recruitment agility for faster, more consistent, and more efficient recruitment processes that enable AI assimilation in HR recruitment. To capitalize on AI tools, HR professionals are advised to cultivate a culture of technological readiness and acceptability within their organizations. Given the dynamic nature of AI technologies, it is suggested that managers promote a learning culture, continuously adapting and acquiring new skills to facilitate effective AI integration to achieve recruitment agility that further enables AI assimilation.

Third, this study highlights the important role of human-AI collaboration in mitigating the inhibiting impact of AI opacity and AI empathy. Our findings advocate for the strategic integration of AI with humans in recruitment processes such that the repetitive and administrative tasks are delegated to AI, while the hiring activities requiring emotional intelligence are delegated to humans. For instance, AI may analyze resumes and rank candidates based on predefined criteria (e.g. skills, experience, and keywords). HR professionals then review the AI's shortlisted applications, ensuring that it align with broader organizational needs and considering factors like culture fit. Another example of human-AI collaboration could be AI can anonymize applicants by removing name, gender, ethnicity, and age to reduce selection bias. Then HR professionals assess anonymized profiles, focusing only on skills while making hiring decisions. Given this embryonic intervention of human-AI collaboration, organizations are encouraged to practice such a collaborative environment to comprehend AI-powered hiring tools alongside human decision makers. Such a collaborative approach is posited to overcome inhibitors and optimize the overall effectiveness of AI assimilation in HR recruitment.

8. Conclusion

This study specifically identified the underlying factors, including AI competency, recruitment agility, AI opacity, and AI empathy, essential for AI assimilation in HR recruitment. Notably, our findings highlight the significance of enablers in driving AI assimilation and the constraining effect of certain factors that organizations may face could be lessened through human-AI collaboration. Our study contributes to the theory development by contextualizing the enabler-inhibitor framework to the HRM domain and positioning human-AI collaboration as a moderator. Based on these results HR decision makers can prioritize important enablers and improve the effectiveness of AI assimilation. Furthermore, our results suggest that HR professionals should collaborate with the AI tools to overcome the effects of inhibitors.

The study findings outline the essential aspects that enable or hinder AI assimilation, laying the foundation for future research. At the same time, our study has a number of limitations. In particular, we note four limitations and propose four research directions. First, future scholars can explore several stages of AI assimilation processes in HR recruitment, such as initiation, adoption, routinization, and extension, that the current study lacks. Second, future exploration can consider additional dimensions of enablers and inhibitors and improve the theoretical model. Third, the collected data is cross-sectional in nature, which may not capture the evolution of AI. Furthermore, the collected data are subjective opinions of individuals. Therefore, longitudinal research with objective data is needed to increase the reliability of our findings. Finally, hiring decision making might vary depending on the types of organizations or industries. Thus, our results may not be generalizable in all organizations or industries. We suggest future researchers may validate our proposed framework in diverse contexts.

References

Allal-Chérif, O., Aranega, A.Y. and Sánchez, R.C. (2021), "Intelligent recruitment: how to identify, select, and retain talents from around the world using artificial intelligence", *Technological Forecasting and Social Change*, Vol. 169, 120822, doi: 10.1016/j.techfore.2021.120822.

Arrieta, A.B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R. and Herrera, F. (2020), "Explainable Artificial Intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI", *Information Fusion*, Vol. 58, pp. 82-115, doi: 10.1016/j.inffus.2019.12.012.

Belhadi, A., Kamble, S., Jabbour, C.J.C., Gunasekaran, A., Ndubisi, N.O. and Venkatesh, M. (2021), "Manufacturing and service supply chain resilience to the COVID-19 outbreak: lessons learned from the automobile and airline industries", *Technological Forecasting and Social Change*, Vol. 163, 120447, doi: 10.1016/j.techfore.2020.120447.

Black, J.S. and van Esch, P. (2020), "AI-enabled recruiting: what is it and how should a manager use it?", *Business Horizons*, Vol. 63 No. 2, pp. 215-226, doi: 10.1016/j.bushor.2019.12.001.

Boyd, K.L. and Andalibi, N. (2023), "Automated emotion recognition in the workplace: how proposed technologies reveal potential futures of work", *Proceedings of the ACM on Human-Computer Interaction*, Vol. 7, CSCW1, pp. 1-37, doi: 10.1145/3579528.

Cadden, T., Dennehy, D., Mantymaki, M. and Treacy, R. (2022), "Understanding the influential and mediating role of cultural enablers of AI integration to supply chain", *International Journal of Production Research*, Vol. 60 No. 14, pp. 4592-4620, doi: 10.1080/00207543.2021.1946614.

Campion, M.C., Campion, M.A., Campion, E.D. and Reider, M.H. (2016), "Initial investigation into computer scoring of candidate essays for personnel selection", *Journal of Applied Psychology*, Vol. 101 No. 7, pp. 958-975, doi: 10.1037/apl0000108.

Cenfetelli, R.T. (2004), "Inhibitors and enablers as dual factor concepts in technology usage", *Journal of the Association for Information Systems*, Vol. 5 No. 11, pp. 16-492, doi: 10.17705/1jais.00059.

Cenfetelli, R.T. and Schwarz, A. (2011), "Identifying and testing the inhibitors of technology usage intentions", *Information Systems Research*, Vol. 22 No. 4, pp. 808-823, doi: 10.1287/isre.1100.0295.

Chamorro-Premuzic, T. and Ahmetoglu, G. (2016), "The pros and cons of robot managers", *Harvard Business Review*, Vol. 12, pp. 2-5.

Chatterjee, S., Rana, N.P., Dwivedi, Y.K. and Baabdullah, A.M. (2021), "Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model", *Technological Forecasting and Social Change*, Vol. 170, 120880, doi: 10.1016/j.techfore.2021.120880.

Chen, A., Yang, T., Ma, J. and Lu, Y. (2023), "Employees' learning behavior in the context of AI collaboration: a perspective on the job demand-control model", *Industrial Management and Data Systems*, Vol. 123 No. 8, pp. 2169-2193, doi: 10.1108/imds-04-2022-0221.

Chowdhury, S., Budhwar, P., Dey, P.K., Joel-Edgar, S. and Abadie, A. (2022a), "AI-employee collaboration and business performance: integrating knowledge-based view, socio-technical systems and organisational socialisation framework", *Journal of Business Research*, Vol. 144, pp. 31-49, doi: 10.1016/j.jbusres.2022.01.069.

Chowdhury, S., Joel-Edgar, S., Dey, P.K., Bhattacharya, S. and Kharlamov, A. (2022b), "Embedding transparency in artificial intelligence machine learning models: managerial implications on predicting and explaining employee turnover", *International Journal of Human Resource Management*, Vol. 34 No. 14, pp. 1-32, doi: 10.1080/09585192.2022.2066981.

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A. and Truong, L. (2023), "Unlocking the value of artificial intelligence in human resource management through AI capability framework", *Human Resource Management Review*, Vol. 33 No. 1, 100899, doi: 10.1016/j.hrmr.2022.100899.

Chuang, S.-H. (2020), "Co-creating social media agility to build strong customer-firm relationships", *Industrial Marketing Management*, Vol. 84, pp. 202-211, doi: 10.1016/j.indmarman.2019.06.012.

Creswell, J.W. (2007), *Qualitative Inquiry and Research Design: Choosing Among Five Approaches*, 2nd ed., Sage, Thousand Oaks, CA.

Daniels, K., Glover, J. and Mellor, N. (2014), "An experience sampling study of expressing affect, daily affective well-being, relationship quality, and perceived performance", *Journal of Occupational and Organizational Psychology*, Vol. 87 No. 4, pp. 781-805, doi: 10.1111/joop.12074.

Flanagan, J.C. (1954), "The critical incident technique", *Psychological Bulletin*, Vol. 51 No. 4, pp. 327-358, doi: 10.1037/h0061470.

Flavián, C., Pérez-Rueda, A., Belanche, D. and Casaló, L.V. (2022), "Intention to use analytical artificial intelligence (AI) in services–the effect of technology readiness and awareness", *Journal of Service Management*, Vol. 33 No. 2, pp. 293-320, doi: 10.1108/josm-10-2020-0378.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50, doi: 10.1177/002224378101800104.

Friedman, G.D. (2023), *Artificial Intelligence Is Increasingly Being Used to Make Workplace Decisions–But Human Intelligence Remains Vital*, available at: https://fortune.com/2023/03/13/artificial-intelligence-make-workplace-decisions-human-intelligence-remains-vital-careers-tech-gary-friedman/ (accessed 25 November).

Fuller, J.B., Raman, M., Sage-Gavin, E. and Hines, K. (2021), "Hidden workers: untapped talent", *Harvard Business School and Accenture*, available at: https://www.hbs.edu/managing-the-future-of-work/research/Pages/hidden-workers-untapped-talent.aspx

Gaur, B. and Riaz, S. (2019), "A two-tier solution to converge people analytics into HR practices", *2019 4th International Conference on Information Systems and Computer Networks (ISCON)*, IEEE, pp. 167-173.

Giermindl, L.M., Strich, F., Christ, O., Leicht-Deobald, U. and Redzepi, A. (2022), "The dark sides of people analytics: reviewing the perils for organisations and employees", *European Journal of Information Systems*, Vol. 31 No. 3, pp. 410-435, doi: 10.1080/0960085x.2021.1927213.

Gioia, D.A., Corley, K.G. and Hamilton, A.L. (2013), "Seeking qualitative rigor in inductive research: notes on the Gioia methodology", *Organizational Research Methods*, Vol. 16 No. 1, pp. 15-31, doi: 10.1177/1094428112452151.

Heilmann, P., Forsten-Astikainen, R. and Kultalahti, S. (2020), "Agile HRM practices of SMEs", *Journal of Small Business Management*, Vol. 58 No. 6, pp. 1291-1306, doi: 10.1111/jsbm.12483.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), “A new criterion for assessing discriminant validity in variance-based structural equation modeling”, *Journal of the Academy of Marketing Science*, Vol. 43 No. 1, pp. 115-135, doi: 10.1007/s11747-014-0403-8.

Höddinghaus, M., Sondern, D. and Hertel, G. (2021), “The automation of leadership functions: would people trust decision algorithms?”, *Computers in Human Behavior*, Vol. 116, 106635, doi: 10.1016/j.chb.2020.106635.

Hoffman, M., Kahn, L.B. and Li, D. (2018), “Discretion in hiring”, *Quarterly Journal of Economics*, Vol. 133 No. 2, pp. 765-800, doi: 10.1093/qje/qjx042.

Holloway, B.B. and Beatty, S.E. (2008), “Satisfiers and dissatisfiers in the online environment: a critical incident assessment”, *Journal of Service Research*, Vol. 10 No. 4, pp. 347-364, doi: 10.1177/1094670508314266.

Hunkenschroer, A.L. and Luetge, C. (2022), “Ethics of AI-enabled recruiting and selection: a review and research agenda”, *Journal of Business Ethics*, Vol. 178 No. 4, pp. 977-1007, doi: 10.1007/s10551-022-05049-6.

Johnson, R.D., Stone, D.L. and Lukaszewski, K.M. (2020), “The benefits of eHRM and AI for talent acquisition”, *Journal of Tourism Futures*, Vol. 7 No. 1, pp. 40-52, doi: 10.1108/jtf-02-2020-0013.

Kannabiran, G. and Dharmalingam, P. (2012), “Enablers and inhibitors of advanced information technologies adoption by SMEs: an empirical study of auto ancillaries in India”, *Journal of Enterprise Information Management*, Vol. 25 No. 2, pp. 186-209, doi: 10.1108/17410391211204419.

Kellogg, K.C., Valentine, M.A. and Christin, A. (2020), “Algorithms at work: the new contested terrain of control”, *The Academy of Management Annals*, Vol. 14 No. 1, pp. 366-410, doi: 10.5465/annals.2018.0174.

Kim, S., Wang, Y. and Boon, C. (2021), “Sixty years of research on technology and human resource management: looking back and looking forward”, *Human Resource Management*, Vol. 60 No. 1, pp. 229-247, doi: 10.1002/hrm.22049.

Lahuis, D.M., Perreault, N.E. and Ferguson, M.W. (2003), “The effect of legitimizing explanations on applicants’ perceptions of selection assessment fairness 1”, *Journal of Applied Social Psychology*, Vol. 33 No. 10, pp. 2198-2215, doi: 10.1111/j.1559-1816.2003.tb01881.x.

Lambrecht, A. and Tucker, C. (2019), “Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of STEM career ads”, *Management Science*, Vol. 65 No. 7, pp. 2966-2981, doi: 10.1287/mnsc.2018.3093.

Langer, M. and König, C.J. (2021), “Introducing a multi-stakeholder perspective on opacity, transparency and strategies to reduce opacity in algorithm-based human resource management”, *Human Resource Management Review*, 100881.

Langer, M. and König, C.J. (2023), “Introducing a multi-stakeholder perspective on opacity, transparency and strategies to reduce opacity in algorithm-based human resource management”, *Human Resource Management Review*, Vol. 33 No. 1, 100881, doi: 10.1016/j.hrmr.2021.100881.

Langer, M., König, C.J. and Busch, V. (2021), “Changing the means of managerial work: effects of automated decision support systems on personnel selection tasks”, *Journal of Business and Psychology*, Vol. 36 No. 5, pp. 751-769, doi: 10.1007/s10869-020-09711-6.

Lee, M.K. (2018), “Understanding perception of algorithmic decisions: fairness, trust, and emotion in response to algorithmic management”, *Big Data and Society*, Vol. 5 No. 1, doi: 10.1177/2053951718756684.

Li, J., Huang, J., Liu, J. and Zheng, T. (2022), “Human-AI cooperation: modes and their effects on attitudes”, *Telematics and Informatics*, Vol. 73, 101862, doi: 10.1016/j.tele.2022.101862.

Liang, H., Saraf, N., Hu, Q. and Xue, Y. (2007), “Assimilation of enterprise systems: the effect of institutional pressures and the mediating role of top management”, *MIS Quarterly*, Vol. 31 No. 1, pp. 59-87, doi: 10.2307/25148781.

Lin, X. and Loi, R. (2021), "Punishing the perpetrator of incivility: the differential roles of moral identity and moral thinking orientation", *Journal of Management*, Vol. 47 No. 4, pp. 898-929, doi: 10.1177/0149206319870236.

Maier, C., Laumer, S., Thatcher, J.B., Wirth, J. and Weitzel, T. (2022), "Trial-period technostress: a conceptual definition and mixed-methods investigation", *Information Systems Research*, Vol. 33 No. 2, pp. 489-514, doi: 10.1287/isre.2021.1047.

Maity, S. (2019), "Identifying opportunities for artificial intelligence in the evolution of training and development practices", *The Journal of Management Development*, Vol. 38 No. 8, pp. 651-663, doi: 10.1108/jmd-03-2019-0069.

Malik, A., De Silva, M.T., Budhwar, P. and Srikanth, N. (2021), "Elevating talents' experience through innovative artificial intelligence-mediated knowledge sharing: evidence from an IT-multinational enterprise", *Journal of International Management*, Vol. 27 No. 4, 100871, doi: 10.1016/j.intman.2021.100871.

Merhi, M.I. and Harfouche, A. (2023), "Enablers of artificial intelligence adoption and implementation in production systems", *International Journal of Production Research*, Vol. 62, pp. 1-15, doi: 10.1080/00207543.2023.2167014.

Mikalef, P., Islam, N., Parida, V., Singh, H. and Altwaijry, N. (2023), "Artificial intelligence (AI) competencies for organizational performance: a B2B marketing capabilities perspective", *Journal of Business Research*, Vol. 164, 113998, doi: 10.1016/j.jbusres.2023.113998.

Miles, M.B. and Huberman, A.M. (1994), *Qualitative Data Analysis: an Expanded Sourcebook*, Sage, Thousand Oaks, CA.

Mirowska, A. and Mesnet, L. (2022), "Preferring the devil you know: potential applicant reactions to artificial intelligence evaluation of interviews", *Human Resource Management Journal*, Vol. 32 No. 2, pp. 364-383, doi: 10.1111/1748-8583.12393.

Molina, M.D. and Sundar, S.S. (2022), "When AI moderates online content: effects of human collaboration and interactive transparency on user trust", *Journal of Computer-Mediated Communication*, Vol. 27 No. 4, p. zmac010, doi: 10.1093/jcmc/zmac010.

Myhill, K., Richards, J. and Sang, K. (2021), "Job quality, fair work and gig work: the lived experience of gig workers", *International Journal of Human Resource Management*, Vol. 32 No. 19, pp. 4110-4135, doi: 10.1080/09585192.2020.1867612.

Oswald, F.L., Behrend, T.S., Putka, D.J. and Sinar, E. (2020), "Big data in industrial-organizational psychology and human resource management: forward progress for organizational research and practice", *Annual Review of Organizational Psychology and Organizational Behavior*, Vol. 7 No. 1, pp. 505-533, doi: 10.1146/annurev-orgpsych-032117-104553.

Pan, Y., Froese, F., Liu, N., Hu, Y. and Ye, M. (2022), "The adoption of artificial intelligence in employee recruitment: the influence of contextual factors", *International Journal of Human Resource Management*, Vol. 33 No. 6, pp. 1125-1147, doi: 10.1080/09585192.2021.1879206.

Park, H., Ahn, D., Hosanagar, K. and Lee, J. (2021), *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, Yokohama.

Pelau, C., Dabija, D.-C. and Ene, I. (2021), "What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry", *Computers in Human Behavior*, Vol. 122, 106855, doi: 10.1016/j.chb.2021.106855.

Peng, C., van Doorn, J., Eggers, F. and Wieringa, J.E. (2022), "The effect of required warmth on consumer acceptance of artificial intelligence in service: the moderating role of AI-human collaboration", *International Journal of Information Management*, Vol. 66, 102533, doi: 10.1016/j.ijinfomgt.2022.102533.

Polli, F., Dolphin, J. and Kassir, S. (2019), "On the basis of brains: how neuroscience and AI advance ethical hiring", *Workforce Solutions Review*, Vol. 10 No. 4, pp. 13-15.

Preston, S.D. and De Waal, F.B. (2002), "Empathy: its ultimate and proximate bases", *Behavioral and brain sciences*, Vol. 25 No. 1, pp. 1-20, doi: 10.1017/s0140525x02000018.

Prikshat, V., Islam, M., Patel, P., Malik, A., Budhwar, P. and Gupta, S. (2023a), "AI-Augmented HRM: literature review and a proposed multilevel framework for future research", *Technological Forecasting and Social Change*, Vol. 193, 122645, doi: 10.1016/j.techfore.2023.122645.

Prikshat, V., Malik, A. and Budhwar, P. (2023b), "AI-augmented HRM: antecedents, assimilation and multilevel consequences", *Human Resource Management Review*, Vol. 33 No. 1, 100860, doi: 10.1016/j.hrmr.2021.100860.

Ranasinghe, V. and Sangaradeniya, Y. (2021), "Agile human resource management", *Human Resource Management in Challenging Environments*, pp. 23-31.

Rivera, L.A. (2015), "Go with your gut: emotion and evaluation in job interviews", *American Journal of Sociology*, Vol. 120 No. 5, pp. 1339-1389, doi: 10.1086/681214.

Roemmich, K., Rosenberg, T., Fan, S. and Andalibi, N. (2023), "Values in emotion artificial intelligence hiring services: technosolutions to organizational problems", *Proceedings of the ACM on Human-Computer Interaction*, Vol. 7, CSCW1, pp. 1-28, doi: 10.1145/3579543.

Saha, N., Gregar, A. and Sáha, P. (2017), "Organizational agility and HRM strategy: do they really enhance firms' competitiveness?", *International Journal of Organizational Leadership*, Vol. 6 No. 3, pp. 323-334, doi: 10.33844/ijol.2017.60454.

Saunders, M.N. (2012), "Choosing research participants", *Qualitative organizational research: Core methods and current challenges*, pp. 35-52, doi: 10.4135/9781526435620.n3.

Saunders, M.N. and Townsend, K. (2016), "Reporting and justifying the number of interview participants in organization and workplace research", *British Journal of Management*, Vol. 27 No. 4, pp. 836-852, doi: 10.1111/1467-8551.12182.

Schluter, J., Seaton, P. and Chaboyer, W. (2008), "Critical incident technique: a user's guide for nurse researchers", *Journal of Advanced Nursing*, Vol. 61 No. 1, pp. 107-114, doi: 10.1111/j.1365-2648.2007.04490.x.

Seeber, I., Waizenegger, L., Seidel, S., Morana, S., Benbasat, I. and Lowry, P.B. (2020), "Collaborating with technology-based autonomous agents: issues and research opportunities", *Internet Research*, Vol. 30 No. 1, pp. 1-18, doi: 10.1108/intr-12-2019-0503.

Sirianni, N.J., Bitner, M.J., Brown, S.W. and Mandel, N. (2013), "Branded service encounters: strategically aligning employee behavior with the brand positioning", *Journal of Marketing*, Vol. 77 No. 6, pp. 108-123, doi: 10.1509/jm.11.0485.

Stohl, C., Stohl, M. and Leonardi, P.M. (2016), "Digital age| managing opacity: information visibility and the paradox of transparency in the digital age", *International Journal of Communication*, Vol. 10, p. 15.

Strauss, A. and Corbin, J. (1998), "Basics of qualitative research techniques".

Tambe, P., Cappelli, P. and Yakubovich, V. (2019), "Artificial intelligence in human resources management: challenges and a path forward", *California Management Review*, Vol. 61 No. 4, pp. 15-42, doi: 10.1177/0008125619867910.

Tsai, W.-C., Chen, H.-Y. and Chen, C.-C. (2012), "Incremental validity of person-organization fit over the big five personality measures", *The Journal of psychology*, Vol. 146 No. 5, pp. 485-509, doi: 10.1080/00223980.2012.656154.

Ulrich, D. and Yeung, A. (2019), "Agility: the new response to dynamic change", *Strategic HR Review*, Vol. 18 No. 4, pp. 161-167, doi: 10.1108/shr-04-2019-0032.

Van Esch, P. and Black, J.S. (2019), "Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting", *Business Horizons*, Vol. 62 No. 6, pp. 729-739, doi: 10.1016/j.bushor.2019.07.004.

Van Esch, P., Black, J.S. and Ferolie, J. (2019), "Marketing AI recruitment: the next phase in job application and selection", *Computers in Human Behavior*, Vol. 90, pp. 215-222, doi: 10.1016/j.chb.2018.09.009.

von Eschenbach, W.J. (2021), "Transparency and the black box problem: why we do not trust AI", *Philosophy and Technology*, Vol. 34 No. 4, pp. 1607-1622, doi: 10.1007/s13347-021-00477-0.

Walter, N., Ortbach, K. and Niehaves, B. (2015), “Designing electronic feedback–analyzing the effects of social presence on perceived feedback usefulness”, *International Journal of Human-Computer Studies*, Vol. 76, pp. 1-11, doi: 10.1016/j.ijhcs.2014.12.001.

Wamba, S.F. (2022), “Impact of artificial intelligence assimilation on firm performance: the mediating effects of organizational agility and customer agility”, *International Journal of Information Management*, Vol. 67, 102544, doi: 10.1016/j.ijinfomgt.2022.102544.

Wang, L., Zhou, Y., Sanders, K., Marler, J.H. and Zou, Y. (2024), “Determinants of effective HR analytics implementation: an in-depth review and a dynamic framework for future research”, *Journal of business research*, Vol. 170, 114312, doi: 10.1016/j.jbusres.2023.114312.

Weisz, E. and Cikara, M. (2021), “Strategic regulation of empathy”, *Trends in Cognitive Sciences*, Vol. 25 No. 3, pp. 213-227, doi: 10.1016/j.tics.2020.12.002.

Wieseke, J., Geigenmüller, A. and Kraus, F. (2012), “On the role of empathy in customer-employee interactions”, *Journal of Service Research*, Vol. 15 No. 3, pp. 316-331, doi: 10.1177/1094670512439743.

Wilson, H.J. and Daugherty, P.R. (2018), “Collaborative intelligence: humans and AI are joining forces”, *Harvard Business Review*, Vol. 96 No. 4, pp. 114-123.

Wong, L.-W., Tan, G. W.-H., Ooi, K.-B. and Dwivedi, Y. (2024), “The role of institutional and self in the formation of trust in artificial intelligence technologies”, *Internet Research*, Vol. 34 No. 2, pp. 343-370, doi: 10.1108/intr-07-2021-0446.

Yu, J., Ma, Z. and Zhu, L. (2023), “The configurational effects of artificial intelligence-based hiring decisions on applicants’ justice perception and organisational commitment”, *Information Technology and People*, doi: 10.1108/itp-04-2022-0271.

Appendix

Table A1. Constructs, Items, and their means, stds, and loadings

Constructs	Items	Mean	Std	Loading
AI Competency	In our organization, we are capable of and continue to experiment with new AI tools and techniques as necessary for hiring/recruitment. *(AIComp1)*	3.49	1.08	0.873
	In our organization, we have a climate that is supportive of trying out new ways of using AI in hiring/recruitment. *(AIComp2)*	3.63	1.01	0.822
	In our organization, we constantly seek new ways to enhance the effectiveness of AI use in hiring/recruitment. *(AIComp3)*	3.48	1.19	0.935
	In our organization, we constantly keep current with new AI innovations to be used in hiring/recruitment. *(AIComp4)*	3.37	1.18	0.898
Recruitment Agility	Since our organization started using AI, the hiring operations have become more flexible. *(Agility1)*	3.31	1.01	0.852
	Since our organization started using AI for hiring/recruitment, the recruitment processes have become more cost efficient. *(Agility2)*	3.50	1.00	0.795
	Since our organization started using AI for hiring/recruitment, our company has been able to complete recruitment processes more quickly. *(Agility3)*	3.66	0.96	0.811
	Since our organization started using AI for hiring/recruitment, it has had greater flexibility in our hiring/recruitment processes to adapt to job market changes. *(Agility4)*	3.42	0.99	Removed
	Since our organization started using AI for hiring/recruitment, it has efficiently redesigned our hiring processes to adapt to job market changes. *(Agility5)*	3.32	1.00	Removed
	Since our organization started using AI for hiring/recruitment, it has been very fast to adapt to the recruitment process without human guidance. *(Agility6)*	3.09	1.08	0.723
AI opacity	We could not understand the decision-making processes of AI very well for hiring/recruitment in our organization. *(AIOpac1)*	2.45	1.06	0.878
	We could not see through AI's decision-making process for hiring/recruitment in our organization. *(AIOpacs2)*	2.46	1.03	0.939
	The decision-making processes of AI are not clear and transparent in hiring/recruitment in our organization. *(AIOpac3)*	2.53	1.11	0.907
AI empathy	In the past while using AI in your organization for hiring/recruitment, have you felt that AI understands human's feelings about things? *(Empathy1)*	2.28	1.19	0.886
	In the past while using AI in your organization for hiring/recruitment, have you felt that AI can see things from a human's point of view? (Empathy2)	2.60	1.17	0.893
	In the past while using AI in your organization for hiring/recruitment, have you felt that AI can understand distinct experiences? *(Empathy3)*	2.53	1.15	0.899
	In the past while using AI in your organization for hiring/recruitment, have you felt that AI can accurately understand emotional cues? *(Empathy4)*	2.08	1.16	0.900

(*continued*)

Table A1. Continued

Constructs	Items	Mean	Std	Loading
Human-AI collaboration	In our organization, we tend to act together with AI teammate when exploiting the inner potential of the team (e.g. optimizing resource allocation during candidate screening). *(Collab1)*	3.36	1.11	0.893
	In our organization, we tend to work with AI teammates who depend on each other when it comes to improving the efficiency of existing resources (e.g. optimizing hiring/recruitment processes). *(Collab2)*	3.31	1.10	0.912
	In our organization, we tend to divide actions with my AI teammate when it comes to improving the efficiency of existing resources (e.g. automating routine hiring/recruitment tasks). *(Collab3)*	3.35	1.05	0.873
	In our organization, we tend to act in a complementary manner with my AI teammate when engaging in creative activities aimed at accomplishing hiring/recruitment tasks (e.g. collectively assessing candidate qualification). *(Collab4)*	3.38	1.13	0.886
AI assimilation	AI tools and services are used across all our hiring/recruitment processes in our organization. *(Assimilation1)*	2.95	1.14	0.893
	AI tools and services are used for decision-making across all our hiring/recruitment processes in our organization. *(Assimilation2)*	2.92	1.12	0.909
	AI tools and services are used to support the development of new hiring/recruitment processes in our organization. *(Assimilation3)*	3.53	1.09	0.797

Source(s): Authors' own work

Corresponding author
Najmul Islam can be contacted at: najmul.islam@lut.fi