“Exploring the nexus of artificial intelligence in talent acquisition: Unravelling cost-benefit dynamics, seizing opportunities, and mitigating risks”

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EXPLORING THE NEXUS OF ARTIFICIAL INTELLIGENCE IN TALENT ACQUISITION: UNRAVELLING COST-BENEFIT DYNAMICS, SEIZING OPPORTUNITIES, AND MITIGATING RISKS

Abstract

The rise in talent management complications led organizations to rely on the latest technologies to automate their routine HRM tasks through AI. This study proposed to examine fundamental aspects of AI in talent acquisition (cost-benefit, opportunities, and risk factors) from the context of strategic analysis and decision-making. 52 respondents from HRM and the information technology departments from fifteen large dairy enterprises, each with more than one thousand employees, were included in the focus group discussion. Both departments were included in the focus group discussion as they heavily employ AI in talent acquisition. The opinions were collected in multiple rounds based on the cost, benefit, opportunity, and risk criteria using the analytical hierarchy process, a multi-criteria decision-making framework. The findings demonstrated that most respondents opinioned AI supports talent acquisition with many opportunities (38.7%) that involve the identification of the best applicants (18.7%) and different benefits (33.2%) to the organization in the form of saving time and cost (16.1%) leading to higher efficacy. The study infers that the application of AI in HRM significantly contributes to talent acquisition, streamlining processes, improving efficiency, and enhancing decision-making. The study recommends that implementing AI in talent acquisition requires a strategic approach, and organizations need to consider factors such as data privacy, ethical use of AI, and ongoing training to ensure successful integration into their hiring processes. Additionally, regular monitoring and adjustments are essential to optimize the effectiveness of AI tools in talent acquisition.

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JEL Classification O15, O31, O32

INTRODUCTION

The emergence of technology and a steady application in HRM familiarized dramatic advancement in HRM functions. Innovation of big data, machine learning (ML), and artificial intelligence (AI) developed ways to deploy AI-based HRM applications. Previously, human resource information systems (HRIS) and electronic HRM (E-HRM) enabled organizations to process data digitally but were restricted only to employee data collection, storage, manipulation, and retrieval of information for various internal and external organizational HR-related purposes. In recent years, when AI was introduced, it opened the opportunities to collaborate with talent acquisition and training processes and also to analyze overall HR functional performances. As a high-end technology, AI was used to streamline HR processes and administrative tasks to improve human efficiency and strategic actions. For instance, today AI through Chabot collects employee queries and mitigates problems quickly with better decisions in very little time. In

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the current trend, most organizations popularly use innovative application tracking systems (ATS), intelligent search engines, data integration and analytical systems, virtual learning systems, and candidate relationship management (CRM). These ideal features and potential benefits of AI adoption have engaged academicians and HR experts to explore its integration with HRIS without any limitations on time and cost factors.

Integrating AI into HRIS solutions is actually making firms' HR teamwork much easier and more effective with sound decisions. Despite improving HR data analysis and developing reports and predictions, AI can be integrated with recruitment and selection, new employee orientation, employee performance management, retention, leadership and administrative tasks, and HR decision-making functions. Some of the positive impacts of AI in HRM manifest in minimizing human recruitment bias. AI provides insight into employees' work experience, performance, and productivity aspects and gives valuable feedback to HR staff to decide on employee retention. Instead of human interaction, digital forms and Chabot are most popularly used to collect employee information and queries in a most organized way. However, AI adds the additional feature of analyzing employee feedback and results after completing the training program. Therefore, AI is seen as an optimistic opportunity for many HR teams as it makes huge manual compilations and typical data analysis easier. It presents data into easily readable reports in just seconds without errors and helps HR staff to automate the transactional workforce, reduce workload, and free up their time to emphasize other most important tasks and decision-making activities.

AI has emerged incredibly and is improving in every field of business. AI works tremendously well, just like the human brain, which has no errors and completes the given task in seconds. Evidently, technology has demonstrated an apparent change in the whole business process, strategy, and workflow in recent decades. Ubiquitously still, there is a lack of practical clarity on other key indicators of organizational effectiveness, namely the opportunities the firm will have through AI implementation, the expected risk, the merits it gains, and consequent changes in the overall human resource and workflow-related cost with respect to the adoption of AI-based HRM applications.

The Saudi government indicates its intention to adopt new technologies to achieve Vision 2030, which aligns with United Nation's sustainable development goals. Though the adoption of AI in the HRM area is limited, its broader sense and future opportunities of AI are promising. However, evaluating the influence of AI implementation on HRM functional performance from a user perspective has not yet been explored. Past research empirically studied the use of AI-based applications in talent acquisition, but it was limited to a specific industry.

1. LITERATURE REVIEW

Artificial intelligence is a crucial component of human resources and overcomes the intricacy of the employment process. Using effective communication, AI technology expedites hiring and improves candidate engagement and overall experience. Consequently, this maintains the firm in a competitive talent marketplace for luring and employing applicants. It is critical to comprehend how AI tools might attract and retain people within an organization. HR practices can have a significant impact on organizational performance measurement. Huselid (1995) and Arthur (1992, 1994) focused on a subset of the relationship between HR practices and financial performance. In this connection, the technology acceptance model (TAM) developed by Davis (1989), a revision of the theory of reasoned action (TRA) was based on perceived ease of use and perceived usefulness. This TAM model was the most extensive and realistic model used by many past research studies demonstrating a significant positive influence on organizational performance (Lee et al., 2013; Abbasi et al., 2011; Lee & Lehto, 2013). From this, it is clear that the TAM model contributes to better organizational performance.

On the other hand, the concept of human capital investments has also evolved many theories that emphasize understanding various conditions and what type of such investment leads to an organization's profitability. Similarly, AlMuhaideb et al. (2019) found that AI can be employed to construct a predictive model for forecasting the occurrence of absences in the context of particular appointments. Chikhaoui and Mehar (2020) proposed that integrating AI inside the entirety of patent law procedures can yield significant time and cost savings. The study proposed a conceptual framework to mitigate individuals' apprehension about potential biases that AI can acquire. Also, Tanveer et al. (2020) emphasized their attention to the applications, advantages, and issues pertaining to sustainable development education in the context of AI. Saba and Leader (2021) aimed to promote aligning laboratory activities with government priorities, including the 2020 government Transformation Plan and Saudi Vision 2030. Fitz-Enz (2000) defined human capital as the quality an individual brings to his job, work accomplishment, a positive attitude or behavior, intelligence, reliability, and commitment. Also, the contingency prediction developed by Delery and Doty (1996) argues the nexus between the use of particular employment practices and organizational performance, which was postulated to be contingent on the organizational strategy. The application of Miles and Snow's (1978) theory of strategy, structure, and process as a contingency approach has illustrated influential predictors of organizational performance (Doty et al., 1993). According to Chatman (1989), person-organization (P-O) fit has similarities between organizational and individual values trends. Other P-O fit studies (Kristof, 1996) investigated a close match between individual and organizational values. Jani and Sayied (2017) explored the role of person-organization fit in the organizational context and successful talent acquisition; they concluded that talent acquisition is an innovative transformation. Though past studies proved the implementation of technology has a positive effect on talent acquisition and the organization's overall performance, such efforts failed to holistically address the specific four dimensions, namely benefits, opportunities, cost, and risk, in the strategic analysis and decision-making process.

AI technology adoption has been noticed in the last few decades with the increase in competitive talent search irrespective of the type of industry, whether in IT/ITES, healthcare, banking, engineering, manufacturing, or any other. Wang (2017) and Jiang et al. (2018) asserted that AI is vigorously reinforcing various HRM activities by technologizing and simplifying HR duties with no stress and improving quick results. Therefore, examining the vital business aspects of AI on human resource talent acquisition (HRTA), namely cost-benefit, opportunities, and risk factors, is also equally imperative.

1.1. Talent acquisition

As businesses cannot expand without the proper talent, the new talent mindset is crucial as a game changer for flourishing firms. Talent acquisition is an emerging approach distinct from simply hiring someone for any job. To satisfy the demands of the organizations, a unique categorization for talent acquisition is necessary. Moreover, firms can only contact the proper high-potential applicants if they substantially adjust their talent acquisition approach (Sahay, 2014). Accordingly, one of the key differences between successful and failed firms is that the most prosperous companies had brutally engaged management on talent. These firms sought out and employed outstanding employees, believing that focusing on talent acquisition would enable them to surpass competition (Burkus & Osula, 2011). In this competitive era, organizations are more conscientious about acquiring the best employees ever before (Walford-Wright & Scott-Jackson, 2018). Therefore, they are critically important to talent management and formulating various talent acquisition strategies. Talent acquisition is a "strategic approach to identifying, attracting, and onboarding top talent to efficiently and effectively meet dynamic business needs" (Bugg, 2015). Pearson (2009) also asserted that technology addresses various methods of communication for an efficient work process. Once an organization earns its reputation through employer branding, it is easy to attract new talented individuals to an organization. It helps in the applicant selection rate with a diversified talent pool. Conversely, it provides an enriched candidate experience during recruitment (Albert, 2019).

Several studies detailing how technological advances have revolutionized human resources and procedures have also been summarized (Cooper et al., 1964; Nadler & Tushman, 1980; Pearson, 2009). Advanced technologies have simplified the tasks of

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HR specialists and ensured that all aspects of the HR department are covered. Additional research shows that HR departments can get more done in less time with the help of AI because they no longer need to rely so heavily on HR professionals. In addition, the use of various technological means provides essential ways for managers to carry out multiple operations without involving the HR department, and the complexities associated with HR tasks can be mitigated accordingly, guaranteeing results in a short period (Rana & Sharma, 2019; Jia et al., 2018).

The risks associated with human biases are reduced because decisions are made using the available data in the system (Bumblauskas et al., 2017). On the other hand, several studies have drawn attention to the varied methods utilized inside the HR team's intelligent decision support system. Knowledge-based systems, neural networks, and fuzzy sets are just a few examples of the smart technologies that have spawned a plethora of new applications because these allow for the development of cognitive abilities that can then be put to use in HR operations (Jiang & Messersmith, 2018; Cooke, 2018).

1.2. Talent acquisition and artificial intelligence

Artificial intelligence is revolutionizing the employment practices at a rapid pace. AI can process large amounts of data more quickly. Using a computer program, the work determines which candidates to recruit by identifying a causal relationship between the job description and the traits of the employees to generate applications. The screening of candidates is the first step in the procedure. At this point, the employment applications are vetted or examined. It comprises selecting a small number of applicants from the combined resumes. The candidate that best fits the requirements is chosen by the AI tool from the database. It evaluates the applicants according to their profiles and compares their profiles with the job description. A portion of HR's administrative work is eliminated, and massive data processing is expedited. This allows hiring managers to take advantage of AI's capabilities using various resources that help objectively screen and onboard prospects.

Talent acquisition is a challenging and valuable function for organizations as it is difficult to get the right talent (Pillai & Sivathanu, 2020). It includes the costs of attracting potential applicants and selecting and providing training for newly recruited employees (Pillai & Sivathanu, 2020). AI plays a vital role in talent acquisition as AI technologies help screen applicants faster and more efficiently. The messages, emails, and different assessment results and details of the further process are sent to the candidate through an automated system. It also reduces the recruiting cost. With the help of AI, employers can post a targeted advertisement for the proper talent acquisition. The organization's information reaches directly to potential candidates through programmatic advertising. It includes different onboarding tasks for applicants; AI technologies handle the different cumbersome tasks of onboarding in the form of designing templates of offer letters, organizing background checks, maintaining employee records, and providing the company with detailed information about rules and policies to newly appointed candidates.

1.3. Theoretical aspects and application of AI techniques in talent acquisition

Technology is a sword with two sides, and one should be conscious of both the positive and negative consequences of using technology. Consequently, HR managers must be technologically knowledgeable when employing various HR solutions such as AI. Nair (2017), Bersin (2018), and Pillai and Sivathanu (2020) summarized various talent acquisition functions and the appropriate AI tools and technology, along with the service providers. The talent acquisition functions range from employer branding, job posting, recruiting, sourcing and selection of resumes, assessment, and screening of profiles, and onboarding tasks, including orientation.

Most of the research on technology adoption is based on numerous technology acceptance frameworks but on an individual viewpoint (Oliveira & Martins, 2011; Shih et al., 2010). These models are typically techno-centric, like the theory of reasoned action (TRA) (Ajzen & Fishbein, 1980), innovation diffusion theory (IDT) developed by

Rogers (2003), the technology acceptance model (TAM) by Davis (1989), UTAUT, a unified theory of acceptance and use of technology by Venkatesh et al. (2003), and theory of planned behavior (TPB) by Ajzen (1991). There are technologies from a company's standpoint, such as the technology organization environment (TOE) framework introduced by Depietro et al. (1990) and the decision technology organization environment (DTOE) introduced by Thong (1991).

Numerous studies have different perceptions about TOE. Awa et al. (2017a, 2017b) explained a need for more appropriateness among task requirements and technology functionality. Oliveira et al. (2019) noticed that the TOE framework leads at an enterprise level. Another framework, task technology fit (TTF), introduced by Goodhue and Thompson (1995), explained its ability to accomplish the required task well. Pillai and Sivathanu (2020) incorporated TOE with the TTF model to provide a detailed understanding and predict AI technology adoption patterns for talent acquisition purposes at an enterprise level. The findings illustrated that TOE is best used to examine the adoption patterns of AI technology and perform actual talent acquisition functions. In contrast, HR executives and managers best use the TTF model. Further, it was added that HR readiness, comparative benefits, cost-effective factors, management support, and pressure from competitors have a positive effect, and challenges over the safety and the confidentiality of information inhibit the widespread use of AI.

Although data analytics and AI are very quickly used in other business functions like marketing, there are many challenges in the HRM field, and approximately only 22 percent of firms currently use it globally. Recent research studies explored the integration of AI in multiple HR functions such as in the recruitment process (Chang, 2010; Kabak et al., 2012; Chen & Chien, 2011; Boz & Kose, 2018; Daramola et al., 2010), performance management (Jing, 2009; Wu, 2009; Lee, 2010; Zhao, 2008; Rashid & Jabar, 2016), human resource development (HRD) and turnover forecasting (Buzko et al., 2016; Strohmeier & Franca, 2015; Sivathanu & Pillai, 2018). The benefit of the AI technique lies in standardizing and measuring the assessment process by saving cost and time and minimizing human biases and errors. AI also contributes to candidate screening with great speed and accuracy from the talent pool as per the organization's predefined standards and potential fit. AI has advanced far ahead in assessing not only the job applicant's intelligence quotient (IQ) but also emotional quotient (EQ) and social quotient (SQ). The employer may evaluate the job seeker's cognitive, social, and behavioral traits, innovative ways to overcome possible risks, and how innovatively the candidate will solve the online game, enabling the recruiter to assess the quality of academic studies in the psychometric tests.

According to Strohmeier and Franca (2015), an information-driven search engine is among the most popular AI strategies utilized in hiring. It understands the search content and looks for the candidate's profile on the web that fits with the semantic aspects of the job posting. After HR staff defines characteristics like educational qualification, experience, job title, age, gender, etc., the knowledge-based search engine uses predefined ontology-focused data extraction (Celik, 2016).

Another AI technique used for recruitment is data mining (DM). Kantardzic (2011) mentioned that DM has four critical features: classification, association, clustering, and prediction. It extracts the candidate's resumes from large databases and uses classification and prediction while screening profiles from massive databases. Strohmeier and Franca (2015) further added that when the assessment procedure is in progress, DM is proper for collecting information from resumes and recommended text mining techniques to obtain thoughts, attitudes, and feelings from an unstructured text. Petrovic-Lazarevic (2001), Tai and Hsu (2006), and Dursun and Karsak (2010) illustrated data mining systems grounded on fuzzy logic for choice-making assistance in the recruitment procedure in order to cut down on the bias of traditional techniques of scrutinizing applicants. After the candidate applies for a job and assesses his profile, the Chatbots interact in textual or audio methods with the job applicant as real-time communication for profile screening and help the applicant to understand the organizational culture and timely changes in the recruitment process (Akash & Anusha, 2018). In this way, AI in HRM is efficient in moving with emerging opportuni-

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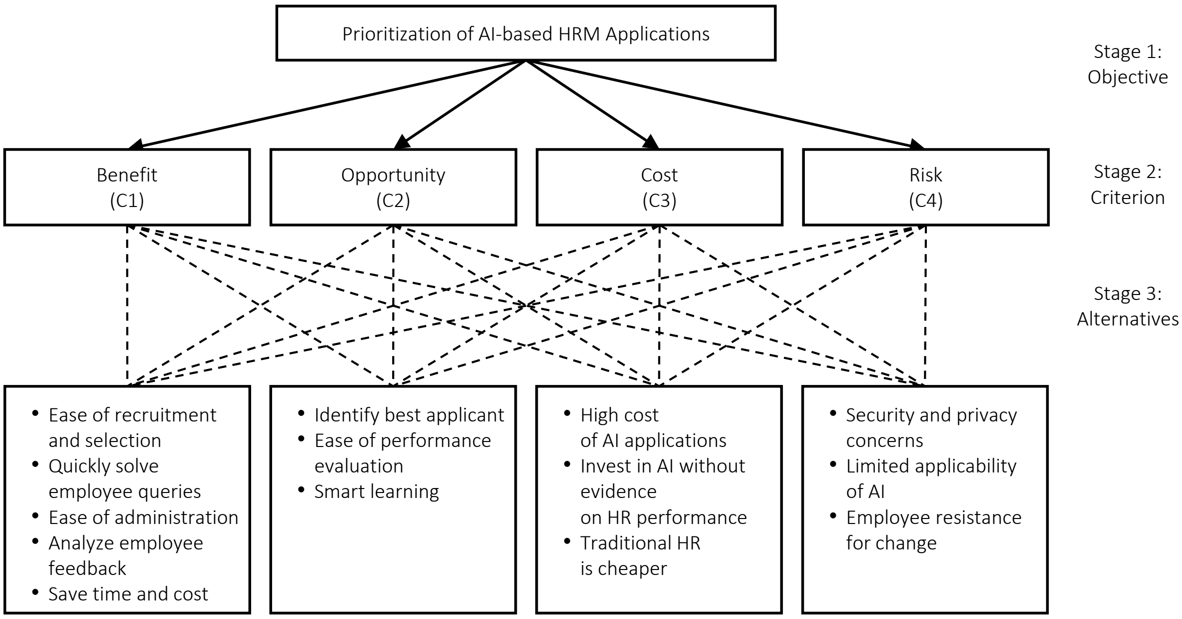

Figure 1. Theoretical framework for AI-based HRM applications

ties and working in a competitive environment at a fast pace by overcoming challenges (Buzko et al., 2016). However, there are negative perceptions and experiences among the candidates in terms of getting employer feedback. So, Chatbots need much improvement to satisfy the job seeker's experience. The latest Chatbots with ML used in staffing are Mya, HireVue, and Wendy. Boz and Kose (2018) revealed other contemporary applications of AI like HireVue and Affectiva, which are used in video-based interviews and even understand the emotions, facial expressions, personality, tone and speaking patterns, and candidates' honesty.

Oracle's HCM cloud division found that AI represents a novel trend in the recruitment process by bridging skill gaps in various HR functional areas. It offers personalized learning by collecting information about employees' skills, projects, learning habits, and core responsibilities. Particularly in Saudi Arabia, implementing AI in HRM departments is rare. While big enterprises focus on benefits and opportunities, medium and small enterprises may emphasize cost and risk factors. From the literature background, choosing AI-based HRM applications by HRM users may not necessarily result in equal weights but involve multi-criteria attributes. Therefore, this study attempted to understand pragmatic viewpoints among industrial HRM department users.

The conceptual underpinnings of the current investigation are laid forth in explicit detail in Figure 1. The study proposed identifying the advantages, opportunities, costs, and risks related to AI-based HRM solutions. Then, the prerequisites for achieving the specified goals are outlined. There are a variety of alternatives to take into account for every parameter. Figure 1 is a common representation of the model hierarchy. Because there are many criteria and subcriteria, it produces a perplexing decision-making environment.

Regarding importance to the aim, each criterion or alternative may not be equal. According to the weighted score, selecting the most relevant criteria and options is necessary. A peer-to-peer comparison is also required to determine the most relevant criteria and alternatives. Because of the nature of this paper, multi-criteria hierarchy analysis tools are ideal. Given the nature of the problem, the analytical hierarchy process (AHP) may be an excellent analysis method.

The primary aim of this study is to evaluate the costs, benefits, opportunities, and risks of AI-based HRM applications from the viewpoint of HRM users. Additionally, the study aims to analyze the relative importance of the aforementioned factors in influencing industrial HRM users' decision to select AI-based HRM applications based on these four factors.

2. METHODOLOGY

To cope with numerous studies questions and bridge the gaps in research studies, it is imperative to use an AHP technique, which Saaty (1980) advised. AHP has emerged as one of the fairly powerful gears of multi-criterion decision-making. This approach is anticipated to develop nice choices with the assistance of the mathematical mixture of numerous judgments approximately to a problem. It develops a multilevel hierarchy and estimates the weights and significance of every alternative with the pairwise comparison (Saaty & Vargas, 1996). Based on the comparison scale developed by Saaty (1980), the ranks are allocated, and the significance of every alternative is assessed. Past studies have used AHP as an effective device to mitigate complicated research issues as a top choice (Khan et al., 2011; Khan et al., 2015; Khan, 2021; Faisal & Naushad, 2020).

A typical AHP methodology comprises a six-step procedure (Kwon & Seo, 2014). In the first step, the hierarchical structure for decision-making is constructed. It includes the setting of goals for the problem taken into consideration, and criteria are decomposed into alternatives or sub-criteria. Upon completion of this task, the hierarchy is put into the form of a questionnaire that is arranged for pair-wise comparison. The questionnaire thus prepared is now being administered among the focus group chosen from large enterprises in Saudi Arabia. The scale for the questionnaire was developed by Saaty (1980), refer to Table 1. Now, the pairwise comparison metrics are formed for each decision maker's responses (members of the focus group).

Table 1. Measurement scale used in the questionnaire

Significance level	Scale Details
1	Both are equally important
2	Weak or not very significant
3	Rather significant
4	Slightly more crucial
5	Extremely crucial
6	Much more notably crucial
7	Very Strongly
8	Extremely Strongly
9	Extremely important

In the second step, a pair-wise comparison of the weights obtained is compiled in the form of a matrix, sometimes known as the "fuzzy positive matrix." In the third step, the weights for these decision elements are calculated using the lambda-Max method. Then, in the fourth step by using eigenvalues and eigenvectors, the consistency of the element's priority is checked to ensure that the pairwise comparison results are consistent. This ensures that results are consistently related to a large sample (Coyle, 2004). The consistency ratio can be estimated as follows:

- Evaluate the highest eigenvector (lmax)
- Estimate the consistency index (μ) for every matrix of order n by the Eq:

$$\mu = \frac{\lambda_{\max} - n}{n-1} \cdot C. \qquad (1)$$

Last but not least, the *CR* of a pair-wise evaluation array is calculated by dividing a matrix's consistency index by the Random Index (*RI*) value shown in Table 1. i.e., $CR = \mu / R$.

The RI calculation is necessary to obtain the results derived from a large number of simulation runs, and it varies according to the matrix's order (Kannan, 2009). The value of the RI for matrices of orders 1-9 is shown in Table 1, which was calculated by approximating random indices with 50,000 simulations (Saaty, 2009). The matrix evaluation is acceptable if CR is equal to or less than 0.1. If the CR value exceeds 0.1 when judgments within the matrix are inconsistent, the evaluation process must be reviewed, reconsidered, and improved (Crowe et al., 1998). Step five comprises the opinions of decision-makers that are integrated. The decision-makers' relative importance is averaged using a mathematical mean. In the final step, the final rankings of the decision are obtained.

The purpose of this particular investigation led to the development of an AHP decision hierarchy to prioritize AI-based HRM applications. Different criteria and sets of alternatives were designed with the help of an extensive review of the literature. Per the most recent data from January 2022, Saudi Arabia has been actively utilizing artificial intelligence (AI) techniques. The Saudi government has recognized the potential of AI in various sectors

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and has taken steps to incorporate AI technologies into different aspects of the country's development. Furthermore, Saudi Arabia's dairy sector is acknowledged as one of the fastest-growing and implements cutting-edge technologies in supply chain management, manufacturing, and human resources. The dairy business was chosen for this study because data gathering was convenient and accessible in this sector. The human resource managers/senior executives from Saudi Arabia's dairy industry were interviewed and consulted as experts, and focus groups were done with them to prioritize weight in a pairwise comparison of these criteria and alternatives. Thus, analysis of the gathered information involved Expert choice® software, which helped automate the entire decision-making process.

3. RESULTS AND DISCUSSION

The results are obtained after the execution of AHP. It contains priority weights and pairwise comparisons, including criterion weight and alternative weights. The AHP scale suggested by Millet and Saaty (2000) was used to assign relative importance ratings and to make comparisons between pairs (from 1 to 9, where 9 is very important and 1 is not). The cumulative score and pair-wise comparisons generated from the investigation are displayed in Figure 2, with the position of the chosen criterion highlighted. Results indicate that "opportunities" are a vastly important criterion for HR managers for AI-based applications in talent acquisition.

Moreover, "benefits" remain the second important criterion for HR managers. Meanwhile, "cost" and "risk" with AI implications are the least important for HR managers. The main reason for the highest weightage of criteria "opportunities" and "benefits" is that HR managers understand the importance of AI-based applications in talent acquisition as it minimizes the chances of human errors. "Cost" and "risk" received little consideration. Most HR professionals accept the opportunities and benefits of AI-based applications, which are more of a form of identifying the best applicants, and these applications also save time, effort, and cost. So, the cost and risk associated with AI-based applications are less than the benefits arising out of them. Thus, investing in AI-based applications for talent acquisition is worthwhile, as AI will streamline hiring procedures and remove potential biases from human observation.

Figure 3 displays the outcomes of comparative alternate scores regarding the current study's aim and identifies the best applicants who contributed the highest to the goal with a priority weight of 18.70%. On the other hand, the limited applicability of AI contributes the lowest, with a minimum weight of 1.3%, which is very low. The alternative identifies that the best applicants gain the highest priority weight, which indicates that by using AI applications in the talent acquisition process, organizations can select the best available employees without biases in human observation. The lowest score for alternative limited applicability of AI denotes the vast possibilities for AI-based applications in this era.

The final phase in using AHP to make the choice is to conduct a sensitivity assessment, which is a crucial part of making decisions. The performance sensitivity analysis is shown in Figures 4 and 5.

The HR managers identify the top five benefits and opportunities alternatives are (1) identifying best applicants with a priority weight (18.70%), (2) saving time and cost with a pri-

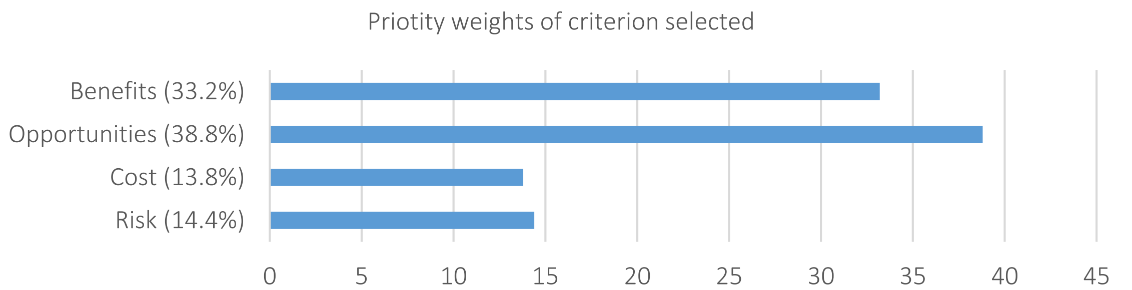

Figure 2. Priority weight for criteria of AI-based application

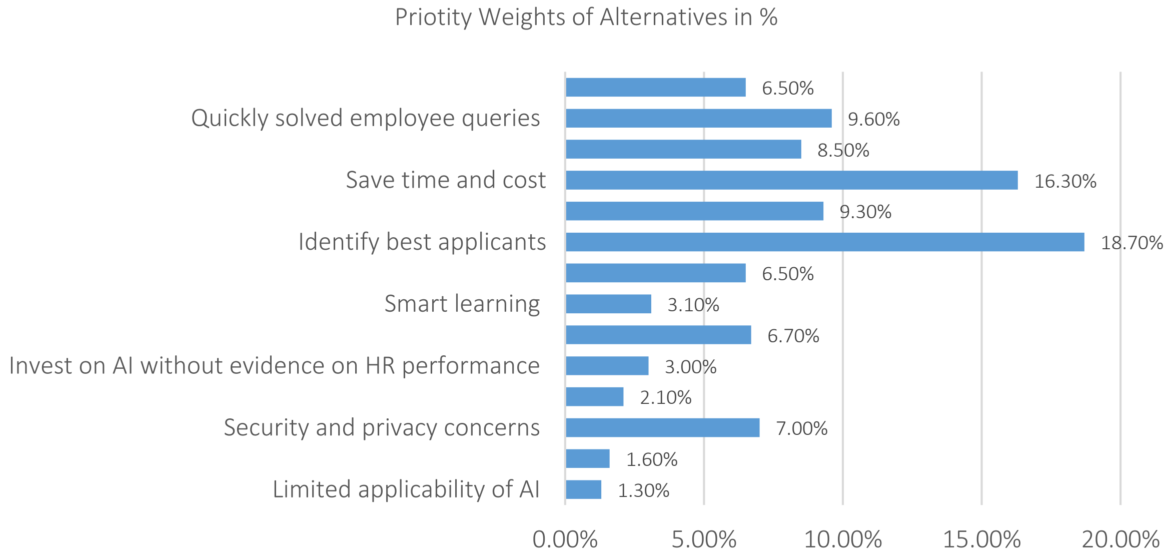

Figure 3. Priority weight for alternatives of AI-based application

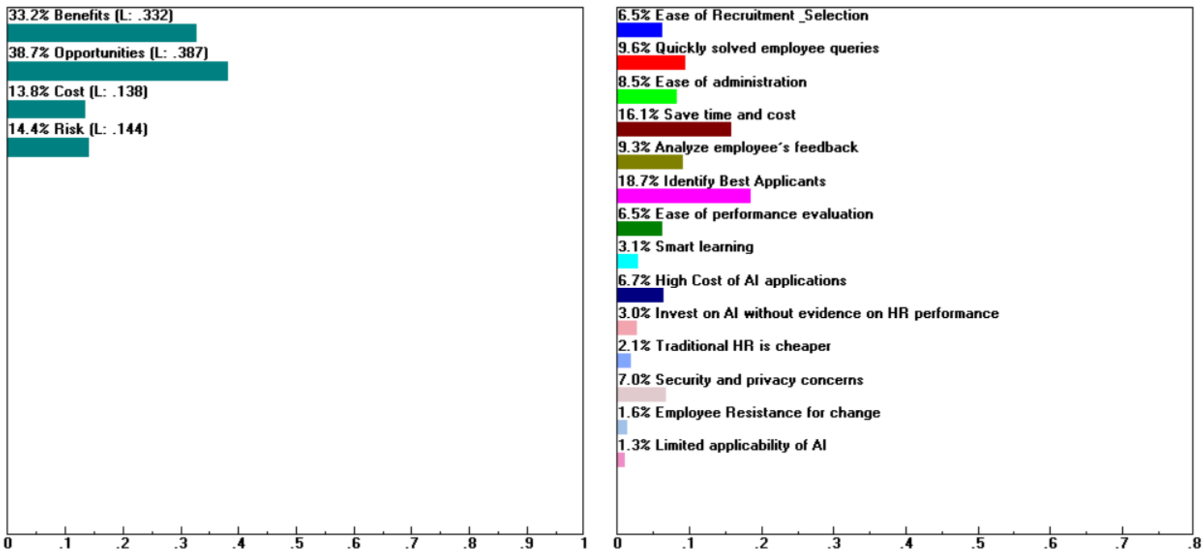

Figure 4. Performance sensitivity analysis

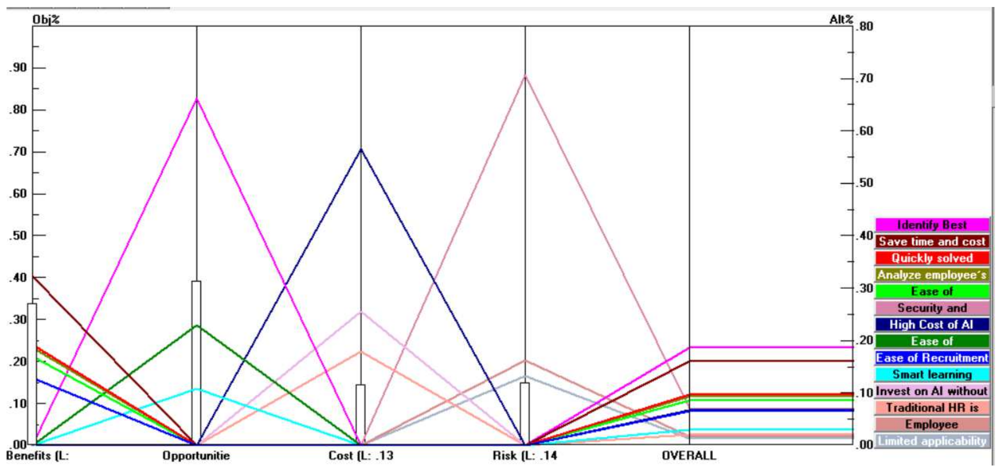

Figure 5. Performance sensitivity analysis

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ority weight (16.30%), (3) quickly solving employee queries (9.60%), (4) analyzing employee feedback (9.30%), and (5) ease of administration (8.5%). Many research studies also strongly perceive that AI has enormous opportunities in performing HRM departmental functions, and firms are currently desperate to shift their working approaches by using these techniques. AI has covered several phases in applicant assessment tools, from testing their intelligence quotient (IQ) to emotional quotient (EQ) to social quotient (SQ). Further, the assessment of candidates through gamification using game-based technology has gained more attention from HR professionals, as it involves and interacts with the applicants enthusiastically and makes it easy for HR employees to recognize the association between academic performance and psychometric testing. This study demonstrates many practical insights to Saudi organizations in transforming the overall performance of firms by reducing the costs incurred in talent acquisition and HR recruitment.

The usage of AI-based applications in HRM has been burgeoning in recent years. AI emerged because its vast applications ease out many traditional and cumbersome processes in talent acquisition. Solutions to different business problems can be arrived at only with the help of an entirely different set of approaches and mindsets. In this backdrop, AI emerged and became a possible alternative to outdated processes. The present study revealed the opportunities and benefits of AI-based applications in talent acquisition processes. Hence, AI's augmented intelligence will make recruiters more proactive in their hiring processes. They can determine the best organization-fit candidates with the help of different AI-based applications. Saudi Arabia is going through transformational changes to attain Vision 2030. AI applications can help attain the human capital-centric part of its vision of 2030.

The study identified several significant applications of AI in hiring and their elements. They are utilizing natural language processing for resume screening (NLP). AI systems examine cover letters and resumes to find pertinent education, experience, and certifications, employing data mining and analysis for candidate sourcing. AI tools can find candidates based on predetermined criteria by searching across various internet platforms, databases, and social networks. Chatbots for first interaction utilize machine learning and NLP. Chatbots communicate with candidates, respond to their questions, and gather preliminary data to deliver a more customized and dynamic experience. Predictive analytics with machine learning and predictive modeling for candidate fit is offered. AI systems use past data to forecast an applicant's potential fit for a given position based on hiring trends and staff productivity. Interview scheduling can be done using automation. AI-driven scheduling systems employ algorithms to determine the best times for interviews, considering the candidate's availability and that of the hiring team. NLP and computer vision are used to analyze video interviews. AI evaluates nonverbal clues, language usage, and other aspects of video interviews to provide insights regarding a candidate's fit for the position. By guaranteeing equitable and inclusive procedures, AI tools can aid in detecting and addressing biases in the recruiting process and fostering diversity, offering support with onboarding using automation and natural language processing. AI-powered Chatbots and virtual assistants can help new hires with onboarding by offering information, responding to inquiries, and easing the transfer. AI can anticipate future attrition risks by evaluating employee data, enabling firms to proactively retain key people. Personalized learning algorithms are used for ongoing education and development. Based on an employee's performance, talents, and career objectives, AI can suggest tailored learning routes for them.

Although these findings are relevant and paramount for policymakers and academicians, there are also some limitations. The findings are predicated on information gathered from Riyadh-based human resource managers of global corporations. The proportion of participants can be raised to improve the outcome. There is scope for future research on medium and small-size enterprises with a larger sample within and outside Saudi Arabia. The current study will be extremely satisfied if it catalyzes additional research on this fascinating and extremely applicable topic.

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CONCLUSION

The study aimed to examine critical aspects of AI in the context of talent acquisition, explicitly focusing on cost-benefit analysis, opportunities, and risk factors. According to the findings of the AHP model, it is clear from this comparison that managers of large enterprises operating in Saudi Arabia opined that the usage of AI-based applications is giving a lot of "opportunities" and "benefits" in talent acquisition. Alternatives adopted in the present study also witnessed a similar trend as "identify best applicants" attained the highest priority rate, which is an element of the criterion "opportunities," followed by "save time and cost," which is an element of criterion "benefits." Hence, the results clearly state that AI plays a significant role in talent acquisition as it is transforming the entire process with technology-driven techniques. AI brings quantum changes in hiring, assessing, and motivating talent and has the potential to bring curative changes.

As mentioned in the technology acceptance model (TAM), the study indicates the perceived benefits of AI-based technology on an organization's performance and a significant change in structure, strategy, and process. The perceived usefulness of AI technology is crucial as it determines the readiness of employees to adopt innovative and sophisticated technological services, enhancing the various dimensional performance of the organization. The study highlights practical inferences to HR managers and the government to reform new strategies by reconsidering technological changes and easing talent acquisition by integrating AI into recruitment. This can further automate the application process, provide high-quality resumes, screen the piles of resumes effortlessly, schedule interviews, and auto-reply the job candidates. The present results indicate the usefulness of AI-based applications in identifying the best applicants and saving time and cost. The findings of this study state that AI usage in talent acquisition is innovative and facilitates ease of use in various HR functions.

AUTHOR CONTRIBUTIONS

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REFERENCES

1. Abbasi, M. S., Chandio, F. H., Soomro, A. F., & Shah, F. (2011). Social influence, voluntariness, experience and the internet acceptance: An extension of technology acceptance model within a South-Asian country context. *Journal of Enterprise Information Management, 24*(1), 30-52. http://dx.doi.org/10.1108/17410391111097410
2. Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T
3. Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting behavior*. Englewood Cliffs, NJ: Prentice Hall.
4. Akash, B., & Anusha, D. K. (2018). Recruitment Chatbot. *International Research Journal of Engineering and Technology, 5*(8), 1248-1250. Retrieved from https://www.irjet.net/archives/V5/i8/IRJET-V5I8212.pdf
5. Albert, E. T. (2019). AI in talent acquisition: a review of AI-applications used in recruitment and selection. *Strategic HR Review, 18(5)*, 215-221. https://doi.org/10.1108/SHR-04-2019-0024
6. AlMuhaideb, S., Alswailem, O., Alsubaie, N., Ferwana, I., & Alnajem, A. (2019). Prediction of hospital no-show appointments through artificial intelligence algorithms. *Annals of Saudi Medicine, 39*(6), 373-381. https://doi.org/10.5144%2F0256-4947.2019.373
7. Arthur, J. B. (1992). The link between business strategy and industrial relations systems in American steel minimills. *Industrial and Labor Relations Review, 45*(3), 488-506. https://doi.org/10.2307/2524274
8. Arthur, J. B. (1994). Effects of human resource systems on manufacturing performance. *Academy of Management Journal, 37*(3), 670-687. Retrieved from https://www.jstor.org/stable/256705
9. Awa, H. O., Ojiabo, O. U., & Orokor, L. E. (2017a). Integrated technology-organization-environment (T-O-E) taxonomies for technology adoption. *Journal of Enterprise Information Management, 30*(6), 893-921. https://doi.org/10.1108/JEIM-03-2016-0079
10. Awa, H. O., Ukoha, O., & Igwe, S. R. (2017b). Revisiting technology-organization-environment (T-O-E) theory for enriched applicability. *The Bottom Line, 30*(1), 2-22. https://doi.org/10.1108/BL-12-2016-0044
11. Bersin, R. J. (2018). *Talent trends technology disruptions for 2018.* Deloitte. Retrieved from https://pdf4pro.com/amp/view/talent-trends-hr-technology-disruptions-for-2018-6722.html
12. Bouchikhi, H., & Kimberly, J. R. (2008). *The soul of the corporation: How to manage the identity of your company.* New Delhi: Pearson Education Inc.
13. Boz, H., & Kose, U. (2018). Emotion extraction from facial expressions by using Artificial Intelligence techniques. *BRAIN – Broad Research in Artificial Intelligence and Neuroscience, 9*(1), 5-16. Retrieved from https://lumenpublishing.com/journals/index.php/brain/article/view/2011
14. Bugg, K. (2015). Best practices for talent acquisition in 21st-century academic libraries. *Library Leadership & Management, 29*(4), 1-14. Retrieved from https://academicworks.cuny.edu/cgi/viewcontent.cgi?article=1012&context=ny_pubs
15. Bumblauskas, D., Gemmill, D., Igou, A., & Anzengruber, J. (2017). Smart maintenance decision support systems (SMDSS) based on corporate big data analytics. *Expert Systems with Applications, 90*, 303-317. https://doi.org/10.1016/j.eswa.2017.08.025
16. Burkus, D., & Osula, B. (2011). Faulty Intel in the war for talent: Replacing the assumptions of talent management with evidence-based strategies. *Journal of Business Studies Quarterly, 3*(2), 1-9. Retrieved from https://www.proquest.com/openview/ee3c348dfaa07526915b3f8148f91a06/1?pq-origsite=gscholar&cbl=1056382
17. Buzko, I., Dyachenko, Y., Petrova, M., Nenkov, N., Tuleninova, D., & Koeva, K. (2016). Artificial intelligence technologies in human resource development. *Computer Modelling & New Technologies, 20*(2), 26-29. Retrieved from http://www.cmnt.lv/upload-files/ns_53art05_Dyachenko.pdf
18. Celik, D. (2016). Towards a semantic-based information extraction system for matching résumés to job openings. *Turkish Journal of Electrical Engineering & Computer Sciences, 24*(1), 141-159. Retrieved from https://journals.tubitak.gov.tr/cgi/viewcontent.cgi?article=2802&context=elektrik
19. Chang, N. (2010). The application of neural network to the allocation of enterprise human resources. *2nd International Conference on E-Business and Information System Security, EBISS2010* (pp. 249-252). Wuhan, China. https://doi.org/10.1109/EBISS.2010.5473417
20. Chatman, J. (1989). Improving interactional organizational research: A model of person-organization fit. *The Academy of Management Review, 14*(3), 333-349. http://dx.doi.org/10.2307/258171
21. Chen, L. F., & Chien, C. F. (2011). Manufacturing intelligence for class prediction and rule generation to support human capital decisions for high-tech industries. *Flexible Services and Manufacturing Journal, 23*(3), 263-289. https://doi.org/10.1007/s10696-010-9068-x
22. Chikhaoui, E., & Mehar, S. (2020). Artificial intelligence (AI) collides with patent law. *Journal of Legal, Ethical and Regulatory Issues, 23*(2). Retrieved from https://www.abacademies.org/articles/artificial-intelligence-ai-collides-with-patent-law-9125.html
23. Cooke, F. L. (2018). Concepts, contexts, and mindsets: Putting human resource management research in perspectives. *Human Re-*

source Management Journal, 28(1), 1-3. https://doi.org/10.1111/1748-8583.12163

24. Cooper, W., Leavitt, H. J., & Shelly, M. W. I. (1964). *New perspectives in organization research*. New York: John Wiley.
25. Coyle, G. (2004). *Practical strategy: Structured tools and techniques*. Pearson Education.
26. Crowe, T. J., Noble, J. S., & Machimada, J. S. (1998). Multi-attribute analysis of ISO 9000 registration using AHP. *International Journal of Quality & Reliability Management, 15*(2), 205-222. https://doi.org/10.1108/02656719810368495
27. Daramola, J. O., Oladipupo, O. O., & Musa, A. G. (2010). A fuzzy expert system (FES) tool for online personnel recruitments. *International Journal of Business Information Systems, 6*(4), 444-462. https://doi.org/10.1504/IJBIS.2010.035741
28. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(2), 319-340. https://doi.org/10.2307/249008
29. Delery, J. E., & Doty, D. H. (1996). Modes of theorizing in strategic human resource management: Tests of universalistic, contingency, and configurational performance predictions. *Academy of Management Journal, 39*(4), 802-835. Retrieved from https://arwana007.files.wordpress.com/2012/02/modes-of-theorizing-in-shrm.pdf
30. Depietro, R., Wiarda, E., & Fleischer, M. (1990). The context for change: organization, technology and environment. The processes of technological innovation. In *The Processes of Technological Innovation, 199* (pp. 151-175). Lexington Books. Retrieved from https://www.scirp.org/reference/referencespapers?referenceid=3415986
31. Doty, D. H., Glick, W. H., & Huber, G. P. (1993). Fit, equifinality, and organizational effectiveness: A test of two configurational theories. *Academy of Management Journal, 36*(6), 1196-1250. Retrieved from https://www.jstor.org/stable/256810
32. Dursun, M., & Karsak, E. E. (2010). A fuzzy MCDM approach for personnel selection. *Expert Systems with Applications, 37*(6), 4324-4330. https://doi.org/10.1016/j.eswa.2009.11.067
33. Faisal, S., & Naushad, M. (2020). An overview of green HRM practices among SMEs in Saudi Arabia. *Entrepreneurship and Sustainability Issues, 8*(2), 1228-1244. http://doi.org/10.9770/jesi.2020.8.2(73)
34. Fitz-Enz, J. (2000). *The ROI human capital: Measuring the economic value of employee performance*. New York, NY: American Management Association.
35. Goodhue, D. L., & Thompson, R. (1995). Task-technology fit and individual performance. *MIS Quarterly, 19*(2), 213-236. https://doi.org/10.2307/249689
36. Huselid, M. A. (1995). The impact of human resource management practices on turnover, productivity, and corporate financial performance. *Academy of Management Journal, 38*(3), 635-672. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1803666
37. Jani, M., & Saiyed, R. (2017). Person-organization fit: Gaining competitive advantage through successful talent acquisition. *Apeejay-Journal of Management Sciences and Technology, 4*(2), 54-60.
38. Jia, Q., Guo, Y., Li, R., Li, Y., & Chen, Y. A. (2018). Conceptual artificial intelligence application framework in human resource management. *Proceedings of the International Conference on Electronic Business* (pp. 106-114). ICEB, Guilin, China. Retrieved from https://iceb.johogo.com/proceedings/2018/ICEB2018_paper_77_full.pdf
39. Jiang, F., Li, J., Du, M., & Wang, F. (2018). Research on the application of artificial intelligence technology in human resource management. *2nd International Conference on Systems, Computing, and Applications (SYSTCA 2018)* (pp. 176-179). https://doi.org/10.25236/systca.18.038
40. Jiang, K., & Messersmith, J. (2018). On the shoulders of giants: A meta-review of strategic human resource management. *The International Journal of Human Resource Management, 29*(1), 6-33. https://doi.org/10.1080/09585192.2017.1384930
41. Jing, H. (2009). Application of fuzzy data mining algorithm in performance evaluation of human resource. *2009 International Forum on Computer Science-Technology and Applications* (pp. 343-346). Chongqing, China. https://doi.org/10.1109/IFCSTA.2009.90
42. Kabak, M., Burmaoğlu, S., & Kazançoğlu, Y. (2012). A fuzzy hybrid MCDM approach for professional selection. *Expert Systems with Applications, 39(3),* 3516-3525. https://doi.org/10.1016/j.eswa.2011.09.042
43. Kannan, G. (2009). Fuzzy approach for the selection of third party reverse logistics provider. *Asia Pacific Journal of Marketing and Logistics, 21*(3), 397-416. https://doi.org/10.1108/13555850910973865
44. Kantardzic, M. (2011). *Data mining: Concepts, models, methods, and algorithms*. Hoboken, NJ: IEEE Press and John Wiley.
45. Khan, S. (2021). Investment priorities of northeast Indian SMEs family business entrepreneurs based on BOCR aspects. *Accounting, 7*(2), 469-478. http://doi.org/10.5267/j.ac.2020.11.003
46. Khan, S., Honnutagi, A. Z., & Kumar, V. K. (2011). Prioritization of green IT parameters for Indian IT industry: Using analytical hierarchy process. *World Journal of Social Sciences (WJSS), 1*(4), 179-194. Retrieved from https://www.researchgate.net/publication/235751095_Prioritization_of_Green_IT_Parameters_for_Indian_IT_Industry_Using_Analytical_Hierarchy_Process
47. Khan, S., Khan, M. S. A., & Kumar, C. S. (2015). Multi-criteria decision in the adoption of cloud computing services for SME's based on BOCR Analysis. *Asian Journal of Management Research (AJMR), 5*(4), 606-619. Retrieved

from https://silo.tips/download/asian-journal-of-management-research-online-open-access-publishing-platform-for--8

48. Kristof, A. L. (1996). Person-organization fit: An integrative review of its conceptualizations, measurement and implications. *Personnel Psychology, 49*(1), 1-49. https://doi.org/10.1111/j.1744-6570.1996.tb01790.x

49. Kwon, H. K., & Seo, K. K. (2014). A fuzzy AHP based multi-criteria decision-making model to select a cloud service. *International Journal of Smart Home, 8*(3), 175-180. http://dx.doi.org/10.14257/ijsh.2014.8.3.16

50. Lee, D. Y., & Lehto, M. R. (2013). User acceptance of YouTube for procedural learning: An extension of the technology acceptance model. *Computers & Education, 61,* 193-208. http://dx.doi.org/10.1016/j.compedu.2012.10.001

51. Lee, S. G., Trimi, S., & Kim, C. (2013). The impact of cultural differences on technology adoption. *Journal of World Business, 48*(1), 20-29. http://dx.doi.org/10.1016/j.jwb.2012.06.003

52. Lee, Y. T. (2010). Exploring high-performers' required competencies. *Expert Systems with Applications, 37*(1), 434-439. https://doi.org/10.1016/j.eswa.2009.05.064

53. Miles, R. E., & Snow, C. C. (1978). *Organizational strategy, structure and process*. New York: McGraw-Hill.

54. Millet, I., & Saaty, T. L. (2000). On the relativity of relative measures–accommodating both rank preservation and rank reversals in the AHP. *European Journal of Operational Research, 121*(1), 205-212. https://doi.org/10.1016/S0377-2217(99)00040-5

55. Nadler, D. A., & Tushman, M. L. (1980). A model for diagnosing organizational behavior. *Organizational Dynamics, 9*(2), 35-51. https://doi.org/10.1016/0090-2616(80)90039-X

56. Nair, P. (2017). *The rise of the AI recruiter: Is HR tech the next to challenge human intuition.*

57. Nicastro, D. (2020, May 18). *7 ways artificial intelligence is reinventing human resources.* CMSwire. Retrieved from https://www.cmswire.com/digital-workplace/7-ways-artificial-intelligence-is-reinventing-human-resources/

58. Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. *The Electronic Journal Information Systems Evaluation, 14*(1), 110-121. Retrieved from https://www.researchgate.net/publication/258821009_Literature_Review_of_Information_Technology_Adoption_Models_at_Firm_Level

59. Oliveira, T., Martins, R., Sarker, S., Thomas, M., & Popovič, A. (2019). Understanding SaaS adoption: The moderating impact of the environment context. *International Journal of Information Management, 49,* 1-12. https://doi.org/10.1016/j.ijinfomgt.2019.02.009

60. Pearson J. (2009, February 17). People – Process – Technology – The eternal triangle. *Deconstructing ITSM.* Retrieved from http://deconstructingitsm.wordpress.com/2009/02/17/people-%E2%80%93-process-%E2%80%93-technology-the-eternal-triangle/

61. Petrovic-Lazerevic, S. (2001). Personnel selection fuzzy model. *International Transactions in Operational Research, 8*(1), 89-105. http://dx.doi.org/10.1111/1475-3995.00008

62. Pillai, R., & Sivathanu, B. (2020). Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. *Benchmarking: An International Journal, 27*(9), 2599-2629. https://doi.org/10.1108/BIJ-04-2020-0186

63. Rana, G., & Sharma, R. (2019). Emerging human resource management practices in Industry 4.0. *Strategic HR Review, 18*(4), 176-181. https://doi.org/10.1108/SHR-01-2019-0003

64. Rashid, T. A., & Jabar, A. L. (2016). Improvement on predicting employee behaviour through intelligent techniques. *IET Networks, 5*(5), 136-142. https://doi.org/10.1049/iet-net.2015.0106

65. Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

66. Saaty, T. (1980). *The analytic hierarchy process*. New York, NY: McGraw-Hill.

67. Saaty, T. L. (1990). How to make a decision: The analytic hierarchy process. *European Journal of Operational Research, 48*(1), 9-26. https://doi.org/10.1016/0377-2217(90)90057-I

68. Saaty, T. L. (2009). Applications of analytic network process in entertainment. *Iranian Journal of Operations Research, 1*(2), 41-55. Retrieved from https://iors.ir/journal/article-1-63-en.pdf

69. Saaty, T. L., & Vargas, L. G. (1996). *Decision making with the analytic network process*. Springer, USA.

70. Saba, T., & Leader, A. I. D. A. (2021). About the Artificial Intelligence and Data Analytics (AIDA) Lab. *2021 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA).* Riyadh, Saudi Arabia. Retrieved from https://ieeexplore.ieee.org/document/9425149

71. Sahay, P. (2014). Design thinking in talent acquisition: A practitioner's perspective. *Strategic HR Review, 13*(4/5), 170-180. https://doi.org/10.1108/SHR-04-2014-0027

72. Shih, K. H., Hung, H. F., & Lin, B. (2010). Assessing user experiences and usage intentions of m-banking service. *International Journal of Mobile Communications, 8*(3), 257-277. http://dx.doi.org/10.1504/IJMC.2010.032974

73. Sivathanu, B., & Pillai, R. (2018). Smart HR 4.0 – How industry 4.0 is disrupting HR. *Human Resource Management International Digest, 26*(4), 7-11. https://doi.org/10.1108/HR-MID-04-2018-0059

74. Strohmeier, S., & Franca, P. (2015). Artificial intelligence techniques in human resource management – A conceptual exploration. In C. Kahraman & S. Çevik Onar (Eds.), *Intelligent techniques in engineering management* (pp. 149-172). Cham: Springer. https://doi.org/10.1007/978-3-319-17906-3

75. Tai, W. S., & Hsu, C. C. (2006). A realistic personnel selection tool based on fuzzy data mining method. *Proceedings of the 9th Joint Conference on Information Sciences (JCIS)*. Kaohsiung, Taiwan.

76. Tanveer, M., Hassan, S., & Bhaumik, A. (2020). Academic policy regarding sustainability and artificial intelligence (AI). *Sustainability, 12*(22), 9435. https://doi.org/10.3390/su12229435

77. Thong, J. (1991). An integrated model of information system adoption in small business. *Journal of Management Information System, 15*(4), 187-214. https://doi.org/10.1080/07421222.1999.11518227

78. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

79. Walford-Wright, G., & Scott-Jackson, W. (2018). Talent rising; people analytics and technology driving talent acquisition strategy. *Strategic HR Review, 17*(5), 226-233. https://doi.org/10.1108/SHR-08-2018-0071

80. Wang, L. (2017). Using Artificial intelligence to improve the level of human resources management. *Sinopec in China, 7,* 53-54.

81. Wu, W. W. (2009). Exploring core competencies for R&D technical professionals. *Expert Systems with Applications, 36*(5), 9574-9579. https://doi.org/10.1016/j.eswa.2008.07.052

82. Zhao, X. (2008). A study of performance evaluation of HRM: Based on data mining. *Proceedings of the 2008 International Seminar on Future Information Technology and Management Engineering* (pp. 45-48). Leicestershire, UK. https://doi.org/10.1109/FITME.2008.133

http://dx.doi.org/10.21511/ppm.22(1).2024.37