administrative sciences

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Viewpoint

The Emerging Technology in Hiring: Insights from Assembly Line Workers and Managers

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Abstract

Hiring assembly line workers is often time- and resource-demanding. Following the call for more effective hiring practices, this article describes the design, development, and implementation of an 'AI-empowered recruitment model', an emerging technology in hiring employees. The raw data for model building were gathered from the assembly line workers and their managers. The dataset comprised two parts. Part-1 data were the occupational codes and personality parameters of the top performers (provided by the performers), whereas Part-2 data were the employability and fitness parameters of the top performers (rated by the managers of the performers). Top performers were defined as the employees who had the highest output of products with the lowest defect rate. Through the use of repetitive data-matching algorithms, the model gradually learned and identified the signs (patterns) of top performers. After cross-validation and external testing, the model became established. The model was then applied to the employee recruitment practice, in which the model achieved its purpose by selecting the best-fit candidates from the pool of applicants within minutes. The AI-empowered recruitment model saved organizational resources and expenses. As there was no use of human labor, administrative delays and errors were minimized, thus improving the efficacy of the hiring practice. Limitations and suggestions for improvement were addressed.

Keywords: AI; assembly line; employee recruitment; hiring; workers

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Received: 17 September 2025
Revised: 4 November 2025
Accepted: 12 November 2025
Published: 26 November 2025

Citation: Chang, K., & Cheng, K.-T. (2025). The Emerging Technology in Hiring: Insights from Assembly Line Workers and Managers. *Administrative Sciences*, *15*(12), 463. https://doi.org/10.3390/admsci15120463

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1. Introduction and Background

Hiring is never easy because it involves the investment of organizational resources, strategic planning, applicant analysis, staff succession planning, and many other aspects of human resource management and practices (Katiraee et al., 2023; Pabolu et al., 2025). In the eyes of organizational leaders and managers, hiring new blood (also known as employee recruitment) is one of the most important tasks in the organization, not only influencing personnel planning and staff management, but also affecting overall organizational performance (Whiting & Martin, 2020). Indeed, an organization equipped with skillful and well-trained employees benefits from better team performance and achieves greater competitive advantage (Taylor & Woodhams, 2022). Although different in their research purposes, prior studies jointly indicate that employee recruitment is crucial to organizational development and that a healthy employee recruitment system helps the organization achieve better performance.

This article focuses on the recruitment of assembly line workers, as such recruitment is often time-consuming and resource-demanding, hence drawing academic interest (Muniz et al.,

2022). Following the call for more effective hiring practices and employee management (e.g., Hunkenschroer & Kriebitz, 2023; Muniz et al., 2022; Pabolu et al., 2025), the current article is keen to describe the design, development, and implementation of an 'AI-empowered model of employee recruitment', an emerging technology in hiring assembly line employees. This article is written on the basis of a management consultancy project. The client is an electronics plant, which is an assembly line manufacturer in Kunshan, China.

During the pandemic (COVID-19), assembly line-oriented companies suffered severely, mainly for the following reasons: (i) assembly line workers share the same job duties, such as simplified and repeated tasks (Muniz et al., 2022); (ii) assembly line workers are employed on rota shifts, such as 8–16, 16–24, and 24–8 shifts (Inman et al., 2004); and (iii) assembly line workers work in units and value comradeship (Corominas et al., 2008). By integrating these reasons, one can easily deduce that working in an assembly line worksite may imply 'close contact possibilities' among workers, such as frequent interaction and regular communication within the units and teams. That is to say, 'close contact' is ordinary and unavoidable among assembly line workers.

However, a series of social and personal distancing measures were adopted to stop the spread of the virus during the pandemic, such as an indoor congregation ban, compulsory facial masks, a two-meter safety distance policy, and frequent hand washing (Ashraf & Goodell, 2022). The slogan of 'anti-close contact' was also applied across the sectors, aiming to decrease the likelihood of contracting COVID-19 (Fazio et al., 2021). Following the aforementioned measures, more and more employees left assembly line companies during the pandemic. Perhaps due to the fear of contracting virus, less and less people were interested in assembly line-based posts, leading to the outcome of staff shortage. Eventually, many assembly line-oriented companies closed their business temporarily or even shut down their factories for good (Guedhami et al., 2022).

2. Management Consultancy and Client Company

In the summer of 2020, the authors (management consultants at the time) were contacted by an electronics plant in Kunshan, China, as the plant managers found it difficult to recruit employees for their assembly line vacancies (see the description of recruitment difficulty in earlier discussions). The authors had worked with the concerned plant in the past and received their appreciation, which explained why the plant recalled them for collaboration in solving the recruitment difficulty.

The plant was privately owned, and its organizational structure comprised a management board (including chair, general manager, finance manager, HR manager, admin staff, and board members; Management Sample = 28) and workforce (including assembly line leaders and employees; Workforce Sample = 250). Two governmental officials were assigned to monitor the business management and operation of the plant (see the roles of governmental officials in Li & Pye, 1992).

According to the client (electronics plant), the minimum requirements for the assembly line vacancies included the following: 18 years old, junior high school graduates, and Chinese nationals only. Gender, region, prior working experience, and other factors were not considered in recruitment. The nature of the assembly line jobs was labor-oriented, including product assembly, circuit board soldering, and other relevant manual tasks. Induction sessions and training were provided to support the new employees, ensuring their settlement and job performance.

In terms of employee recruitment methods, the concerned plant was familiar with conventional employee recruitment approaches. These approaches included, for instance, job advertisements in local newspapers and vocational schools, paper-based application forms, paper-based selection, manual shortlisting, face-to-face interviews, and oral announce-

ment of job offers. Although conventional approaches are functional and largely sound, these approaches consume more time and organizational resources; for instance, when implementing conventional recruitment approaches, administrative errors and unexpected delays often occur throughout different stages of candidate selection (Chang et al., 2024a), which in turn compromise the efficacy of employee recruitment (Chowdhury et al., 2023).

After a series of consultation meetings, the plant managers consented to the HR intervention strategy. That is, consultants were authorized to develop an AI-empowered employee recruitment model, with the following conditions: (i) The model ownership belonged to the plant. The model should be developed on feedback from the existing workforce; hence no additional administration and cost were involved. (ii) Once established, the model should be applied to the internet-based employee recruitment, including the pools of job applicants (for the assembly line vacancies) and appointing the best-fit candidates. (iii) Although the model is potentially capable of handling all recruitment procedures without the need of human interventions, the plant managers reserve the right for the appointment of applicants. (iv) The model should be used for the recruitment of new assembly line employees only, containing no further HR implications, such as performance appraisals and redundancy scheme. (v) All gathered data should be anonymized and used for the consultancy purpose only. Any forms of consultancy outputs must not contain personal and organizational identifiers. Only consultants could access the password-protected data, which were stored in a secure server with a password. The gathered data should be destroyed after 36 months.

3. Literature Review on AI-Empowered Hiring

Artificial intelligence (AI) is a type of computer-generated intelligence. AI was originally designed to integrate information into resource management, helping people solve real-world problems. More importantly, AI implies a capability of self-learning and development (see full discussion of AI in Engelbrecht, 2007). Nowadays people's life is often assisted and enriched by AI through various applications, such as navigation APPs in mobiles, wearable devices for health monitoring, and intelligence-driven utensils at home (Chang et al., 2024b; Chowdhury et al., 2023). Scholars define AI as a set of nature-inspired computational methodologies and approaches to address complex real-world problems (Loia et al., 2023). Recent studies also describe AI as a strategic data processor and platform, not only integrating cyber–physical worlds, but also offering intelligence-driven services (Khan et al., 2021; Zeb et al., 2022).

The merits of AI are many and vary. AI helps lubricate the human–machine interface, leading to a better manufacturing outcome (Baroroh et al., 2021). AI is capable of analyzing human behaviors, along with important implications for health intervention and crime prevention (Loia et al., 2023; Sddique & Adeli, 2013). AI has the ability to sense the environment: AI can think, learn, and then take action as a result. In the office, for instance, machine learning algorithms (a variant of AI) assist human colleagues in carrying out routine and mundane tasks, and AI-empowered chat-bots are widely utilized in customer services (PwC, 2022). AI has also earned its reputation in the field of employee management practices, particularly from the perspective of talent recruitment and human capital sustainability. Take a global energy company for instance; HR managers have built an internal talent marketplace after learning that nearly half of employees who left said they could not find their next career opportunity at the company. By uploading their profile to the platform, employees can receive AI-suggested development and career opportunities based on their skills, competencies, and ambitions, encouraging internal mobility, talent retention and new employee recruitment (McKinsey, 2022; Troisi et al., 2024). Another example is as follows: through the application of intelligent automation (a variant of AI-empowered

staff management system), managers can develop different approaches in managing existing employees, recruiting new employees, and enhancing firm performance, leading to better organizational competitive advantages (Hunkenschroer & Kriebitz, 2023; Vrontis et al., 2022).

The current article focuses on the efficacy and applicability of AI in hiring practice, based on a consultancy case. Compared to the AI-assisted approach, conventional approaches (e.g., interviews, profile screening and paper-based selection) are still functional, but they tend to spend more organizational resources and the process is often lengthy and pricey (Ernst & Young LLP, 2018; Taylor & Woodhams, 2022). Following the line of AI research above, scholars are keen to explore whether AI-empowered recruitment methods help managers deliver a fairer, faster, and more economic recruiting service (Chang et al., 2024b; Loia et al., 2023). Scholars have also called for more research to examine the applicability of AI-empowered methods in recruiting practices, aiming to evaluate the merits and efficacy of such methods (Bian et al., 2021; Pan et al., 2022).

To respond to the calls above, the current article is therefore written with three important reasons. Firstly, the paucity of AI-empowered recruitment knowledge is looming (e.g., Gonzales et al., 2019; Vrontis et al., 2022), so there is a need to analyze the design and developmental process of AI-empowered recruitment methods. The concerned analysis and its findings will help advance the knowledge of AI's value and function in recruitment. Secondly, AI has claimed its reputation in resource analysis and logistics management, but its applicability on employee recruitment is still at the infancy stage (Chang et al., 2024b; Ernst & Young LLP, 2018; Wang et al., 2017). The current article is therefore keen to scrutinize the implementation of AI-empowered employee recruitment models. Findings will bring new insights to the employee recruitment literature. Finally, through the analysis of AI-empowered recruitment model, scholars can develop a better understanding of AI-assisted models in recruiting employees, in line with the aforementioned calls (Hunkenschroer & Kriebitz, 2023; Pan et al., 2022). Insights from the model evaluation will also provide reference guides for the future managerial practitioners and policy makers in the field of AI-empowered employee recruitment and management.

4. Method for the Model Development

This section introduces the design and development of the employee recruitment model, in which the architecture and rationale for each component is explained. The acquisition of raw data is clarified through the machine learning algorithms (a variant of AI-based computation; Engelbrecht, 2007). A conceptual chart (Figure 1) is presented to clarify the configuration of the model. Details are outlined below:

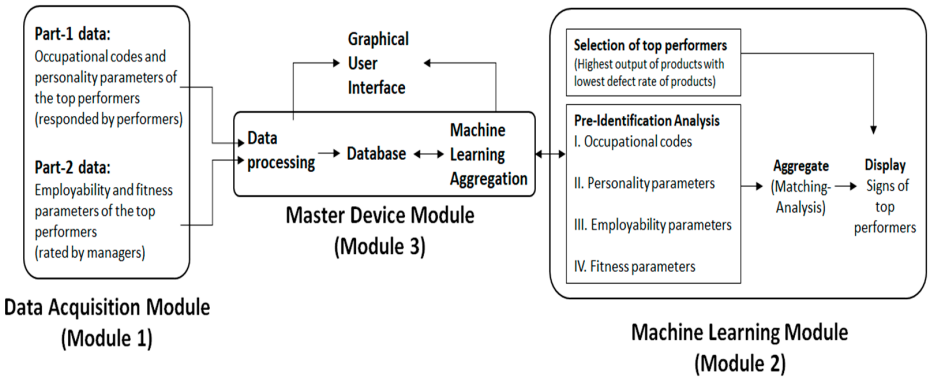


Figure 1. The structure of the employee recruitment model (Source: Authors' own work).

4.1. Architecture of the Model

As shown in Figure 1, the overall architecture of the model can be deconstructed into three modules, each serving a dedicated purpose.

The first module is the data acquisition system, which is responsible for acquiring raw data from two sources, comprising Part-1 data and Part-2 data. Specifically, Part-1 data (X) includes the occupational codes and personality parameters of the top performers (provided by the performers, i.e., assembly line workers), and Part-2 data (Y) includes the employability parameters and fitness parameters of the top performers (rated by the managers of performers). The data collected (i.e., X and Y) are then delivered to the machine learning system (the second module) for processing, and to the master device (the third module) to be fused together for the purpose of monitoring.

The second module is the machine learning system (i.e., the application of artificial intelligence; Bonaccorso, 2018), which is responsible for extracting features and making predictions based on the raw input from the first module.

The third module is the master device, which is responsible for controlling the development of the recruitment model. The master device also records the processed data from the previous two modules into a database and provides a graphical user interface server (see discussion of GUI server in Wang et al., 2017) for the monitoring of the entire system.

4.2. Source of the Data

The raw data for model building were collected from the existing personnel performance data of assembly line employees and their managers (client company). Employees and managers were not involved in the design and testing of model building, aiming to ensure the independence and validity of model development. Three strategies were adopted to ensure research ethics compliance: (i) data use should align with the original participant consent and purpose; (ii) the privacy and confidentiality of individuals should be maintained during data mining, integration, and interpretation; and, finally, (iii) the model should be validated without individual and organization identities.

Specifically, the datasets comprised two parts: Part-1 data were the occupational codes and personality parameters of the top performers (responded by the performers), whereas Part-2 data were the employability parameters and fitness parameters of the top performers (rated by the managers of top performers).

Top performers were defined as the employees who had the highest output of products with the lowest defect rate. A small portion of the employees were identified as 'top performers' (N = 25), approximately 10% of the total employees (250). Then 25 top performers were selected for data entry; that is, these performers formed the sample for the model building, which was composed of 19 female employees and 6 male employees, along with an average age of 22.52 years old (SD = 4.44). The ratio of gender distribution (i.e., more women, fewer men) was normal, as the majority of assembly line workers are female employees in China. This ratio is not a type of career discrimination, but a genuine reflection of workforce composition in China. Similar cases include, for instance, nursing workforce (female-dominated), building industry (male-dominated), seamen (male-dominated), and kindergarten staff (female-dominated).

Demographic data (e.g., age, gender) were collected for the administrative purpose and not utilized in model building. The Part-1 and Part-2 datasets of the sample were later inputted to the data-matching analysis (note: the drawback of limited sample will be discussed in Limitations). Details of the datasets are outlined below:

Occupational codes: According to John L Holland (originator of the occupational codes), the occupational codes help people understand their career orientation and potentials through the examination of multiple personal- and vocational-based characteristics. These

characteristics include, for instance, Realistic, Investigative, Artistic, Social, Enterprising and Conventional (Campbell & Borgen, 1999; Nauta, 2010). Sample questions included the following: (i) Are you able to operate tools and machinery? (ii) Can you make original crafts, dinners, school or work projects? (iii) Do you like to be responsible for details? Answers to the questions were provided by the top performers through measurement scales.

Personality parameters: The 16 Personality Factor (16PF) is a self-reported instrument for personality analysis. The 16PF describes individual's capacity for insight, self-esteem, cognitive style, internalization of standards and other personality aspects (R. B. Cattell, 1995; H. E. Cattell & Schuerger, 2003). Sample questions included the following: (i) You spend a lot of your free time exploring various random topics that pique your interest. (ii) Seeing other people cry can easily make you feel like you want to cry too. (iii) You usually stay calm, even under a lot of pressure. Answers to the questions were provided by the top performers through measurement scales.

Employability parameters: A series of questions were developed to explore the employability of employees in the pre-set workplace (i.e., assembly line environment). Sample questions included (i) *the employee has previous work experience in the assembly line workplace; (ii) the employee has basic understanding of assembly line environment; and (iii) the employee has shared his/her experience/knowledge of assembly line with fellow colleagues.* Answers to the questions were provided by the managers of top performers through measurement scales.

Fitness parameters: A series of questions were developed to measure how employees fit their jobs. Sample questions included the following: (i) the employee has shown willingness to work in a dust-free environment; (ii) the employee has shown willingness to work in night shifts (rota-based); and (iii) the employee has shown willingness to live in the shift-based dormitory. Answers to the questions were provided by the managers of top performers through measurement scales.

As both employability and fitness parameters were assessed through self-rated questions, a strategy of quality assurance was arranged. Prior to the data collection, a pilot study was conducted to ensure the accuracy and clarity of questions, in which one management expert, one manager, and three assembly line employees were invited to review the proposed questions, aiming to improve the validity of questions. Questions were then revised in line with the feedback, aiming to improve the accuracy and clarity of the questions. By doing so, the pilot study improved the quality of self-rated questions, facilitating the implementation of data-matching analysis later on (see similar strategy in Engelbrecht, 2007; Sddique & Adeli, 2013).

Social desirability concerns: Social desirability is the tendency for people to present themselves in a generally favorable fashion, in which higher level of social desirability means less trustworthiness and more bragging tendency in the self-expression, thus bringing biases to the data analysis (He et al., 2014). Krumpal (2013) indicated that, to improve the quality of data collection and alleviate the social desirability bias in analysis, social desirability shall be considered during the surveys. Sample questions included the following: (i) No matter who I am talking to, I am always a good listener. (ii) I never hesitate to go out of my way to help someone in trouble. (iii) I am always careful about my manner or dress.

In addition, social desirability scale was only used to filter out 'unsuitable employees (potentially socially biased employees)' but not utilized in model development. In the given dataset, as no employees showed signs of social desirability (i.e., over-reporting desirable behavior or under-reporting undesirable behavior), the same dataset (sample) was adopted for further model building.

4.3. Establishment of the Model and Pattern Building

As it is shown in Figure 1, through the continuous data-matching analysis (repetitive algorithms; Mohammed et al., 2016), the model gradually learned and understood the 'signs of the top performers', i.e., the patterns of match—the best combination of different parameters, including occupational codes, personality parameters, employability parameters, and fitness parameters. Specifically, during the implementation of repetitive algorithms, it became salient that top performers may demonstrate different patterns (i.e., different combination of codes and parameters). From the perspective of ecological validity, these patterns are important during the implementation of machine learning (Bonaccorso, 2018). These patterns also reflect the reality, for instance, assembly line workers may employ different methods or adopt different strategies, aiming to achieve the lowest defect rate. For the same reason, the repetitive algorithms continued for the purpose of model fine-tuning and validation (Mohammed et al., 2016). When the algorithms were set, further quality control measures followed.

4.4. Cross-Validation, External Testing and Quality Control

To examine the model accuracy and control the margin of errors, a series of measures were arranged. Firstly, a cross-validation test was adopted to examine the model's predictive performance by splitting a dataset into training and testing sets, training the model on the training set, and evaluating it on the testing set. The process is repeated, using different subsets for training and testing, to provide a more robust estimate of the model's ability to generalize to new, unseen data and to prevent overfitting (see model refinement in: Mohammed et al., 2016).

Secondly, two management scholars were invited to review the model, and their views were adopted to refine the model further. Through the reviewing process, the model became matured when it showed sound capability in recognizing the patterns of top performers accurately. Both cross-validation and external testing served as the first line of quality control of the newly built model.

Thirdly, to examine the applicability of the newly built model, a reverse-check strategy was conducted (Bonaccorso, 2018); that is, when an individual processes the identified patterns, she/he shall be defined as a top performer by the model. The reverse check was operated again and again, in which the identified patterns were repeatedly tested and tuned, until no errors reported. Both reverse check and tuning work served as the second line of quality control of the model.

The aforementioned measures were time-consuming but meaningful, as these validation measures contributed to the establishment of the employee recruitment model (see model building guidelines in Mohammed et al., 2016). Once the model was established (workable), it was recommended to the management team for the application of assembly line employee recruitment.

5. The Application of the Model

At the stage of model application, authors (consultants) utilized the data generated by the HR team from the client company. No further primary data was collected. Same as the model development stage, three strategies were adopted to ensure research ethics compliance (see strategies in the Section 4.2). Employees and managers from the client company were not involved in the current stage, further enhancing the independence and validity of model application.

Following the establishment of the employee recruitment model, the internet-based recruitment tasks were conducted by the client managers. The recruitment tasks included, for instance, crafting assembly line job specification documents and publishing job adverts

on local media, job websites, as well as the e-bulletin boards of local vocational schools. In addition, for the sake of employee recruitment ethics and data transparency, there was a statement in the job advert, indicating that AI is included in employee recruitment.

After job adverts were published, job applicants registered their interest online. Once checked by the filter (filter explained later), the qualified applicants received plant information, job specification, and web links to the questionnaires through their mobiles or emails. Non-qualified applicants (i.e., rejected applicants) were also notified for the sake of courtesy. The filter was set by the plant managers, along with pre-set filtering criterions. These were, for instance, age (i.e., 18+ years old), nationality (i.e., Chinese only), and educational level (i.e., junior high school graduate and above). The recruitment tasks above were largely congruent with the existing recruitment policies (on the client's side), hence incurring no additional cost. Moreover, as the model was designed to handle the candidate profiling and identify the best-fit candidates, no job interview was needed, further saving client's expenses and resources in recruiting activities.

The questionnaire comprised a number of questions, including occupational codes, personality parameters, employability parameters, fitness parameters and social desirability measures (the same questions were used for the model building). After completing all questions on the website, job applicants received an email, acknowledging the completion of their application task. All communication emails were managed by the existing HR team, hence adding no additional costs to the client.

When job applicants completed the questionnaires online, their answers (raw data) were automatically coded and stored at a secured server, serving for the execution of the newly built employee recruitment model. The efficacy of recruiting job applicants was reasonable, as 1072 applicants registered their interest online within one week and 967 applicants were approved by the filter, yielding a reasonable filtering rate (90.21%). All job adverts were removed from the websites and e-bulletins afterwards.

The raw data were then used for executing the model, in which applicant selection and best-fit candidate identification tasks were conducted, respectively. Based on the outcome of model execution, 122 of the 967 filter-approved applicants were identified as the best-fit candidates; namely, these applicants showed more performance potential (i.e., signs of the top performer) than other applicants. Their demographics were outlined below: gender (female = 79.50%, male = 20.49%), age (means = 28.55, SD = 8.73), and educational level (junior high school = 61.47%, and above junior high school = 38.52%). A reverse-check technique was also carried out to monitor the model applicability (Bonaccorso, 2018; Mohammed et al., 2016), indicating that all model-selected candidates processed the identified signs (patterns) of the top performer.

The next step was the confirmation of job offering. Once approved by the plant management board, the HR team on the client's side informed the model-selected candidates via email and mobile, with an information notice of the job offer. Guided by the HR team, these candidates were then invited to sign the letter of employment online, which in turn verified the employee's job title, remuneration, benefits, insurance, tax, and commencement dates. In the first week of the employment, both induction sessions and worksite trainings (i.e., employee orientation program) were arranged to support the new employees, ensuring their settlement and job performance.

6. Discussion and Conclusions

Artificial intelligence (AI) has been widely applied to people management in the workplace, not only lubricating employee–machine interaction, but also creating a more productive and healthier environment (Baroroh et al., 2021; Chang et al., 2024a). In terms of employee recruitment, managers are interested in innovative AI-empowered methods,

aiming to improve the efficacy of their recruitment practices (Hunkenschroer & Kriebitz, 2023; Vrontis et al., 2022). Interestingly, although AI-empowered recruitment approach has drawn much attention, scholars have mixed views about its efficacy and therefore have called for more research to examine its applicability and efficacy (Bian et al., 2021; Pan et al., 2022). Aligning with this line of research, an AI-empowered recruitment model (titled 'employee recruitment model') was designed, built, and successfully implemented, on the basis of a management consultancy case.

The newly built model is informative and meaningful in three ways. Firstly, the model successfully resolved the problem of staff shortage, which troubled the client company during the pandemic (COVID-19). Following the implementation of employee recruitment model, new assembly line workers were successfully recruited, saving organizational resources and costs. Secondly, through the design and development of the model, this article has clarified the complexity of the AI-empowered recruitment approach (see sample architecture in Figure 1). The successful application of the model also confirmed the applicability and efficacy of AI-empowered employee recruitment approach, which is particularly important to the assembly line-oriented companies, such as electronics plants and steel manufacturers. Thirdly, AI has demonstrated its merits in the domain of employee recruitment and selection, providing an alternative approach in hiring new employees. This article now turns to discuss the theoretical and practical implications, in line with the AI-recruitment literatures.

6.1. Contribution to the Literature

Earlier literature review indicates that scholars have mixed views about the efficacy of AI-empowered employee recruitment approaches. Scholars have called for more research to (i) understand whether AI-empowered approaches help managers deliver a fairer, faster, and more economic employee recruitment service (Chang et al., 2024b; Loia et al., 2023), and (ii) evaluate the applicability of AI-empowered recruitment methods, models, and practices (Bian et al., 2021; Pan et al., 2022). To respond to the calls above, scholars have focused on three contextual factors of AI-empowered recruitment approaches. These are ethical, operational, and applicant factors. This article now turns to discuss the factors in line with the newly built model, aiming to advance knowledge of AI-empowered recruitment. Details are given below:

Ethical factor: AI-empowered employee recruitment methods can fulfil the recruitment needs by selecting the ideal job applicants from the applicant pools and identifying the best-fit candidates with the highest performance potential (Chang, 2024). The newly built model, for example, is capable of identifying the applicants with different levels of performance potential, ranging from 'high potential (possible best performer)', 'regular potential (possible average performer)' to 'low potential (possible limited performer)'. Having said that, however, scholars have found the risks of data reliance in AI-empowered methods and raised ethical concerns about AI-driven selection (Mujtaba & Mahapatra, 2019). According to Hunkenschroer and Kriebitz (2023), errors and biases may occur during the candidate selection, jeopardizing the fairness of employee recruitment. Inspired by these studies, two measures should be adopted to design, test, and run the model, ensuring all the steps are fairly and accurately operated. These are *social desirability measures* (He et al., 2014) and *reverse check* (Mohammed et al., 2016). The rationale is that an AI-empowered model might not reach its maximum efficacy until the ethical factors are reviewed and responded, particularly when such model is relatively new to the organizations and HR practitioners. Following the same logic, ethical factors shall be considered during the design, development, and implementation of the AI-empowered employee recruitment models.

Operational factor: In the management consultancy case (on which the current article is based), the efficacy of AI-empowered employee recruitment model is salient, bringing benefits to both managers and the organization. Yet, these AI-empowered models may still have their shortcomings; for instance, using the AI-empowered models may trigger fear and distrust in the recruitment team, as the team members may worry about the consequence, such as task replacement and job insecurity (Ore & Sposato, 2022). From a different but relevant perspective, Cheng et al. (2022) claim that managers do not feel comfortable about the AI-driven recruitment practices, as managers and AI may compete for the ownership of decision-making in candidate shortlisting, and some managers even feel that AI compromises their leadership and status in the workplace. Echoing this line of research, the current article has advanced knowledge of AI-empowered recruitment applicability in two ways. Firstly, the tension between AI application and recruitment staff could be resolved through communication and collaboration. Through consultants–staff meetings, for instance, staff's concerns could be better addressed, and their views also help refine hiring methods. Secondly, although the employees and managers from the client company were not involved in the model building for the sake of model independence, there might be benefits to the client company being involved during the model building. Through the conversation (e.g., information exchange and discussion), the client company can better understand the model and appreciate its merits more, hence speeding up the model implementation.

Applicant factor: AI-recruitment research and similar studies have praised the applicability of AI and its merits in the field of employee recruitment practices, ranging from accurate profile analysis and fair candidate selection to efficient recruiting systems (Hunkenschroer & Kriebitz, 2023; Johansson & Herranen, 2019; Ore & Sposato, 2022). Among these studies, one particular theme has drawn extra attention; that is, does an AI-empowered recruitment approach affect job applicants? To answer the question, several studies have been conducted, but their findings seem inconclusive. For instance, Van Esch et al. (2019) indicated that the perception of AI-empowered employee recruitment approaches affects the likelihood that job applicants complete the application process. If applicants feel positive about AI, when they learn that AI is included in the recruitment practices, they are more likely to complete the application. Yet, other studies actually tell a different story, as job applicants do not necessarily know whether AI is applied to the recruitment practices (Albert, 2019; Cheng et al., 2022) and there is no direct evidence to judge whether AI-empowered recruitment approaches affect job applicants (Kot et al., 2021; Pan et al., 2022). Following this line of research, the current article has advanced knowledge of AI-empowered recruitment method in two ways. Firstly, AI-empowered recruitment approach does not necessarily affect job applicants, at least in the current case where 1072 applicants registered their interests online within one week and 967 applicants were approved by the filter. The overall recruiting efficiency was satisfactory. Secondly, there was a note at the bottom of job adverts, explaining that AI was applied in the employee recruitment practices. Following the model execution, the outcome was also satisfactory; namely, 122 applicants were identified as the best-fit candidates. Jointly, one can conclude that AI-empowered recruitment approach does not necessarily affect job applicants and thus should be widely promoted.

Additionally, the extant AI-recruitment literature has proposed potential challenges in AI-assisted recruitment methods (e.g., Chang et al., 2024a; Pan et al., 2022), and the current findings have enriched this line of research by highlighting the importance of 'candidate factor', such as the personal characteristics measured by psychometrics and skill-set assessments. To be precise, both psychometrics (e.g., personality analysis and social desirability analysis) and skill-set assessments (e.g., vocational knowledge and job

skills) are incorporated into the design and implementation of the employee recruitment model (Figure 1), because these candidate factors are crucial to the identification of 'top performers', which in turn facilitate the analysis of pattern-matching mechanisms. Based on the earlier literature review, candidate factors are never mentioned in the field of AI-empowered employee recruitment approaches; hence, the current paper has brought new insights to the AI-recruitment literature. The key finding is as follows: although the contextual factors (ethical, operational, and applicant factors) are crucial to the development of AI-empowered recruitment methods (e.g., Cheng et al., 2022; Hunkenschroer & Kriebitz, 2023; Ore & Sposato, 2022), candidate factors are also important and contribute to the applicability of AI-empowered recruitment methods.

6.2. Practical Implications

During the pandemic, many assembly line-oriented companies suffered staff shortages and some of these companies closed their business temporarily, such as the electronics plant reported in the current article. The reasons for staff shortages included, for instance, social and personal distancing measures (Ashraf & Goodell, 2022) and fear of contracting COVID-19 (Fazio et al., 2021). When the social and personal distancing measures were lifted near the end of the pandemic, the phenomenon of staff shortage still remained (Guedhami et al., 2022). Fortunately, the newly built model successfully responded to the sufferings of these companies, not only recruiting/identifying the best-fit candidates from the pools of job applicants, but also saving organizational resources. With a sufficiently large workforce on board, assembly line companies should be able to restore their businesses and achieve prosperity soon, particularly since good employees are crucial to team performance and organizational success (Taylor & Woodhams, 2022; Whiting & Martin, 2020).

To tackle staff shortage, managers are encouraged to consider AI in their employee recruitment policies and hiring practices, such as AI-empowered job design and placement (Pan et al., 2022) and AI-driven candidate selection criteria (Albert, 2019). From a different but relevant perspective, scholars also indicate that AI-empowered recruitment process makes it possible for systems to work similarly to the human brain in terms of data analysis and the ability to build an effective systematic engagement to process data in an unbiased manner (Fraij & László, 2021). Indeed, an unbiased recruiting process is critical to an organization's commitment to employee equality, diversity, and inclusion and is hence recommended (Ali et al., 2023).

Next, conventional employee recruitment methods (e.g., paper-based application forms, postal submission, and face-to-face interviews) are popular and easy to use, but they are also known for the administrative errors and unexpected delays for mundane tasks, hence leading to a lower efficacy of recruitment (Taylor & Woodhams, 2022; Whiting & Martin, 2020). Compared to the conventional methods, the AI-empowered methods (such as the newly built model in the current article) have provided an alternative option of employee recruitment, with less consumption of organizational resources but an accelerated process of recruitment. Moreover, as AI-empowered recruitment methods do not involve human labor in candidate profiling and selection, both administrative errors and unexpected delays are likely to be minimized, which in turn contributes to the efficacy of the employee recruitment practice.

Interestingly, some scholars have warned that AI-empowered recruitment approaches may not always work and, sometimes, may even have side effects (Ore & Sposato, 2022). According to Cheng et al. (2022), managers may feel threatened because they worry AI may compromise their performance; for instance, if managers and AI show discrepancies in candidate assessment, conflicts may occur during the decision-making process. Van Esch et al. (2019) also indicated that job applicants may feel anxious if they know the recruitment

process involves AI and that some applicants may drop out due to the anxiety. As such, managers should consider a dry run (pilot project) prior to large-scale implementation, as per the phrase 'a stitch in time saves nine'.

In addition, although the newly built employee recruitment model is designed for the assembly line workers, managers and HR practitioners can still benefit from its developmental process, along with the AI-assisted employee recruitment flowchart (Figure 2). As shown in the flowchart, the employee recruitment process usually comprises multiple elements (stages), ranging from 'recruitment starts' and 'identify skills and hiring needs' to 'induction, settlement and career trainings'. The newly built model is informative and applicable to the dashed circle, which covers four important recruitment elements. These are 'formulate job specification', 'advertise jobs and review applications', 'shortlist applicants and interview candidates', and 'appointment and contract'. Thus, managers may consult the flowchart and apply AI to the dashed circle, further improving the efficacy of their employee recruitment policies and practices.

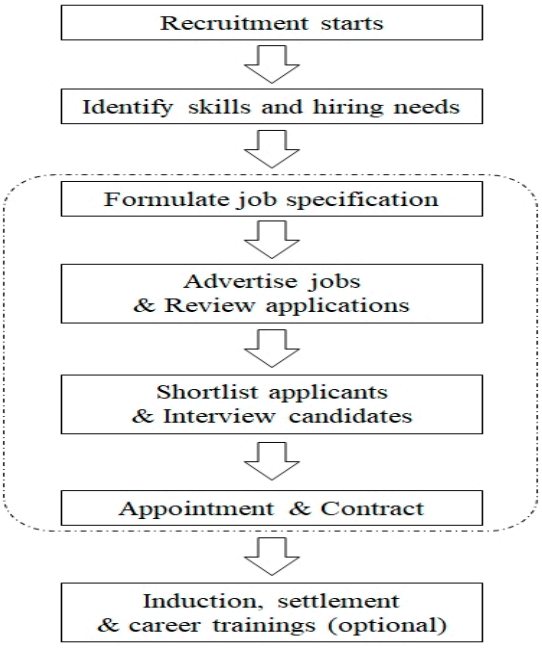


Figure 2. AI-assisted employee recruitment flowchart (Source: Authors' own work). Note. The newly built model is applicable to the dashed circle (four elements), aiming to improve the efficacy of employee recruitment practices.

6.3. Limitation and Suggestions

Although the newly built model is informative and applicable to the employee recruitment practices, its efficacy should be interpreted with caution. For instance, as the electronics plant (client company) does not carry out any follow-up survey to confirm whether the model-appointed applicants are genuine top performers after the appointment, a plan for monitoring the long-term performance of model-selected employees should be arranged. Future research should respond to the same drawback, examining the predictive validity of the model, particularly when such validity is crucial to the model implementation and refinement (Roman-Gonzalez et al., 2018). Using virtual applicants with model implementation (i.e., integrating two recruiting systems) may provide additional layer of rigor, further enhancing the efficiency and efficacy of recruiting practices (Note: A virtual applicant is an individual who applies for a job entirely online, without any in-person meetings.)

The newly built model has been successfully applied to employee recruitment practices and saved organizational resources; however, whether the model affects the existing staff still remains unknown. Cheng et al. (2022) indicate that managers may not like technology-driven management tools (such as the AI-empowered employee recruitment model in the current project), as they may feel insecure and lose authority. In the eyes of managers, technology (such as AI) may have the potential to take over their ownership of decision-making and compromise their influence at work (Cheng et al., 2022). Future research may continue this line of research, exploring the implementation of different management methods, including their implications for employee perception, attitude, and behavior.

The newly built model is only applicable to the recruitment of assembly line workers, such as the jobs described in the current article. The model is probably not applicable to other cognition-demanding and heuristics-oriented jobs, because these jobs may involve complex job characteristics and/or possess different definitions of 'top performers' (Chang et al., 2024a; Hunkenschroer & Kriebitz, 2023). Future research may explore the applicability of the AI-built recruitment model for more complex and challenging jobs.

The development of the AI-empowered recruitment model is based on raw data, inputted by humans. The model validity may suffer from potential bias embedded in self-rated scales, such as subjective measurement of occupational codes, employability, and fitness parameters during the data collection for model building. Future scholars may add objective measurements of ability specific to assembly line workers (e.g., dexterity tests, problem-solving), with the aim of reducing bias and enhancing objectiveness in data collection.

Finally, the core of the newly built model is repetitive data-matching algorithms (RDA). As only 25 top performers are selected for the model building, the spectrum of RDA is relatively small and thus limited. Future studies may include a broader range of employees for module building, such as average and poorer performers. In doing so, the model can learn not only 'what works' but also 'what does not work'. In a similar vein, Sddique and Adeli (2013) indicated that the performance of AI-driven models relies on multiple factors, such as feed-in data accuracy, data stability, data richness, and time of data collection. Due to the limited data access, unfortunately, authors cannot repeatedly measure top performers, so the data stability and richness are not controlled (or optimized). For the same reason, future studies may consider a wider scope and add multiple layers of data collection, so the model quality can be further refined.

6.4. Summary

The AI-empowered model was successfully applied to the employee recruitment practices and tackled the staff shortage problems at the client company. AI-empowered recruiting models have their merits, such as hiring efficiency, high accuracy, and no human delays. Having said this, however, AI-empowered models must be utilized with caution, as it may bring unexpected side effects to incumbent managers and employees. Prior to the full implementation of AI-empowered models in the organization, a pilot practice (or pre-test) at a target group is therefore recommended. Through the examination of pilot practice, potential impacts and unwanted effects can be alleviated to the minimum, further maximizing the function of AI-empowered models.

Author Contributions: Conceptualization, K.C. and K.-T.C.; methodology, K.C.; software, K.-T.C.; validation, K.C. and K.-T.C.; formal analysis, K.C.; investigation, K.C.; resources, K.C.; data curation, K.C.; writing—original draft preparation, K.C.; writing—review and editing, K.C. and K.-T.C.; visualization, K.C.; supervision, K.C.; project administration, K.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The research reported was conducted in accordance with the Institutional Research Ethics Guideline (REF: BNS192), and the dataset was newly collected and never being used for publication.

Informed Consent Statement: The raw data for model building were collected from the existing personnel performance data of assembly-line employees and their managers in an electronics plant in Kunshan, China. We authors adopted strategies to ensure research ethics compliance in three ways: (i). we ensured that data use aligned with the original participant consent and purpose; (ii). we maintained the privacy and confidentiality of individuals during the data mining, integration and interpretation; and, finally, (iii). we validated the model without individual and organization identities.

Data Availability Statement: Data available on request from the authors after publication.

Acknowledgments: The authors would like to express his sincere gratitude to two colleagues (Professors Tariq Khan and Muhammad Nisar Khan) who have offered valuable comments to an earlier version of this manuscript. The insight provided by colleagues and their constructive criticism has greatly improved the paper.

Conflicts of Interest: The authors received no financial support for the research, authorship, and publication of this manuscript. The authors declare no competing interests in the manuscript, submission and publication. The manuscript is original and is not under consideration or published elsewhere. Some parts of the manuscript were discussed in the institutional workshop (2025), but the full-text of manuscript has not been published.

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