



The use of Artificial Intelligence (AI) in the hiring process: Job applicants' perceptions of procedural justice

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ABSTRACT

Using Artificial Intelligence (AI) for hiring is becoming a common practice among the employers. However, there is a lack of empirical evidence in academia about how job applicants react to such utilization. In this empirical study, we tried to investigate the relationship between perceived (by job applicants) use of AI in the hiring process (PUAHP) and job applicants' perceived procedural justice (PPJ) using an extension of the Technology Acceptance Model (TAM) as mediators [perceived ease of use (PEU), perceived usefulness (PU) and perceived trust (PT)]. The study was conducted based on primary data collected from 418 job applicants in Bangladesh. We used SPSS 26 for descriptive statistics and partial least squares structural equation modeling (PLS-SEM) through SmartPLS 4.0. The study identified that, first of all, PUAHP has a significant positive relationship with the dependent variable, PPJ. Second, PUAHP was also found to be significantly correlated with all three mediators (PEU, PU and PT). Third, PEU, PU and PT were identified to have significant positive relationships with PPJ. Finally, regarding the mediating effects, we found that all three mediators partially mediated the relationship between PUAHP and PPJ. Although, there are sufficient empirical studies that have focused on the use of AI in the hiring process, comparatively less attention has been put so far particularly on job applicants' perceptions of such an use of AI in the hiring process. Therefore, this study can add value to the existing knowledge by reducing such lacking. Moreover, we used three components of the extended TAM as mediators which is an unique effort in academia. Furthermore, the study was conducted based on primary responses in an emerging economy which is also rare in academia.

1. Introduction

A faster and ever-changing technological development has forced the organizations to use Information Technology (IT) for the hiring process to avail themselves of the cost-effectiveness and time saving advantages (Frail & László, 2021). The present research studies have emphasized mostly on using IT advancements or developments in technology to simplify the recruiting process, therefore acquiring a more productive and efficacious version of human resource management (HRM) procedures. The recent rapid growth of Artificial Intelligence (AI) has

generated considerable attention among human resource (HR) professionals as it has taken many industries and corporations into a new world which is particularly based on technology.

The present growth in the application of AI in workforce management, i.e., HRM activities, particularly in the recruitment process, may be described as the emerging epoch of "HR advancement", as AI is being utilized in the entire hiring strategy by transforming repetitive, routine tasks once carried out by human recruitment experts. This shift has resulted in a consistently expanding body of literature on this widespread transformation (Upadhyay & Khandelwal, 2018). Nevertheless,

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the extent to which the job applicants' perspectives on using AI as a tool has not been thoroughly investigated. Thus, there is a need for conducting more empirical research studies (subsequently, published papers) within the body of existing knowledge. This study is an attempt to fill such a gap, which is the most evident contribution according to us.

Most of the papers that have been published so far argued/proved that AI can be beneficial for the HRM functions/practices. Specifically, the authors of those papers concluded that the influence of AI on the recruitment process is beneficial, as this technological advancement may be effectively used in different stages of the recruitment process (Frail & László, 2021). Furthermore, AI has the capability to streamline and automate repetitive everyday procedures, allowing the recruiters to allocate their time and effort toward more critical matters related to enhancing performance and fostering growth (Frail & László, 2021). van Esch and Black (2019) stated that the present and future advancements in AI-enabled hiring may improve productivity and elevate the AI-enabled recruiting process from being considered a luxury to an essential component. Although recruitment and hiring do not bear the same meaning in the HRM context, this study considered both the terms interchangeably.

Notably, this shift has been possible due to AI-enabled hiring transition from an experimental phase to a mainstream phase in the hiring process. As a result, academics and researchers are becoming increasingly interested in revealing the different aspects of this topic (Zhang, 2024). Such academic concern about using AI for the recruiting process is evident from the increasing number of recent articles exploring different facets of this field of study. Researchers have recently identified algorithmic bias in hiring decisions, examining it from both legitimate and technological standpoints (Hunkenschroer & Luetge, 2022). Other scholars, such as Figueroa-Armijos et al. (2023) and Dattner et al. (2019) explored ethical perceptions and beliefs in organizations that use AI for hiring, as well as the privacy concerns of the applicants during AI-based recruitment and selection. Additionally, Kelley (2022) investigated the adoption of AI applications in the hiring practices; Lavanchy et al. (2023) discussed the perceptions of employees on fair algorithm-oriented recruiting, whereas Weinert et al. (2020) explored the influence of AI-based recruiting in the perspective of talent attraction. Pan et al. (2022) investigated employers' reactions on the adoption of AI in the employee selection process.

However, despite several benefits AI can offer in the hiring process, adopting it can also bring a few concerns and is not free of controversy. The notable issue of great concern in this instance is the inherent biases of the AI algorithms. The effectiveness of AI algorithms relies mainly on the quality of raw data used (in this context, job related data produced by job applicants), the training and the expertise of the users [(in this context, both the job applicants (for job application) and the recruiters (for applicant selection)]. Moreover, if the data itself are biased; the algorithms will inevitably provide biased decisions for applicant selections as well (Danks & London, 2017). Besides, the data used for training the users of the AI system can also be biased toward individual male or female applicants. In that case, the algorithm will prefer a specific category of applicants throughout the recruiting process. An example occurred with Amazon's AI recruiting tool, which autonomously developed a bias toward the male candidates (Horodyski, 2023). Subsequently, Amazon retracted the AI tool due to its identification of unfair outcomes. Thus, the company's efforts to rectify this discrimination proved ineffective (Dastin, 2018). Consequently, a recent focus has been noticed on developing explainable AI models and techniques to restrict biased judgements in AI-driven recruitment and selection. The Concept of Anxiety and Trust (CAT) model was initiated by Lee and Cha (2023), where the scholars explained the terms "organizational fairness" and "complexities related to administrative accountability and transparency" to examine and elucidate the AI algorithm applications in the employee recruitment and selection process. Hence, job applicants may form their own perceptions of procedural justice (PPJ) concerning these biases or issues arising from using AI-driven technologies for recruitment

objectives.

In addition, there is a growing apprehension about the ethical implications of employing AI in the recruitment process. This pertains to the ethicality of using AI-driven recruitment tools and the potential impact of moral perceptions on job applicants' trust in the organizations that employ such tools. Pertinently, Da Motta Veiga et al. (2022) advocated that algorithms related to AI are typically not accessible or useable by any general users because of their proprietary right constraints. Moreover, there is apprehension over the potential displacement of human employment due to automation (Păvăloaia & Necula, 2023), as well as legal considerations surrounding the final decision-making process for job applicants, which some countries still require to be conducted by the human authority (Laurim et al., 2021, p. 5495). Finally, several domains have apprehensions over individual privacy and data security. On the other hand, Stahl and Wright (2018) indicated that AI's capacity to amass and integrate substantial quantities of personal data gives rise to apprehensions over safeguarding the privacy rights of the general people. Hence, we argue that recruitment experts should be meticulously aware of both the benefits and drawbacks of using AI for applicant evaluation in the hiring process. Moreover, job applicants should be assured that any AI-based hiring process is fair and impartial.

We argue that more and more empirical studies, specifically examining the AI's utilization in the hiring process, are still needed. Besides, a minimal focus has been given so far by academics on the empirical examinations of job applicants' perceptions related to AI technology employed in their recruiting process and the attraction of talents (Horodyski, 2023; Hunkenschroer & Luetge, 2022). Likewise, there are only a few empirical research papers that have provided clear evidence regarding applicants' perceptions of using AI for hiring (Gonzalez et al., 2022; Kassir et al., 2023). Therefore, there is a significant deficiency of research studies in this specific field of workforce management. This dearth of attention from academics might be ascribed to several evident factors. Prior research has predominantly examined the tangible advantages of AI technology from the standpoint of employers or hiring professionals, such as cost and labour savings, enhanced speed, improved task efficiency, fostering relationships between the employers and the job seekers, fair talent acquisition, collecting and managing a high volume of candidate resumes; and automation or AI-based hiring procedures (Rashid & Kausik, 2024). These benefits significantly influence the overall transformation of the recruitment industry. Employers do not generally give much consideration to the viewpoints of job seekers, especially when the labor market is dominated by the them (employers), meaning more people are looking for jobs than there are available positions. Therefore, the viewpoints of job seekers toward the use of AI-based technologies in the hiring process are still relatively new in the academic field. On the other hand, Hunkenschroer and Luetge (2022) conducted a similar investigation where they identified that researchers inevitably have so far fallen behind in revealing the applicants' standpoints compared to actual implementations and swiftly changing technological progress. According to Jaser et al. (2022), the application of AI in staffing operations may not be new, but regarding the incorporation of job applicants in this process, is likely an inevitable development; and there is still a lack of research on this issue. Another scholar, Horodyski (2023), advocated that more research knowledge and investigations are required on the subjective experience of job seekers during AI-based job interviews and the subsequent impact of these experience on them. Particularly, in an emerging economy like Bangladesh, such an empirical study focusing on job applicants' perceptions of using AI in the hiring process is quite unique. Bangladesh is a labour-abundant country with a high number of unemployed graduates. Therefore, this empirical study can be a guiding point for the upcoming researchers who want to focus on AI-based technological application in the hiring process.

Another unique contribution of this study is the incorporation of two factors of the Technology Acceptance Model (TAM): perceived ease of

use (PEU) and perceived usefulness (PU) as mediators. In addition, we incorporated another factor, perceived trust (PT), as mediator. The TAM is a widely used model introduced by Davis (1989) to elucidate the factors influencing the users' (here, the job applicants') adoption of a certain technology (Hirschheim, 2007; Sohn & Kwon, 2020). While job applicants prefer an application system and applying process to be easy, useful and trustworthy, they also expect that such process will be free of bias and reflect procedural justice (Hosain et al., 2020, 2021; Hosain & Mustafi, 2023). Although there are adequate research studies that applied the three factors of the extended TAM as independent constructs, these factors have not been used as mediators between the relationship of perceived (by job applicants) use of AI in the hiring process (PUAHP) and PPJ.

We intend to address the need for more literature on the use of AI in the hiring process. Based on the existing arguments and findings, we developed the following research questions to be answered by this study.

RQ1: What is the relationship between perceived (by job applicants) use of AI in the hiring process (PUAHP) and job applicants' perceptions of procedural justice (PPJ)?

RQ2: Do perceived ease of use (PEU), perceived usefulness (PU) and perceived trust (PT) mediate the relationship between PUAHP and PPJ?

2. Literature review

2.1. PPJ of the applicants

Procedural justice pertains to the equity of rules and processes used by organizations when making choices on individuals' selection for jobs (Folger et al., 2022; Hausknecht et al., 2004). Based on the concept of procedural justice, perception of fairness in the hiring process must be compromised if certain conditions are not met. These conditions include applying fairness consistently to all the candidates and throughout the process, ensuring that there is no bias, making sure that the selection choices are contingent on accurate information, implementing mechanisms to ensure the accuracy of selections, following ethical and moral standards; and considering the opinions of all groups affected by the selection decision (Colquitt et al., 2001). In this study, PPJ was considered as the single dependent construct.

2.2. PUAHP

According to Upadhyay and Khandelwal (2018), the application of AI in HRM has been one of the most significant movements among the hiring professionals since 2018. On the other hand, Stuart and Norvig (2016) referred to information extraction as a process where information and knowledge can be collected by scanning a text. Particularly, in hiring new employees, AI can be utilized for extracting information that can make the entire process of resume scanning and extraction of pertinent information automated (Johansson & Herranen, 2019) that were previously conducted manually. Since the number of job applications has enlarged and can even overwhelm the hiring professionals, such automated systems can rank the job applicants to speed up the hiring process. Earlier, the HR professionals usually manually evaluated the received job applications, whereas applicant ranking systems can be created with the assistance of AI that can make the hiring professionals' evaluation tasks more convenient and efficient (Johansson & Herranen, 2019).

Applicant ranking system works through the power of AI algorithms while the recruiters provide training data to the AI algorithms, from where they (AI algorithms) can learn the scoring function of the applicants (Johansson & Herranen, 2019). Chatbots, the AI-driven recruitment assistants enable personal and up-to-date connection possibilities with job applicants via emails, text messages or dialogue boxes. There are some computer-supported job matchmaking tools developed in

order to ease the workload of recruiters. Such tools include software that sorts resumes and can be implemented by exploiting learning-based techniques and algorithms (Montuschi et al., 2014). In this study, PUAHP was considered as the single independent construct.

2.3. PUAHP and PPJ: earlier studies regarding job applicants' perceptions

PUAHP and PPJ are the two important constructs/variables or points of interest in our study. We considered the first one as the single independent and the next one as the single dependent construct. Empirical studies focusing on job applicants' perceptions of AI-enabled hiring process are still rare in HRM academia. Based on the Organizational Justice Theory (OJT), Gilliland (1993) proposed the Applicant Reactions model (ARM), which posits that procedural justice or fairness, acts as a mediator between the characteristics of the selection process and the responses of job seekers. Previous research (for example, Konradt et al., 2020) suggested that the PPJ of job applicants might differ throughout the recruiting process, as individuals hold various standards at different stages of the process. Therefore, it is important to examine how the sense of fairness in recruiting techniques is affected by the level of digitization in each step of the application process.

During the application and screening stage, job applicants have the chance to provide additional or modified information about themselves through selection methods that rely on technology. These methods offer a greater technological advantage compared to more traditional methods, such as printed job application, where modification cannot be made once submitted (Hiemstra et al., 2019). By including a link to their social media (SM) profile, job applicants can offer additional information beyond what is typically provided in a traditional CV. This includes insights from their SM posts or likes, which can provide a more comprehensive understanding of applicants' personality and behaviors (Hosain et al., 2020, 2021; Hosain & Mustafi, 2023). Similarly, video applications or online resumes may provide further comprehensive information about applicants by including supplemental visual and audio elements (Hiemstra et al., 2019). Nevertheless, earlier research indicated that many job seekers need help to see the potential benefits of providing supplementary information during the application and screening phase (Hosain and Liu, 2020). However, they primarily worried about the fairness of the hiring process, particularly concerning the extensive use of digital technologies. In this regard, Ingold and Langer (2021) suggested that resumes based on SM are considered less equitable compared to traditional resumes. This particular outcome is consistent with the previous discovery made by Stoughton et al. (2015), who advocated that examining the social networks of job candidates diminishes their feeling of fairness throughout the hiring process.

However, there are also conflicting perspectives supported by limited scholarly research. For instance, Chen (2023) highlighted the significant impact of AI at every stage of the recruitment process. He found that integrating humans and AI facilitates the optimization of processes and enhances hiring efficiency. By using AI, recruiters may effectively eradicate self-serving prejudice and discrimination, hence providing equitable chances to all applicants (Abdelhay et al., 2023). In another similar study, Gupta and Mishra (2022) addressed the ethical issues associated with the use of AI in the recruiting process, particularly with data privacy and preference biases. They contended that biases might inadvertently arise from algorithmic programming inputs and the subconsciousness of the programmers. However, it is crucial to deal with these concerns to guarantee a fair and equitable selection. Pertinently, Nikitha (2022) stated that the HR professionals perceive the use of AI for recruiting as time-efficient and effective since it effectively screens out unqualified applications, resulting in an improved job-applicant matching. She contended that AI can significantly mitigate injustice when it is trained with accurate facts.

The use of AI in the recruiting process is seen favourably by the job applicants, leading to an improvement in their entire application experience (van Esch et al., 2019). In this pertinent, Laurie et al. (2021)

emphasized the need to ensure openness in AI algorithms to foster confidence between recruiters and job applicants. Rezzani et al. (2020) outlined the challenges associated with conducting AI research that spans several fields and ideas. They asserted that incorporating these viewpoints might pose challenges; thereby, it is essential to augment the utilization of AI for the applicant selection process. Moreover, the research conducted by van Esch et al. (2019) suggested that when job applicants express favorable opinions about the use of AI in the hiring process, it may result in increased acceptance rates and more favorable outcomes compared to conventional approaches. Therefore, we propose the following research hypothesis.

H1. There is a positive relationship between PUAHP and PPJ, i.e., job applicants have favorable perceptions of procedural justice regarding the use of AI in the hiring process.

2.4. The TAM

The TAM has been widely regarded as the most influential and commonly utilized model for assessing individuals' acceptance and adoption of a specific technology. It has been extensively studied and established in the fields of management and information literature (Huang & Liao, 2015; Jawad et al., 2022; Laurim et al., 2021, p. 5495; Natasia et al., 2022; Tahar et al., 2020). The concept of TAM was adapted from the Theory of Reasoned Action, which was initially explained by Fishbein and Ajzen (1975). However, the Theory of Reasoned Action was later appropriately reintroduced by Davis (1989), where the scholar posited that adopting new technology by humans is influenced by two separate indicating factors, PU and PEU. The TAM model has been extensively used (and, still being used by researchers) to examine users' perceptions of accepting (or rejecting) and adopting a novel technology. In our study, we used this model (the TAM) as the basis of identifying the aspects influencing the job applicants' perceptions and adoption of AI-oriented techniques for the recruitment process. However, in addition, we incorporated one more variable, PT, with the original two. One of the unique characteristics of this empirical study is that we considered the initial two factors of the TAM as well as extended it by adding one more factor, PT, and used all three factors as mediators to test their mediating roles in the relationship between PUAHP and PPJ.

2.4.1. PUAHP and PEU

Davis (1989) explained the term PEU as any individual's perception of the level of utilizing a specific technology or automation system that would reduce his/her effort or difficulties. Moreover, PEU is followed by the concepts of "ease of work" and "reduction of difficulties or superior human efforts". On the other hand, effort is a finite resource that a person may allocate to several tasks for which he/she is accountable (Davis, 1989; Radner and Rothschild, 1975). Assuming all other factors are the same, individuals are more likely to embrace a technology or system that is perceived as easy to use compared to others (Davis, 1989). They highlighted the above-mentioned argument's assertion that adopting AI technology requires a particular condition. Thus, according to the present study, employment seekers perceive that AI-oriented tools for their recruitment are handy and can be inclined to support the application process. Therefore, in our research, we suggest to test the following research hypothesis.

H2. PUAHP has a positive relationship with PEU.

2.4.2. PUAHP and PU

According to Davis (1989), within numerous variables that may affect a technology or system adoption/use, there are basically two substantial factors. First, individuals' adoption or rejection of a novel technology is often influenced by their perceptions of its ability to enhance their work performance, known as PU. Pertinently, Horodyski (2023) explained PU as the probability of seeking an employment,

which aggressively advocates for the use of technology; and individuals are encouraged to employ AI in hiring the job applicants due to its numerous advantages. Second, there are inherent benefits regarding employing AI, such as the desire or need to accomplish a goal or obtain an incentive as quickly as possible. According to van Esch and Black (2019), using innovative technology throughout the job application process is likely to make the potential employee feel satisfied. Other scholars, such as Davis et al. (1992) and Webster and Martocchio (1992), also previously indicated similar arguments. Finally, extrinsic incentives, including pleasure and the positive impacts of technology usage, have been included by van Esch et al. (2019). Thus, the use of AI tools in the recruiting process is justified because job applicants are willing to have them in their application process as long as they are advantageous (Venkatesh, 2000). Therefore, we propose that:

H3. PUAHP has a positive relationship with PU.

2.4.3. PUAHP and PT

Trust may be defined as the "positive anticipation that users have towards service providers" (Mayer et al., 1995). Trust is comprised of three main elements: honesty, ability and compassion (Palvia, 2009). Integrity pertains to the capacity of service companies to uphold their responsibilities. Ability refers to the stakeholders having sufficient technical knowledge and skill to fulfil their obligations. Ultimately, benevolence refers to a service provider's commitment to safeguarding the interests of the users. Trust is the primary factor influencing the consumers' perceptions in any technological context (Jawad et al., 2022; Mallat, 2007; Yan et al., 2009). It can be assumed that the job applicants will have positive perceptions regarding the use of AI-based tools for hiring if the recruiters can ensure that their concerns will be addressed (Lavanchy et al., 2023; Folger et al., 2022; Acikgoz et al., 2020; Suen et al., 2020). According to a study conducted in Singapore, Srivastava et al. (2010) proposed a trust-theoretic model and identified trust as the most significant construct compared to other factors.

We propose that if job applicants trust AI-enabled hiring process that is free of procedural bias and unexpected prejudices, they will perceive it as positive and form a positive PPJ from their points. On the other hand, if they believe that organizations are using AI-based tools that are biased or prejudiced and developed to reject or select particular applicants, they will not trust such technology, thus, develop a negative perception regarding the procedural justice of those particular organizations. Hence, we propose to test the following research hypothesis.

H4. PUAHP has a positive relationship with PT.

2.4.4. PEU and PPJ

We argue that although initially AI-based tools may seem complicated to use for the application process and may produce the perception of biasness from job applicants' end, they can eventually remove such accomplices once they are used to the application process (Horodyski, 2023). We further argue that it is the recruiters' role to remove the confusion and fear of biasness among job applicants. They can do it through proper communication with job applicants and supply the right information to the AI algorithm. Based on such an argument, it can be claimed that job applicants who presume that AI tools are convenient to use, will form a positive procedural justice perception of the applying organization. We thereby propose to test the following research hypothesis.

H5. PEU has a positive relationship with PPJ.

2.4.5. PU and PPJ

While applying for a job, applicants look for the usefulness of any technology that the hiring organizations can offer. Using AI may have several inherent values, including the desire to execute a definite goal/reward in the shortest possible duration. Thus, utilizing a superior technology while applying for a job should offer a certain extent of

perceived enjoyment or usefulness to the prospective applicants (Davis et al., 1992; van Esch & Black, 2019; Webster & Martocchio, 1992). Such an extrinsic motivation might influence job applicants to use similar technology (van Esch et al., 2019; Venkatesh, 2000) since applicants form an internal PPJ. Hence, the willingness of job applicants to adopt AI tools in their job application process confirms using such tools in the hiring process if they find them useful. Moreover, it will create a positive PPJ regarding the overall hiring process and the hiring organization.

H6. PU has a positive relationship with PPJ.

2.4.6. PT and PPJ

We propose that if job applicants trust AI-enabled hiring process that is free of procedural bias and unexpected prejudices, they will perceive it as positive and form a positive PPJ from their standpoints (Lavanchy et al., 2023; Folger et al., 2022; Acikgoz et al., 2020; Suen et al., 2020). On the other hand, if they believe that organizations are using AI-based tools that are biased or prejudiced and developed to reject or select particular job applicants, they will not trust such a technology and develop a negative perception of procedural justice of those particular organizations. Hence, we propose to test the following research hypothesis.

H7. PT has a positive relationship with PPJ.

2.4.7. Mediating roles of PEU, PU and PT

While job applicants prefer an application system and process to be easy, useful and trustworthy, they also expect that such process will be free of bias and reflect procedural justice (Hosain et al., 2020, 2021; Hosain & Mustafi, 2023). Although there are a limited number of research studies that applied the two factors of the TAM (PEU and PU) as mediators between the relationship of AI-based hiring process and PPJ, it can be strongly argued that job applicants will definitely prefer all the factors (PEU, PU and PT) that they can enjoy while applying for a job;

and at the same time, will expect a free and fair procedure from the hiring organization (Lavanchy et al., 2023; Suen et al., 2020). Thus, we argue that PEU, PU and PT mediate the positive relationship between PUAHP and PPJ and hence want to testify the following research hypotheses.

H8. PEU mediates the positive relationship between PUAHP and PPJ.

H9. PU mediates the positive relationship between PUAHP and PPJ.

H10. PT mediates the positive relationship between PUAHP and PPJ.

2.5. Conceptual framework

Fig. 1 indicates the conceptual framework of this empirical study.

3. Research methodology

3.1. Nature of data and the respondents

As the intention of this empirical research is to present its results with numerical values, it applied a quantitative methodology. In order to gather data for just one instant in time, we used a cross-sectional sample survey. Besides, we opted for primary data since this study was intended to be based on job applicants' perceptions of the use of AI for the hiring process. Job applicants' perceptions can be broadly defined as "their internal feelings and beliefs regarding an organization's hiring process and decision". In this empirical study, we tried to endeavor job applicants' perceived procedural justice toward the utilization of AI in the hiring process.

Secondary data, as we believe, were not suitable for finding the answers of the perception-based intended research questions. The respondents were purposefully recruited from different areas of Bangladesh. The respondent base included those job applicants who were either looking for jobs for the first time (fresh graduate job seekers)

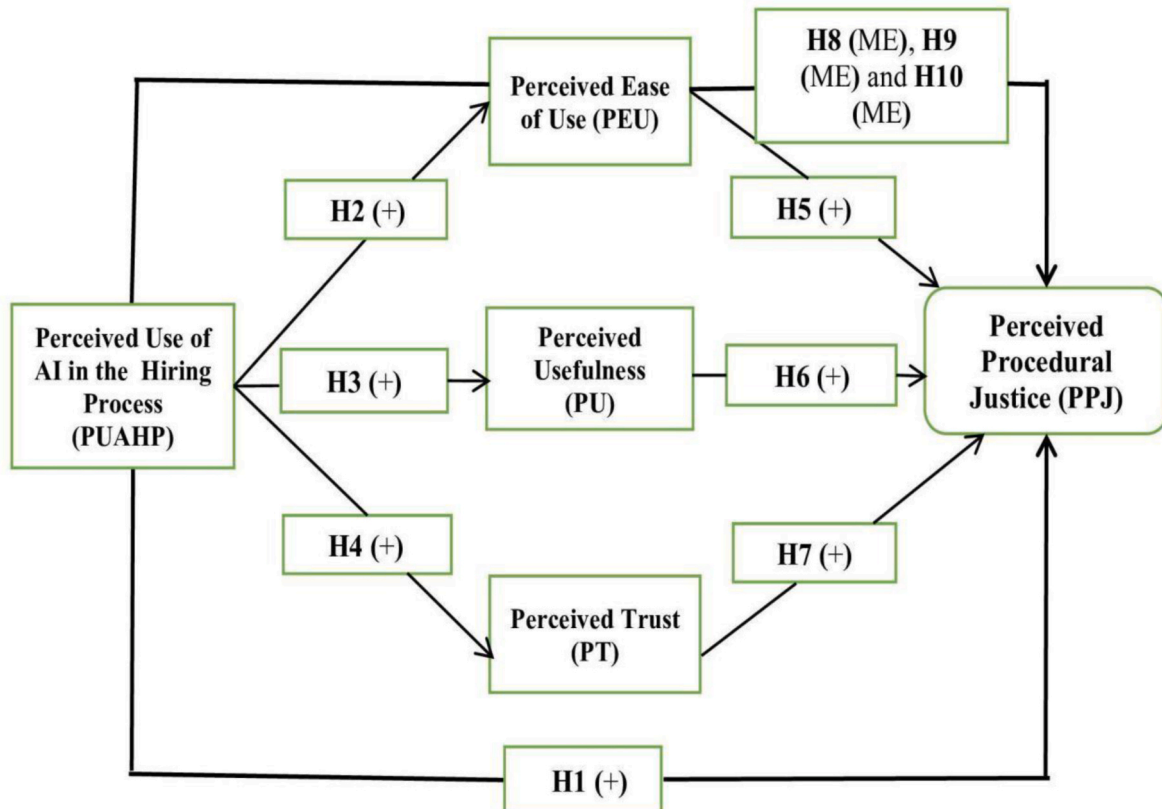


Fig. 1. ME = Mediating effect; Source: Researchers' own elaboration.

or those who were already serving at the current organizations but were looking for better ones (secondary applicants). All the respondents were informed about the use of AI in the hiring process (such as, its benefits, risks and the procedure).

We first introduced our research objectives to the potential respondents. We initially took oral consents from the willing respondents and later obtained written “Letter of Consent to Participate” from each respondent. In addition, we collected “Letter of Approval” from those organizations where some of the respondents (secondary applicants) were working at the time collecting data. The data were collected between the time period of May 2024 to July 2024.

3.2. Sampling technique and sample size determination

This research employed “purposive sampling” technique to select the appropriate respondents since it was designed with some specific objectives. Purposive sampling is a suitable sampling technique when the researchers intend to gather specific types of primary data they want from a specific group of samples (here, the individual job applicants). Additionally, as the respondents of this study were required to possess exclusive knowledge or the research itself had specific criteria established by us, purposive sampling was the best option (Sekaran & Bougie, 2010). According to Blumberg et al. (2011), purposive sampling is the appropriate choice when the researchers use the samples to conform to some specific criteria. We used purposive sampling technique to collect data from those individuals who could provide us adequate information regarding the various perception-oriented constructs of this study such as PUAHP, PEU, PU, PT and PPJ. Another reason to use purposive sampling, a non-probability sampling technique, was that the sampling frame or the exact population itself was unknown to us based on the opinions of Malhotra and Das (2017). In this study, it was not possible for us to ascertain exactly how many people were seeking their first jobs (fresh graduate job seekers) as well as how many were seeking better opportunities (secondary job seekers).

To ascertain the appropriate sample size for conducting structural equation modeling (SEM), we followed the advice of Faul et al. (2009) and used G*power test. The significance of G*power analysis in determining the optimal sample size for social science investigations has also been emphasized by Memon et al. (2017) and Hair Jr et al. (2021). According to G*power analysis, a research model with five components requires minimum of 177 samples, while a medium effect size of 255 samples is needed for achieving 80 % power at a 5 % level of significance (Faul et al., 2009). According to Malhotra and Das (2017), structural equation modeling (SEM) calls for at least three items or scales for each variable and a commonality of at least 0.5 is ideal. There was a total of five implicit variables examined in this study, whereas each variable had at least five items to measure. Based on the above recommendations and discussions, we believe that the intended sample size (more than 400) was sufficient to go on with the next stage.

To achieve the minimum required sample size of the respondents (as determined using G*power software), the initial distribution of 500 surveys was aimed at increasing the likelihood of collecting diverse and representative responses from individual job seekers. Based on the above criterion, we primarily selected a sample pool of 500 job applicants (primary and secondary) purposively. They were properly informed regarding the objectives and nature of the study, survey items and questionnaire filling procedure. After disbursing the questionnaires, we received back 442 filled up questionnaires (with a response rate of 88.4 %) from them. However, we discovered that 418 of those completed questionnaires were properly filled up, valid and useable. In accordance with established literature, a valid response rate of 83.6 % can be deemed favorable as indicated by Baruch and Holtom (2008). Previously, Karim et al. (2023) achieved 79 %, Shahneaz et al. (2020) achieved 77.9 %, Mahmud et al. (2023) achieved 47.2 % and Amin and Rubel (2020) obtained 44.37 % response rate in the context of Bangladesh. Therefore, we can claim that evaluating a total of 418

different samples was empirically acceptable while conducting this study.

3.3. Measurement scales, pre-test and pilot study

As a measurement tool, we developed a well-designed, 25-item survey instrument. The survey items were collected from prior literature available. To measure PPJ, all the five items were adapted from Folger et al. (2022), Acikgoz et al. (2020) and Hausknecht et al. (2004). The five items of PUAHP were adapted from Upadhyay and Khandelwal (2018). The five items of PEU were adapted from Davis (1989) and Davis et al. (1992). The five items of PU were adapted from Horodyski (2023) and van Esch and Black (2019). The five items of PT were adapted from Lavanchy et al. (2023), Folger et al. (2022) and Acikgoz et al. (2020). However, it should be noted that we did not find the exact research items that matched our research constructs. Rather, some of the items were collected from the literature and previous study findings, since some of our research constructs were not exactly used in any previous research (such as PUAHP). In addition, all the research items were slightly modified (adapted) according to the requirements of our study's constructs. This research utilized a “5-point Likert Scale” to get appropriate perceptions from our respondents where 1 indicated “Strongly Disagree” and 5 indicated “Strongly Agree”.

We pre-tested the survey instrument, including its scales, to ensure its accuracy and reliability. We used the “protocol” method by choosing 16 samples to make sure the survey instruments were substantial in terms of language and layout. Additionally, a pilot study was carried out with 32 respondents to ensure that the items of the questionnaire were reliable enough to proceed. Regarding this issue, previous researchers (for example, Memon et al., 2017) recommended that a sample size ranging from 10 to 30 respondents is sufficient for administering a pre-test. Thus, we contend that the sample sizes of both the pre-test and pilot study were appropriate enough due to these justifications.

3.4. Data analysis techniques

In order to examine the data and evaluate the suggested model, this research applied a partial least squares structural equation modeling (PLS-SEM) through PLS 4.0. When performing regression analysis, a PLS-SEM is the appropriate method of choice, particularly for evaluating the mediating effects (Hair et al., 1998). A strong and important statistical method, structural equation modelling (SEM), combined with path analysis and factor analysis, was used. At the same time, SEM examined all the hypothesized relationships. Specifically, we conducted a confirmatory factor analysis (CFA) to assess the components' validity and reliability as well as the structural fit with our theoretical model. Our data analysis was carried out using the 4th edition of Smart PLS (PLS 4.0) (Hair et al., 2021).

4. Analysis and interpretation

4.1. Respondents' profile

Table 1 presents the demographic information of the respondents. The table indicates that three-thirds (75.60 %) of the respondents were male. Nearly half of the respondents (48.08 %) were aged between 18 and 22 years followed by 23–27 years (32.30 %).

Regarding education, it was identified that majority of the respondents (74.88 %) had Master degrees while a quarter of them (25.12 %) completed Bachelor. Lastly, it was revealed that a large number of sample respondents (80.38 %) were fresh graduates looking for their first employments while 19.62 % of them were looking for better ones.

4.2. Common method bias (CMB)

This study applied Harman's single factor test to determine whether

Table 1
Respondents' demography.

Components	Category	Numbers	Proportion
Gender	Male	316	75.60
	Female	102	24.40
	Total (n)	418	100
Age level (Year)	18–22	201	48.08
	23–27	135	32.30
	28 and more	82	19.62
	Total (n)	418	100
Education	Bachelor	105	25.12
	Master	313	74.88
	Total (n)	418	100
Job status	Fresh graduates and unemployed	336	80.38
	Currently employed but looking for a better job	82	19.62
	Total (n)	418	100

Source: Survey questionnaire

“common method variance”, or CMB presented an imminent threat to our empirical investigation as recommended by Podsakoff et al. (2003). Based on Harman's single-factor test, CMB becomes problematic when the first component accounts for the majority portion of variation (Harman, 1976). After conducting an un-rotated exploratory component analysis on all the questionnaire items, we found that the first factor explained less than half, i.e., 50 % of the variation (29.24 %; please see Appendix A, Table A1), meaning that CMB was not severely flawed. Therefore, based on the criteria of Podsakoff et al. (2003), CMB did not impact the results of our study.

Additionally, this research included another two distinct methods to examine if there was any potential common method bias (CMB) throughout the partial least squares structural equation modeling (PLS-SEM) validation procedure. In accordance, first of all, this research adhered to Kock's (2015) guidelines for PLS-SEM verification methods to assess the presence of multicollinearity among the latent variables. All variation inflation factor (VIF) values, ranged from 1.000 to 1.226, were below the critical threshold of 3.3 (Refer to Appendix A, Table A2) and were determined to be within the acceptable limit. Second, there was little correlation between the novel marker variable (M1) and the established latent variables. According to M1, which denotes enabling situations (Podsakoff et al., 2024), none of them were statistically significant. The above mentioned discussion indicates that CMB was not a concern in this research.

4.3. Measurement model

In order to determine if the indicators used in this research were valid and reliable, a confirmatory factor analysis, in short, CFA was applied to verify the data. Convergent validity was examined at the same time to determine the item loading scores, average variance extracted (AVE) and composite reliability (CR) of this research. The loading scores of all indicators were higher than the cut-off levels proposed by Vinzi et al. (2010) and Hair et al. (2013), as shown in Table 2. The item scores below 0.70 were considered unsatisfactory loading scores; thus, according to the recommendation of Hair et al. (2013), 4 items were eliminated. Thus, items with such values (below 0.70) [PU5 (0.668), PPJ4 (0.376), PPJ5 (0.323) and PT1 (0.642)] were discarded. Following the advice of Hair et al. (2014), all the constructs were deemed suitable since their AVE values were more than 0.50. Moreover, all the constructs' composite reliability (CR) ratings were above the threshold value of 0.70. Thus, the measurement model of this study was supported by its convergent validity. Table 2 shows the CFA outputs.

This study used HTMT analysis to assess the discriminant validity. In contrast to the Fornell and Larcker's (1981) criterion (Table 3), the HTMT analysis (Table 4) used in this investigation is significantly superior, as demonstrated by Henseler et al. (2015). In addition, in the HTMT analysis, as indicated in Table 4, all the values were lower than

Table 2
Measurement model (CFA outputs).

Item codes	Constructs and items	Item loadings	Cronbach's alpha	CR	AVE
	Perceived Ease of Use		0.923	0.943	0.768
PEU1	I prefer ease and user-friendliness in searching and applying for a job.	0.795			
PEU2	I prefer not to apply through those websites that are difficult to surf.	0.900			
PEU3	I can easily navigate and use the job sites that use AI for applying new jobs.	0.930			
PEU4	I perceive AI as a handy tool for job application.	0.824			
PEU5	I believe that using AI for hiring is handy and free of bias.	0.924			
	Perceived Trust		0.850	0.900	0.694
PT2	I trust using AI tools for hiring can be impartial and fair.	0.749			
PT3	It depends on the recruiters whether or not AI tools can be used fairly.	0.789			
PT4	I prefer AI-based hiring to a traditional one.	0.891			
PT5	In my view, AI-based hiring can be welcomed by the job applicants if trusted.	0.893			
	Perceived Usefulness		0.829	0.886	0.661
PU1	Using AI tools for hiring purposes is useful and effective.	0.814			
PU2	I perceive that the recruiters who use AI can save time that can be devoted to more important tasks.	0.831			
PU3	AI tools are useful for both the recruiters and the applicants.	0.834			
PU4	The AI tools that are used for hiring should be useful and multi-purposive.	0.772			
	Perceived Use of AI for in Hiring Process		0.904	0.929	0.722
AH1	AI is a blessing of modern science.	0.850			
AH2	AI can be used for the hiring purposes.	0.886			
AH3	AI can save cost and time in hiring activities.	0.888			
AH4	AI can spare hiring professionals from manual, repetitive tasks (such as, CV sorting) and they can devote to more important hiring tasks (such as, interviewing applicants).	0.819			
AH5	If properly instructed, the AI-based hiring process can be bias less, quick and efficient.	0.803			
	Perceived Procedural Justice		0.768	0.866	0.685
PPJ1	Procedural justice is an important factor to build the relationship between	0.877			

(continued on next page)

Table 2 (continued)

Item codes	Constructs and items	Item loadings	Cronbach's alpha	CR	AVE
PPJ2	the recruiters and the applicants. If I do not trust an organization's hiring process, I will not apply for that organization's job.	0.853			
PPJ3	The hiring policies and practices of any organization should be based on fairness, ethics and justice.	0.746			

Note: The items **PU5**: AI is a blessing for the recruiters as well as for the job applicants as it has reduced the hiring complexities and time (scored 0.668); **PT1**: Trust is an important factor in adopting and using a new AI technology (scored 0.642); **PPJ4**: It is the responsibility of the hiring organizations to make the hiring process fair, ethical and impartial (scored 0.376); and **PPJ5**: I believe that using AI for the hiring process can be effective and impartial only if the hiring professionals want it to be (scored 0.323) were needed to be eliminated from the measurement model due to poor factor loadings (item score < 0.70); Source: Smart-PLS 4.0.

Table 3

Discriminant validity (Fornell-Larcker criterion).

Constructs	PUAHP	PEU	PPJ	PT	PU
PUAHP	0.850				
PEU	0.252	0.876			
PPJ	0.432	0.398	0.827		
PT	0.275	0.155	0.356	0.833	
PU	0.333	0.323	0.685	0.220	0.813

Source: Smart-PLS 4.0

Table 4

Discriminant validity (HTMT ratio).

Constructs	PUAHP	PEU	PPJ	PT	PU
PUAHP					
PEU	0.268				
PPJ	0.517	0.471			
PT	0.313	0.170	0.447		
PU	0.377	0.369	0.551	0.260	

Source: Smart-PLS 4.0

the threshold (0.850) proposed by Henseler et al. (2009). Therefore, it was risk-free to proceed with additional tests on all the latent constructs. Consequently, the constructs' reliability and validity were confirmed; and the measurement model was suitable for additional analysis. Table 3 represents the values from Fornell-Larcker criterion.

Additionally, Table 4 demonstrates the results from the test of Heterotrait-Monotrait (HTMT) ratio.

4.4. Structural model

We evaluated the structural model and tested the hypothesized associations using Smart-PLS version 4.0. First, the R^2 values were examined to find out the degree to which the research model explained the data. R^2 stands for the explanatory power of a predictor on the outcome construct. R^2 value for PEU was 0.063, representing that PUAHP explained 6.3 % variance in PEU. On the other hand, R^2 for PPJ was 0.564, implying that PEU, PT, PU, along with PUAHP explained 56.4 % variance in PPJ. Similarly, R^2 value for PT was 0.076 and PU was 0.111 representing that PUAHP explained 7.6 % variance in PT and 11.1 % in PU.

Moreover, to determine the predictive significance of the path

model, the blindfolding examination was employed with an omission distance rating of 7. According to Table 5, the endogenous components in the questionnaire had Stone-Geisser's Q^2 values that were more than zero ($Q^2_{PEU} = 0.045$, $Q^2_{PPJ} = 0.377$, $Q^2_{PT} = 0.052$, $Q^2_{PU} = 0.071$). In this regard, according to Hair et al. (2021), if the path model shows satisfactory predictive relevance, the test for cross-validation is confirmed. Table 5 shows the results from the predictive relevance test.

Furthermore, based on the suggestion of Amin and Rubel (2020), this study revealed that the VIF values in Table 6 of all the constructs were lower than 3.3, indicating no problem with multicollinearity issues.

Following that, a bootstrapping procedure with one tail was used with a total of 5000 sub-samples in order to determine the path coefficients, weights and significance (Hair et al., 2021). Evidently, as seen in Table 7 and Fig. 2, the path from PUAHP to PPJ was found to be significantly positive ($\beta = 0.167$; $p < 0.05$) indicating hypothesis H1 representing the only direct relationship as valid. The path from PUAHP to PEU ($\beta = 0.252$; $p < 0.05$), PUAHP to PU ($\beta = 0.333$; $p < 0.05$), PUAHP to PT ($\beta = 0.275$; $p < 0.05$), PEU to PPJ ($\beta = 0.155$; $p < 0.05$), PU to PPJ ($\beta = 0.543$; $p < 0.05$) and PT to PPJ ($\beta = 0.167$; $p < 0.05$) were also found positive and statistically significant. Therefore, all the research hypotheses, H2 to H7 were significantly positive and proved to be valid based on the statistical outcomes. Such outcomes may have appeared due to the unique characteristics of the Bangladeshi job market where the number of graduates are much more higher than the number of vacant jobs. Therefore, job applicants may have prioritized ease of use, fairness and usefulness rather than privacy or ethical issues. Table 7 shows the results of hypotheses tests indicating the single direct effect and specific indirect effects.

Nevertheless, according to the recommendation of Preacher and Hayes (2008), we evaluated how PEU, PT and PU mediated the connection between PUAHP and PPJ. Relatedly, Table 8 displays the outcomes of the structural model's mediating influences, revealing that the relationship between PUAHP and PPJ was partially mediated by PEU, PT and PU.

Table 8 shows that all the three mediators (PEU, PU and PT) mediated the direct relationship between PUAHP and PPJ due to having positive beta values and corresponding p values less than 0.05. However, all the three mediation types were partial since the direct relationship was significantly positive and all the corresponding indirect relationships were also significantly positive.

5. Discussion

According to the results identified, PUAHP has a significant positive relationship with the dependent variable, PPJ. The outcome is supported by several earlier findings reported by Abdelhay et al. (2023); Chen (2023); Gupta and Mishra (2022); Nikitha (2022); Hiemstra et al. (2019); Konradt et al. (2020); Rezzani et al. (2020); and Van Esch et al. (2019). On the other hand, PUAHP was found to be positively related to PEU which is supported by a scant studies conducted by Horodyski (2023) and Danks and London (2017). PU was identified to have a significant positive relationship with PUAHP consistent with earlier findings of Horodyski (2023) and van Esch et al. (2019). Finally, PUAHP was found to have a significant positive association with PT duly supported by Lavanchy et al. (2023); Folger et al. (2022); Acikgoz et al. (2020); and Suen et al. (2020).

Table 5

Predictive relevance.

Constructs	R^2	Adjusted R^2	Q^2 values
PEU	0.063	0.061	0.045
PPJ	0.564	0.560	0.377
PT	0.076	0.073	0.052
PU	0.111	0.109	0.071

Source: Smart-PLS 4.0

Table 6

VIF values for the constructs.

Constructs	PUAHP	PEU	PPJ	PT	PU
PUAHP		1.000	1.207	1.000	1.000
PEU			1.150		
PPJ					
PT			1.108		
PU			1.226		

Source: Smart-PLS 4.0

Table 7

Hypotheses testing (Direct effects and specific indirect effects).

Hypotheses	Paths	Std. beta	Std. error	T statistics	p values	Decisions
H1	PUAHP → PPJ	0.167	0.163	4.544	0.000	Significant
H2	PUAHP → PEU	0.252	0.252	6.183	0.000	Significant
H3	PUAHP → PU	0.333	0.337	7.460	0.000	Significant
H4	PUAHP → PT	0.275	0.275	5.727	0.000	Significant
H5	PEU → PPJ	0.155	0.156	4.825	0.000	Significant
H6	PU → PPJ	0.543	0.548	9.666	0.000	Significant
H7	PT → PPJ	0.167	0.164	3.734	0.000	Significant

Source: Smart-PLS 4.0

Regarding the relationships between the mediator and the dependent variable, this study identified that PEU has significant positive relationship with PPJ. This finding is consistent with the studies conducted by [Chen \(2023\)](#) and [Nikitha \(2022\)](#). PU was identified to have a

significant positive relationship with PPJ supported by the findings reported by [Horodyski \(2023\)](#). Lastly, we found that PT is also significantly connected with PPJ. This finding is also consistent with [Lavanchy et al. \(2023\)](#); [Folger et al. \(2022\)](#); [Acikgoz et al. \(2020\)](#); and [Suen et al. \(2020\)](#). Therefore, our findings sufficiently matched with the earlier ones although the study context and perspectives may differ. However, we believe that AI is an indispensable tool for modern business and management while hiring, an important function of HRM, is no exception.

Therefore, all the research hypotheses were found to be valid and are supported by the earlier research outcomes. The research questions were also answered clearly. Such outcomes indicate that our selection of the model and variables were appropriate. However, such outcomes might not be generalized due to the unique nature of specific country culture and individual perceptions affected by the local cultures and preferences. The findings also support the basic argument of the TAM indicating that individuals (job applicants) prefer a technology which is useful, easy to use and can be trusted. Therefore, we can also claim that the theory we adopted was appropriate.

6. Implications

6.1. Academic implications

Although we can observe rapid progress regarding the use of AI-based technology for different HRM functions, in general, using the algorithm for the hiring process; the academia is still lagging in coping with the pace of its use. In particular, there is still a limited number of empirical studies about job applicants' reactions to the AI-based recruitment process ([Hunkenschroer & Luetge, 2022](#); [Laurim et al., 2021](#), p. 5495; [van Esch & Black, 2019](#)).

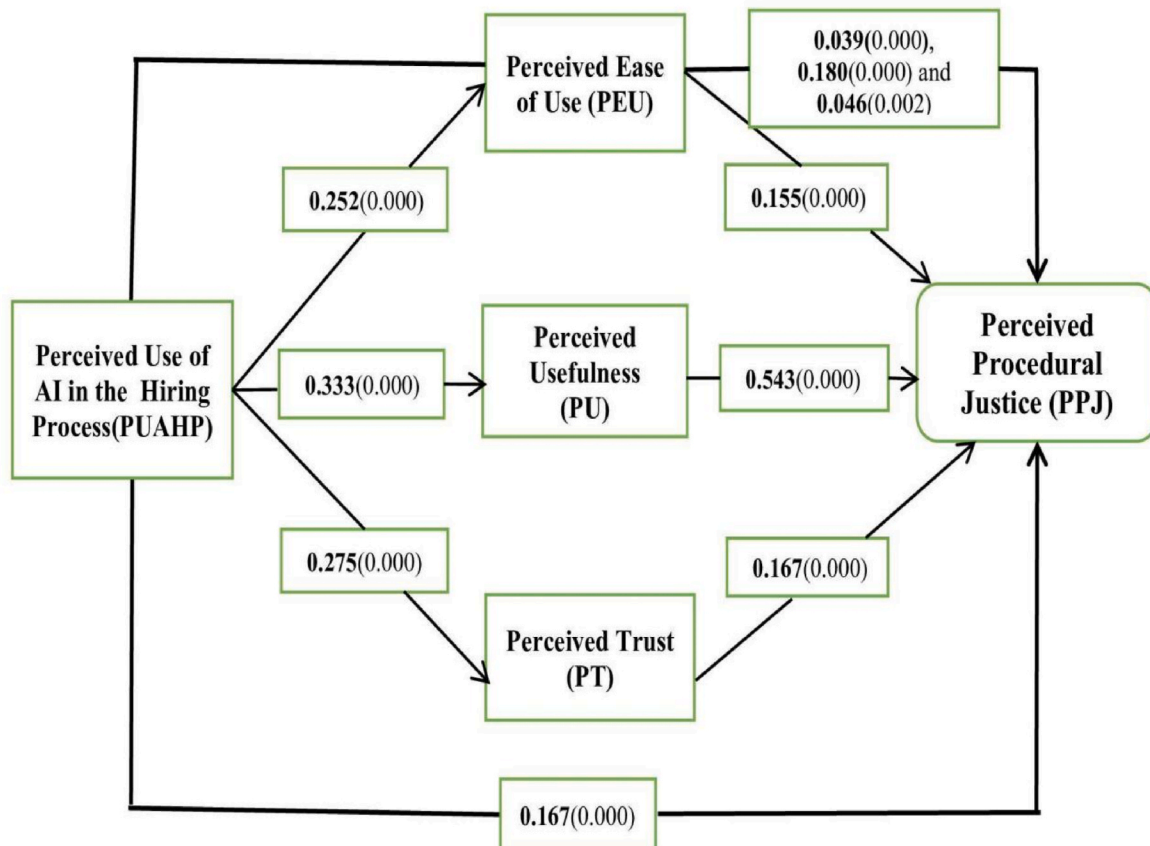
**Fig. 2.** PLS-SEM Results; Source: Smart-PLS 4.0.

Table 8
Mediating effects.

Hypotheses	Paths	Std. beta	Std. error	T statistics	P values	Mediation types
H8	PUAHP→ PEU→ PPJ	0.039	0.039	3.691	0.000	Partial mediation
	PUAHP→ PPJ (Direct effect)	0.167	0.163	4.544	0.000	
	PUAHP→ PEU (Indirect effect)	0.252	0.252	6.183	0.000	
	PEU→ PPJ (Indirect effect)	0.155	0.156	4.825	0.000	
H9	PUAHP→ PU→ PPJ	0.180	0.185	5.358	0.000	Partial mediation
	PUAHP→ PPJ (Direct effect)	0.167	0.163	4.544	0.000	
	PUAHP→ PU (Indirect effect)	0.333	0.337	7.460	0.000	
	PU→ PPJ (Indirect effect)	0.543	0.548	9.666	0.000	
H10	PUAHP→ PT→ PPJ	0.046	0.045	3.168	0.002	Partial mediation
	PUAHP→ PPJ (Direct effect)	0.167	0.163	4.544	0.000	
	PUAHP→ PT (Indirect effect)	0.275	0.275	5.727	0.000	
	PT → PPJ (Indirect effect)	0.167	0.164	3.734	0.000	

Source: Smart-PLS 4.0

The findings of this study provided a comprehensive range of favorable and unfavorable arguments about the utilization or avoidance of AI technology in the hiring process, which were very limited in prior research studies. This research can enhance the existing literature by introducing additional criteria for accepting AI-based hiring, highlighting the primary concerns of job applicants about this technology; and providing an overview of the current level of acceptance (from the standpoint of job applicants) of AI in the hiring process. Hence, this work might serve as a valuable resource for the upcoming scholars in seeking to explore supplementary aspects that can impact the acceptability of AI used for various HRM practices.

Additionally and most importantly, we used the extended TAM as the mediators on the relationship between PUAHP and PPJ by the job applicants. Therefore, this paper can open a new avenue for the academics in investigating different factors that might possibly affect such relationship(s). Future research studies might focus on the different angles of applicants perceptions regarding the use of AI in different HRM functions using different variables or respondents.

6.2. Managerial implications

The implications of our results have managerial importance when considering the decision to include AI in the hiring process. Algorithms may enhance organizational adaptability by promptly reacting to job applicants and perhaps mitigating prejudice in the recruitment process (Cowgill, 2021; Kleinberg et al., 2018). Nevertheless, technology may also give rise to ethical, regulatory and privacy considerations that HR managers must consider. With the progression of novel technologies,

algorithms have the potential to identify personal characteristics (such as family status, political beliefs or physical and mental fitness) indirectly and often more accurately without explicit agreement. Consequently, if job applicants perceive AI-based recruitment as unjust or violating their privacy rights, they may be less inclined to apply for positions advertised by that organization (Lavanchy et al., 2023).

Moreover, Lavanchy et al. (2023) advocated that job seekers are inclined to recognize unjust recruitment procedures as evidence of "malfunctioning" organizations. In response, applicants who perceive unfair treatment are more inclined to develop negative attitudes toward such organizations. This, in turn, can diminish their willingness to accept the job offers, reduce their commitment to those organizations and job satisfaction, deter others from applying or purchasing those organizations' products or services and potentially increase the likelihood of a lawsuit (Alder & Gilbert, 2006; Lavanchy et al., 2023). Job applicants' opinions of AI-enabled hiring procedures might contribute to a comprehensive knowledge of how AI-based hiring choices can be both efficient and morally acceptable, as stated by Lavanchy et al. (2023) and Leicht-Deobald et al. (2019). Procedural fairness is believed to be important in predicting overall work attitudes, such as trust and commitment. When individuals perceive a fair procedure, it may help reduce their inclination to respond adversely to unfavorable results (Lavanchy et al., 2023).

Various strategies have been proposed by various researchers to enhance the legitimacy of AI, including anthropomorphizing algorithms (Waytz et al., 2014), increasing the perception of authenticity (Jago, 2019), providing explanations of how AI works (Yeomans et al., 2019) and delivering more sorts of information (Bigman & Gray, 2018). While several proposed solutions show promise, these results also emphasize the absence of a definitive method to eradicate AI aversion, especially in specific situations like different HRM functions. Hiring managers can implement algorithms in a way that elicits favorable reactions from job applicants. In addition, organizations should provide job applicants with a clear explanation of how their personal information will be utilized in the recruiting process. This ex-post explanation may effectively express the essential aspects involved in the decision-making process (Kim & Routledge, 2022). Recruiters may exemplify the objective fairness of relying on analytics compared to only relying on human decision-makers. Organizations have the option to combine algorithms with a human decision-maker who may evaluate the qualitative elements.

7. Limitations and suggestions for the upcoming studies

This study has several drawbacks. First of all, this study considered only job applicants' perceptions of AI's applications concerning its usefulness, ease of use and perceived trust in utilizing it (AI) for the recruitment purposes. Such a narrow focus made the scope of this study limited as it did not consider other possible factors influencing the use of AI in the hiring process, nor did it consider other alternative technologies that may be potentially applied to the hiring process. Second, this research did not investigate the ethical, privacy and legal issues associated with using AI for recruiting.

Third, this study did not investigate the variations in demographic characteristics, such as gender, countries, industries or age of the respondents. This aspect might be a compelling avenue for the future researchers to explore. To be more specific, the age of job applicants might have a significant influence on the degree to which AI technology is accepted and the degree to which they are inclined to utilize this technology in the process of applying for job positions. Last of all, this research was carried out using the primary data collected from a single nation. Utilizing a distinct set of study respondents and altering the questionnaire or survey platform may have provided divergent replies, enhancing our understanding of AI-driven hiring technology. The results of the subsequent studies may shed lights on the extent to which job applicants are willing to make use of AI and other technological

breakthroughs throughout the application process, as well as the ways in which this may influence their attitudes toward the organizations they are applying to and their likelihood of applying for the job positions.

8. Conclusion

Based on the results of this empirical study, job applicants have a positive disposition toward the application of AI technology in the process of hiring new employees. According to the outcomes of this empirical study, all three TAM technology acceptance factors, perceived usefulness, perceived ease of use and perceived trust, have favorable associations with perceived procedural justice. Therefore, it was found that respondents from Bangladesh have positive perceptions of AI-driven hiring process. The results are primarily consistent with studies that were conducted before, which also discovered that job applicants are content with the perceived use of AI-based resources in the recruiting process and perceive the job application process to be more useful, easy to use, trustworthy and attractive. Based on the findings of this study, the use of AI in the hiring practices can be validated.

There may be practical ramifications for both the apparent benefits and drawbacks of AI technology. Regarding the positives, AI provides a plethora of advantages, such as faster response times, a more accessible interface, more useful features, higher quality, more objective hiring processes and an overall better user experience. On the other side, concerns about AI's lack of human contact and its unreliability are its main downsides. Algorithm biases, speech/text recognition and insufficient optimization for video interviews further demonstrate the technology's immaturity. Also, when dealing with AI, one must be more open and honest. Moreover, AI may cause privacy, equality, legality and ethical issues. HR experts and software developers may find stagnation points in AI to be valuable development as they work to improve AI technologies and make them more suitable for the use of different HRM functions.

In conclusion, AI is a gift of modern science and technology.

Appendices.

Table A1
Harman's Single Factor test (Common method biasness test)

Component	Initial Eigen values			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.310	29.241	29.241	7.310	29.241	29.241
2	3.145	12.582	41.823			
3	2.452	9.808	51.631			
4	2.355	9.418	61.049			
5	1.086	4.342	65.391			
6	1.074	4.296	69.688			
7	1.004	4.016	73.703			
8	0.863	3.453	77.157			
9	0.615	2.458	79.615			
10	0.607	2.430	82.045			
11	0.601	2.404	84.448			
12	0.503	2.013	86.462			
13	0.443	1.771	88.233			
14	0.422	1.689	89.922			
15	0.390	1.559	91.481			
16	0.349	1.396	92.877			
17	0.335	1.342	94.219			
18	0.301	1.206	95.425			
19	0.281	1.122	96.547			
20	0.246	0.983	97.530			
21	0.228	0.913	98.443			
22	0.219	0.878	99.321			
23	0.162	0.647	99.967			
24	0.006	0.025	99.993			
25	0.002	0.007	100.000			

Therefore, it cannot be completely overlooked. What we can do is to make attempts to reduce its weaknesses and improve the technology to get optimum solution for HRM. In this perceptive, the data input as well as the operational activities should be error or bias-free so that the decision can be fair, impartial and optimum. Whether we accept it or not, technology is dominating and will continue to dominate the organizational functions in the upcoming times. Therefore, it is better to embrace technology and try to get the best out of it.

CRediT authorship contribution statement

Md Sajjad Hosain: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Data curation, Conceptualization. **Mohammad Bin Amin:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Gouranga Chandra Debnath:** Writing – review & editing, Visualization, Validation, Software, Resources, Methodology, Data curation. **Md Atikur Rahaman:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition.

Declaration of competing interest

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

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Note: Extraction method: Principal Component Analysis; Source: SPSS 26.

Table A2
Multi-collinearity test

	AH	PEU	PPJ	PT	PU
AH					
PEU		1.000			
PPJ			1.207		
PT			1.150		
PU			1.108	1.000	1.000
			1.226		

Data availability

Data will be made available on request.

References

Abdelhay, S., Korany, H., Marie, A., & Fareen, A. (2023). Artificial Intelligence Applications in the recruitment process opportunities and challenges. *European Chemical Bulletin*, 7, 1008–1019.

Acikgoz, Y., Davison, K. H., Compagnone, M., & Laske, M. (2020). Justice perceptions of artificial intelligence in selection. *International Journal of Selection and Assessment*, 28 (4), 399–416.

Alder, G. S., & Gilbert, J. (2006). “Achieving ethics and fairness in hiring: Going beyond the law. *Journal of Business Ethics*, 68(4), 449–464.

Amin, M. B., & Rubel, M. R. B. (2020). Human resource management practices and employee knowledge sharing behavior: Mediating role of knowledge sharing intention. *Asian Journal of Empirical Research*, 10(5), 150–151.

Baruch, Y., & Holtom, B. C. (2008). Survey response rate levels and trends in organizational research. *Human Relations*, 61(8), 1139–1160.

Bigman, Y. E., & Gray, K. (2018). People are averse to machines making moral decisions. *Cognition (The Hague)*, 181, 21–34.

Blumberg, B., Cooper, D. R., & Schindler, P. S. (2011). *Business research methods* (11th Eds.). New York: McGraw Hill.

Chen, Z. (2023). Collaboration among recruiters and artificial intelligence: Removing human prejudices in employment. *Cognition, Technology & Work*, 25(1), 135–149.

Colquitt, J. A., Conlon, D. E., Wesson, M. J., Porter, C. O. L. H., & Ng, K. Y. (2001). Justice at the millennium: A meta-analytic review of 25 years of organizational justice research. *Journal of Applied Psychology*, 86(3), 425–445.

Cowgill, B. (2021). *Bias and productivity in humans and algorithms: Theory and evidence from resume screening*. Working paper, Columbia Business School.

Da Motta Veiga, Figueroa-Armijos, M., & Clark, B. (2022). Artificial Intelligence in Hiring and Applicant Attraction: The Role of Ethical Perceptions. In , Vol. 2022, No. 1. *Academy of Management Proceedings* (p. 10291). Manor, NY: Briarcliff. <https://doi.org/10.5465/AMBPP.2022.10291abstract>.

Danks, D., & London, A. J. (2017). Algorithmic bias in autonomous systems. 26th *International Joint Conference on Artificial Intelligence*, 4691–4697. Pittsburgh, USA, August, 2017.

Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against women. <https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G>. (Accessed 20 September 2023).

Dattner, B., Chamorro-Premuzic, T., Buchband, R., & Schettler, L. (2019). The legal and ethical implications of using AI in hiring. *Harvard Business Review*, 25, 1490–1523.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319–339.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology*, 22(14), 1111–1132.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, 41(4), 1149–1160. <https://doi.org/10.3758/BRM.41.4.1149>

Figueroa-Armijos, M., Clark, B. B., & da Motta Veiga, S. P. (2023). Ethical perceptions of AI in hiring and organizational trust: The role of performance expectancy and social influence. *Journal of Business Ethics*, 186(1), 179–197.

Fishbein, M., & Ajzen, I. (1975). *Beliefs, attitude, intention and behavior: An introduction to theory and research*. Reading, MA: Addison-Wesley.

Folger, N., Brosi, P., Stumpf-Wollersheim, J., & Welp, I. M. (2022). Applicant reactions to digital selection methods: A signaling perspective on innovativeness and procedural justice. *Journal of Business and Psychology*, 37, 735–757.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, 12, 382–388.

Frail, J., & László, V. (2021). A literature review: Artificial intelligence impact on the recruitment process. *International Journal of Engineering and Management Sciences*, 6 (1), 108–119.

Gilliland, S. W. (1993). The perceived fairness of selection systems: An organizational justice perspective. *Academy of Management Review*, 18(4), 694–734.

Gonzalez, M. F., Liu, W., Shirase, L., Tomczak, D. L., Lobbe, C. E., Justenhoven, R., & Martin, N. R. (2022). Allying with AI? Reactions toward human-based, AI/ML-based, and augmented hiring processes. *Computers in Human Behavior*, 130, Article 107179.

Gupta, A., & Mishra, M. (2022). Ethical concerns while using Artificial Intelligence in recruitment of employees. *Business Ethics and Leadership*, 6(2), 58–66.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). *Multivariate data analysis* (5th Eds.). Upper Saddle River, New Jersey, USA: Prentice Hall.

Hair, J. F., Astrachan, C. B., Moisesco, O. I., Radomir, L., Sarstedt, M., Vaithilingam, S., & Ringle, C. M. (2021). Executing and interpreting applications of PLS-SEM: Updates for family business researchers. *Journal of Family Business Strategy*, 12(3), 100392.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis*. California, USA: Pearson Education.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook* (p. 197). Springer Nature. <https://library.oapen.org/handle/20.500.12657/51463>.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance. *Long Range Planning*, 46(1–2), 1–12.

Harman, H. H. (1976). *Modern factor analysis*. Chicago: University of Chicago press.

Hausknecht, J. P., Day, D. V., & Thomas, S. C. (2004). Applicant reactions to selection procedures: An updated model and meta analysis. *Personnel Psychology*, 57(3), 639–683.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43, 115–135.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing*, 20, 277–319.

Hiemstra, A. M. F., Oostrom, J. K., Derous, E., Serlie, A. W., & Born, M. P. (2019). Applicant perceptions of initial job candidate screening with asynchronous job interviews. *Journal of Personnel Psychology*, 18(3), 138–147.

Hirschheim, R. (2007). Introduction to the special issue on quo vadis TAM-issues and reflections on technology acceptance research. *Journal of the Association for Information Systems*, 8(4), 9–17.

Horodyski, P. (2023). Applicants’ perception of artificial intelligence in the recruitment process. *Computers in Human Behavior Reports*, 11(4), Article 100303.

Hosain, M. S., Hossin, M. A., Xiaohua, Y., Aktaruzzaman, M., & Mustafi, M. A. A. (2020). “Social networking information and pre-employment background checks: The mediating role of sustainable organizational reputation. *Sustainability (Basel)*, 12(8), 3090.

Hosain, M. S., Liu, P., & Mustafi, M. A. A. (2021). “Social networking information and pre-employment background check: Mediating effects of perceived benefit and organizational branding. *International Journal of Manpower*, 42(7), 1279–1303.

Hosain, M. S., & Mustafi, M. A. A. (2023). “Social networking information and job applicants’ background check: Mediating and moderating effects of employers’ behavioral intention and legal consideration. *Middle East Journal of Management*, 10 (5), 467–498.

Huang, T. L., & Liao, S. (2015). A model of acceptance of augmented-reality interactive technology: The moderating role of cognitive innovativeness. *Electronic Commerce Research*, 15(2), 269–295, 2015.

Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics*, 178(4), 977–1007.

Ingold, P. V., & Langer, M. (2021). Resume= resume? The effects of blockchain, social media, and classical resumes on resume fraud and applicant reactions to resumes. *Computers in Human Behavior*, 114, Article 106573.

Jago, A. S. (2019). Algorithms and authenticity. *Academy of Management Discoveries*, 5 (1), 38–56.

Jaser, Z., Petrakaki, D., Starr, R. R., & Oyarbide-Magaña, E. (2022). *Where automated job interviews fall short*. Harvard Business Publishing Education. Web article <https://hbr.org/2022/01/where-automated-job-interviews-fall-short>. (Accessed 20 September 2023).

Jawad, A. I., Parvin, T., & Hosain, M. S. (2022). Intention to adopt mobile-based online payment platforms in three asian countries: An application of the extended technology acceptance model. *Journal of Contemporary Marketing Science*, 5(1), 92–113.

Johansson, J., & Herranen, S. (2019). The application of Artificial Intelligence (AI) in Human Resource Management: Current state of AI and its impact on the traditional recruitment process. *Bachelor thesis submitted to the Business*. School of Jonkoping University. May, 2019.

- Karim, M. M., Amin, M. B., Ahmed, H., Hajdú, Z., & Popp, J. (2023). The influence of leadership styles on employee performance in telecom companies of Bangladesh. *Management*, 21(3), 671–681.
- Kassir, S., Baker, L., Dolphin, J., & Polli, F. (2023). AI for hiring in context: A perspective on overcoming the unique challenges of employment research to mitigate disparate impact. *AI and Ethics*, 3(3), 845–868.
- Kelley, S. (2022). Employee perceptions of the effective adoption of AI principles. *Journal of Business Ethics*, 178(4), 871–889.
- Kim, T. W., & Routledge, B. R. (2022). Why a right to an explanation of algorithmic decision-making should exist: A trust-based approach. *Business Ethics Quarterly*, 32(1), 75–102.
- Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J., & Mullainathan, S. (2018). Human decisions and machine predictions. *Quarterly Journal of Economics*, 133(1), 237–293.
- Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration*, 11(4), 1–10. <https://doi.org/10.4018/ijec.2015100101>
- Konradt, U., Oldeweme, M., Krysz, S., & Otte, K.-P. (2020). A meta-analysis of change in applicants' perceptions of fairness. *International Journal of Selection and Assessment*, 28(4), 365–382.
- Laurim, V., Arpacı, S., Prommegger, B., & Krcmar, H. (2021). Computer, whom should I hire?—acceptance criteria for artificial intelligence in the recruitment process. *Proceedings of the 54th Hawaii international conference on system sciences, Hawaii, USA*.
- Lavanchy, M., Reichert, P., Narayanan, J., & Savani, K. (2023). Applicants' fairness perceptions of algorithm-driven hiring procedures. *Journal of Business Ethics*. <https://doi.org/10.1007/s10551-022-05320-w> (ahead of publication) No (ahead of publication), pp. (ahead of publication).
- Lee, C., & Cha, K. (2023). FAT-CAT—explainability and augmentation for an AI system: A case study on AI recruitment-system adoption. *International Journal of Human-Computer Studies*, 171(1), Article 102976.
- Leicht-Deobald, U., Busch, T., Schank, C., Weibel, A., Schafheitle, S., Wildhaber, I., & Kasper, G. (2019). The challenges of algorithm-based HR decision-making for personal integrity. *Journal of Business Ethics*, 160(2), 377–392.
- Mahmud, A., Ding, D., Hasan, M., Ali, Z., & Amin, M. B. (2023). Employee psychological reactions to micro-corporate social responsibility and societal behavior: A structural equation modeling analysis. *Current Psychology*, 42(20), 17132–17146.
- Malhotra, N., & Das, S. (2017). *Marketing research: An applied orientation* (6th ed.). New Delhi, India: Dorling Kindersley (India) Pvt. Ltd.
- Mallat, N. (2007). Exploring consumer adoption of mobile payments – a qualitative study. *The Journal of Strategic Information Systems*, 16(4), 413–432.
- Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, 20(3), 709–734.
- Memon, M., Ting, H., Ramayah, T., Chuah, F., & Cheah, J. (2017). A review of the methodological misconceptions and guidelines related to the application of structural equation modeling: A Malaysian scenario. *Journal of Applied Structural Equation Modeling*, 1(1), 1–13. [https://doi.org/10.47263/JASEM.1\(1\)01](https://doi.org/10.47263/JASEM.1(1)01)
- Montuschi, P., Gatteschi, V., Lamberti, F., Sanna, A., & Demartini, C. (2014). Job recruitment and job seeking processes: How technology can help IT. *IT Professional*, 16, 41–49.
- Natasia, S. R., Wiranti, Y. T., & Parastika, A. (2022). Acceptance analysis of NUADU as e-learning platform using the Technology Acceptance Model (TAM) approach. *Procedia Computer Science*, 197, 512–520.
- Nikitha, M. (2022). A study on effectiveness of E-recruitment method in IT industries in Bangalore city, India. *International Journal for Research in Applied Science and Engineering Technology*, 10(8), 67–74.
- Palvia, P. (2009). The role of trust in e-commerce relational exchange: A unified model. *Information and Management*, 46(4), 213–220.
- Pan, Y., Froese, F., Liu, N., Y. Hu, Y., & Ye, M. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *International Journal of Human Resource Management*, 33(6), 1125–1147.
- Pavaloia, V. D., & Necula, S. C. (2023). “Artificial intelligence as a disruptive technology—a systematic literature review. *Electronics*, 12(5), 1102.
- Podsakoff, P., MacKenzie, S., Lee, J., & Podsakoff, N. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879–903.
- Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix. *Annual Review of Organizational Psychology and Organizational Behavior*, 11(1), 17–61.
- Radner, R., & Rothschild, M. M. (1975). On the allocation of effort. *Journal of Economic Theory*, 10(3), 358–376.
- Rashid, A. B., & Kausik, M. A. K. (2024). AI revolutionizing industries worldwide: A comprehensive overview of its diverse applications. *Hybrid Advances*, 7, Article 100277.
- Rezzani, A., Caputo, A., & Cortese, C. G. (2020). An analysis of the literature about the application of artificial intelligence to the recruitment and personnel selection. *BPA Applied Psychology Bulletin*, 68, 25–33.
- Sekaran, U., & Bougie, R. (2010). *Research methods for business: A skill building approach*. London: John Wiley & Sons.
- Shahneaz, M. A., Amin, M. B., & Eni, L. N. (2020). The Interplay between the psychological factors and entrepreneurial intention: An empirical investigation. *The Journal of Asian Finance, Economics and Business (JAFEB)*, 7(12), 139–146.
- Sohn, K., & Kwon, O. (2020). Technology acceptance theories and factors influencing Artificial Intelligence-based intelligent products. *Telematics and Informatics*, 47, Article 101324.
- Srivastava, S. C., Chandra, S., & Theng, Y. L. (2010). Evaluating the role of trust in consumer adoption of mobile payment systems: An empirical analysis. *Communications of the Association for Information Systems*, 27(1), 561–588.
- Stahl, B. C., & Wright, D. (2018). “Ethics and privacy in AI and big data: Implementing responsible research and innovation”. *IEEE Security & Privacy*, 16(3), 26–33.
- Stoughton, J. W., Thompson, L. F., & Meade, A. W. (2015). Examining applicant reactions to the use of social networking websites in pre-employment screening. *Journal of Business and Psychology*, 30(1), 73–88.
- Stuart, R., & Norvig, P. (2016). *Artificial intelligence: A modern approach* (3rd ed.). Upper Saddle River, New Jersey, USA: Prentice Hall Press.
- Suen, H.-Y., Chen, M. Y.-C., & Lu, S.-H. (2020). Does the use of synchrony and artificial intelligence in video interviews affect interview ratings and applicant attitudes? *Computers in Human Behavior*, 98, 93–101.
- Tahar, A., Riyadh, H. A., Sofyani, H., & W.E. Purnomo, W. E. (2020). Perceived ease of use, perceived usefulness, perceived security and intention to use e-filing: The role of technology readiness. *The Journal of Asian Finance, Economics and Business*, 7(9), 537–547.
- Upadhyay, K. A. K., & Khandelwal, K. (2018). Applying artificial intelligence: Implications for recruitment. *Strategic HR Review*, 17(5), 255–258.
- van Esch, P., & Black, J. S. (2019). Factors that influence new generation candidates to engage with and complete digital, AI-enabled recruiting. *Business Horizons*, 62(6), 729–739.
- Van Esch, P., Black, J. S., & Ferolie, J. (2019). Marketing AI recruitment: The next phase in job application and selection. *Computers in Human Behavior*, 90, 215–222.
- Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, 11(4), 342–365.
- Vinzi, V. E., Chin, W. W., Henseler, J., & Wang, H. (2010). *Handbook of partial least squares*, 201. Berlin: Springer. No. 0.
- Waytz, A., Heafner, J., & Epley, N. (2014). The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal of Experimental Social Psychology*, 52, 113–117.
- Webster, J., & Martocchio, J. J. (1992). Microcomputer playfulness: Development of a measure with workplace implications. *MIS Quarterly*, 16(2), 201–226.
- Weinert, S., Günther, E., Rüger-Muck, E., & Raab, G. (2020). Artificial intelligence in personnel selection and its influence on employer attractiveness. *Marketing Science & Inspirations*, 15(3), 22–35.
- Yan, A. W., Md-Nor, K., Abu-Shanab, E., & Sutanonpaiboon, J. (2009). Factors that affect mobile telephone users to use mobile payment solution. *International Journal of Economics and Management*, 3(1), 37–49.
- Yeomans, M., Shah, A. K., Mullainathan, S., & Kleinberg, J. (2019). Making sense of recommendations. *Journal of Behavioral Decision Making*, 32(4), 403–414.
- Zhang, P. (2024). Application of Artificial Intelligence (AI) in recruiting and selection: The case of company A and company B. *Journal of Business and Management Studies*, 6(3), 224–235.