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Cracking the AI recruitment code: Striving for transparency in finding the right person–job fit

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ABSTRACT

The use of artificial intelligence (AI) has significantly enhanced the efficiency of resume screening; however, discrepancies in person–job fit assessments between AI and human evaluators can adversely affect the recruitment process. This study introduces the concept of "person–job fit perception difference" to describe these discrepancies and proposes a theoretical model outlining the relationships among person–job fit perception difference, AI transparency, and algorithmic literacy. Based on data from a 2 × 3 factorial-design experiment (N = 286), the findings reveal that both external transparency and functional transparency of AI recruitment systems negatively influence the person–job fit perception difference. Additionally, two distinct aspects of algorithmic literacy moderate different pathways in this process.

1. Introduction

The integration of artificial intelligence (AI) into human resource management (HRM) has drawn significant attention as a transformative tool in recent years [1,2]. In AI-driven recruitment, resume screening processes utilize AI technology for tasks such as resume analysis, talent tagging, and person–job fit assessment. Existing research highlights AI's role in recruitment, including its impact on candidate acceptance [3], perceptions of fairness [4], and the optimization of HRM practices [5]. While AI has disrupted traditional HRM practices and streamlined recruitment processes, its application raises critical questions about decision-making accuracy and trust.

In recruitment scenarios, person–job fit serves as a fundamental criterion for evaluating candidate suitability. However, a critical challenge emerges: Despite advances in AI-driven resume screening and candidate evaluation, discrepancies in person–job fit assessments between AI and human evaluators persist. These discrepancies pose risks to human–AI collaboration, as misalignments undermine trust and decision compatibility. For instance, when AI prioritizes technical skills while HR professionals emphasize cultural fit, such divergences can lead to suboptimal hiring outcomes. Addressing this gap is crucial—not only because improved alignment enhances employee engagement [6] and job satisfaction [7], but also because it enables synergistic human–AI decision-making where cognitive and affective dimensions complement each other [8].

The ideal of HR professionals fully trusting AI decisions remains elusive due to algorithmic bias and epistemic limitations. To mitigate these discrepancies, scholars increasingly emphasize AI transparency as a pivotal mechanism. From socio-legal and computer science perspectives, AI transparency is a multifaceted concept tailored to specific use-case scenarios [9]. The European Commission's High-Level Expert Group on Artificial Intelligence (AI HLEG) provides reference standards for evaluating transparency in its 2019 report, *Ethical Guidelines for Trustworthy Artificial Intelligence* [10]. The AI HLEG defines transparency as the clarity and traceability of an AI system's processes, decisions, and underlying data and algorithms [10]. Furthermore, the EU's General Data Protection Regulation (GDPR) empowers individuals to intervene, express opinions, seek explanations for automated decisions involving personal data, and contest those decisions [11]. The demand for transparency stems from two primary factors. First, users of AI systems face epistemic limitations [12] due to the systems' complexity, reliance on big data, and machine learning, which often obscure full comprehension. This creates a need for operational-level transparency. Second, in scenarios where AI systems influence social outcomes, such as job eligibility, loan approvals, or bail decisions, concerns about bias and discrimination have emerged [12,13]. These issues directly affect users'

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0378-7206/© 2025 Elsevier B.V. All rights reserved, including those for text and data mining, AI training, and similar technologies.

ability to make informed decisions. Thus, it is crucial to explore ways to enhance employees' understanding of AI principles and decision-making mechanisms through greater transparency, thereby reducing human–AI decision-making discrepancies and improving collaborative efficiency. However, transparency alone cannot resolve discrepancies unless users possess the capacity to interpret AI's logic—a challenge that introduces the third pillar of our framework.

This is where algorithmic literacy becomes critical. As algorithmic platforms permeate recruitment, users must understand not just what decisions AI makes, but also how and why those decisions occur within socio-technical contexts. Algorithmic literacy refers to the understanding of how algorithms operate within economic, political, and social contexts, as well as the ability to engage critically with algorithmic platforms [14]. It encompasses recognizing the role of algorithms in everyday life, grasping their basic functionality, and understanding their impact on personal and societal interactions. Studying Internet users' algorithmic literacy is crucial for understanding how individuals navigate and evaluate algorithmically curated digital environments [15]. In AI-driven recruitment, algorithmic literacy enables individuals to better assess the outcomes of AI recommendations and information screening processes. This critical understanding can reduce distrust stemming from a lack of transparency in AI-driven decisions.

Motivated by these considerations, this study seeks to provide a comprehensive understanding of the implications of AI transparency and algorithmic literacy in recruitment contexts. Specifically, it examines how the transparency of AI recruitment systems affects person–job fit perception differences and explores whether algorithmic literacy moderates this relationship. By addressing these gaps, the study aims to improve collaborative efficiency between humans and AI in recruitment processes, ultimately fostering the development of fairer, more transparent, and effective AI-driven HRM practices. The study addresses the following research questions:

RQ1. How does AI transparency influence the difference in person–job fit perception between human HR professionals and AI?
RQ2. How does algorithmic literacy influence the effect of AI transparency on the difference in person–job fit perception between human HR professionals and AI?

To address the research questions, we propose a model that examines (1) the influence of two dimensions of AI transparency—external transparency and functional transparency—on person–job fit perception difference and (2) the moderating effects of two sub-dimensions of algorithmic literacy—accountability perception and fairness perception—on these relationships. An experimental methodology was employed to test the hypotheses. Specifically, a factorial design was utilized to manipulate external transparency (two levels) and functional transparency (three levels) within a simulated resume screening process, resulting in six experimental groups (2 × 3). Analysis of valid data (N = 286) reveals that both external and functional transparency impact the perception difference in person–job fit between humans and AI negatively. Additionally, accountability perception and fairness perception significantly moderate these effects.

This study makes two key contributions to the existing literature on AI recruitment and HRM. First, it advances theories on AI transparency and person–job fit. By leveraging the concept of person–job fit, our experimental findings demonstrate that transparency in AI decision-making can reduce human–AI decision-making discrepancies, and highlight the importance of transparency in recruitment scenarios. Also, the study introduces algorithmic literacy as a moderating variable, extending existing theories of algorithmic literacy and addressing a notable research gap in the context of recruitment. These insights offer guidance for improving algorithmic literacy and incorporating it into business education and training programs.

Second, the study explores how AI can better support and optimize recruitment processes, enabling human HR professionals to focus on more strategic tasks. By examining factors influencing decisions made by humans and AI during recruitment, this research contributes to the development of more effective AI recruitment tools that minimize the need for human intervention. These findings have significant implications for the HRM field, providing solutions to alleviate time-consuming and repetitive recruitment tasks while ensuring fairness and transparency. Ultimately, this research aims to foster a more efficient and equitable recruitment process, benefiting both employers and job seekers.

2. Literature review

2.1. AI recruitment

AI recruitment refers to the use of AI technology during the recruitment and selection of job applicants [16,17]. AI itself is defined as "the ability to systematically interpret external data correctly, learn from that data, and adapt that learning to use them to achieve specific goals and tasks" [18]. AI techniques, such as sophisticated machine learning (ML) methods, natural language processing, and speech recognition, can be applied to four commonly accepted phases of the recruitment process: outreach, screening, assessment, and facilitation [19]. As illustrated in Fig. 1, these stages can be carried out efficiently and quickly with the involvement of AI. This study focuses on the use of AI for the CV screening process, as it is a crucial step for improving person–job fit. Decision-making methods such as hesitation fuzzy set have been discussed at length to enhance the person–job fit [20] for AI recruitment, but there are also concerns regarding potential biases and ethical implications.

The literature on AI recruitment broadly falls into three categories. First, from the enterprise practice perspective, scholars propose that AI can be a promising alternative to reduce human workload and improve practitioners' understanding of its advantages and limitations [21]. However, some raise privacy concerns about AI and warn against its recruitment practices. Second, papers establish ethical considerations for AI recruitment from a technical perspective, revealing the risk of introducing different types of algorithmic bias [22]. Finally, some papers assess people's perceptions of AI recruitment empirically. Some studies suggest that people perceive algorithm-driven decisions to be less fair than human decisions [23], while others examine how external factors influence applicants' responses to the use of AI in recruitment [3]. However, a research gap exists in understanding the reasons for human disagreement with AI decisions, which this paper aims to address.

In contrast to the scholars who have raised ethical concerns about AI recruitment, there are also those who have proposed various positive ideas for its improvement. They contend that algorithmic bias is easier to identify and remove than human bias, and that new AI techniques have the potential to increase the accuracy of the selection process, surpassing human personality inferences [24]. Therefore, if the factors influencing human and AI decision-making can be clarified, it will aid in the promotion of AI systems in recruitment and enhance recruitment efficiency.

2.2. Person–job fit

Person–job fit has been defined as the match between an individual's personality, knowledge, skills, and abilities and the requirements of a specific job[25]. Person–job fit has long been a crucial aspect of recruitment processes, and HR traditionally employs two perspectives to determine job fit: the demand–supply perspective and the demand–competency perspective[26]. The demand–supply perspective examines whether the candidate's goals, psychological needs, and other attributes align with the job's characteristics and attributes, while the demand–competency perspective considers the job task's requirements in terms of the performer's competencies [27]. HR progressively assesses the compatibility of the candidate's competencies with the job

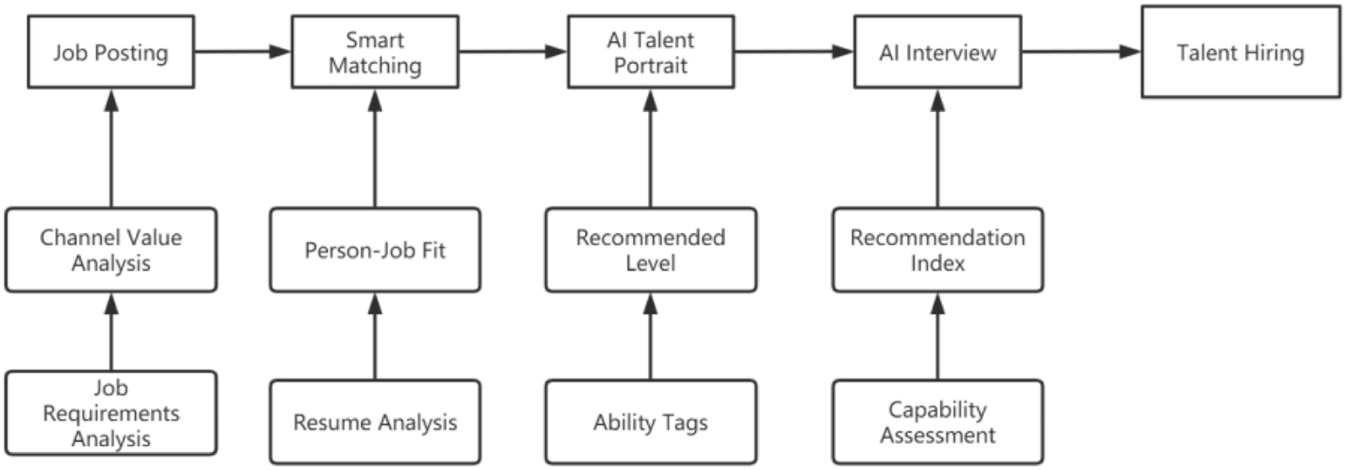

Fig. 1. AI involved in the recruitment process.

requirements during the resume screening, written tests, and interviews.

Two types of job fitting in recruitment have emerged: consistency fitting and complementary fitting [28]. Consistency fitting refers to the alignment of the basic characteristics of the individual with the basic characteristics of the organization, while complementary fitting refers to the ability of the organization and the individual to complement each other in terms of traits [29]. A mature measurement scale of competency job fitting has gradually been developed, which adopts a multidimensional view to measure person–job fit, dividing job fitting into four dimensions of value fitting, personality fitting, competency fitting, and attitude fitting [30]. The scale's content is shown in Appendix A. With the prevalence of online job search and the increasing use of online recruitment systems, the process of analyzing applicant profiles to identify those that best match the specifications of a given job can bring significant gains in efficiency and cost savings [31–33]. However, the difference between human and AI perceptions of whether a candidate's resume meets the job requirements, known as "person–job fit perception difference," has not been explored fully in current research.

By organizing and summarizing the literature pertaining to person–job fit, we discern that research on the concept definition, measurement methods, and associated impacts of person–job fit has reached a relatively mature stage. Further studies should examine the impact of AI on the accuracy of person–job fit perceptions and the potential implications for HR decision-making. Additionally, exploring the potential for AI to augment human decision-making processes in recruitment could offer valuable insights into improving recruitment practices.

2.3. AI transparency

In recent years, the use of AI for decision-making in various industries has become increasingly prevalent, with machine learning systems being widely deployed in real-world social settings. However, the use of these systems, trained on large data sets, has raised concerns regarding transparency and the need for more ethical decision-making practices [34]. The calls for transparency are rooted in the ethical questions that arise about public and private decision-making processes that may be obscured by AI systems [35,36]. When AI-involved decision-making processes impact the lives and opportunities of individuals and societies significantly, it is imperative to gain knowledge about these processes.

From the perspective of the news media, scholars have divided transparency into four dimensions, data, models, reasoning, and interfaces, confirming that there are many aspects of the algorithm system that can be disclosed to promote truth-telling in the media industry, and the disclosure process depends on transparency norms [37]. From the engineering perspective of algorithmic decision-making, scholars have proposed dimensions and methods for enhancing the transparency of algorithmic decisions. Their research indicates that AI systems can make decisions with little or no human interaction due to their ability to appear objective, rational, quick, and inexpensive, which is in high demand [38]. However, algorithmic decision-making systems can also make decisions in problematic ways, such as being wrong or discriminatory. In response to this issue, scholars have proposed enhancing the transparency of algorithmic decision-making through the process and model dimensions and discussed how auditing and testing can improve the transparency of algorithmic decisions to a certain extent, avoiding errors and discrimination by enhancing transparency. Additionally, philosophical and psychological perspectives have been explored in the context of credit approval scenarios, studying the impact of transparency on understanding, fairness, and trust [39].

In the field of recruitment, the transparency of artificial intelligence presents some unique challenges and requirements. First, the transparency of AI in the recruitment process focuses primarily on the fairness and interpretability of algorithmic decisions to ensure that no specific group's career opportunities are affected by algorithmic biases [13,40]. For instance, studies have shown that the application of AI in recruitment may lead to discrimination against certain social groups, as algorithms may unintentionally learn and amplify biases present in the data [13]. The transparency of AI in recruitment also involves clearly explaining the AI decision-making process and its outcomes to candidates. This is particularly important in the public sector, as the use of AI for recruitment may lead to political discussions and public attention [41]. Additionally, transparency includes the regulation and auditing of AI recruitment tools to ensure they comply with legal and ethical standards, preventing discrimination and unfair practices [42]. Specifically in the recruitment field, the challenges of AI transparency include algorithmic biases [43], privacy issues [42], and trust crises [44].

As we begin to delve into transparency research, we note that there has been a lack of consensus among scholars regarding the classification of transparency over the years. Some scholars argue that transparency in AI should be viewed from a systems perspective rather than focusing on individual algorithms or components [45]. In his study, Walmsley divides transparency into two broad categories: "externalities" that relate to the relationship between AI systems and external factors such as developers and users, and "functional transparency," which pertains to how the system itself works internally [12]. The specific categories are outlined in Table 1.

The first dimension, external transparency, comprises three distinct sub-types. The first sub-type pertains to "outward meta-level transparency," which is explicitly cited in the European Commission's guidelines on trustworthy AI. This level of transparency stresses the importance of openly communicating the purposes of AI systems, as well

Table 1
Specific categories.

Dimensionality	Factors
External transparency—The development dimension	Transparency on values/system design principles/premise assumptions
External transparency—The using dimensions	An honest description of what a system can actually (and cannot) do
External transparency—The deployment dimension	Users are aware of how much they interact with AI systems rather than humans
Functional transparency	How a system makes a specific judgment or construction on a particular occasion
	How the system weights and combines several factors

as disclosing the values and motivations that drive their development and deployment. Such information can be crucial for users of the systems, as they may need to consider these factors when interpreting the outputs of the AI algorithms. The development of AI systems that are "interpretable" is emphasized, as noted by Francis [46]. The second sub-type of external transparency concerns "descriptive external transparency," which refers to how AI is portrayed in the media or by other actors. Research has shown that there is a significant amount of false propaganda about AI, which can create unrealistic expectations and undermine the credibility of AI in the eyes of the public [47]. Therefore, it is crucial to ensure that any descriptions of AI systems are honest and accurately reflect what they can and cannot do. This sub-type of transparency emphasizes the need for an honest description of the capabilities of AI systems. The third sub-type of external transparency relates to users' awareness of whether they are interacting with an AI system or a human. As AI continues to advance and improve in customer service applications, users may be confused about whether they are interacting with a human or an AI system [48]. Ensuring transparency at the user level requires a clear understanding of whether the person on the other end of the phone an AI system or a human is. An individual's comprehension of the design principles behind the AI resume screening system influences their perception of differences between themselves and the AI. Within the context of external transparency, we interpret this understanding as an awareness of the principles guiding AI system development and deployment.

The second dimension, functional transparency, pertains to the internal workings of the system itself and concerns how the system makes specific judgments or suggestions on specific occasions, or how the system weights or combines several factors in assigning weights [12]. In the dimension of functional transparency, we interpret the individual's understanding of the design principles of the AI resume screening system as the comprehension of the AI system scoring weight and training data.

Based on the literature review of AI transparency, it is evident that research on the definition of concepts related to AI transparency, measurement methods, transparency division dimensions, and the impact brought about by AI transparency is constantly evolving and improving. With a transparent AI system, HR can better understand the logic behind candidate screening and evaluation, thereby enhancing trust in the recruitment outcomes. By clarifying the impact of AI transparency on person–job fit perception difference, our research has the potential to inform the development of more ethical and effective AI recruitment practices. This could lead to a shift in how AI systems are designed, implemented, and evaluated in the context of HRM, ensuring that AI is used to enhance rather than hinder the recruitment process.

2.4. Algorithmic literacy

In academia, it is widely acknowledged that technology is not neutral. The significance of algorithms has been increasing across all levels of industry, and as a result, concepts such as information literacy and data literacy have ultimately led to the emergence of algorithmic literacy. Although this concept has only been introduced in recent years, it has already been established that algorithmic literacy encompasses the social processes and practices of reading and writing about algorithm generation and meaning [49]. To be considered algorithmically literate, individuals must be aware of the existence of algorithms and the crucial roles they play in their daily lives, whether these roles are positive or negative [50].

According to Barocas and Selbst [51], algorithmic literacy will become increasingly critical in the context of news consumption and information access in the coming years. Furthermore, algorithmic literacy is also being utilized increasingly as a response to problems associated with algorithms. It can help individuals assess whether media, companies, and governments are using AI technologies correctly to avoid serious bias and protect users' privacy [52]. Algorithmic literacy can also aid in addressing issues such as discrimination, information and power asymmetries, and opacity in algorithmic decision-making [50]. These examples demonstrate that algorithmic literacy is a prerequisite for making judgments about whether and to what extent users can accept collaborative platforms involving algorithms. Additionally, it highlights the importance of algorithmic literacy for developers in managing their platforms and algorithms.

Researchers have also identified various methods for improving algorithmic literacy. For example, a study found that when subjects in an experiment were given the opportunity to reflect on their participation, they shifted to more critical and rhetorical responses. Similarly, asking subjects to write down their algorithmic awareness helped to improve algorithmic literacy [49]. Drawing on these theories, other researchers have developed and validated a conceptual framework for algorithmic literacy, which includes proposed meanings and measures of algorithmic literacy such as accountability perception and fairness perception. Fairness perception refers to an individual's perception that an algorithm should not have discriminatory or unfair consequences. Accountability perception refers to the individual's awareness that providers of an automated decision system should be held responsible for the results of their programming decisions [49]. They have also created a more sophisticated measurement scale, as seen in Appendix B.

From examination of the relevant literature, it becomes evident that the issue of algorithmic literacy has drawn attention from scholars and the public to a certain extent. Some researchers have delved into the factors influencing algorithmic literacy and their effects. Previous studies have also confirmed that algorithmic literacy can be enhanced through training. However, there remains a paucity of academic articles that specifically analyze the practical application of algorithmic literacy and conduct in-depth evaluations from the audience's perspective. AI recruitment scenarios, in particular, suffer from a research gap regarding the impact of algorithmic literacy among AI system users on recruitment outcomes supported by AI. Therefore, this paper introduces algorithmic literacy as a variable to explore its influence and role in AI recruitment, aiming to bridge the theoretical gap and offer insights for enterprise human resource management.

3. Hypothesis development

Previous studies have confirmed the impact of AI transparency on trust in and adoption of AI recommendations in the credit scenario [39]. Yu et al. found that AI transparency positively affects employees' trust in AI [53]. Mercado et al. investigated the impact of intelligent agent transparency levels on the performance and trust of operators within the context of human–agent collaboration for autonomous vehicle dispatching tasks [54]. Their findings revealed that increased transparency improves both task performance and trust. Lyons et al. examined the influence of intelligent machine transparency on trust during collaborative human–machine efforts to execute emergency aircraft landing procedures [55]. The research outcomes suggest that higher levels of transparency are associated with greater trust in the machine by the operators. Hancock et al. propose that trust in human–AI interaction facilitates increased acceptance of suggestions provided by the intelligent agent and a greater willingness to collaborate [56]. We believe that higher trust in AI encourages individuals to make decisions that align with AI recommendations, reducing discrepancies between human and AI decision-making. This suggests that transparency helps bridge this gap by improving users' understanding of AI functioning and decision-making processes. When users clearly understand how AI operates, they are more likely to trust its outcomes, leading to greater reliance on its suggestions and closer alignment during collaborative decision-making.

In this study, the discrepancy between human and AI decision-making is manifest as the person–job fit perception difference, which reflects the consistency of human–AI collaboration. According to Walmsley's [12] criteria for AI transparency, AI transparency is divided into external transparency and functional transparency. Accordingly, this study examines the influence of these two dimensions of transparency on the person–job fit perception difference. The following hypotheses are proposed:

Hypothesis 1: External transparency negatively impacts the person–job fit perception difference.
Hypothesis 2: Functional transparency negatively impacts the person–job fit perception difference.

Algorithmic literacy is essential for assessing whether AI technologies are employed appropriately by media, companies, and governments to mitigate severe biases and protect user privacy [52]. It also addresses issues such as discrimination, informational and power asymmetries, and opacity in algorithmic decision-making [50]. Algorithmic literacy plays a dual role: For developers, it facilitates better platform and algorithm management, and for users, it enhances the acceptance of algorithmic participation in collaborative platforms. Burrell [57] and Haider et al. [58] highlight the significance of data literacy and algorithmic literacy in promoting transparency during AI adoption. Empirical studies further reveal that algorithmic literacy influences trust in algorithms, user perceptions of personalized recommendations, and the accuracy of recommendations in over-the-top (OTT) platforms [49]. These findings suggest that algorithmic literacy may also shape trust in AI and its adoption in AI-driven recruitment. As discussed earlier, higher trust in AI leads to decision-making alignment with AI, thereby reducing discrepancies between human and AI decisions. Hence, we hypothesize that under conditions of external and functional transparency, variations in algorithmic literacy among test subjects moderate the person–job fit perception difference.

Two critical dimensions of algorithmic literacy are accountability perception and fairness perception. Accountability perception pertains to the responsibility of developers and users of AI systems [49]. It reflects the belief that external transparency is related to accountability and can moderate its relationship with person–job fit perception differences. The European Parliament has proposed that autonomous decision-making should not exempt humans from responsibility, emphasizing that individuals must remain accountable for decision-making processes to ensure traceability [59]. From the perspective of ethical responsibility, clarifying the subject of responsibility for AI decision-making can enhance traceability, which is crucial to building public trust [60,61]. When individuals perceive a high level of accountability, this perception implies their awareness of a responsible party for AI decision-making, which diminishes skepticism about AI's ethical dimensions. This attenuation of ethical concern arises from the knowledge that accountability mechanisms are in place, ensuring that there will be consequences for any misuse or unethical application of AI. Therefore, the negative relationship between external transparency and the perception difference of person–job fit may be weakened when accountability is perceived to be high. Based on this reasoning, we propose:

Hypothesis 3: Accountability perception negatively moderates the effect of external transparency on person–job fit perception difference. The higher accountability perception, the weaker the negative effect between external transparency and person–job fit perception difference.

Numerous studies have been conducted to investigate fairness perception, which has been found to be influenced by the educational and work backgrounds of individuals, leading to different perceptions of algorithmic decisions [62]. In particular, students in higher education tend to possess greater knowledge about algorithms and exhibit greater trust in them than the general public. Ongoing exposure to algorithmic fairness has increased individuals' awareness of potential biases in decision-making and in data or algorithmic interactions [63]. We propose that individuals with high levels of fairness perception will exhibit a greater sensitivity to the level of functional transparency in AI recruitment systems. When fairness perception is high, individuals may perceive a decrease in transparency as a threat to the fairness of the AI system, leading to increased perception difference. Conversely, when fairness perception is low, individuals may be less concerned about transparency, and the relationship between transparency and perception difference may be less pronounced. That is, as fairness perception increases, the negative impact of functional transparency on person–job fit perception difference becomes more pronounced. Considering this, we propose the following hypothesis. Fig. 2 shows the research model of this study:

Hypothesis 4: Fairness perception moderates the relationship between functional transparency and person–job fit perception difference, with a positive effect. Specifically, the greater the fairness perception, the greater the negative effect between functional transparency and person–job fit perception difference.

4. Methodology

4.1. Research design

Referring to the experimental ideas of Shin [49] and Liu [64] et al., this study designed a situational experiment for the resume screening aspect of AI recruitment. The experimental participants, assumed to be recruitment leaders, were required to analyze job requirements and candidates' resumes to make person–job fit judgments of ability. Based on the relevant research, the AI algorithm was found to achieve a 72 % elimination rate and a 73 % hit rate in the product manager position, indicating that the AI system is more accurate in matching analysis of positions with product experience. Therefore, the recruitment position provided in the experimental process was product manager, and the job candidates also had certain work experience as product managers.

In this paper, we adopt the experimental design method of factorial design and use external transparency (2 levels: with and without transparency) and functional transparency (3 levels: high transparency, low transparency, and no transparency) to conduct 2 × 3 experimental groupings to simulate the resume screening process of AI recruitment. We manipulate the level of transparency by providing participants with varying degrees of information about the AI system, as described in the next Section 4.2. The participants in this experiment were mainly HR or employees with relevant recruitment experience in enterprises, with a total of 286 participants. Each participant participated in only one set of experiments, and the experiments were conducted online. The AI system used in this experiment was provided by WonderCV,[1] and the experimental operation and data collection were completed by Sojump (also known as Wenjuanxing). WonderCV is a job search and recruitment platform empowered by AI to optimize resumes intelligently for users,

[1] https://www.wondercv.com/jobscan/index.

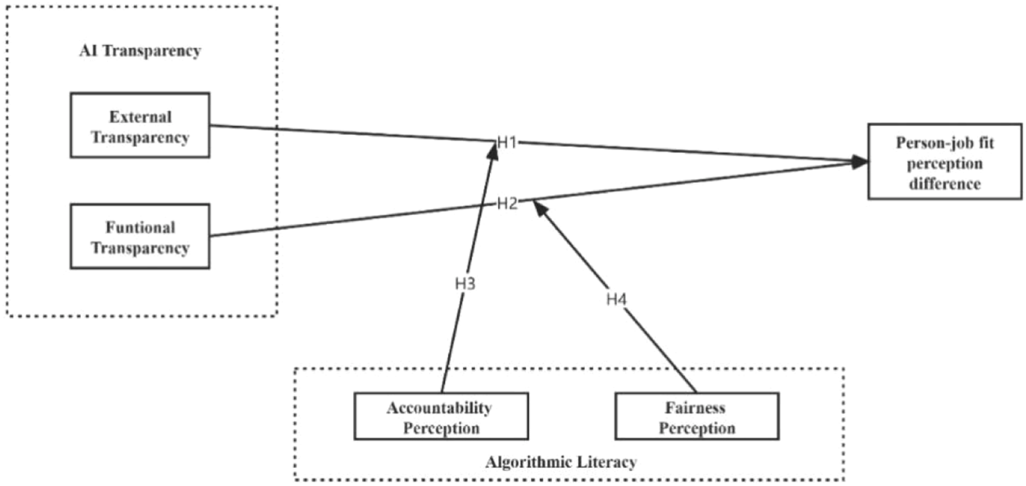

Fig. 2. Research model.

match jobs accurately, and recommend them to corporate HR. As shown in Figs. 3 and 4, after users upload their resumes and provide job descriptions, WonderCV AI Lab employs AI algorithms (including natural language processing, machine learning, and deep learning) to match resumes with job positions. It analyzes the core tags of resumes based on multiple dimensions such as skills, expertise, and relevant experience and provides scoring and evaluation accordingly.

Participants learned how the AI resume screening system worked and scored the relevant metrics under different transparencies.

Before the formal experiment, a preliminary study was conducted with 10 participants per group. Participants were asked to rate their perceptions of our manipulations on a 7-point Likert scale, ranging from "very little" to "very much," in response to the following questions: "To what extent do you understand the principles behind the development of the AI resume assessment system?" and "To what extent do you understand how the AI resume evaluation system works? For example, how were the scores of 1–7 arrived at?" The results of the manipulation check are presented in Tables 2a and 2b. The scores of the different

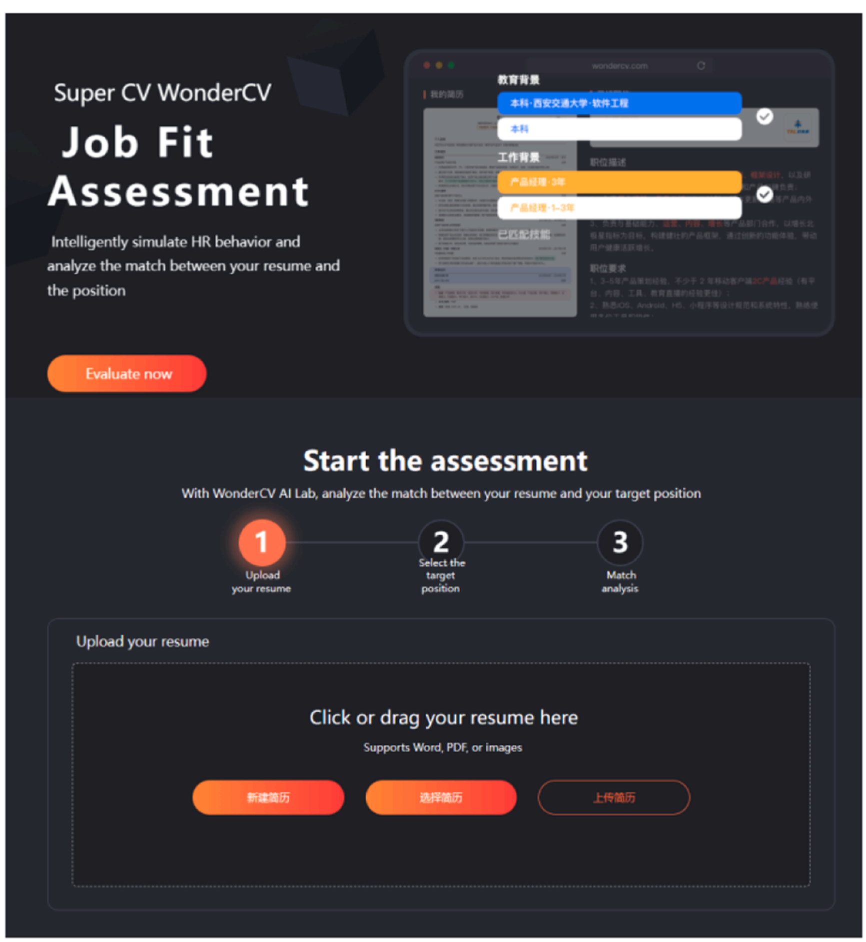

Fig. 3. The initial interface of the WonderCV job matching degree assessment.

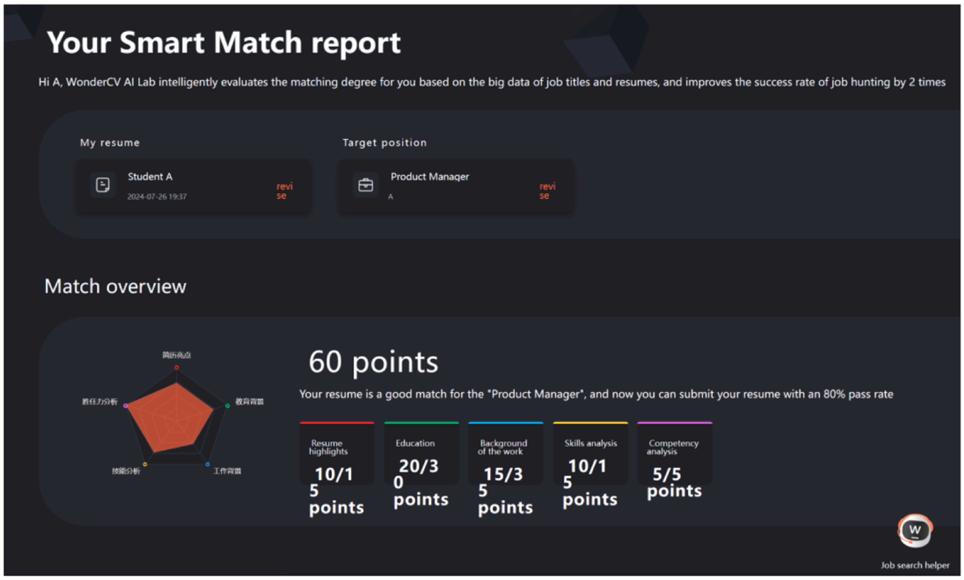

Fig. 4. The interface of the Smart match report and match review.

Table 2a
External transparency manipulation test (pre-experiment).

Title item	External Transparency (Mean ± SD)		F	p
	No Transparency (n = 30)	With Transparency (n = 30)		
What do you know about the principles of AI resume evaluation system development of the rationale?	3.17 ± 1.26	4.07 ± 1.34	7.188	0.010**

*$p < 0.05$;.
** $p < 0.01$.

experimental groups were found to be significantly different, with higher scores observed in the group with high transparency. This outcome demonstrates the effectiveness of the experimental manipulation.

The formal experimental procedure is depicted in Fig. 5. Initially, participants were instructed to review the job information and the candidate's resume (as detailed in Appendix D) and were informed about the AI system's role in assisting with resume screening and its ability to assess the job match between the candidate and the job based on ability. Subsequently, participants were asked to score the job match on a Likert 7-point scale (as detailed in Appendix A), which was treated as the pre-test score and converted to the human score. The difference between the pre-test human score and the AI score was then converted into a percentage scale, and this difference was considered as the perception difference in person–job fit before the transparency manipulation. Following the transparency manipulation (such as education or AI evaluation information), participants were asked to make another judgment regarding the candidate's fit with the job. The difference between the post-test human score and the AI score was also converted into a percentage scale, and this difference was considered as the perception difference in person–job fit after the transparency manipulation.

Following the completion of these experiments, participants were asked to complete a scale of algorithmic literacy and provide data based on their perceptions. To this end, a well-established scale developed by Shin et al. (as detailed in Appendix B) was employed. Furthermore, basic information, such as age, education, years of work, and field of work of the participants, was collected to ensure that the experimental participant population matched the intended experimental subjects (refer to Appendix C and Appendix E for further details).

4.2. Data processing

The key variables examined in this study were external transparency, functional transparency, algorithmic literacy, and person–job fit perception differences. External transparency and functional transparency were classified into two levels (no transparency/with transparency) and three levels (no transparency/low transparency/high transparency), respectively, based on Walmsley's criteria. In the context of the present experiment, these transparency levels were defined with respect to the resume screening scenario, as presented in Table 3. In terms of external transparency, two levels were designed: an informed transparency group with a system development principles education served as the experimental group, and an uninformed opaque group without such education served as the control group. For functional transparency, three distinct conditions were implemented in the resume screening scenario: The no transparency control group received only the AI's final person-job fit score without further details. The low

Table 2b
Functional transparency manipulation test (pre-experiment).

Title item	Functional transparency (Mean ± SD)			F	p
	No Transparency (n = 20)	Low Transparency (n = 20)	High Transparency (n = 20)		
What do you know about AI Resume Evaluation System work process?	2.95 ± 0.69	3.80 ± 1.44	4.80 ± 1.11	13.701	0.000**

*$p < 0.05$;.
** $p < 0.01$.

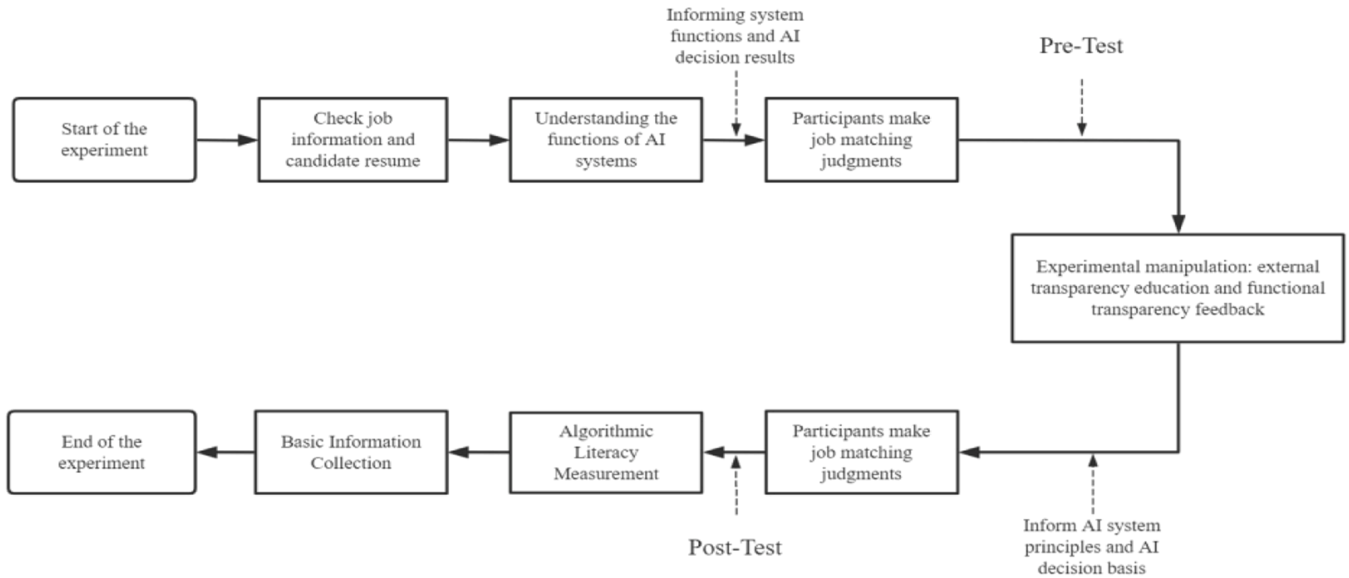

Fig. 5. Experimental process.

Table 3
Variables and level of transparency.

Variables	Level	Definition
External transparency	No transparency	No education on AI system development principles
	With transparency	Education on AI system development principles
Functional transparency	No transparency	No additional evaluation other than the person–job fit score given by the AI system
		Feedback of evaluation information
	Low transparency	Inform the AI system information about how the system evaluates the candidate in each dimension
	High transparency	Inform the AI system about the evaluation of the candidate in each dimension and tells the system how to weight each dimension

transparency experimental group received additional feedback on how the AI system evaluates candidates across various dimensions. The high transparency experimental group was further provided with explicit explanations of the AI's weighting mechanism. Participants in this group were provided with a comprehensive understanding of the AI system's weighting mechanism. This included insights into how the system assigns weights to different resume attributes based on the job requirements, as well as how these weights contribute to the overall evaluation of the resume. Participants were also given a visual representation of the weighting process, such as a radar chart, to help them understand the relative importance of each attribute in the system's decision-making process. Due to the involvement of two factors and three levels, the experiment was divided into six groups.

The person–job fit perception difference examined in this experiment is the disparity between human and AI perceptions of person–job fit. This disparity was defined by the formula

$$\mathrm{Diff} = |F_{\mathrm{Person}} - F_{\mathrm{AI}}|.$$

Here, Diff refers to the person–job fit perception difference, F_{Person} represents the experimental participants' perception of person–job fit, and F_{AI} denotes the AI's assessment of person–job fit.

As the dependent variable, Diff_after denotes the person–job fit perception difference after the manipulation of AI transparency. Diff_before represents the person–job fit perception difference prior to the manipulation of AI transparency. Since the primary aim of this experiment was to investigate the impact of AI transparency on this difference, the pretest difference Diff_before is used as a covariate.

5. Results

5.1. Analysis of reliability and validity

Reliability, also known as internal consistency, is used to assess whether data collected are reliable and trustworthy, and whether research participants have responded to the questions asked in a serious and truthful manner. In this study, the reliability analysis of the scales used was conducted using SPSS, and the results are presented in Table 4. The Cronbach's α coefficients of the overall scale, the person–job fit scale, and the algorithmic literacy scale were all above 0.8, indicating that the scales had good reliability and their internal consistency was strong.

Validity analysis is a critical step in assessing the accuracy and reliability of quantitative data, particularly for attitude scale questions. Validity analysis can be classified into three types: content validity analysis, exploratory factor analysis, and validation factor analysis. In this study, content validity was ensured for the scales used since they were developed by previous researchers based on an extensive literature review. To assess the convergent validity of each scale, validation factor analysis was conducted using SPSS. The validity was verified by calculating the KMO and Bartlett's test. The KMO values were found to be 0.756 and 0.908, indicating that the data were appropriate for extracting information. Additionally, all p-values were <0.05, which passed Bartlett's test.

5.2. Manipulation check

To ensure the validity of the questionnaire results in this study, several measures were taken, including testing the validity of the

Table 4
Analysis of reliability.

		Cronbach's α	Number of items
Overall scale		0.861	16
Person–job fit by HR		0.850	4
Algorithmic literacy	Accountability perception	0.890	6
	Fairness perception	0.878	6

transparency manipulation in the pre-experiment and the formal experiment. Analysis of the manipulation test results showed significant differences in the scores of manipulation test items for different experimental subgroups, and the experimental groups with high transparency scored higher on the manipulation test questions. This finding indicates that the manipulation of transparency was effective and valid.

Tables 5a and 5b

5.3. Hypothesis test

5.3.1. Direct effect

In this section, we employed linear regression to test hypothesis 1 and hypothesis 2, to verify the effect of external transparency and functional transparency on the variation of person–job fit perception difference. The results of the data analysis are presented in Table 6.

The results of the data analysis reveal that there is a significant negative correlation between the external transparency of AI and the change in the person–job fit perception difference. Specifically, the higher the level of external transparency, the lower the person–job fit perception difference. Therefore, hypothesis 1 is supported. Additionally, the analysis shows that there is a significant negative correlation between the transparency of AI functions and the change in the person–job fit perception difference. That is, the higher the level of functional transparency, the lower the person–job fit perception difference. Therefore, hypothesis 2 is supported.

5.3.2. Moderation effect

In this study, the concept of algorithmic literacy was used to examine the role of accountability perception as a moderator variable, with perceived external transparency as the independent variable and person–job fit perception difference as the dependent variable. The results of the moderating effect test are presented in Table 7a. The p-values of the interaction terms were all found to be <0.01, indicating that the findings are statistically significant. The coefficient of the interaction term was positive, suggesting that accountability perception as a moderator variable has an attenuating effect on the negative relationship between external transparency and the change in person–job fit perception difference. Thus, hypothesis 3 was supported. Specifically, accountability perception has a negative moderating effect on the relationship between external transparency and the person–job fit perception difference, meaning that accountability perception inhibits the main effect.

To better understand the moderating role of accountability perception, we conducted a simple slope analysis of the aforementioned relationships. A simple plot of the slope is shown in Fig. 6, which provides an intuitive depiction of the effects. It is evident from the results that when the level of accountability perception is high, the negative effect of external transparency on the person–job fit perception difference is weakened. Conversely, when the level of accountability perception is low, the negative effect of external transparency on the person–job fit perception difference is enhanced.

Table 5a
External transparency manipulation test.

Title item	External transparency (Mean ± SD)		F	p
	No transparency ($n = 144$)	With transparency ($n = 142$)		
What do you know about the principles of AI resume evaluation system development of the rationale?	3.19 ± 1.54	4.40 ± 1.59	42.580	0.000**

*$p < 0.05$;.
** $p < 0.01$.

Then we utilized the concept of algorithmic literacy to explore the moderating role of fairness perception as a moderator variable, functional transparency perception as the independent variable, and person–job fit perception difference as the dependent variable for the moderating effect test. The results of the moderating effect test are presented in Table 7b, and it is observed that the p-values of the interaction terms were all found to be <0.01, indicating statistical significance. The coefficient of the interaction term was negative, suggesting that fairness perception, as a moderator variable, strengthens the negative relationship between functional transparency and the change in person–job fit perception difference. Therefore, hypothesis 4 was supported. Fairness perception has a significant positive effect on the relationship between functional transparency and the person–job fit perception difference.

To provide an intuitive understanding of the regulatory role of fairness perception, we conducted a simple slope analysis of the aforementioned relationships. The simple slope line plots are presented in Figs. 7a and 7b It is evident from the results that under the two levels of functional transparency, when the level of fairness perception is high, the negative effect of functional transparency on person–job fit perception difference is enhanced. Conversely, when the level of fairness perception is low, the negative effect of functional transparency on person–job fit perception difference is weakened.

6. Discussion

6.1. Discussion of the results

This study provides a comprehensive review of the theories and research on AI recruitment, AI transparency, algorithmic literacy, and person–job fit. Through conceptual definitions, related impacts, and measurement methods, the study examines the application of AI in job hunting and recruitment scenarios. Furthermore, this study proposes a hypothesis on the influence of AI transparency and algorithmic literacy on the person–job fit perception difference and verifies it through experimental data analysis.

The results of the study demonstrate that both external transparency and functional transparency have a negative impact on the perceived differences between humans and AI. The experiment confirms that increasing the transparency of the AI system can reduce the person–job fit perception difference, which facilitates the adoption of AI decision-making. This finding suggests that enhancing transparency can increase public trust in AI and reduce the cognitive differences between human HR and AI systems in screening candidates' resumes.

Additionally, this study further confirms that the accountability perception and fairness perception, as measured by the algorithmic literacy index, significantly moderates the aforementioned pathways. Accountability perception negatively moderates the relationship between external transparency and reduced the person–job fit perception difference (i.e., higher accountability weakens transparency's effect). Conversely, fairness perception positively moderates the impact of functional transparency on the person–job fit perception difference. These findings suggest that various aspects of algorithmic literacy may have varying effects on public perceptions of AI. Therefore, while recognizing the importance of controlling and improving algorithmic literacy levels in the AI recruitment process, it is also crucial to accelerate the standardization of the AI accountability system to reverse public perceptions.

6.2. Theoretical contributions

This study makes several theoretical contributions. First, it highlights the impact of transparency in AI recruitment practices on discrepancies between human and AI decision-making. The findings confirm that both external and functional transparency of AI systems negatively affect the person–job fit perception difference, suggesting that greater

Table 5b
Functional transparency manipulation test.

Title item	Functional transparency (Mean ± SD)			F	p
	No transparency ($n = 90$)	Low transparency ($n = 93$)	High transparency ($n = 103$)		
What do you know about AI Resume Evaluation System work process?	3.10 ± 1.36	3.55 ± 1.71	4.69 ± 1.52	27.775	0.000**

*$p < 0.05$;.
** $p < 0.01$.

Table 6
Regression test.

	Standardized coefficients	t	p
Constant	–	12.134	0.000**
External transparency	−0.257	−4.706	0.000**
Functional transparency	−0.173	−3.093	0.002**
Diff_before	0.331	5.909	0.000**
R^2	0.169		
Adj R^2	0.160		
F	$F = 19.134$, $p = 0.000$		

DV:Diff_after.
$N = 286$.
*$p < 0.05$;.
** $p < 0.01$.

Table 7a
Accountability perception moderation effect.

	Model 1	Model 2	Model 3
Diff_before	0.286**	0.317**	0.318**
External transparency-1.0	−5.160**	−5.588**	−5.643**
Accountability perception		−0.787**	−1.377**
External transparency-1.0 × Accountability perception			0.939**
R^2	0.141	0.197	0.216
$\triangle R^2$	0.141	0.056	0.019
F	$F = 23.214$, $p = 0.000$	$F = 23.042$, $p = 0.000$	$F = 19.332$, $p = 0.000$

DV:Diff_after.
$N = 286$.
*$p < 0.05$;.
** $p < 0.01$.

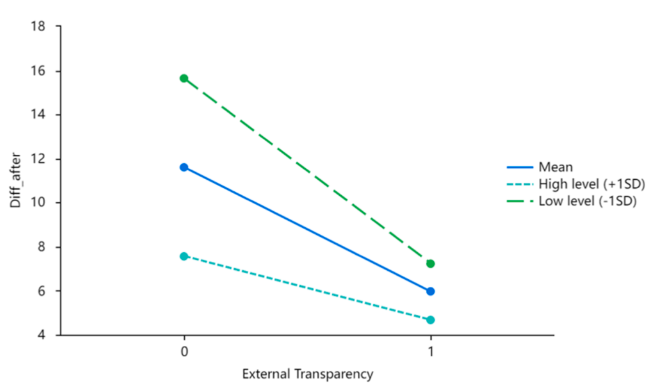

Fig. 6. Simple slope plot of external transparency.

transparency reduces perceived differences between human and AI evaluations of person–job fit. Furthermore, this study addresses a theoretical gap by investigating the role of transparency in AI-human decision-making within the context of recruitment. By clarifying how transparency influences person–job fit perception differences, it

Table 7b
Fairness perception moderation effect.

	Model 1	Model 2	Model 3
Diff_before	0.303**	0.352**	0.385**
Functional transparency-1.0	−2.355	−2.609*	−2.831*
Functional transparency-2.0	−4.476**	−4.088**	−3.917**
Fairness perception		−0.762**	−0.230
Functional transparency-1.0 × fairness perception			−0.539
Functional transparency-2.0 × fairness perception)			−1.332**
R^2	0.104	0.164	0.193
$\triangle R^2$	0.094	0.152	0.176
F	$F = 10.899$, $p = 0.000$	$F = 13.798$, $p = 0.000$	$F = 11.133$, $p = 0.000$

DV:Diff_after.
$N = 286$.
* $p < 0.05$;.
** $p < 0.01$.

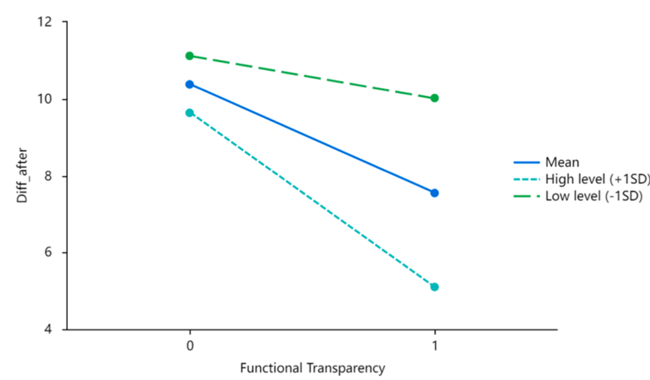

Fig. 7a. Simple slope plot of functional transparency (low transparency).

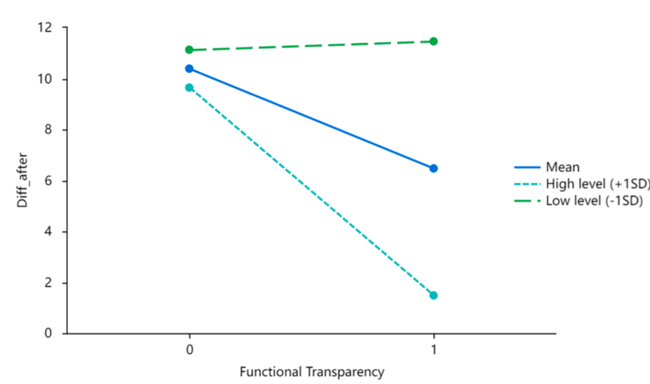

Fig. 7b. Simple slope plot of functional transparency (high transparency).

provides valuable insights for improving the effectiveness of AI-assisted decision-making in recruitment practices.

Second, this study introduces algorithmic literacy as a moderator variable in AI recruitment scenarios, which is an innovative approach compared with previous studies that mainly considered algorithmic literacy as an independent variable. The concept of algorithmic literacy has opened up new avenues for exploring the factors that influence the different perceptions of human and AI systems in the job matching process. This conclusion sheds light on the theory of cognitive differences between humans and AI in recruitment processes and represents a valuable theoretical contribution to the research direction of AI recruitment.

The proposed model delineates a clear theoretical framework for understanding the dynamics of AI recruitment. On one hand, this framework builds upon and complements existing models and frameworks in the literature. For example, it aligns with the principles of fairness, accountability, and transparency outlined in the ethical framework of AI development. Furthermore, we align with the philosophical and psychological explorations in credit approval scenarios [39] by examining the multifaceted impact of transparency on understanding, fairness, and trust within AI recruitment. On the other hand, our framework uniquely positions algorithmic literacy as a pivotal variable that can mediate these impacts, offering a novel lens through which to view the complex interactions between transparency and human–AI cognitive differences in the job matching process. The results highlight the importance of transparency and algorithmic literacy in reducing the person–job fit perception difference.

6.3. Practical implications

This study provides practical guidelines for AI recruitment, emphasizing the importance of transparency in AI systems during the hiring process. Higher transparency during resume screening leads to lower person–job fit perception difference, which reflects the consistency of human–AI collaboration. To increase external transparency, developers should disclose more information about the AI system to the public, including what the system can and cannot accomplish during the hiring process, maintaining transparency in the values and design principles of AI system design, and disclosing the data characteristics used in AI system training.

The study also examines the moderating effect of algorithmic literacy on transparency's relationship with person–job fit perception differences. The study finds that accountability perception weakens the effect of external transparency on person–job fit perception differences, while fairness perception strengthens the effect of functional transparency on person–job fit perception differences. Therefore, AI-related legislation should promote public guidance on accountability perception to improve trust in AI systems, and incorporating AI moral knowledge into AI education can improve perceptions of AI system fairness.

Overall, the practical contribution of this paper lies in its potential to enhance the effectiveness and efficiency of AI-based recruitment processes. By identifying the cognitive differences between humans and AI in job matching, the paper offers valuable insights that can inform the development of AI systems that can better meet the requirements of companies seeking to streamline their recruitment process. Furthermore, the paper highlights the importance of algorithmic literacy for humans, which can help to improve the consistency of human and AI decision-making and reduce the need for human supervision in the recruitment process. Ultimately, the findings of this paper have practical implications for organizations seeking to optimize their recruitment process and leverage the benefits of AI technology.

6.4. Limitations and future research

It is important to acknowledge the limitations of this study. First, the experiment only focuses on the product manager position and the participants are mainly product practitioners, which may limit the generalizability of the findings to other job types and populations. Therefore, future research should explore the effects of transparency and algorithmic literacy on recruitment processes in other job types and with more diverse participant samples. Second, the current AI resume screening system only assesses candidates' abilities and may not provide a comprehensive assessment of values, personality, and attitude, which limits the overall person–job fit assessment. Future research could explore the development or use of an AI system that provides a more comprehensive assessment of person–job fit.

Furthermore, this study primarily focuses on the effects of AI transparency and algorithmic literacy on the recruitment process, without exploring ways to improve transparency or increase algorithmic literacy. Future studies could investigate strategies to improve transparency, such as promoting public disclosure of AI system fundamentals and values, increasing public oversight of AI training data. Additionally, research could explore effective methods for increasing algorithmic literacy, such as incorporating AI moral education into training programs for employees and the general public.

Additionally, future studies could explicitly examine trust in AI as both an antecedent and outcome of human–AI alignment: for example, how trust interacts with transparency and literacy to shape sustained collaboration, and how contextual factors (e.g., organizational accountability mechanisms) modulate these relationships. This would extend socio-technical trust theories while addressing the distinct role of trust highlighted in prior literature.

7. Conclusions

This study demonstrates that enhancing AI transparency—through external transparency (e.g., disclosing system principles) and functional transparency (e.g., explaining algorithmic weighting)—significantly reduces person–job fit perception differences between humans and AI in recruitment. Experimental results confirm that transparency fosters trust and alignment in human–AI collaboration. Furthermore, algorithmic literacy moderates these effects: accountability perception weakens the impact of external transparency, while fairness perception amplifies functional transparency's influence, underscoring the nuanced role of user cognition. Theoretically, this work extends AI transparency frameworks to recruitment contexts and positions algorithmic literacy as a critical moderator, enriching human–AI interaction literature. Practically, organizations should adopt transparency-by-design AI systems (e.g., visual explanations of decision logic) and integrate algorithmic ethics training to bridge human–AI cognitive gaps. Limitations include the focus on competency-based assessments and a single job type. Future research should explore multidimensional AI evaluations (e.g., personality/cultural fit) and diverse occupational contexts. Longitudinal studies could further validate transparency's sustainability in reducing perception discrepancies. By prioritizing transparency and literacy, AI can evolve from an opaque tool to a collaborative partner, advancing equitable and efficient recruitment practices.

CRediT authorship contribution statement

Aihui Chen: Writing – review & editing, Writing – original draft, Validation, Methodology, Funding acquisition, Conceptualization. **Feifei Han:** Writing – review & editing. **Xinyi Zhang:** Writing – original draft. **Yaobin Lu:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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References

[1] A.L. Hunkenschroer, C. Luetge, Ethics of AI-enabled recruiting and selection: a review and research agenda, J. Bus. Ethics 178 (4) (2022) 977–1007.
[2] A. Rai, P. Constantinides, S. Sarker, Editor'S comments: next-generation digital platforms: toward human–AI hybrids, MIS. Q. 43 (1) (2019) p. iii–x.
[3] P. van Esch, J.S. Black, Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting, Bus. Horiz. 62 (6) (2019) 729–739.
[4] A. Lambrecht, C. Tucker, Algorithmic bias? An empirical study of apparent gender-based discrimination in the display of STEM career ads, Manage Sci. 65 (7) (2019) 2966–2981.
[5] X. Xu, et al., Industry classification with online resume big data: a design science approach, Inf. Management 57 (5) (2020) 103182.
[6] I.K. Enwereuzor, L.I. Ugwu, O.A. Eze, How transformational leadership influences work engagement among nurses: does person-job fit matter? West J. Nurs. Res. 40 (3) (2018) 346–366.
[7] Y. Peng, C. Mao, The impact of person–Job fit on job satisfaction: the mediator role of self efficacy, Soc. Indic. Res. 121 (3) (2015) 805–813.
[8] G. He, et al., Human-agent collaborative decision-making in intelligent organizations: a perspective of human-agent inner compatibility, Adv. Psychol. Sci. 30 (2022) 2619–2627.
[9] S. Larsson, F. Heintz, Transparency in artificial intelligence, Internet. Policy. Rev. (2020) 9.
[10] Ethics Guidelines for Trustworthy AI, European Commission High-Level Expert Group on Artificial intelligence, 2019.
[11] D.H. Hagos, D.B. Rawat, Recent advances in artificial intelligence and tactical autonomy: current status, challenges, and perspectives, Sensors 22 (2022), https://doi.org/10.3390/s22249916.
[12] J. Walmsley, Artificial intelligence and the value of transparency, Ai Society 36 (2) (2021) 585–595.
[13] A. Peña, et al., Bias in multimodal AI: testbed for fair automatic recruitment, in: 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2020.
[14] A. Koenig, The algorithms know me and I know them: using student journals to uncover algorithmic literacy awareness, Comput. Compos. (2020) 58.
[15] L. Dogruel, P. Masur, S. Joeckel, Development and validation of an algorithm literacy scale for internet users, Commun. Methods Meas. 16 (2) (2022) 115–133.
[16] A.L. Hunkenschroer, A. Kriebitz, Is AI recruiting (un)ethical? A human rights perspective on the use of AI for hiring, AI Ethics (2022) 1–15.
[17] R. Aggarwal, M.J. Lee, V. Midha, Differential impact of content in online communication on heterogeneous candidates: A field study in technical recruitment, Inf. Syst. Res. 34 (2) (2022) 609–628.
[18] A. Kaplan, M. Haenlein, Siri, Siri, in my hand: who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence, Bus. Horiz. 62 (1) (2019) 15–25.
[19] J.S. Black, P. van Esch, AI-enabled recruiting: what is it and how should a manager use it? Bus. Horiz. 63 (2) (2020) 215–226.
[20] C. Zhang, et al., Multigranulation rough set model in hesitant fuzzy information systems and its application in person-job fit, Int. J. Mach. Learn. Cybern. 10 (4) (2019) 717–729.
[21] D. Bîgu, M.-V. Cernea, Algorithmic Bias in Current Hiring Practices: An Ethical Examination, 2019.
[22] L. Yarger, F.C. Payton, B. Neupane, Algorithmic equity in the hiring of underrepresented IT job candidates, Online Inf. Rev. 44 (2) (2020) 383–395.
[23] D.T. Newman, N.J. Fast, D.J. Harmon, When eliminating bias isn't fair: algorithmic reductionism and procedural justice in human resource decisions, Organ. Behav. Hum. Decis. Process. 160 (2020) 149–167.
[24] T. Chamorro-Premuzic, et al., The datafication of talent: how technology is advancing the science of human potential at work, Curr. Opin. Behav. Sci. 18 (2017) 13–16.
[25] A.L. Kristof-Brown, Perceived applicant fit: distinguishing between recruiters' perceptions of person-job and person-organization fit, Pers. Psychol. 53 (3) (2000) 643–671.
[26] S. Hennekam, K. Follmer, J.E. Beatty, The paradox of mental illness and employment: a person-job fit lens, Int. J. Hum. Resource Manag. 32 (15) (2021) 3244–3271.
[27] Z. Ma, et al., Team-level high-performance work systems, self-efficacy and creativity: differential moderating roles of person–job fit and goal difficulty, The Int. J. Hum. Resource Manag. 32 (2) (2021) 478–511.
[28] P.M. Muchinsky, C.J. Monahan, *What is person-environment congruence? Supplementary* versus *complementary models of fit*, J. Vocat. Behav. 31 (1987) 268–277.
[29] C. Sirén, S. Thorgren, M. Järlström, Self-directed career management and mobility: the risk of lock-in effects from person–job fit, Int. J. Hum. Resource Manag. 32 (6) (2021) 1368–1389.
[30] Q. Zhang, An Empirical Study of the Relationship Between Assessment Tools, Recruiter Quality and Job Matching, University of Electronic Science and Technology of China, 2018.
[31] E. Faliagka, et al., On-line consistent ranking on e-recruitment: seeking the truth behind a well-formed CV, Artif. Intell. Rev. 42 (3) (2014) 515–528.
[32] C. Zhu, et al., Person-job Fit: adapting the right talent for the right job with joint representation learning, ACM Trans. Manage. Inf. Syst. 9 (3) (2018) 12.
[33] C. Qin, et al., An enhanced neural network approach to person-job fit in talent recruitment, ACM. Trans. Inf. Syst. 38 (2) (2020) 15.
[34] Q.V. Liao, et al., Designerly understanding: information needs for model transparency to support design ideation for AI-powered user experience, in: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, Hamburg, Germany, 2023 9.
[35] L. Floridi, et al., AI4People-An ethical framework for a good AI society: opportunities, risks, principles, and recommendations, Minds. Mach. 28 (4) (2018) 689–707.
[36] M. Hind, et al., Experiences with improving the transparency of AI models and services, in: Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems, Association for Computing Machinery, Honolulu, HI, USA, 2020, pp. 1–8.
[37] N. Diakopoulos, M. Koliska, Algorithmic transparency in the news Media, Dig. Journal. (2016) 1–20.
[38] B. Waltl, R. Vogl, Increasing transparency in algorithmic- decision-making with explainable AI, Datenschutz und Datensicherheit - DuD 42 (10) (2018) 613–617.
[39] J. Lu, et al., Good explanation for algorithmic transparency, in: Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society, 2020.
[40] C. Schumann, et al., We need fairness and explainability in algorithmic hiring, in: Adaptive Agents and Multi-Agent Systems, 2020.
[41] F. Keppeler, No thanks, dear AI! understanding the effects of disclosure and deployment of artificial intelligence in public sector recruitment, SSRN Electron. J. (2023).
[42] C. Fernández-Martínez, A. Fernández, *AI and recruiting software: ethical and legal implications.* Paladyn, J. Behav. Robot. 11 (1) (2020) 199–216.
[43] E. Hocken, G. King, AI in the hiring process, Strateg. HR Rev. 22 (3) (2023) 81–84.
[44] O. Ore, M. Sposato, Opportunities and risks of artificial intelligence in recruitment and selection, Int. J. Organ. Anal. 30 (6) (2022) 1771–1782.
[45] F. Doshi-Velez, M. Kortz, R. Budish, et al., Accountability of AI under the law: The role of explanation, in: arXiv: 1711.01134, 2017.
[46] C. Francis, A tapestry of values: an introduction to values in science, Agroecol. Sustain. Food Syst. 44 (2) (2020) 276–278.
[47] G.a.D. Marcus, Ernest. Rebooting AI: Building Artificial Intelligence We Can Trust, Pantheon Books, New York, 2019.
[48] S. Prabhudesai, et al., Understanding uncertainty: how lay decision-makers perceive and interpret uncertainty in Human-AI decision making, in: Proceedings of the 28th International Conference on Intelligent User Interfaces, Association for Computing Machinery, Sydney, NSW, Australia, 2023, pp. 379–396.
[49] D. Shin, A. Rasul, A. Fotiadis, Why am I seeing this? Deconstructing algorithm literacy through the lens of users, Internet Res. 32 (4) (2022) 1214–1234.
[50] S. Banerjee, A.Y.K. Chua, Calling out fake online reviews through robust epistemic belief, Inform. Manag. 58 (3) (2021) 103445.
[51] S. Barocas, A.D. Selbst, Big Data's disparate impact, Calif. Law Rev. 104 (3) (2016) 671–732.
[52] L. Rainie, J.Q. Anderson, Code-Dependent: Pros and Cons of the Algorithm Age, 2017.
[53] L. Yu, Y. Li, F. Fan, Employees' Appraisals and trust of artificial intelligences' Transparency and opacity, Behav. Sci. 13 (4) (2023) 344.
[54] J.E. Mercado, et al., Intelligent agent transparency in Human-agent teaming for multi-UxV management, Human Fact. 58 (3) (2016) 401–415.
[55] J.B. Lyons, et al., Shaping trust through transparent design: theoretical and experimental guidelines. Advances in Human Factors in Robots and Unmanned Systems, Springer International Publishing, Cham, 2017.
[56] P.A. Hancock, et al., A meta-analysis of factors affecting trust in human-robot interaction, Hum. Factors 53 (5) (2011) 517–527.
[57] J. Burrell, How the machine 'thinks': understanding opacity in machine learning algorithms, Big. Data Soc. 3 (1) (2016) 2053951715622512.
[58] Haider, J. and O. Sundin, *Invisible Search and Online Search Engines*. Taylor and Francis.
[59] 2020/2013, E.P.P., Artificial intelligence: questions of interpretation and application of international law in so far as the EU is affected in the areas of civil and military uses and of state authority outside the scope of criminal justice. 2021.
[60] Z. Porter, et al., Unravelling responsibility for AI, ArXiv. (2023) **abs/2308.02608**.
[61] S. Beckers, Moral responsibility for AI systems, ArXiv. (2023) **abs/2310.18040**.
[62] F. Marcinkowski, et al., Implications of AI (Un-)fairness in higher education admissions the effects of perceived AI (Un-)fairness on exit, voice and

organizational reputation, in: ACM Conference on Fairness, Accountability, and Transparency (FAT), ASSOC Computing Machinery, Barcelona, SPAIN, 2020.
[63] M.K. Lee, Understanding perception of algorithmic decisions: fairness, trust, and emotion in response to algorithmic management, Big. Data Soc. 5 (1) (2018).
[64] B.J. Liu, In AI we trust? Effects of agency locus and transparency on uncertainty reduction in human-AI interaction, J. Comput.-Mediat. Commun. 26 (6) (2021) 384–402.

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