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Article

Human-AI Collaboration in Urban Digital Transformation: Balancing Efficiency and Human Values in Shanghai's AI-Enabled Talent Recruitment

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Abstract: In the context of the urban digital revolution, recruitment through AI technologies has become common practice to address competition in the labor market. However, it is still unclear how the effectiveness of such recruitment is connected with humanistic values. For this research, an exploratory qualitative research design was used, involving semi-structured interviews with eight human resource professionals in Shanghai. Based on the results, the use of AI in recruitment led to increased efficiency mainly when screening candidates through high-volume, standardized processes, although the promised efficiency was not delivered in practice because the introduction of the AI system increased the workload. Patterns of human-machine cooperation were observed in different companies: tech companies and foreign companies are inclined to adopt interactive adjustment approaches, while state-owned enterprises retain human-dominated decision-making. Transparency of algorithms was still lacking in numerous instances, and there was an asymmetry in the accountability framework of algorithms, wherein disobeying algorithms carries more personal consequences than obeying them. The more experienced professionals became more autonomous in their work, while the less experienced professionals depended more on the algorithm. Issues like management support, information accuracy, and departmental integration have a major impact on implementation. This study contributes to the theory of human-machine collaboration by proposing the concept of asymmetric algorithmic accountability, which captures the uneven distribution of organizational consequences for following versus overriding AI recommendations and shapes practitioner behavior in ways that extend beyond individual trust or algorithmic transparency.

Keywords: AI Recruitment; Human-Machine Collaboration; Human-Centered Values; Asymmetric Algorithmic Accountability; Algorithmic Transparency; Human Resource Management

1. Introduction

Rapid advances in the application of AI in recruiting software have created a problem for businesses where the use of such software can result in considerable efficiency gains but at the same time pose significant questions regarding how human logic and integrity are maintained when decisions are made. With its central position in the digital economy of China, Shanghai is well-known for its talent agglomeration. In terms of talent migration, Shanghai retains its position as the city with the largest net talent inflow among the megacities of China. Nonetheless, the demand for AI specialists is higher than the supply of such specialists, with an approximate ratio of 3:1 between demand and supply in fields like R&D of large language models. The shortage has prompted more firms to use AI

to recruit talent to gain an edge over their competitors. The creation and use of AI-based recruiting technologies have been transformed from optional tools to essential ones [1]. The application of technology including intelligent resume screening, candidate matching, and video interviewing has been widely researched and proven to increase the efficiency of the entire recruiting process [2].

However, the realization of these efficiencies is still not assured. The adoption of AI technology in the hiring process may improve efficiencies while at the same time introducing ethical issues. The usage of those technologies may result in discrimination on the basis of gender, race, and age of the persons [3]. AI models are traditionally considered black boxes, and therefore, it is extremely difficult for a person to comprehend the mechanism of making decisions according to the algorithm [4]. Also, controlling the candidates' attitudes towards the use of AI models in recruitment is rather complicated since candidates tend to favor human-made decisions [5]. The problem in question is not only interesting for scientific debate. Practically, HR specialists often encounter the same kind of issue and think about whether process orientation should prevail over personal judgment. The central challenge stays the same—how can one ensure human values in pursuit of efficiency in hiring procedures?

However, it is worth mentioning that the existing literature does not consider the problem that occurs due to the introduction of AI tools for recruitment. To start, the current body of research on AI-HRM cannot integrate efficiency and humanism aspects theoretically [6]. Moreover, empirical research in the area mostly focuses on studying organizations located in North America and Western Europe, which makes this field lack practitioners' views from developing countries, including China [7]. Importantly, geographic location is not the only difference since China's technological revolution in major cities includes specific elements, such as state-driven creation of AI policy in different industries and a context where the state coordinates training and allocating talent [8]. Taking into account such features of the Chinese context together with growing competition in cities' struggle for AI talent and rapid development of platform businesses, certain institutional factors may influence the process of recruiting AI talent differently than current theories suggest. In particular, when it comes to AI-HRM, quantitative research dominates and helps explore correlations between constructs; still, it does not provide insight into how HR professionals manage conflicts they face [9]. Previous research on AI-HRM has studied such factors as trust in AI, algorithmic transparency, and algorithm aversion that affect individuals' perceptions and experiences with AI tools. Nonetheless, the way practitioners' behaviors are influenced by organizational-level accountability structures remains unstudied. This issue refers to institutional mechanisms that influence whether and how HR specialists make their own judgments while working in conjunction with AI technologies.

This paper examines the problem of organizational efforts to balance efficiency-oriented goals and human-oriented values in the deployment of AI-driven recruitment technologies in connection with the digital transformation process of Chinese cities, especially Shanghai. The following research questions inform the analysis: (1) How do the HR practitioners from Shanghai perceive the impact of AI recruitment technologies on efficiency? (2) How do the HR practitioners perceive the importance of human-oriented values of transparency and agency when using AI recruitment technologies? (3) What facilitates or hinders the deployment of human-oriented AI recruiting technologies? To address these research questions, a qualitative exploratory methodology was used, with primary data collected through interviews with eight HR professionals from Shanghai.

The most valuable theoretical contribution made by the study includes the formulation of asymmetric algorithmic accountability. While trust pertains to the willingness of individuals to trust in a system and transparency is associated with the interpretability of algorithmic methods, asymmetric algorithmic accountability refers to the structural reality at the level of the organization: whenever AI-based recommendations become available, the cost of overriding those recommendations becomes individualized, while the cost of implementing those recommendations, no matter the result, is assumed by the organization since doing so is procedurally correct. Rejection of the algorithm's recommendation means that the practitioner becomes personally responsible for the failure to perform properly, but acceptance of it shields the practitioner from such blame regardless of the results. Hence, asymmetric algorithmic accountability creates rational incentives for practitioners to adopt the decision made by the algorithm. Namely, inexperienced staff may find themselves incapable of developing autonomous evaluation when their early-career decision-making is left to automation. With the help of asymmetric algorithmic accountability, it becomes possible to expand the scope of analysis of the human-machine collaboration theory by adding a new dimension to it—organizational accountability mechanisms—to traditional dimensions such as trust and transparency. The study views AI-based hiring procedures as an example of a two-fold process where the focus is both on efficiency and

on humans. This research contributes to the literature on human-machine collaboration in three main ways: firstly, by proposing a notion of asymmetric algorithmic accountability that demonstrates how incentive structures of organizations can influence the process of human-machine interaction; secondly, by examining the patterns of interaction in context-specific environments within the Chinese institutions; thirdly, by providing empirical insights into human-machine collaboration that can be used by managers to preserve professional judgment during AI-assisted hiring.

2. Literature Review

2.1. The Evolution of AI Recruitment Technology and Efficiency Debates

The development of recruitment technologies with the help of artificial intelligence represents an evolutionary approach starting from the simple automation of tasks and ending with the use of intelligent algorithms. In the earliest applicant tracking systems (ATS), keyword searching was the main tool for sorting out resumes. That implied that such systems were limited to data management only. However, thanks to machine learning and natural language processing innovations, there emerged intelligent systems that today enable ATS to conduct semantic analysis, candidate profiling, and predictions of job-matching [10]. What is more, according to some claims, certain ATS can assess candidates' cognitive abilities and personality by analyzing video interviews. It has become possible to implement AI solutions in every stage of recruitment procedures, including job postings optimization, smart resume screening, chatbot-based pre-interviews, and video interview evaluation.

The major driving force behind the utilization of AI technologies lies in boosting efficiency. International organizations are faced with two challenges, including problems related to personnel recruitment and increasing application volumes. AI technologies are viewed by international organizations as the best solution to improve hiring efficiency, with expected cost reductions [11]. The efficiency gains mentioned by the vendors include hiring candidates 50% faster, screening ten times more resumes, and reducing hiring costs by 40%. The expected benefits have resulted in growth within the market of AI-based recruitment platforms and raised the bar for performance.

However, there remains a disparity between the promises made and those delivered. The problem of algorithmic bias becomes the most critical concern. This is because biases present within databases and biases unintentionally placed in algorithms themselves represent major problems. Furthermore, the lack of clarity about the usage of the "black box" algorithms in AI prevents the identification of these biases and, therefore, the resolution of associated issues [12]. The empirical findings indicate that the application of AI-based recruiting procedures results in negative consequences, especially for non-binary individuals, women, minorities, and disabled individuals [13]. Effectiveness, validity, and justice in conducting video interviews through AI recruitment tools have not received adequate attention, showing clear deficiencies in discriminant validity in extant studies [14].

Another crucial consideration in AI-enabled recruiting is the reaction of job applicants. The automated nature of AI-driven recruiting reduces the sense of control experienced by candidates, resulting in increased levels of ambiguity and uncertainty among candidates in recruitment interviews [15]. The emotional state can impact behavior, as job candidates' attitudes towards AI-enabled recruiting determine application intentions [16]. The use of human recruiters alongside AI systems has proven to yield positive reactions from applicants, although this is contingent upon the pre-existing knowledge applicants have about AI-based recruitment systems [17]. Purely technology-oriented substitutes might prove detrimental, while a combination of human and AI recruitment might be more effective. However, what has yet to be determined through this body of literature is how the disparity between the promises of vendor efficiency and the realities of practice experiences plays out organizationally and how practitioners manage that disparity through their work.

2.2. Human-Machine Collaboration Theory and Its Applicability to Recruitment Contexts

Human–machine interaction theory provides key insights into the conflict between efficiency and human-centric issues in the context of AI-based recruitment. The basic principle of hybrid intelligence is that people and artificial intelligence each have certain competencies that could be complemented by each other in working together [18]. People can deal effectively with uncertainty, engage in ethical thinking, use social skills, and develop emotional connections. On the other hand, AI machines perform excellently at pattern recognition, big data analysis, consistency, and stamina. The best approach to hybrid intelligence is synergy rather than substitution.

How can the idea of hybrid intelligence be used in the context of recruiting? In line with research on hybrid problem-solving, three modes of human-machine collaboration are distinguished: autonomous search, where the machine works alone and results in exploration; sequential search, where the collaboration between human and machine is conducted in turns and produces incremental optimization; and interactive search, where the collaboration happens simultaneously, producing recombinative results [19]. The following is how this may be understood in the context of recruitment: AI system carries out the initial resume screening before HR evaluates the outcomes; AI provides the ranking of the candidates, which HR references; and HR interacts with the AI system in real-time to change the selection criteria.

Machines as "team members" rather than just tools have expanded the field of research. Studies conducted using such an approach recognize three areas of design and 17 sets of factors that may either lead to positive or negative effects [20]. The attempts to develop human-centered interpretations of human-machine teams indicate that the current research has been mostly technology-based or engineering-based, with few human-centered approaches developed [21]. Six principles govern the design of intelligent organizations in relation to human-machine interaction: augmentation, relevance, substitution, diversity, collaboration, and explanation [22]. The principle of explanation dictates that the reasoning process used by AI for decision-making should be clear and traceable to human beings, and this is especially important in human resource decision-making, such as hiring employees.

Trust is another critical element of human-machine interaction that involves cognitive and affective components. Cognition-related factors like transparency, reliability, and feedback influence trust, while anthropomorphism influences affective components of trust [23]. Studies on explainable AI indicate that the process of explaining the decision involves various stages, with the most crucial one being the ability of the AI system to provide reasons for its decision and the capability of the person receiving the reason to comprehend the rationale behind it [24]. It means that the transparency of the system should be designed in a way that does not overwhelm the users [25].

However, even an effectively designed system can face rejection by its users. Several elements have been found to affect the acceptance or rejection of algorithmic decision-making by users, classified into four levels: algorithm attributes, user attributes, task attributes, and organizational attributes [26]. Within human resource management, the sense of justice varies between AI-influenced decision-making processes and human decision-making processes, with the latter being viewed as more dignified despite the former being acceptable when the results are favorable [27]. Therefore, the use of AI technology in hiring systems depends on how the systems operate and what kind of results they produce. The question that requires further examination concerns the impact of such accountability mechanisms on practitioners' willingness to think independently when they come up with a judgment that conflicts with what the algorithm recommends. The question of who ends up paying for a situation where a practitioner challenges the system needs to be answered.

2.3. Limitations of Existing Research

Based on the previous discussion, this study highlights some of the research gaps that it aims to fill. The process of knowledge creation in relation to AI-HRM is disjointed. Relevant literature is scattered in areas like information systems, organizational behavior, human resource management, and computer science. Theories arise because academics come from various academic fields, and in certain situations, theories are completely opposite to each other. This is mainly due to a lack of interdisciplinary communication among academics, and there is a need for more theories [28]. An integrated viewpoint that provides insight into how HRM practitioners use these tools, interpret system-generated results, and balance efficiency and humanity requires an interdisciplinary perspective.

The geographical distribution of research has major consequences. The majority of literature written in the last five years, on AI technology and its usage in the recruitment process focuses on companies operating in North America and Western Europe. As mentioned in the introduction, the institutional context in China has features that impact how the AI labor market works. This includes the strong involvement of the government in both the development of the AI sector and the distribution of the workforce [8], the presence of state, private, and foreign firms with different levels of accountability, and the competitive pressure resulting from the fast-paced digitization of cities. Shanghai is one of those cities.

From a methodological perspective, the reliance of the field on survey and experimental research designs constrains the extent of possible insights. Although surveys and experiments can be instrumental in uncovering link-

ages between variables and testing causality, they fail to encompass the process and experience aspects that are central to AI-powered recruitment. Indeed, AI-powered recruitment takes place in a highly complex organizational setting where the use, interpretation, and rejection of such systems by human resource management practitioners are linked to organizational processes and professional identities.

Additionally, there is no agreement on the definition and measurement of fairness. Fairness can mean different things to different organizations, HR practitioners, and candidates. The definition and measurement of fairness in AI recruitment should be further studied across disciplines [29].

Lastly, and most relevant to the current study, existing research on human-machine cooperation in the context of recruitment has focused mainly on issues of trust, transparency, and user acceptance, whereas there is an urgent need to explore how accountability within organizations impacts the actions of the practitioners. The question of who should be responsible for following or ignoring the machine's recommendation is vital to the topic of professional autonomy but has been largely neglected theoretically.

The research contributes to a provisional theoretical framework that considers the impacts of AI-based recruitment as the result of the relationship between efficiency and humanism, specifically considering the role of accountability disparities in moderating such a relationship. Organizational type, experience, data accuracy, and digitalization maturity level also influence the results. **Figure 1** presents this conceptual framework.

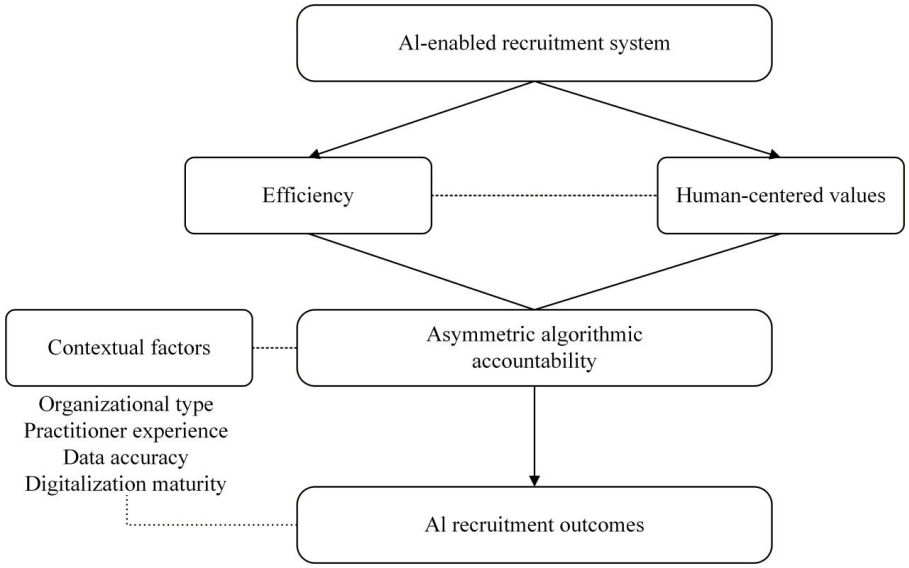


Figure 1. Conceptual framework of AI-enabled recruitment.

3. Research Methods

3.1. Research Design and Context

This study employs an exploratory qualitative research methodology using interviews as the primary data source. The research questions posed in this study concern the experiences and practices of human resource management practitioners who utilize AI technologies in their work routines. Such research questions have a process-oriented nature and are concerned with the way the outcomes of AI technologies are understood and negotiated, as well as the process of interaction between HRM practitioners and AI technologies over time. This kind of research cannot be categorized under any pre-existing variables or measured using ordinary tools, making qualitative research more suitable for this study [30]. The selection of Shanghai as the research location is based on its prominent position in the development of AI in China. According to the figures revealed by the Shanghai Municipality Commission of Economy and Informatization in March 2026, the total number of large AI companies in Shanghai was 394 during 2025, with an economic scale exceeding 637 billion RMB. The reason behind the rapid growth rate lies in the extensive digitalization in Shanghai firms and stiff competition for labor in the area, resulting in an atmosphere where AI recruitment platforms are used beyond experimental trials.

3.2. Sample and Data Collection

Purposeful sampling was applied to select HR personnel in Shanghai utilizing AI technology for recruiting purposes. Initially, individuals were identified using the personal connections that the researcher had in the area of human resource management, as well as contacts gained via LinkedIn and professional associations in the HR industry. Further contacts were acquired via snowball sampling, in which initial interviewees recommended their fellow employees from other companies, meeting the selection criteria. The selection criteria involved the principle of maximal variability, ensuring the variety of individuals along several lines, including organization type (government-owned, private, foreign), industries, organizational level, and degree of utilization of AI in recruiting processes. In particular, the selected individuals varied across all organizational levels, from recruitment specialists to directors. Overall, a total of eight HR individuals were included in the final sample. The information on the interviewees is provided in **Table 1**.

Table 1. Basic Information of Interviewees.

ID	Gender	Industry	Organization Type	Organization Size	Position	Years in HR	Duration of AI Recruitment Use
P1	Female	Technology/Internet	Private Enterprise	Large	Recruitment Manager	8 years	3 years
P2	Female	Finance	Foreign Enterprise	Large	HR Director	15 years	2 years
P3	Male	Manufacturing	State-owned Enterprise	Large	Recruitment Supervisor	6 years	1.5 years
P4	Female	Professional Services	Private Enterprise	Medium	Recruitment Specialist	3 years	1 year
P5	Male	Technology/Internet	Foreign Enterprise	Large	HRBP	10 years	3 years
P6	Female	Pharmaceutical/Healthcare	Private Enterprise	Medium	Recruitment Manager	7 years	2 years
P7	Female	Finance	State-owned Enterprise	Large	HR Manager	12 years	1 year
P8	Male	Manufacturing	Foreign Enterprise	Medium	Recruitment Supervisor	5 years	2.5 years

The interviews took place from October to December 2025 through remote or personal visits, ranging from 45 min to 1 h. All interviews were conducted in Mandarin Chinese. The interview guidelines had three themes: (1) AI use and process, which included the kind of AI recruitment systems used by the company, the range of functions performed by the tools, and how often AI is used in recruiting processes; (2) efficiency and human value perception, which discussed how efficient the tool improved the recruitment process, experience with transparency and explainability, perspective on human autonomy, and candidate experience; and (3) implementation difficulties and coping mechanisms. However, the interview guide was formulated to be open-ended rather than a rigid set of instructions. After conducting the initial two interviews, certain questions were modified to reflect the language used by professionals while talking about their relationship with AI. Abstract questions had to be revised to make them context-specific, thus ensuring that the practitioners would refer to their experience and not make theoretical claims.

The interviews' audio records were the main data source and were recorded with the consent of the interviewees. The total number of transcriptions is 70,000 characters. An average transcription of each interview was approximately 7,000–10,500 characters depending on how heated the discussion became. Since all interviews took place in Mandarin Chinese, transcriptions had to be translated into English by the researcher. The researcher is fluent in both languages and possesses extensive experience in translation services. To make sure that there were no mistakes in translation, the back-translation method was used for some transcripts randomly selected from the total pool. Differences between the original transcript and the back-translated version were reviewed until consistency was achieved. The key terms and phrases that were culturally bound were kept as such with the English equivalent provided.

The criterion of data saturation was continuously considered during data gathering. Data saturation occurred after conducting the sixth interview since core themes emerged constantly from all participants with reference to the issues of the perception of efficiency, human-machine interaction, and the implementation process. Two more interviews were conducted to confirm this conclusion, and since no new themes arose from them, data collection came to an end. Despite the small number of participants being interviewed (eight), it seems appropriate for a qualitative study, which places emphasis on depth rather than breadth. Considering the information power approach, this small sample seemed appropriate under the current circumstances.

3.3. Data Analysis and Research Quality

The data analysis took place based on the reflexive thematic analysis [31], with a set of sequential steps consisting of data familiarization, creation of codes, exploration of themes, examination of themes, definition of themes, and the development of a report at the end. The analysis was executed via NVivo 14. The technique comprised deductive and inductive coding methods. The deductive codes were obtained based on the theoretical constructs outlined during the literature review, among which were categories like efficiency perception, algorithm transparency, AI trust, human agency, and modes of hybrid intelligence cooperation. The pre-existing categories served as a template for structuring data. On top of that, the inductive method was used simultaneously in order to identify patterns in the interviews independently of any theory. When inductively generated codes overlapped with deductive categories, they were merged; when they did not fit any existing category, they were retained as new codes. As a result, an initial set of 87 codes was generated, then further narrowed down to 14 sub-themes which were eventually categorized into three broad themes corresponding to the research questions posed. Asymmetric algorithmic accountability was not part of the original coding structure, but it was an emergent concept that came up when a recurring theme in the dataset could not be satisfactorily conceptualized using any pre-existing theoretical ideas. Reflexive memos were kept during the whole analysis process as a way of recording how the researcher's understanding of the material changed and instances where past presuppositions may have colored the coding process.

In analyzing data, consistencies as well as differences among different participants who came from various organizations and hierarchies were considered. Transcripts were grouped by organizational type, and coded segments were compared across these groups to identify patterns that were shared across contexts as well as those that appeared to be specific to particular organizational settings. For instance, codes related to algorithmic transparency appeared across all organizational types but carried different practical implications depending on whether the organization was a foreign enterprise with compliance requirements or a state-owned enterprise with documentation obligations. The discussion of the findings is sufficiently detailed to enable readers to determine the transferability of the results. Member checking was conducted through the presentation of initial interpretations to three individuals selected from different organizations. The response was mainly supportive of the researcher's interpretation, but also highlighted areas that needed more focus, and these were included in the final analysis. The research process maintained consistent coding and thorough documentation of the codes. **Table 2** presents the thematic structure with representative quotations for each sub-theme.

Table 2. Thematic Structure and Representative Quotations.

Theme	Sub-Theme	Representative Quotation
Efficiency perceptions	Screening speed improvement	"Reduced the duration of the initial selection process from two to three days to about half a day" (P1)
	Accuracy and bias tradeoffs	"There were some good candidates whose resumes were not properly formatted or did not contain the right keywords" (P4)
	Gap between promised and actual efficiency	"It would be best to be skeptical when vendors claim efficiency can be increased by specific percentages" (P2)
	Data quality dependency	"Initially, my company received resumes in bad shape, with no standard format and non-standard tags" (P5)
	Implementation workload	"At first there was not enough faith in the system, which led to people continuing to do their jobs the old way and then using the system to double-check" (P6)
Transparency and human agency	Algorithmic opacity	"In a way, it is like a black box. Input goes in, output comes out, and I don't quite know what happens between those two" (P1)
	Organizational approaches to transparency	"The vendors should clearly explain the logic behind the screening process because without that, they won't pass the compliance test" (P2)
	Accountability asymmetry	"If the person hired ends up having problems, then it's my responsibility… So gradually it becomes safer to just go along with the system" (P4)
	Senior practitioners: augmented agency	"With less repetition in screening, we can focus on talent mapping, communication between candidates, and recruitment strategy advice" (P5)
	Junior practitioners: constrained agency	"Feeling like I'm working for the system" (P4)
Implementation factors	Management support	"The success of the project will face obstacles if it is implemented exclusively by the HR Department, without support from the executives" (P2)
	Departmental cooperation	"No matter how intelligent the system is, garbage in, garbage out" (P6)
	System integration challenges	"Data does not move from human capital management, recruitment, assessment, and new AI systems" (P1)
	Organizational culture	"Government organizations prefer stability and therefore have low adoption rates of new technology" (P7)

Ethical approval for the study was obtained from the institutional review board for research in the humanities and social sciences. All participants were apprised of the goals of the study and how the data would be utilized, and all gave their informed consent in writing. Participant data were kept confidential during storage and analysis, using codes P1–P8 for the participants. The researcher is academically qualified in HR management and organizational behavior. Before conducting the research, the researcher had assumed that the use of AI-powered recruitment software tools would mostly revolve around issues of efficiency, with human-related matters being secondary in terms of priority for companies. However, after conducting interviews, the practitioner's experience with such tools proved more complex than originally hypothesized by the researcher. The actual experience of practitioners differed from initial assumptions and necessitated reflexivity on behalf of the researcher.

4. Findings

4.1. Human-Machine Collaboration Patterns and Efficiency Perceptions

AI recruiting technology adoption at the firms conducting interviews was different in many ways. Tech firms, internet firms, and foreign firms appeared more willing to adopt the AI recruiting technology suite, which included resume analysis, talent evaluation, and interview scheduling. Meanwhile, state firms and mid-size private firms relied on single-purpose AI technology, specifically intelligent resume filtering.

In terms of collaboration models, three different methods were identified through the interviews, as shown in **Table 3**. The majority of interviewees applied a sequential method where AI screening was conducted prior to human screening. The AI screening tools provided results to HR staff members on a daily basis and sorted candidates based on matching scores. HR staff then focused on high scorers, whereas middle and low scorers were evaluated quickly or ignored altogether. According to P1, such an approach "reduced the duration of the initial selection process from two to three days to about half a day". The company where P3 worked found this approach particularly beneficial during peak recruitment seasons.

> *"During peak season, several thousand resumes can come in within a week. Screening all of them manually is simply impossible. After getting the system, at least the obviously unsuitable ones can be filtered out first, and then we can concentrate our energy on reviewing the rest. The efficiency improvement in this area is tangible and real. Otherwise, we would literally have to work overtime until we collapsed." (P3)*

Table 3. Human-Machine Collaboration Patterns by Organization Type.

Organization Type	Dominant Pattern	AI Role	Representative Participants
Technology/Internet	Interactive adjustment	Co-learner	P1, P5
Foreign enterprises	Sequential review with compliance oversight	Screener with accountability requirements	P2, P8
State-owned enterprises	Human-dominant	Process legitimizer	P3, P7
Medium private enterprises	Sequential review	Efficiency tool	P4, P6

Some organizations adopted an interactive form of collaboration, as described by P5 as a "continuous learning process." For instance, when recruiting employees, he noted that individuals who had the requisite technical skills faced difficulties integrating into teams and hence altered the weights for soft skills in the system. The interactive model assumed some level of understanding on the part of practitioners about how the system worked. Consequently, such solutions appeared to be used more often in firms that are highly digitalized. For state-owned enterprises, the use of AI was considered mainly as supportive technology, but not as a decision maker. This point was well highlighted by P7 when stating, "The company's position is very definite: AI is a tool, but not a decision-maker." In regard to managerial and key technical roles, P7 noted that "resume processing in the system is more symbolic; the actual screening is performed by human evaluators." P3 made a similar observation: In his organization, the system was not considered more reliable but rather for its ability to show compliance with the process.

Efficiency improvement proved to be the most commonly mentioned benefit of using AI technologies in recruitment. All eight interviewees noted efficiency improvement during preliminary selection, although it could be applied only to highly standardized and automated procedures. With the increase in job level and decision complexity, there is a significant reduction in the use of AI. In other words, efficiency gains were conditional on task type: AI performed well in high-volume, standardized screening tasks but contributed little to complex evaluative

decisions that required contextual judgment.

However, efficiency gains did not necessarily translate into improvements in accuracy or fairness, and these three dimensions did not always move in the same direction. There is a trade-off between efficiency and accuracy, such that the system may sacrifice accuracy for efficiency. One of the participants, P4, noted that in reviewing rejected resumes, "there were some good candidates whose resumes were not properly formatted or did not contain the right keywords." P8 drew attention to the particular circumstances of manufacturing frontline workers:

> *"In our manufacturing industry, many frontline workers are older with lower educational levels. Their resumes are written quite simply, and some are even handwritten, requiring us to help enter them into the system. This type of resume definitely suffers in AI evaluation, receiving very low match scores. But that doesn't mean these people are unsuitable for the positions. After so many years of work, many veteran craftsmen have very solid technical skills. We pay special attention to this point. We cannot let technological barriers keep suitable people out." (P8)*

These two cases are proof positive that the program favors skills of presentation over credentials. For people who lack an ideal resume, this issue is particularly significant. The problem pointed out by P4 is one of inaccuracy, which means that the application of keyword matching creates false negatives in the case of qualified applicants. On the other hand, the situation highlighted by P8 involves issues related to discrimination, in that the criteria used in evaluating individuals unfairly penalize members of specific demographics, such as seniors and uneducated individuals.

Moreover, consideration must be given to the gap between the expected increase in efficiency and the results actually obtained. Although the differences existed in terms of the levels of efficiency of software vendors and HR managers, the position of P2 management was quite cautious: "One must be very wary of vendor statements claiming increases in efficiency by a certain percentage." During the implementation stage, the extra workload was considerable, whereas improvements were lower than what vendors expected later on. P6's case is relevant in this respect: in the beginning, there was insufficient confidence in the system, which resulted in people carrying out their duties in the traditional manner and cross-checking their results with the help of the system. In fact, during the implementation stage, the workload became greater in the short term as practitioners carried out two tasks in parallel – a manual process followed by an automated one. The extra workload eventually decreased with time because of growing confidence in the system and better quality data; however, the final outcome still proved to be lower than initially claimed by vendors. The length of the transition period depended on the accuracy of the data entered into the system and the extent of its adoption and integration. Even though the transition period ended, some participants in the interviews viewed the outcome as a minor improvement.

4.2. Transparency and Human Agency Experiences

Algorithmic transparency stood out as the issue most mentioned in relation to human-centered values. In general, it was observed that interviewees showed little understanding of how the algorithm worked. To illustrate, participant P1 described her experience using the system in these words: "In a way, it is like a black box. Input goes in, output comes out, and I don't quite know what happens between those two." The relatively vague nature of the training offered by vendors hampered users' ability to justify the system's decisions. Lack of clarity was associated with difficulties in implementing the system. An example is provided by Participant P3, who indicated that "I also could not explain the rationale behind the decision made by the system, so I suggested conducting another screening manually."

Various organizations showed different focuses on transparency and methods for dealing with the issue. International companies had to adhere to the rules made by their parent companies, which is why explainability was taken into consideration when evaluating vendors. Participant P2 shared that "the vendors should clearly explain the logic behind the screening process because without that, they won't pass the compliance test." State-owned enterprises focused on transparency due to accountability concerns. P7 explained:

> *"State-owned enterprises emphasize having documentation for everything. Recruitment problems require accountability, and if AI was used, it becomes very troublesome if you can't explain why this person was*

screened out or why that person was recommended. So while we use it, key stages still require human oversight to leave an audit trail. You can't tell leadership that AI decided this and I don't know why." (P7)

Private organizations showed some apathy towards the transparency of the technology; their primary goal being functional efficiency and scalability, they gradually ventured into exploring the threshold between humans and machines. Nonetheless, regardless of differing goals, the outcome was always the same, and not one of the users felt they were sufficiently aware of the mechanisms that went into the system's decision-making process.

It appeared that perceptions about the role of human agency differed depending on the level of experience of those participating in the discussions. Experienced and senior participants looked upon the technology in terms of its ability to allow engaging in high-priority activities. As P5 expressed, "With fewer repetitive tasks performed during the screening stage, it will enable me to focus on talent mapping, communications between candidates, and advice on the recruitment strategy, among others." Likewise, participant P2 also expressed similar ideas: "My personal impression is that thanks to AI, we can focus on more important activities, such as having the conversation on talent planning with the BU heads, developing the image of the company, etc." However, the less experienced users saw the technology as reducing human agency. As participant P4 stated, they "sometimes feel like they were working for the system":

"The system says this person is suitable, so you schedule an interview; the system says that person won't work, and you don't have much basis to overturn it. Of course I can choose not to follow the system, but if the person hired ends up having problems, then it's my responsibility. Who bears that responsibility? So gradually it becomes safer to just go along with the system. After all, if the system recommended them and something goes wrong, it's easier to explain." (P4)

In P4's account, there is an imbalance in the allocation of responsibility between the practitioner and the system. Overruling the algorithm involves some risks on the part of the person involved, while following the recommendation of the algorithm, even though it may produce unfavorable results, can be considered reasonable because it carries no risk. P6 made this claim from the perspective of a manager, adding, "They don't have enough experience, so a system that backs them up is more comforting." However, she made another observation at the same time: "I'm concerned that, in the long run, they won't get a chance to develop judgment." The two arguments presented in P6 contradict each other. While the system's provision of short-term support for junior workers could be hindering their professional growth in the long run, there is no apparent solution in the current organizational culture.

The gap between senior and junior professionals' experience levels has been constant among all organizations, as illustrated in **Table 4**.

Table 4. Perceptions of Human Agency by Practitioner Experience.

Practitioner Experience Level	AI as Augmenting	AI as Constraining
Senior/Managerial (P1, P2, P5, P7)	Frees time for strategic work; maintains decision authority	—
Mid-level (P3, P6, P8)	Acknowledges efficiency gains	Recognizes the risk of junior staff dependence
Junior/Specialist (P4)	—	Feels pressure to comply with the system; limited basis for overriding

Another aspect of human-centered design is concerned with candidate experience. P1 mentioned that based on the feedback from candidates, the interactions "seemed to be mechanical, without any human element." As a result, they improved the wording used for automated responses and added some human elements at specific checkpoints. P5 offered a somewhat unique perspective by stating, "a bad candidate experience is passed on through word of mouth and affects recruiting, particularly in an industry like ours, where the network is not extensive." While many participants thought about the candidate experience, whether this thinking would actually lead to better system designs was unclear.

4.3. Factors Facilitating and Hindering Implementation

The introduction of recruitment technology systems driven by artificial intelligence gives rise to complex issues associated with the organizational context, the technological context, and the human context that go well beyond

mere technical implementation. The contexts are not separate but interrelated, and together affect the process of implementation.

The most influential factor was executive endorsement. In the opinion of participant P2, "the success of the project will face obstacles if it is implemented exclusively by the HR Department, without support from the executives." From her perspective, the possibility for implementation arose because "the CEO supported the process and called it digitizing the company at the executive board meeting." It is extremely hard to achieve integration and coordination without it. Obstruction to implementation was most notable at the public company where P3 worked because the problem lay in a lack of interest in AI and other new technologies. The only possible way forward, therefore, was through the process of gradual implementation: starting with resume screening, then showing the outcome to management before scaling up systematically.

Cooperation from hiring departments proved equally critical but often difficult to ensure in practice. P6 stated bluntly that "no matter how intelligent the system is, garbage in, garbage out":

> *"Many business owners provide extremely general descriptions of the position available, and they change their expectations each time. One day they say they need three years of work experience, the other day it changes to two, and finally, it becomes necessary to have experience in leading a team. Of course, as expected, the results will be inaccurate. The problem does not lie with artificial intelligence because its output depends on the input. The cost of communication in this process is rather high sometimes and even higher than manually sorting through resumes." (P6)*

In situations where the efficiency of the system is compromised due to unclear input information, the technology itself ends up being blamed, leading to the erosion of faith in AI-driven recruitment within the organization, thus making it difficult to implement. This, in turn, increases conflicts between the HR department and other departments.

Data quality and system integration posed constant technical hurdles that were related to the organizational issues mentioned earlier. As Participant P5 explained, "Initially, my company received resumes in bad shape, with no standard format and non-standard tags." After the implementation of the system, almost seven months were spent cleaning the data, which far exceeded expectations. Looking back, data management should have been done before implementing the system since the need for such was only realized when the implementation process had already started. Another issue that the interviewees experienced was inefficiencies due to having several systems running concurrently. As participant P1 mentioned, "Data does not move from human capital management, recruitment, assessment, and new AI systems, and there is an extra task of manually exporting data." Sometimes, the advantages of increased efficiency due to the use of AI technology were offset by the process of transferring data. The above statements reveal that the efficiency improvement observed in Section 4.1 was directly related to the data infrastructure.

The culture of an organization had a significant effect on the adoption of AI technology by employees. According to participant P7, "Government organizations prefer stability and therefore have low adoption rates of new technology." While introducing the technology into practice, some employees showed resistance out of fear of being replaced by the new technology. On the other hand, the atmosphere within technology and internet companies was completely different, as participant P1 noted: " The adoption rate of AI technology in the technology and internet industry is high, hence less persuasion is required." In cases where problems arose, the predominant response was to "give feedback and iterate," treating the AI implementation as a product requiring iterative improvement. "The manufacturing setting is unique," P8 explained, "as our HR team is older, and hence some people find themselves less familiar with the technology, leading to the need for further training."

Implementation results were affected by the capability of the vendor as well as the quality of services offered. As P4 pointed out, "whenever there was an issue with the system and end-users called the vendor for assistance, they received different responses depending on the issue at hand, ranging from immediate resolution to leaving some tickets unattended for several days". In addition, as pointed out by P3, "some changes to the desired features required scheduling by the vendor, which sometimes took several months to be accomplished".

As a solution to the above-mentioned issues, various strategies have been adopted by the involved organizations, according to the interviews. Gradual implementation became one of the main methods, starting from sim-

pler tasks like resume screening and scaling up as time went on. P2 explained the concept of "delegation of high-frequency, low-risk tasks to AI, while low-frequency, high-risk tasks remained the human domain." While screening resumes on a large scale using AI was possible, the hiring decision itself, negotiating salaries, and conducting background checks remained in the hands of humans. Establishing proper boundaries helped reduce stress resulting from the roles of the practitioners. Apart from this, a platform was created through which departments in P5 could work together. As observed in the case study, "there was a project team for recruiting employees specialized in AI, including representatives from HR, IT, and the business unit."

5. Discussion

5.1. Theoretical Dialogue and Contributions

Results of this study will be useful in developing theoretical knowledge in three related areas: (1) discrepancies between expected and actual efficiency in recruiting through artificial intelligence, (2) variations in human-computer interactions depending on the context of those interactions, and (3) the role of accountability in practitioners' actions.

It should be noted that the discrepancy between expected and actual efficiency gain is not a discovery because the same conclusion was drawn by researchers conducting previous studies in other settings [32,33]. Nevertheless, this research sheds light on particular factors causing reduced efficiency gains. Poor quality data is associated with decreased efficiency, imprecise job descriptions of HR recruiters may lead to inefficient output and employees' doubts create parallel computer-human interaction operations. As seen from the discussion above, efficiency gains cannot be considered to be an automatic consequence of applying AI technology for recruiting. In other words, efficiency gains depend on several determinants, including data management, process redesign, and change management [34].

Moreover, the results indicate that improvement of efficiency may lead to a decline in accuracy. For instance, such statements as "screened out for lack of keyword match" and "poorly evaluated by the AI because the resume was not in any particular format" clearly demonstrate the obvious and inherent limitations of algorithmic screening techniques. The latter are supposed to be efficient and quick but certainly not accurate. Front-line manufacturing employees, candidates following a non-conventional career path, and individuals with weak skills regarding resume writing are presumed to stay disadvantaged in accordance with the efficiency paradigm. Academic debates over the problem of objectivity, efficiency of technological tools, and their implications for equal access have already been analyzed regarding algorithmic recruitment bias [35]. However, the present research provides some additional empirical insights into the problem of recruitment in China. Algorithmic recruitment bias does not refer to the final result of using artificial intelligence but is the key element of the whole process.

Regarding human-machine collaboration practices, the emergence of three human-machine interaction practices in the present research contributes to the existing theoretical framework on the use of hybrid intelligence in recruiting activities. These collaboration practices, including sequential review, interactive adjustment, and human dominance, did not appear by coincidence, but rather were largely affected by the degree of digitalization, accountability culture, and resources. Although it can be said that the interactive adjustment method would yield the highest innovative performance [19], its implementation in recruiting depends on whether recruiters possess adequate knowledge of how the system works and whether the organization can conduct experimentation iteratively. It is expected to take place in high-tech organizations and multinational organizations, but not in SOEs and SMEs.

The "human-dominant" approach found among state-owned companies can be viewed, according to hybrid intelligence theory, as an underestimation of AI's capabilities; however, from the perspective of organizational rationality, such an approach remains consistent internally because of a predominant tradition of accountability at such enterprises, which necessitates that decision-making be not only documented but also validated. The ambiguity of AI compromises this prerequisite, and the safeguarding of human discretion is a logical strategy in achieving the balance between technology and organization. Progressive integration in AI and HRM [36] may not precisely describe the reality in practice. Firms have different levels of integration in AI within their HRM practices, adopting the levels that fit their individual institutional logic instead of pursuing integration as an end in itself. There is no best answer for human-machine collaboration; what matters most is the outcome, not the degree of maximization.

The theoretical value of the study lies in the introduction of the notion of asymmetrical accountability in relation to algorithms and its impact on professional autonomy. The difference between current literature based on problems of trust and transparency and the paper presented here is that the role of accountability in relation to the congruence of the professional behavior and AI-based mechanism is revealed. That is why the findings reveal a certain tendency which means asymmetry of accountability between the professional and the machine, thus contributing more to our understanding of human-computer interactions. Asymmetric accountability in the interview is shown to affect the behavior of the practitioners by the way of distributing consequences from compliance or non-compliance with the algorithm. Even those practitioners who do not trust or even understand the imperfection of the machine still follow the outputs of the latter because of certain norms of conduct in their organizations. This type of accountability can lead to dependence on such systems, making it difficult for the professionals to disobey AI decisions. The technology-HRM development paradox is that situations in which technologies are expected to boost human abilities often end up constraining the development of the human resources in question [37]. An example of such a situation occurs when recruiting employees, whereby experienced professionals let algorithms dictate outcomes.

The experiences of the senior members differed from those of their juniors. The senior people tended to make arguments about how the introduction of artificial intelligence created a situation that facilitated focus on necessary work, while their juniors always found themselves faced with constraints in exercising their skills. These differences may be explained by the mechanisms of power in organizations. Individuals in more senior-level roles have more institutional resources to establish priorities and greater discursive capabilities to define the relationship between humans and machines. Thus, the issue of power relations in AI-powered recruitment extends beyond the dyad formed by organizations and job applicants [38] to include relations between practitioners at various organizational levels. Inquiry into the actors who benefit or lose from implementing AI technologies in organizations is therefore both technological and organizational.

A unique perspective provided through the case of Shanghai provides insights into the situation-specific nature of AI use in recruitment. The balanced approach of the state-owned companies represents their focus on maintaining an accountable culture along with stability, while the principle of "feedback and iteration" followed by the technology firm reflects the goal of achieving maximum efficiency of AI systems. Digitalization in terms of governmental policy acts as an extrinsic stimulus towards the introduction of AI, which contrasts with Western countries, where market dynamics serve as the main driver. The nature of strategic human resource management as a tool for governance at the point of connection between human and technical factors [39] depends on different institutional contexts. Intensifying competition for a qualified workforce is contributing to an increased need for efficiency along with a growing focus on candidates' experience.

5.2. Practical Implications

The insights imply a staged process for implementing AI-driven recruiting systems based on successful approaches described by the practitioners participating in this study. First, the organizations can implement AI in areas with large volumes of activity and relatively low risks. The practice of P3 who "started small and let the data speak" by first introducing resume screening, demonstrating its success to management, and subsequently scaling up, as well as P2's idea of "delegating high-frequency low-risk activities to AI and delegating low-frequency high-risk activities to humans," are examples of such an approach. Second, the organizations can enhance cooperation between humans and artificial intelligence by continuously adjusting the latter. P5's approach to changing the weights of soft skills of candidates in the system after observing their hiring results, as well as the establishment of a cross-functional project team in his company that includes members from HR, IT, and business units, are examples of this approach. Third, organizations can consolidate the division of responsibilities between AI and human recruiters by assigning standardized recruitment tasks to AI and leaving decision-making processes to human managers. In this regard, P2's company achieved this stage by creating compliance audits requiring vendors to make algorithms explainable, while P7's company kept the final decision rights at the disposal of humans. An incremental strategy seems more reasonable than a drastic one because one should take into account the strength of AI in managing high-frequency activities.

The methods used to promote transparency are influenced by the structure of the organization, but the common denominator is the same. In the foreign firm where P2 works, audits were conducted to confirm that the ven-

dors had enhanced the algorithmic explainability of the process. Conversely, in the government-owned company where P7 works, human-based decision-making was used to reduce the probability of failure linked to opaque AI systems. The fundamental idea is to have practitioners make decisions based on the interpretation of the outputs of the system through an evidence-based approach. It requires the cooperation of three major groups, which include manufacturers that embed explainability into the designs of the system, buyers that use the aspect as one of the parameters for evaluation, and regulators.

The phenomenon of novices agreeing with the decision of the algorithm to avoid blame has implications for organizational design. To prevent the occurrence of the issue, it is crucial to set up a scenario where juniors gain judgment expertise, sustain constructive tension between the recommendations of the systems and judgment, and eliminate excessive concentration of responsibility for the conformity of algorithms. It requires an organizational design to meet this objective. The concept that AI can complement, rather than substitute the competencies of experts, should be incorporated into the management plan of organizations.

Moreover, the reports by the respondents highlight the need for coordination and information consistency across various departments. The existence of clear and stable job descriptions from the recruiting department is a precondition for the efficient functioning of the system. For instance, the HR department should strive to define its expectations rather than shifting the burden of expectation to the system.

5.3. Research Limitations and Future Directions

The results of the study need to be analyzed within the context of certain limitations. Although there were differences in the organizational types, industries, and hierarchical levels among some respondents, no respondent came from a small business firm. The methods used for recruiting AI employees by small business firms may be significantly different from those used by large and medium-sized firms because of limited resources. Besides, all interviewees were from Shanghai, which is an autonomous city leading in technological progress and competition within the Chinese labor market. This implies that the generalization and transferability of the results might need serious consideration.

Self-reporting used in semi-structured interviews could introduce social desirability and recall biases. Additionally, participants appeared to lack knowledge about the rules that guide the functioning of the AI technology. The participants' perception of the AI system as a "black box" further supports the fact that they do not comprehend how the AI system operates. This study does not include observations on the day-to-day human interaction with AI systems nor access to any system operational records. Including such data in future studies can lead to a more accurate portrayal of human-AI collaboration behaviors.

This research provides a cross-sectional analysis of AI-enabled recruitment practices in the second half of 2025. The rise of generative AI technology is setting new standards for technology use within recruitment [40]. Collaborative and efficient behaviors can change depending on technological advances. Perception and usage of AI are dynamic variables among practitioners. In previous literature, some studies have examined the role of personality characteristics and technology acceptance in relation to AI usage [41]. How perception evolves through experience and is transferred across generations can be further studied.

The current research solely focused on the HR practitioners' experiences without considering the views of other key players, including hiring managers, applicants, and the IT system providers. As suggested by the results, the views of the applicants, as well as the experiences of the marginalized population, were reflected only indirectly via the practitioners' accounts. To examine "what is involved in tackling recruitment discrimination" [42], it is important to include the applicants in the study. The study that takes into consideration all the stakeholders' perspectives can aid in gaining a greater understanding of how AI-based recruitment works. In addition, such a study will offer more insights into what "human-centered values" could mean. Further studies can be based on the present research while considering different cultures and cities.

6. Conclusion

The study examines the use of AI recruiting systems within Shanghai firms from the standpoint of HR professionals. As the research demonstrates, statements regarding the efficiencies of recruiting processes due to AI technologies require some rethinking because the efficiencies of using such technologies have proven to be highly

overestimated by their manufacturers. There are certain requirements for the effective implementation of AI recruiting tools. The findings indicate that efficiency gains were concentrated in high-volume, standardized screening tasks, while improvements in accuracy and fairness did not necessarily follow the same trajectory. Choosing human-machine cooperation scenarios is largely affected by the organization's level of digital development, its accountability culture, and resource availability. Different institutions have different forms of specialization in the allocation of tasks to people versus machines, each defined by its own logic. Asymmetries in the design of algorithmic accountability generate logical reasons to trust the suggestions made by algorithms, which may pose problems for novices. Interventions designed to improve human productivity might unwittingly undermine professional discretion.

The power relations described above show that the impact of AI on the autonomy of individual actors depends on hierarchical structures in organizations. Employees in higher organizational positions tend to perceive AI as an instrument for engaging in high-value activities, while employees in lower organizational positions are forced to follow instructions from AI systems. If such a pattern continues, AI-based hiring practices can result in even greater stratification of competencies inside companies, something that deserves serious thought from managers and academics alike.

AI-based hiring systems are constantly changing, as new technologies like generative AI present new issues. Companies need to constantly reevaluate their understanding of the boundaries between humans and machines, since this will define whether AI-assisted hiring will serve as an improvement for human performance.

Author Contributions

Conceptualization, T.L. and S.Y.; methodology, T.L.; software, T.L.; validation, T.L. and S.Y.; formal analysis, T.L.; investigation, T.L.; resources, T.L.; data curation, T.L.; writing—original draft preparation, T.L.; writing—review and editing, T.L. and S.Y.; visualization, T.L.; supervision, S.Y.; project administration, S.Y. Both authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data supporting the findings of this study are not publicly available due to privacy and confidentiality commitments made to the participants during informed consent. Requests for access to anonymized portions of the data may be directed to the corresponding author.

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Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

During the preparation of this manuscript, the authors used Grammarly solely for language refinement. No AI tools were used for data analysis, interpretation, or generation of scientific content. All outputs were critically

reviewed and edited by the authors. The authors take full responsibility for the integrity and accuracy of the work.

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