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EMPIRICAL ANALYSIS OF THE ROLE OF ARTIFICIAL INTELLIGENCE IN HUMAN RESOURCES RECRUITMENT AND SELECTION

Vidushi Nain [1]
Hari Shankar Shyam

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A B S T R A C T

This study provides an empirical evaluation of AI's function in the field of human resources (HR) hiring and selection. Human resources departments may save time and effort by using sophisticated algorithms and machine learning to efficiently sort through piles of applicants and make well-informed decisions. The potential for AI to lessen the prevalence of unconscious bias in the recruiting process is an especially particular advantage. Furthermore, the incorporation of AI into the recruiting process has improved the candidate experience via the use of real-time interaction technologies such as chatbots. Despite its benefits, integrating AI into HR is not without its share of difficulties, most notably protecting employee data and avoiding becoming too dependent on digital tools. The research highlights the need of a unified strategy, which strikes a balance between the efficacy of AI and that of human judgment.

1. INTRODUCTION

The field of Human Resources Management (HRM) has seen a continuous evolution, shaped by a multitude of external forces. Organizations are driven to constantly innovate and adapt in order to maintain their competitive advantage due to the pressures of globalization, improvements in information technology, and modern social upheavals. The advent of many contemporary technologies, particularly Artificial Intelligence (AI), has significantly altered the characteristics of employment, consequently necessitating the Human Resources (HR) field to strive for optimum results in their endeavors.

Human Resource Management (HRM) has changed a lot over the years, and new technologies have been a big part of that. The integration of Artificial Intelligence (AI) into recruiting and selection procedures has significantly altered conventional human resources (HR) methodologies, hence offering a range of difficulties and prospects. The popularity of AI-driven technologies and processes has increased as global organizations strive for efficiency, objectivity, and scalability in their talent acquisition efforts.

The term "Artificial Intelligence" encompasses the emulation of human intellect in computers, which are designed to exhibit human-like thinking and imitate human activities (Järvelä et al., 2023). Within the realm

[1] Corresponding author: Vidushi Nain
Email: vidushinain1@gmail.com

of Human Resource Management (HRM), artificial intelligence (AI) serves to enable the automation of monotonous operations, forecast potential outcomes via the analysis of extensive datasets, and provide valuable insights that may prove challenging for human assessors to discern (Davenport et al., 2020).

The primary objective of this research is to conduct an empirical examination of the function and consequences of artificial intelligence (AI) in the recruiting and selection procedures used by companies. The urgency to comprehend the influence of AI-powered technologies on HR practices, corporate results, and larger social consequences arises as these tools become more prevalent.

Throughout history, the processes of recruitment and selection have been susceptible to the influence of human biases, mistakes, and inconsistencies (Breaugh, 2008). The potential of artificial intelligence (AI) is in its capacity to address and mitigate these challenges, offering a more effective, impartial, and evidence-based methodology. As an example, algorithms powered by artificial intelligence have the capability to efficiently analyze a large volume of applications within a matter of seconds. These algorithms may identify prospective applicants by applying predetermined criteria (Pandey et al., 2023). Furthermore, artificial intelligence (AI) has the potential to play a significant role in improving the applicant experience, tailoring job suggestions to individual preferences, and even forecasting a candidate's future performance via comprehensive data analysis (Chui et al., 2016).

Nevertheless, the incorporation of artificial intelligence (AI) into the field of human resources (HR) gives rise to significant inquiries about ethical considerations, the need for transparency, and the possibility of biases inherent in the algorithms used (Cachat-Rosset & Klarsfeld, 2023). As companies navigate through these complex circumstances, it is essential to rely on empirical research, such as the one mentioned, to provide insights into optimal strategies, potential challenges, and the dynamic interaction between people and machines within the recruiting domain.

The area of human resources management has seen significant transformation in the areas of recruiting and selection due to remarkable advancements in technology. The complex interconnection between sophisticated technology and the ever-changing corporate environment has brought about a significant transformation in conventional techniques of staff selection, leading to a shift towards a more technology-driven approach in the acquisition of qualified individuals. The use of artificial intelligence (AI) tools in the field of human resources (HR) recruitment has seen a notable increase. This is shown by the regular implementation of advanced automated systems for the purposes of scouting and shortlisting potential applicants, as well as facilitating communication with such prospects (Varma et al., 2023). These AI tools serve to streamline and improve the whole selection process. This research aims to comprehensively examine the impact of artificial intelligence (AI) on human resources (HR) recruiting by investigating the extent to which AI will influence the recruitment of human candidates. In light of the emergence of artificial intelligence (AI), what transformations may be anticipated in the recruiting environment for human recruiters? Furthermore, what are the respective tasks that companies and human resource managers will undertake throughout this transformative process?

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENTS

The incorporation of Artificial Intelligence (AI) into diverse corporate operations, particularly in the domain of Human Resources (HR) recruiting and selection, has garnered significant attention from both scholars and professionals.

The Evolution of Artificial Intelligence in Human Resource Management (HRM): Traditionally, HRM activities were mostly administrative in nature, mainly dependent on human decision-making processes. The emergence of Big Data and sophisticated analytics has facilitated the integration of artificial intelligence (AI) into the field of human resources (HR) (Cascio & Montealegre, 2016). Artificial intelligence (AI) technologies, ranging from chatbots to predictive analytics, have significantly improved the efficiency, consistency, and overall candidate experience within human resources (HR) procedures.

Efficiency and objectivity are two prominent advantages of using artificial intelligence (AI) in the realm of recruiting. Artificial intelligence (AI) algorithms have the capability to rapidly analyze extensive volumes of data, enabling them to evaluate thousands of applications within a timeframe that would typically allow a human reviewer to assess just a small number (Wang Y., 2023). Furthermore, the optimal design of AI tools has the potential to mitigate biases that may impact human decision-making, hence enhancing objectivity in the process.

Davenport et al. (2020) emphasized the capacity of artificial intelligence (AI) to forecast the likelihood of applicant achievement by using a blend of CV information, assessment outcomes, and even social media engagement. Artificial intelligence (AI) models have the capability to undergo training in order to discern patterns that exhibit correlation with personnel who have achieved success, hence offering valuable insights that beyond conventional evaluation methodologies.

The integration of artificial intelligence (AI) into the recruiting process enables a heightened level of personalization. One example of technology that may enhance the experience and engagement of candidates is chatbots, which have the ability to deliver real-time replies to their inquiries (Rejeki & Sulistyowati, 2023).

The use of AI technology has the potential for impartiality; yet, there is a growing apprehension over the presence of biases ingrained into AI algorithms, which often mirror prejudices present in the data used for training (Sinclair, 2023). If left unattended, this issue has the potential to sustain systematic prejudice in the process of making recruiting choices.

The evolving role of HR professionals is being influenced by the increasing integration of AI technologies in recruiting processes, leading to a move towards greater strategic responsibilities. According to Feldman and Russo (2023), individuals in this role assume the responsibilities of mediators, translators, and regulators of artificial intelligence (AI) within the context of recruiting. Their primary objective is to ensure the ethical and efficient use of AI technology.

Organizational Transformation: The incorporation of artificial intelligence (AI) into human resources (HR) procedures requires a shift in the culture and thinking of the business. It is crucial to engage in ongoing training and adapt to technological advancements in order to ensure that artificial intelligence (AI) enhances human decision-making rather than replacing it (Dell'Acqua et al., 2023).

The Technology Acceptance Model (TAM) is a seminal theoretical framework in the domain of information systems, which was first proposed by Fred Davis during the latter part of the 1980s. The objective of this study is to gain insights into and make predictions about user behavior in relation to the adoption of technology. This is achieved by placing emphasis on two key constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). The construct of Perceived Usefulness (PU) refers to the extent to which a user perceives that a system will enhance their work performance. On the other hand, PEOU represents the extent to which a user anticipates that the system will be simple to use. According to the key work by Davis (1989), users' attitudes towards technology are directly influenced by their perceptions, which in turn impact their intentions to use the technology. Ultimately, these intentions determine the actual use of the system. The factors under investigation in this study include the perceived utility, perceived simplicity of use, and user acceptability of information technology. The citation provided is in the format of an academic journal article, namely from MIS Quarterly, volume 13, issue 3, pages 319-340. The model has undergone several iterations during its existence, progressing through extensions such as TAM2, TAM3, and amalgamating with other models to give rise to constructs like the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh & Davis, 2000). This paper presents a theoretical expansion of the technology acceptance model (TAM) via the analysis of four longitudinal field experiments. The citation provided is from an academic journal article titled "Management Science" in volume 46, issue 2, pages 186-204. The authors of the article are Venkatesh and Bala (2008). The Technology Acceptance Model 3 (TAM3) and a proposed research agenda on treatments. The citation provided is from an academic source, namely the journal "Decision Sciences," volume 39, issue 2, pages 273-315. The authors of the article are Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D., and the publication year is 2003. The acceptability of information technology by users: Striving for a consolidated perspective. The source cited is "MIS Quarterly" with page numbers ranging from 425 to 478. The Technology Acceptance Model (TAM) continues to be widely recognized and used in the field of technology adoption research.

2.1 Attitude Towards Usage Human Resources Recruitment and Selection

The concept of attitude in the context of Human Resources (HR) recruitment and selection pertains to the views and beliefs held by HR professionals, hiring managers, and applicants about the use of many tools, approaches, and platforms in the process of recruiting. In the contemporary era of technology, there has been a notable transition towards the use of online job portals, Applicant Tracking Systems (ATS), screening technologies based on artificial intelligence, and platforms for conducting video interviews. The primary objective of these tools is to optimize the recruiting process by improving the precision of applicant selection. Nevertheless, the acceptance of these technologies is often dependent on the perceived utility and simplicity of their implementation, similar to the Technology Acceptance Model. For example, the effectiveness of an Applicant Tracking System (ATS) may be recognized; but, if it is seen as burdensome, human resource professionals may exhibit reluctance in completely incorporating it into their operational procedures (Davis, 1989). The factors influencing the acceptability of information technology by users include the perceived utility, perceived ease of use, and user acceptance The candidate's perspectives on digital interviewing tools or AI-based evaluations may differ depending on their perceptions of fairness, transparency, and possible biases inherent in these phenomena of talent being transformed into data. the progressive impact of technology on the study of human potential in the workplace.

H1: Attitude towards usage human resources recruitment and selection has a significant impact on behavioral intention to use human resources recruitment and selection.

2.2 Perceived Usefulness

The concept of Perceived Usefulness (PU) has significant importance in the examination of technology acceptance and use, particularly within the theoretical framework of the Technology Acceptance Model (TAM) (figure 1). The concept of PU, as first introduced by Fred Davis in his influential publication in 1989, pertains to the extent to which a user holds the belief that the use of a certain technological tool would improve their overall job performance or effectiveness in completing tasks (Davis, 1989). The factors influencing the acceptability of information technology by users include the perceived utility, perceived ease of use, and user acceptance. Fundamentally, the likelihood of humans adopting and using a technology is influenced by their perception of its benefits and worth in relation to their jobs. According to Davis's study, the variable of Perceived Usefulness (PU), in conjunction with Perceived Ease of Use (PEOU), has a substantial influence on individuals' attitudes towards the adoption of technology, their intentions to use it, and their subsequent actual utilization of the system. Throughout the years, the construct of perceived usefulness (PU) has consistently shown its efficacy as a reliable indicator for predicting the adoption of technology in many domains and technological applications. This substantiates its fundamental significance in comprehending the intricacies of technology integration within personal and professional settings.

H2: Perceived Usefulness has a significant impact on behavioral intention to use human resources recruitment and selection.

2.3 Perceived ease of Use

The concept of Perceived Ease of Use (PEOU) has significant importance in the field of technology adoption and is widely highlighted in the Technology Acceptance Model (TAM) developed by Fred Davis. The concept of Perceived Ease of Use (PEOU) pertains to an individual's perception of the level of effort required to use a certain system or technology (Davis F. D., 1989). The factors influencing the acceptability of information technology include the perceived utility, perceived ease of use, and user acceptance. The citation provided is in the format of a scholarly journal article, namely from the MIS Quarterly, volume 13, issue 3, spanning pages 319-340. In essence, it encompasses the user's evaluation of the level of simplicity and ease of use shown by a given technology. Based on the Technology Acceptance Model (TAM), the perception of a technology as being user-friendly has a favorable impact on an individual's attitude towards its use. This subsequently impacts their desire to utilize the technology, ultimately leading to its actual adoption and usage. Furthermore, the construct of seen Ease of Use (PEOU) has a direct impact on another pivotal component of the Technology Acceptance Model (TAM), namely Perceived Usefulness. This is due to the fact that technologies that are seen as being more user-friendly are typically regarded as more beneficial in terms of their utility. The significance of Perceived Ease of Use (PEOU) is highlighted, emphasizing the crucial role of intuitive design and user experience in the process of creating and deploying novel technologies. Over the course of many decades, the significance of Perceived Ease of Use (PEOU) has persisted as a fundamental aspect in the field of technology acceptance study, highlighting its continuing relevance as technologies continue to advance.

H3: Perceived Ease of Use has a significant impact on behavioral intention to use human resources recruitment and selection.

2.4 Trustworthiness of artificial intelligence

The discussion of the trustworthiness of artificial intelligence (AI) systems has garnered considerable attention due to their growing integration into several facets of human existence. Trust in artificial intelligence (AI) is a complex concept that involves several dimensions, including the dependability and resilience of AI systems, the level of openness they exhibit, and the ethical implications they give rise to. Dignum (2019) posits that the concept of trustworthiness in artificial intelligence (AI) is centered on the assurance that these systems exhibit predictable behavior, maintain transparency in their operations, and are used responsibly by relevant stakeholders. The High-Level Expert Group on AI, established by the European Commission, recommends that the development of trustworthy AI should include key concepts such as openness, fairness, and responsibility, with a simultaneous focus on safeguarding user safety and privacy. Nevertheless, the process of establishing trustworthiness is not devoid of difficulties. As emphasized by Buolamwini and Gebru (2018), the use of biased training data might result in biased outputs, hence engendering a lack of confidence in the systems. The establishment of methods to maintain the trustworthiness of evolving AI is crucial in order to safeguard the technology's societal benefits and prevent any inadvertent damage.

H4: Trustworthiness of artificial intelligence has a significant impact on behavioral intention to use human resources recruitment and selection.

2.5 Behavioural Intention to Use Human Resources Recruitment and Selection

Behavioral intention, within the domain of human resources (HR) recruitment and selection, refers to the probability of employers, recruiters, and HR professionals embracing and using certain tools, technologies, or approaches throughout their recruiting procedures. The Technology Acceptance Model (TAM), as established by Davis (1989), posits that an individual's desire to embrace a technology is primarily influenced by their perception of its utility and ease of use. Within the field of human resources, this phenomenon may be seen via the integration of digital platforms, applicant tracking systems, artificial intelligence-powered evaluation tools, and several other developing technologies. Moreover, Parry and Tyson (2008) conducted an observation indicating that the inclination of HR professionals to include e-recruitment systems is considerably impacted by their judgments about the strategic worth and effectiveness of these platforms. With the growing digitization of recruitment and selection processes, it is crucial for employers to comprehend behavioral intention. This knowledge may assist them in predicting possible obstacles to adoption and customizing their methods to properly harness the advantages of contemporary HR technology.

H5: Behavioral intention to use human resources recruitment and selection has a significant impact on actual usage of human resources recruitment and selection.

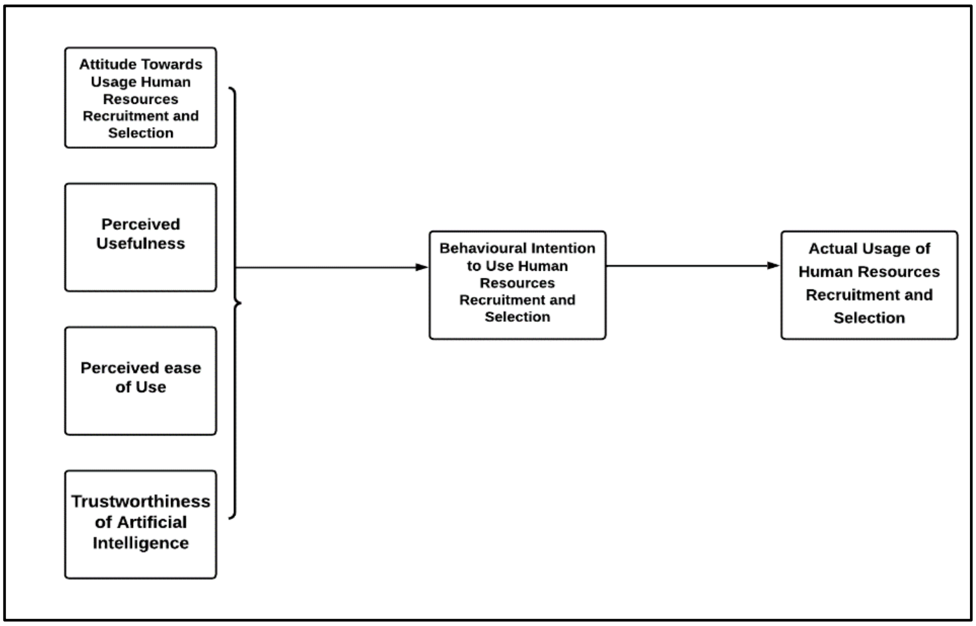

Figure 1. Conceptual Framework

3. DATA COLLECTION

The research results of this study are based on a combination of primary and secondary sources. The secondary data was obtained from several scholarly sources, including journals, conference papers, internet publications, and the Scopus database. The majority of the study's material was derived from original data collected using a structured survey. The survey was divided into four discrete portions. The primary phase of the study was the collection of demographic data from the participants, including variables such as age, gender, and yearly income. The next segments of the survey were customized to correspond with the study goals, assessing the participants' level of knowledge and willingness to embrace the integration of artificial intelligence (AI) in the recruiting and selection processes of human resources (HR). The researchers used a five-point Likert scale in order to assess the participants' degree of understanding and receptiveness towards AI-driven HR technologies. The survey was originally disseminated via the use of Google Forms, with a primary focus on reaching out to individuals within the researchers' personal network on social media platforms such as Facebook and WhatsApp. The objective was to collect replies from a randomly selected sample size ranging between 420 and 450 participants. However, a total of 50 replies were eliminated from the analysis owing to either missing data or the presence of overt bias. Subsequently, the data was subjected to a rigorous purification procedure in order to guarantee its precision and uniformity. The primary objective of this study was to gain insight into the propensity of human resource professionals to use artificial intelligence in the context of recruiting and selection procedures. The research explored the underlying factors that contribute to this tendency and the specific measures used to incorporate artificial intelligence with human resources. In order to enhance the rate of response and guarantee the provision of truthful feedback, several guarantees were sent to potential participants on the maintenance of their anonymity.

4. ANALYSIS AND RESULTS

The evaluation of the suggested model was conducted using the partial least squares analysis (PLS) methodology. The technique outlined by Anderson and Gerbing supports the use of a two-step strategy. The analytical evaluations were performed using Partial Least Squares (PLS) methodology, with the selected software for this specific task being Smart PLS 4.0.

4.1 Construct reliability

The present research examined the convergent and discriminant validity of constructs associated with the function of Artificial Intelligence (AI) in the domain of Human Resources (HR) Recruitment and Selection. In order to test the convergent validity of the study, many statistical measures were used, including the Average Variance Extracted (AVE), factor loadings, and Cronbach's alpha. The determination of the percentage of variance captured by the assessed constructs was accomplished using the Average Variance Extracted (AVE) method. The findings of the study revealed that all items under examination had factor loadings more than 0.70, which suggests strong convergent validity in accordance with the criteria set by Hair et al. (2011). Cronbach's alpha was used to assess the internal consistency of the scales. It is worth mentioning that all the constructs exhibited Cronbach's alpha values over 0.70, indicating a high level of internal consistency. This observation is consistent with the results reported by Hair et al. (2006). This highlights the effectiveness of the measuring items in accurately reflecting the fundamental nature of artificial intelligence in human resources procedures. In addition, the researchers conducted tests to assess the composite reliability of these constructs. It was found that all of the constructs above the criterion of 0.70, as established by Carmines and Zeller (1979), indicating a high level of reliability. In order to enhance comprehension of the capacity of latent constructs to effectively characterize observable data, the Average Variance Extracted (AVE) was calculated. The research demonstrated great convergent validity and reliability of scales, as shown by the AVE values ranging from 0.86 to 0.94, as shown in Table 1. These findings highlight the constructs' potential to explain a substantial portion of the variation in AI's function in HR recruiting and selection.

Table 1. Construct reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ATUHRRS	0.841	0.852	0.893	0.675
AUHRRS	0.838	0.842	0.925	0.861
BIUHRRS	0.889	0.890	0.919	0.694
PEU	0.887	0.894	0.922	0.747
PU	0.875	0.898	0.913	0.723
TAI	0.908	0.918	0.942	0.845

Table 1 presents the reliability and validity measures for several constructs pertaining to the empirical examination of Artificial Intelligence in the context of Human Resources Recruitment and Selection. The Cronbach's alpha coefficient of 0.841 for the construct ATUHRRS suggests a significant degree of internal consistency across the items comprising this category. The composite reliability ratings, namely rho_a at 0.852 and rho_c at 0.893, indicate that the elements inside this construct have robust collective dependability. The AVE score of 0.675 indicates that about 67.5% of the volatility in the observed data can be attributed to this particular construct. The AUHRRS has a Cronbach's alpha coefficient of 0.838, indicating a satisfactory level of internal consistency. The construct demonstrates accurate measurement, as shown by composite reliabilities of 0.842 (rho_a) and 0.925 (rho_c). The AVE value of 0.861 demonstrates a high level of robustness, indicating that 86.1% of the observed variation is well accounted for by this construct. The construct BIUHRRS has a Cronbach's alpha coefficient of 0.889, indicating a high level of internal consistency. The composite reliability metrics, namely rho_a at 0.890 and rho_c at 0.919, provide strong evidence for the durability and stability of this construct. The average explained variance (AVE) of 0.694 indicates that the construct under consideration explains about 69.4% of the variability seen in the data. The PEU has a Cronbach's alpha coefficient of 0.887, indicating a robust level of internal consistency. The construct's dependability is confirmed, as shown by the rho_a value of 0.894 and the rho_c value of 0.922. A coefficient of determination (AVE) of 0.747 indicates that this particular concept accounts for 74.7% of the variation observed. In the context of psychometric assessment, the Cronbach's alpha coefficient for the construct of PU is determined to be 0.875, hence suggesting a commendable level of internal consistency. The dependability of the measure is underscored by composite reliability scores of 0.898 (rho_a) and 0.913 (rho_c). The AVE value of 0.723 indicates that it explains about 72.3% of the total observed variation. Finally, the TAI has a noteworthy Cronbach's alpha coefficient of 0.908, indicating a substantial degree of internal consistency. The construct's robustness is clear, as shown by the composite reliability values of 0.918 (rho_a) and 0.942 (rho_c). The calculated average of 0.845 exhibits statistical significance, indicating that it has the ability to account for 84.5% of the variability found in the data.

4.2 Discriminant validity

The research established discriminant validity by examining the correlation between the ideas and the squared average variance extracted (AVE). According to the guidelines established by Fornell and Larcker (1981), the square root of the Average Variance

Extracted (AVE) for each construct within the domain of Artificial Intelligence in Human Resources Recruitment and Selection was determined to be higher than the maximum correlation observed between any two constructs. This finding provides evidence of strong discriminant validity. In order to enhance the differentiation between these constructs, the research performed a computation of the square root of the Average Variance Extracted (AVE) in conjunction with the assessment of construct correlations. The aforementioned results may be corroborated by consulting Table 2 in the primary scholarly article. Furthermore, the issue of common method bias, a possible worry in surveys that are self-administered, was mitigated by using Harman's single-factor test as suggested by Harman (1976). In order to assess the potential influence of common technique bias, a comprehensive dataset was subjected to a PLS exploratory component analysis. In the present factor analysis, component loadings that reached a threshold of 50% were considered to be statistically significant. It is worth noting that the major component was responsible for a mere 27.46% of the overall variation. This implies that there is no significant bias caused by common technique factors in the dataset, aligning with the recommendations of Podsakoff et al. (2003) in the context of the empirical examination of AI's impact on HR recruiting and selection.

Table 2. Discriminant validity

	ATUHRRS	AUHRRS	BIUHRRS	PEU	PU	TAI
ATUHRRS						
AUHRRS	0.867					
BIUHRRS	0.508	0.523				
PEU	0.799	0.780	0.323			
PU	0.801	0.873	0.420	0.859		
TAI	0.662	0.623	0.507	0.683	0.630	

Table 2 presents a comprehensive examination of discriminant validity by displaying the interrelationships among components pertaining to the empirical investigation of Artificial Intelligence in the context of Human Resources Recruitment and Selection. The correlation between Attitude towards Using HR Recruitment and Selection (ATUHRRS) and Actual Use of HR Recruitment and Selection (AUHRRS) is 0.867. The observed high correlation suggests a robust link between people' views regarding the usage of AI tools in the field of human resources and their subsequent adoption of these technologies. The study findings indicate that the Behavioral Intention to Use HR Recruitment and Selection (BIUHRRS) exhibits a positive correlation of 0.508 with the Attitude Towards Using HR Recruitment and Selection (ATUHRRS) and a positive correlation of 0.523 with the Actual Usage of HR Recruitment and Selection (AUHRRS). This implies that there exists a moderate correlation between the behavioral intention of persons to embrace artificial intelligence (AI) in the context of human resources (HR) recruitment and selection, and their attitudes towards its use as well as their actual utilization of it.

The concept of Perceived Ease of Use (PEU) has significant relationships of 0.799, 0.780, and 0.323 with ATUHRRS, AUHRRS, and BIUHRRS, respectively. This finding suggests that the impression of the ease of using artificial intelligence (AI) in human resources (HR) operations is significantly correlated with individuals' attitudes and actual use, but only modestly connected with their behavioral intention.

There are notable relationships between Perceived Usefulness (PU) and several constructs. Specifically, PU has a correlation coefficient of 0.801 with ATUHRRS, 0.873 with AUHRRS, 0.420 with BIUHRRS, and 0.859 with PEU. This finding demonstrates a significant correlation between perceived usefulness and the other variables, underscoring the significance of perceived advantages of artificial intelligence in the context of human resources recruiting and selection. Finally, the construct of TAI has varying degrees of association with other constructs, specifically: a correlation coefficient of 0.662 with ATUHRRS, 0.623 with AUHRRS, 0.507 with BIUHRRS, 0.683 with PEU, and 0.630 with PU. The observed results indicate a significant correlation between the acceptability and integration of artificial intelligence (AI) technology in human resources (HR) procedures and other relevant parameters. In general, the correlations shown in Table 2 demonstrate the interrelationships between these dimensions, indicating the interdependence of attitudes, perceptions, intents, and actual use within the domain of AI's involvement in HR recruiting and selection.

4.3 R square

In the empirical analysis of the impact of Artificial Intelligence on Human Resources Recruitment and Selection, the R-square (R2) value is utilized as a metric to gauge the extent to which the fluctuations in the effectiveness or outcomes of AI-driven HR recruitment and selection can be attributed to alterations in the predictors or independent variables. In essence, R2 serves as a measure of the degree to which AI characteristics or traits impact human resources (HR) procedures (Gupta et al 2024). A greater R2 coefficient suggests that the chosen artificial intelligence attributes have a significant influence on the results of human resources recruiting and selection processes.

In contrast, the correlation coefficient provides insight into the characteristics and strength of the linear association between certain artificial intelligence (AI) attributes and human resources (HR) recruiting and selection results. The coefficient in question exhibits a range spanning from -1 to +1. When the coefficient approaches the extremes (-1 or +1), it indicates a more pronounced link, whether negative or positive. Conversely, a coefficient of 0 signifies the absence of any relationship. In the context of this research, a coefficient of determination (R2) equal to or greater than 0.01 was deemed acceptable, indicating that the artificial intelligence (AI) predictors were able to account for a minimum of 1% of the variability seen in the outcomes linked to heart rate (HR). However, it is crucial to supplement the R2 value with the correlation coefficient in order to get a comprehensive comprehension, including not only the strength but also the direction of the link between AI features and the efficacy of HR recruiting and selection.

Table 3. R square

	R-square	R-square adjusted
AUHRRS	0.707	0.701
BIUHRRS	0.892	0.871

Table 3 presents the R-square and modified R-square values pertaining to two constructs that are associated with the empirical investigation on the influence of Artificial Intelligence in the domain of Human Resources Recruitment and Selection. The R-square value for the construct AUHRRS is 0.707, indicating that about 70.7% of the variability in the actual use of AI tools in HR recruitment and selection can be accounted for by the independent variables or predictors being examined. The corrected R-square value, which incorporates the number of predictors included in the model, is somewhat lower at 0.701 or 70.1%. The little decrease seen in the adjusted R-square suggests that the model remains robust and is not substantially affected by the introduction of factors that may not be meaningful. Likewise, in the case of the construct BIUHRRS, the R-square value exhibits a significant magnitude of 0.892, signifying that approximately 89.2% of the variability in behavioral intention to employ AI in HR recruitment and selection can be ascribed to the factors that exert influence as examined in the study. The adjusted R-square value of 0.871, equivalent to 87.1%, indicates that a substantial percentage of the variability in behavioral intention is accounted for by the model, even after considering the influence of the predictors. This finding highlights the effectiveness of the model in explaining the observed outcomes. To summarize, the R-square values shown in Table 3 provide robust evidence supporting the significant impact of the chosen independent variables on both the practical use and the behavioral inclination to employ AI technologies in HR recruiting and selection procedures. The elevated values serve to underscore the importance and meaningfulness of the selected predictors in elucidating the constructs within the context of the investigation.

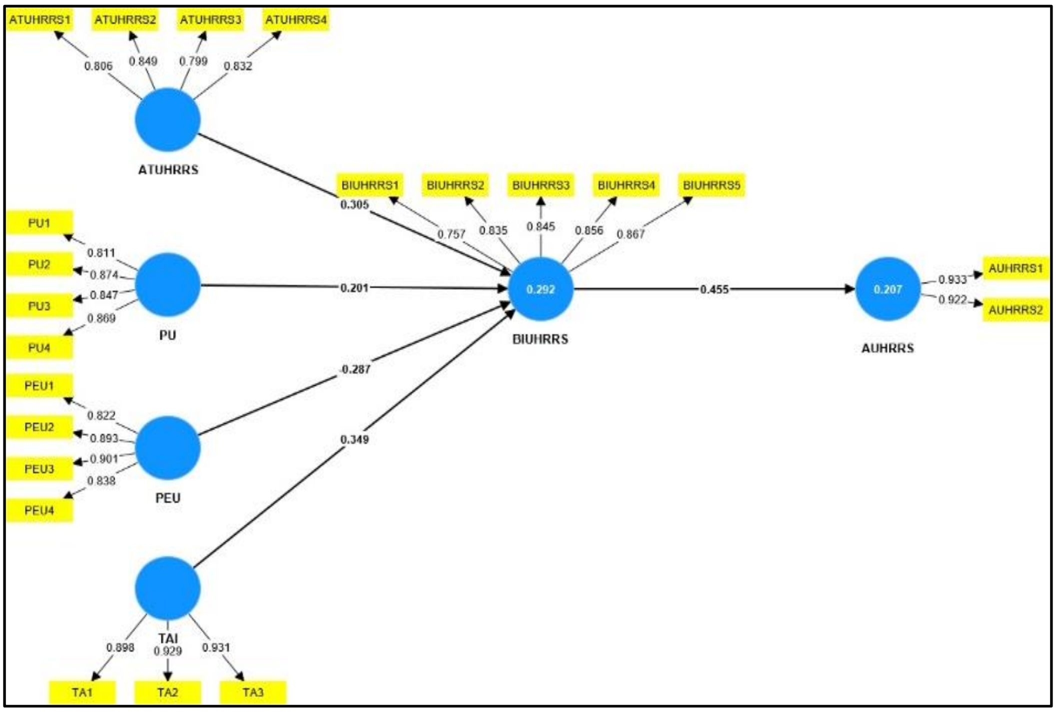

Figure 2. Structural Model

The figure 2 provided appears to be a structural model, possibly derived from a structural equation modeling (SEM) analysis or a path analysis. The model displays various latent variables (represented by the circles) and observed variables (represented by the rectangles). The arrows indicate the paths and relationships between the variables, and the numbers beside the arrows represent path coefficients or loadings. From the figure 2 provide a descriptive summary, but I cannot provide specific references since the context and sources of the model are not provided. Here's a brief description based on the image:

Latent Variables: PU, PEU, TAI, BIHURRS, AUHRRS
Observed Variables: The observed variables seem to be measurements or indicators of the latent variables. For instance, PU1, PU2, PU3, and PU4 are indicators of the latent variable PU. Similarly, TAI1, TAI2, and TAI3 are indicators for TAI.

Path Coefficients: The numbers alongside the arrows represent the strength and direction of the relationships between the variables. For instance, there's a coefficient of 0.922 between BIHURR5 and AUHRRS, indicating a strong positive relationship between these two constructs.

Loadings: The numbers adjacent to the arrows connecting latent variables to their indicators are factor loadings. These indicate how strongly each observed variable is related to its corresponding latent variable. For instance, PU1 has a loading of 0.811 on PU, suggesting a strong relationship.

5. CONCLUSION

The empirical investigation of the impact of artificial intelligence (AI) on recruiting and selection processes in human resources (HR) has yielded significant findings. The use of artificial intelligence has greatly enhanced the efficiency and expediency of the recruiting process. Automation solutions have the capability to rapidly analyze large quantities of resumes, therefore expediting and enhancing the efficiency of the shortlisting process. The use of contemporary techniques has significantly reduced the time required for completing tasks that were conventionally time-consuming, which may span over several weeks. since a result, firms are now able to enhance their responsiveness within a dynamic job market, since these tasks can now be accomplished within a matter of hours or days. AI-powered tools can be designed to assess candidates purely based on qualifications and skills, reducing unconscious biases that may arise in human-driven selections. Nevertheless, it is essential to acknowledge that artificial intelligence (AI) models have the potential to reinforce biases if their training is not conducted properly. This underscores the need of ongoing vigilance and improvement in the development and use of these tools. The use of artificial intelligence (AI) empowers human resources (HR) professionals to make informed decisions based on data analytics. Predictive analytics has the capability to anticipate the likelihood of an employee's achievement, while machine learning exhibits the capacity to detect patterns that may elude human observation. The use of an empirical method yields superior hiring outcomes and has the potential to decrease employee turnover. The use of AI chatbots and virtual assistants may significantly improve the applicant experience by facilitating engagement with candidates outside regular working hours, delivering immediate feedback, and offering guidance throughout the application process. Interactions of this kind provide the potential to enhance the candidate's overall experience and bolster the employer brand of a firm. Despite the many advantages offered by AI, it is not devoid of obstacles. There have been expressed concerns over privacy, data security, and the excessive dependence on technology at the expense of human judgment. In addition, the use and comprehension of AI technologies include a learning curve, hence requiring HR personnel to undergo training and orientation. The integration of artificial intelligence (AI) with human resources (HR) is still in its early developmental phase. With the continuous advancement of technology, an increasing number of firms are incorporating artificial intelligence (AI) into their recruiting and selection procedures. It is expected that the role of AI will grow further, perhaps extending to many aspects such as onboarding, training, and employee engagement. In brief, the field of human resources recruitment and selection is undergoing a significant transformation due to the integration of artificial intelligence. The significance of human judgment and ethical issues should not be underestimated, despite the various advantages that include improved efficiency and better candidate experiences. The integration of artificial intelligence (AI) in the field of human resources (HR) is more influential in shaping future practices. It is crucial to adopt a balanced strategy that effectively combines technological advancements with human expertise and understanding.

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Vidushi Nain
Sharda School of Business Studies, Sharda University, Greater Noida,
India
vidushinain1@gmail.com
ORCID 0009-0008-4313-8129

Hari Shankar Shyam
Sharda School of Business Studies,
Sharda University,
Greater Noida
India
harishankar.shyam@sharda.ac.in
ORCID 0000-0002-2305-922X