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Investigating the Use of Artificial Intelligence in Talent Acquisition Procedures

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Abstract: This study explores the application of artificial intelligence (AI) in the context of Human Resource Management (HRM), specifically within Talent Acquisition Procedures (TAP). In contrast to prior research, it contributes a significant theoretical model to elucidate the effective implementation of AI in TAP. The study focuses on the underexplored impact of the recruitment phase, incorporating the critical perspective of recruitment professionals. It extends technology adoption theory within information systems by integrating insights from HRM literature. Qualitative findings from this study reveal the suitability of AI in specific TAP phases, such as sourcing, pre-screening/pre-selection, and candidate engagement. Notably, there is a discernible reluctance to adopt AI in the TAP pre-planning and interview stages. The study provides current insights to inform HRM practitioners and organizations seeking to integrate AI into their Talent Acquisition Procedures.

Keywords: Artificial Intelligence, Deep Learning, Employment, Machine Learning, Talent Acquisition Procedures, AI/ML.

I. INTRODUCTION

Artificial Intelligence (AI) is revolutionizing the Human Resource (HR) industry, particularly in the area of recruitment. It offers innovative solutions that streamline time-consuming activities, automate resume screening, and enhance candidate matching, enabling more efficient and effective decision-making by HR professionals. AI improves recruitment quality by ensuring standardized job matching and utilizing intelligent screening techniques. This automated resume screening system significantly reduces the burden on recruiters, preventing disruptions to their workflow and the candidate experience, while minimizing the need for IT support. The process of hiring and selecting the right candidates is crucial for an organization's success.
Traditionally, organizations have employed less technologically advanced methods, such as newspaper ads or employee referrals, to attract qualified applicants [1]. However, these traditional recruitment approaches are becoming less efficient due to the significant time investment involved and a lack of consistently optimal results [2]; [3].

Since the late 1990s, the labor market has faced economic challenges marked by a heightened demand for highly skilled candidates [4]. To stay competitive and meet customer demands in this technologically advanced environment, organizations must prioritize talent acquisition [5]. Hiring has evolved from a basic human resource function to a crucial strategic concern for organizations, recognizing talent as a source of value and competitive advantage. In contemporary times, organizations have identified attracting, selecting, and retaining talent as their primary strategic focus [6]. E-recruitment systems are gradually gaining prominence, surpassing traditional methods in response to this shift [7].

The adoption of AI tools gained popularity among recruiters in 2018 [8]. Careful talent selection is imperative for companies to ensure the achievement of organizational goals. The challenges associated with talent selection stem from the decision maker's numeracy, vision, analytical skills, and internal bias [9]. The emergence of a new era in recruitment, empowered by artificial intelligence, is equipping employers to address the complexities of the hiring process.

With the onset of the COVID-19 outbreak in 2020, offices were locked down, physical distancing measures were implemented, and masks became a necessity. The virtual office, while offering flexibility, presented challenges for HR recruitment. Issues included scheduling interviews, selecting suitable candidates, and encouraging resume submissions without face-to-face interactions [10]. Artificial intelligence emerges as a solution to these challenges, as it can provide a range of services related to HRM practices [11]

In the present day, companies are embracing the adoption of "Digital Recruiting 3.0," with the pivotal shift centering on the application of AI in the recruitment process [6]. With the assistance of AI, recruiters can efficiently manage substantial volumes of information to identify the most suitable candidates. Moreover, AI enables recruiters to go beyond evaluating a candidate's personality traits and traditional resume, assessing whether there is a compatible match. The impartiality of artificial intelligence is evident as it treats all candidates equally during the resume screening process [8]. The increasing prevalence of AI in recruiting is rooted in the belief that AI tools can establish an equitable process, delivering high-quality and optimal results in a more efficient and cost-effective manner compared to human efforts [12]. The revolutionary impact of AI systems is replacing the repetitive tasks that were traditionally carried out by professional recruiters.

Nevertheless, potential conflicts may arise concerning shared control between humans and autonomous systems, exemplified by situations like conflicts in interactions between drivers and AI-based support. Therefore, the interaction between AI and humans in various application domains necessitates advancements in state-of-the-art technology. Shared control scenarios are defined by the Competence-Availability-Possibility-to-act (CAP) framework [13]. This CAP-based autonomy is further broken down into diverse scenarios of shared control within or between workspaces, and the application of this approach is validated in a car driving scenario.

A study [14] found that an effective recruitment process can lead to better employee retention, job satisfaction, and overall organizational performance. By attracting and selecting the best candidates, organizations can improve productivity, customer satisfaction, and profitability. Additionally, a well-designed recruitment and selection process can enhance the employer's brand and attract top talent. As a result, organizations are eager to adopt new technologies in the recruitment and selection process to reap the benefits [15].

Volvo, a leading Swedish luxury vehicle manufacturer, implemented an innovative approach to recruitment by transforming their Brussels Motor Show into a job fair. Their "Recruiting Car" featured an AI-powered interview system that evaluated candidates for service technician positions at the Volvo plant. Candidates were asked job-related questions and required to identify parts through simulations, providing a unique and engaging recruitment experience.
One of the most promising trends in recruitment and selection is the use of artificial intelligence (AI). AI can streamline the recruitment process by automating routine tasks, such as screening resumes, scheduling interviews, and keeping candidates updated on their progress. AI can also analyze data from candidate assessments and job performance to identify patterns and insights that can help organizations make better hiring decisions. According to a report [16], AI technologies can reduce the time to hire, improve the candidate experience, and enhance the quality of hires, making them an attractive option for many organizational leaders.

Despite the potential benefits of AI, its adoption in recruitment and selection is challenging and complex. This is because the recruitment and selection process involves multiple stakeholders with different perspectives on AI. Organizations may see AI as a tool to achieve cost-effective strategic goals, while recruiters, hiring managers, and other stakeholders may have concerns about potential biases and ethical issues [17]. Additionally, using AI in recruitment and selection raises concerns about potential biases and ethical issues, which can lead to trust issues [18]. To mitigate these risks, organizations need to establish clear guidelines and governance frameworks to ensure that AI algorithms are transparent, fair, and unbiased [19]. This requires careful consideration of the selection and application of AI in business processes like recruitment and selection. Therefore, the decision to adopt AI in the recruitment and selection process cannot solely be driven by its capabilities or strategic leadership. It requires the involvement and collaboration of various stakeholders in the decision-making process. This means that the adoption of AI in the recruitment and selection process should be based on a shared understanding and acceptance of its potential benefits and limitations by all stakeholders involved.

To address this issue, this study explores the suitability of using artificial intelligence (AI) in the different phases of the recruitment and selection process from the perspective of recruitment and selection practitioners, including recruiters, hiring managers, and HR executives. To achieve this goal, the study proposes a new conceptual framework that integrates the recruitment phase into the well-known Unified Theory of Acceptance and Use of Technology (UTAUT) model. This is because recent research has emphasized the need for new theoretical models to understand emerging phenomena like AI [20]. Researchers have responded to this need by developing new theoretical frameworks, such as the UTATU-OM (Operations Management) model, to address the complexities of AI applications.

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By adopting this contextualized theoretical framework, the study provides a more comprehensive understanding of the complexities and applicability of AI in the recruitment and selection process. It contributes to the literature by proposing a novel theoretical framework that can guide future research and practice in AI in recruitment and selection. Additionally, the study provides managerial insights into the suitability of different phases of the recruitment process for adopting AI.

This research paper is organized into several sections. The first section provides an in-depth examination of the recruitment and selection process, covering its fundamental principles and functions. Subsequently, an investigation of AI applications in the recruitment and selection process is presented, drawing upon insights from various literature studies. Following this, the theoretical framework employed in this study, namely the Unified Theory of Acceptance and Use of Technology (UTAUT), is elucidated as the foundational basis for the development of the research's conceptual framework. The subsequent sections elaborate on the research design, outlining the data collection approach, and expounding on the chosen data analysis methods. A comprehensive account of the research findings and their implications is then provided, culminating in the concluding remarks that encapsulate the overall outcomes of the investigation.

II. LITERATURE REVIEW

Cutting-edge AI technology empowers machines to learn, make decisions, think logically, and react systematically, enabling the deployment of AI-based software in recruitment. This automation transforms the majority of the recruitment process, enabling machines to analyze big data swiftly and predict probable outcomes.

A. Automation Chatbots, and Enhanced Efficiency

Presently, data-driven recruitment, enhanced candidate experience, social media recruiting, video job interviews, and AI-based screening of application forms have emerged as solutions to time-consuming recruitment challenges. Virtual assistants are adept at connecting with candidates, storing and evaluating applications, and interacting with recruiters to manage the candidate database for future reference. They can scrutinize users' browsing history and post job advertisements across companies on various websites to reach potential candidates. Chatbots are widely used to extract basic information from candidate resumes and automatically match requirements with candidate skill sets. These chatbots utilize a blend of AI and natural language processing technology for enhanced human-like interaction. Mya and Olivia are examples of chatbots that engage on company websites to conduct initial screening and assist candidates with application completion, scheduling, providing application status updates, feedback, and instant responses to basic queries. They foster proactive bonding between companies and candidates, reducing the hiring cycle and creating a single source of reliability for passive candidates, making them feel valued.

Applicant Tracking System (ATS) software is being adopted by most hiring managers to improve hiring quality and automate the process of searching for prospective candidates matching specific parameters. ATS gathers profiles from various sources, such as social media, job portals, and networking sites, to enhance efficiency. Additionally, ATS documents employee records and maintains compliance with government regulatory frameworks.

B. Talent Acquisition Procedures (TAP)

Talent Acquisition Procedures (TAP) are crucial in identifying suitable candidates to meet an organization's human capital needs, significantly impacting organizational growth and performance [21]. TAP encompasses various functions, including recruitment planning, sourcing, pre-selection, selection, communication, and engagement with candidates and other stakeholders [22];[23]; [24] provide a detailed description of ten stages within TAP, covering defining requirements, attracting candidates, screening applicants, interviewing, testing, assessing candidates, obtaining references, checking applicants, offering employment, and following up. Given the multifaceted and complex nature of TAP, it is essential to prioritize strategies to attract and identify the most suitable candidates for the organization. The following paragraphs elaborate on each of these phases in detail.

C. Present Utilization of Artificial Intelligence

The adoption of this ground-breaking technology is enchanting various industries, with startup companies leading the way in leveraging its advantages for their business. Below, we discuss some companies that have already integrated AI into their recruitment processes.

- Skillate: Developed by SAP Labs, Skillate's AI platform enables recruiters to scan candidates' resumes from social media databases, validating their bio-data and matching their skillsets with available job positions.

- Hirevue: A US-based company, Hirevue employs video intelligence to analyze candidates' video interviews, providing employers with deeper insights and facilitating quicker decision-making for recruiters.

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- Interviewed: Based in San Francisco, Interviewed offers a suite of automated screening tools for programming tests, personality assessments, and language skills. Candidates undergo simulations before final selection.

- Entelo: Entelo uses predictive algorithms to browse social profiles and identify candidates most likely to leave their current jobs.

- Koru: An automated online talent screening platform, Koru utilizes predictive analytics and AI to enhance hiring outcomes, particularly in investment banks.

- Zoom & Montage: These teleconferencing software solutions incorporate AI to assist recruiters in selecting suitable candidates through video conferencing. They also facilitate the screening of candidates for face-to-face interviews across various rounds, gaining a comprehensive understanding of each candidate.

- Textio: Operating on predictive data analysis, Textio identifies potential candidates for high-profile jobs by analyzing language patterns and styles from documents posted by companies.

- Panna: Panna is an AI-driven hiring repository with features like dynamic questions, expert evaluation, interview documentation, video conferencing, and voice and face recognition. Designed with machine learning, it validates applicants' video interviews to detect malpractice or unusual movements.

- Harver: Harver's algorithms calculate a candidate's score based on alignment with the company's job requirements, predicting the likelihood of success in the selected role. This information empowers companies to make informed decisions before hiring.

- XOR.ai: XOR.ai leverages AI chatbots to automate the initial stages of recruitment by engaging with candidates, answering queries, and pre-screening applicants.

- Ideal: Ideal uses AI algorithms for resume screening to identify and shortlist candidates who closely match the job requirements, streamlining the initial selection process.

- Robolink: Robolink incorporates robotic process automation (RPA) in recruitment, automating repetitive tasks such as resume parsing, data entry, and interview scheduling to enhance efficiency.

- Vervoe: Vervoe integrates AI to create skills assessments and simulations that evaluate candidates' practical abilities, providing a more comprehensive understanding of their capabilities beyond traditional resumes.

- Talview: Talview employs AI-driven video interviewing and assessment tools to evaluate candidates’ cognitive abilities, personality traits, and job-related skills in a virtual setting.

- Beamery: Beamery uses AI to enhance candidate relationship management (CRM), helping recruiters build and nurture relationships with potential candidates over time through personalized engagement.

- PredictiveHire: PredictiveHire utilizes natural language processing (NLP) and machine learning to analyze candidate responses in interviews, providing insights into their suitability and potential cultural fit.

- Yobs: Yobs integrates AI to match candidates with suitable job opportunities based on their skills, preferences, and career goals, creating a more personalized and efficient job search experience.

III. CATEGORIES OF AI AND THEIR IMPACT ON COGNITIVE WORKLOAD

There are three types of AI. Firstly, we have Artificial Narrow Intelligence (ANI), often referred to as weak AI, which is specialized for specific products, services, or tasks [25]. Secondly, there is Artificial General Intelligence (AGI), characterized by its ability to replicate human cognitive activity to the point of being indistinguishable from human intelligence [26]. Lastly, there is Artificial Super Intelligence (ASI), which not only replicates human intelligence but surpasses it in terms of overall intelligence. Currently, what exists is primarily narrow AI, but the coming decade is expected to witness the rapid development of other AI types as well, accumulating vast amounts of data in the process.

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Assessing the cognitive workload of users is frequently a central consideration in human-computer systems research, particularly when exploring tasks specific to artificial intelligence (AI). Humans have a finite capacity for processing information, relying on external cues, such as the environment, to alleviate cognitive strain, given the constraints of elements like short-term memory in the brain [27]. AI plays a pivotal role in problem-solving, effectively offloading human cognitive effort to what is metaphorically referred to as the "global brain" [28].

In pursuit of adaptation and personalization goals, information systems particularly scrutinize cognitive effort within the realm of human-computer interaction [29]. Researchers, such as [30], often utilize user perception to investigate the cognitive workload of users and its variations. Enhanced AI support frequently results in reduced cognitive demands on users. A study conducted by [31] involved job seekers with professional work experience engaging in role-playing scenarios simulating job interviews. The findings revealed that users in systems with heightened AI support experienced diminished levels of cognitive burden during these simulated interviews.

IV. MATERIALS AND METHODS

A. Deep learning and neural network method

A neural network represents a computer model comprising numerous artificial neurons interconnected to emulate the structure and functioning of a biological neural network. In the era of deep learning, methodologies for target identification based on neural networks are highly sought after. Deep learning seeks to train computers in executing tasks that humans naturally excel at. This technology is pivotal, allowing autonomous vehicles to discern stop signs, differentiate pedestrians from streetlight posts, and is considered crucial in various applications.

Within the realm of deep learning, computer models directly acquire the ability to perform classification tasks from images, text, or sound. These models often attain remarkable levels of accuracy, occasionally surpassing human capabilities. The typical approach involves training models with extensive labelled data and a neural network architecture characterized by numerous layers.

Learning in a neural network closely mirrors our conventional learning process. Initially, we perform a task, receive feedback from an instructor, and use that feedback to enhance our performance in subsequent attempts. Similarly, in a neural network, the difference between the actual value and the predicted value is employed to calculate an error value, which is then sent back through the system. This error is scrutinized for each layer of the network and utilized to adjust the thresholds and weights for the subsequent input. The closer the actual value aligns with the projected value, the smaller the error becomes. This iterative process, known as backward propagation, is continuously applied throughout the network until the error value is minimized.

In Figure 1 depicted below, the four variables outlined (such as the applicant's experience, education, skills, responsibilities, etc.) establish connections with neurons through synapses. Initially, the system introduces fresh data into the input layer. Subsequently, the node values are computed in hidden layers 1 and 2, respectively. In the output layer, the system computes the output value and, by assessing the difference between the actual value and the predicted value, determines the error value, which is then transmitted back to the system through reverse propagation. This iterative process contributes to the reduction of error with each successive run, signifying the ongoing learning of the network.

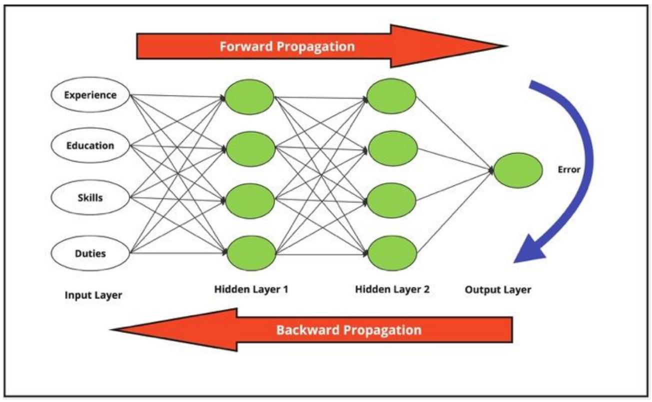

Fig. 1 Deep learning and neural network

Emerging technologies on the horizon introduce novel perspectives to current information processing and artificial intelligence methodologies, exemplified by advancements such as quantum computing. The integration of quantum

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computers into artificial intelligence, known as Quantum AI, represents a transformative development. In contrast to classical computers that employ a binary system, quantum computers introduce a base-3 system. This distinction allows quantum computers to not only select 1 or 0 bits but also both simultaneously, creating a third state. Consequently, the processing capabilities of quantum computers experience a significant enhancement, potentially adding unprecedented computing power to AI applications. Quantum AI serves as an interdisciplinary realm, combining quantum computing and artificial intelligence, fostering mutual complementarity between the two disciplines. Artificial intelligence stands to benefit from the information processing capabilities of quantum computing, facilitating the development of innovative AI algorithms. Conversely, quantum science can leverage deep learning techniques from artificial intelligence to enhance the manipulation of microscopic systems.

B. Technology Adoption

The Unified Theory of Acceptance and Use of Technology (UTAUT), formulated by Venkatesh, integrates eight technology acceptance models to offer a comprehensive approach to comprehending technology adoption [20]. This framework aims to elucidate both the intention to use technology and the actual usage of technology from the end user's perspective. It considers a range of factors influencing behavioural intentions and actual use, including performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT is widely acknowledged as a highly effective framework, accounting for up to 70% of the variance in technology adoption usage [20]. Notably, it distinguishes between behavioural intention and use behaviour, recognizing that the intention to adopt or use technology may not necessarily translate into actual use [32]. These constructs are illustrated in Figure 2.

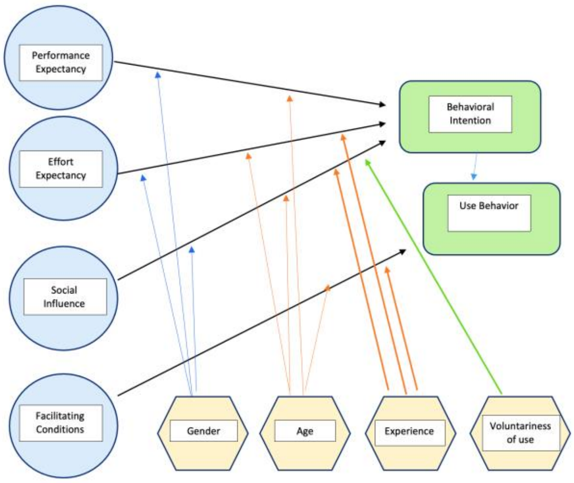

Fig. 2 AI- TAP/RSP adoption model (Sources: [20])

C. Behavioural Intentions (BI)

Behavioral intentions (BI) represent "the subjective probability that a person will perform a given behavior" [32]. Within the framework of the Unified Theory of Acceptance and Use of Technology (UTAUT), BI is acknowledged as the most robust predictor of use behavior [20]. Nonetheless, intentions do not invariably manifest into actual user behavior, and various factors can impact the relationship between intentions and behavior [32].

Performance expectancy, denoting an individual's perception of the extent to which using a system enhances job performance, is recognized as the most influential predictor of behavioural intentions and has been operationalized in diverse ways [20]. However, it might not encompass all expectations individuals hold regarding technology, particularly in regulated sectors like healthcare, where compliance with regulations is paramount [33]. Consequently, the more comprehensive construct of perceived usefulness, which incorporates expectations of usefulness, applicability, and performance, may be more pertinent in such contexts.

To address the limitations of the performance expectancy construct in technology adoption research, [33] proposed using benefit expectations (BE) as an alternative construct. BE encompasses various factors such as performance, usefulness,

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and applicability, providing a more comprehensive representation of individuals' expectations of technology. Thus, BE may be more suitable to use than PE in specific contexts.

Recognizing the significance of understanding individuals' expectations and perceptions of technology adoption, this research opts to employ the BE construct instead of PE. This decision aims to contribute to the existing literature on technology adoption by offering a more nuanced understanding of the factors influencing actual user behaviour.

D. Social Influence (SI)

As per [20], social influence denotes the extent to which an individual perceives the beliefs of others, especially those they deem significant, that they should adopt the new system. This construct encompasses the influence of various sources, including managers, supervisors, and colleagues within the organization. Research indicates that social influence significantly predicts behavioral intention, and its impact manifests through different channels, such as compliance and internalization [20]. Hence, the UTAUT model underscores the significance of social influence in the context of technology adoption, emphasizing the need to consider the influence of diverse actors within the organization.

E. Facilitating Conditions (FC)

Facilitating conditions, as articulated in the UTAUT model, pertain to the extent to which an individual perceives that the organizational and technical infrastructure is in place to support the utilization of the system [20]. This construct is shaped by factors such as perceived behavioural control on the system, compatibility, and facilitating conditions. Apart from predicting behavioural intentions, it has been identified as a predictor of technology use behaviour within the study's context. The measurement of this construct involves considering several factors, including the availability of resources to acquire knowledge about the system, the system's compatibility with other systems, and the availability of help or support, among other aspects [34]; [20]. However, it has been proposed that when both performance expectancy and facilitating conditions coexist, the impact of facilitating conditions on behavioural intentions is non-significant. [20] suggest that facilitating conditions only exert a significant impact on behaviour when performance expectancy is low. Additionally, [35] propose that facilitating conditions may directly impact behaviour, but only in scenarios where performance expectancy is not a significant factor. Empirical evidence by [36] supports the notion that facilitating conditions significantly influence mobile commerce usage only when performance expectancy is low. This observation implies that facilitating conditions do not notably affect behavioural intentions when performance expectancy is high. Consequently, it can be inferred that facilitating conditions play a more pronounced role in influencing behavioural intentions when performance expectancy is low [20].

F. Effort Expectancy (EE)

Effort expectancy is characterized as the level of ease associated with using the system [20]. This construct is founded on the concepts of perceived ease of use, complexity, and ease of use. Effort expectancy is gauged through metrics such as the clarity and understandability of system interaction, the ease of acquiring proficiency in using the system, and the ease of learning to use the system. It is anticipated that effort expectancy will positively influence behavioural intentions. However, it has been proposed that this factor holds significance primarily in the initial stages of technology adoption and diminishes in importance over time [20]. Consequently, it suggests that effort expectancy is not universally applicable throughout the entire life cycle of the technology but rather is pertinent primarily during the early stages of technology adoption.

G. Use Behaviour (UB)

The UTAUT model characterizes use behaviour as the actual extent to which a technology or system is employed. [20] have recognized that behavioural intention is the most influential predictor of user behaviour, with this intention being shaped by facilitating conditions. The UTAUT model acknowledges that these influences are subject to moderation by various contextual factors, such as gender, age, experience, and the voluntariness of use, constituting specific user attributes, according to [20].
Expanding upon the Unified Theory of Acceptance and Use of Technology (UTAUT) model, the introduction of recruitment phases as a conceptual framework contributes to a more contextualized understanding of AI adoption in the recruitment process. Incorporating recruitment phases into the conceptual framework accommodates the specific requirements of the recruitment process, providing recruitment specialists with enhanced insights into AI adoption in the recruitment process.

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V. DISCUSSION

A. AI for Talent Acquisition Procedures

The current study examined the influence of talent acquisition phases on the inclination to embrace AI in the recruitment process. The talent acquisition phases scrutinized encompass pre-planning, sourcing, pre-screening, interviews, and candidate engagement & communication. The results indicate that TAP professionals exhibit a greater inclination to utilize and embrace AI in sourcing and pre-selection, contrasting with pre-planning and candidate engagement & communication. While attitudes toward pre-planning and candidate engagement vary, a majority of participants express reluctance to employ AI in the interview phase. The underlying reasons for these decisions are primarily linked to enhancing the candidate experience through human interactions, skepticism about AI's capabilities for specific recruitment phases like interviews, limitations in infrastructure, such as data availability used by AI technologies, and the inherent nature of the business or industry, such as manufacturing or transportation.

B. Managing High Volume Hiring.

Leveraging artificial intelligence (AI) holds significant potential for tapping into a vast pool of candidates through the utilization of big data capabilities and sophisticated algorithms, thereby reducing the manual involvement of human recruiters. According to [37], AI plays a crucial role in identifying potential candidates and engaging them through personalized messaging, utilizing extensive data for analyzing and targeting underrepresented groups. They also highlight AI's contribution to diversity and inclusion efforts by formulating targeted recruitment strategies based on data insights. Similarly, [38] emphasize AI's ability to analyze data from diverse sources, including social media, online job boards, and internal databases, to effectively access a broad candidate pool. Furthermore, they suggest that AI can predict job performance and identify talent gaps in the recruitment process. These findings align with the perspectives shared by TAP professionals in this study, affirming the value of AI in the sourcing stage, particularly for high-volume hiring. Consequently, the integration of AI into the recruitment process emerges as a promising approach to expanding reach across a diverse candidate pool.

C. Managing Non-Specific Job Group Hiring.

The research outcomes suggest that TAP professionals express a preference for employing AI in the recruitment of non-specific job categories, particularly white-collar roles like software engineers, sales and marketing professionals, and accountants. Specialized positions such as pilots, mechanics, and C-level executives may not align well with AI-based recruitment practices, making generic job groups more suitable for this approach.

These findings align with earlier research. For instance, [39] showcased the potential of AI in recruiting employees across diverse industries, illustrating its ability to automate processes, reduce bias, and improve overall efficiency. Similarly, [40] identified AI's applicability in recruiting white-collar professionals such as managers, economists, and lawyers, emphasizing its role in candidate selection, screening, and communication.

Collectively, these studies, coupled with the results of the present research, provide substantial evidence supporting the notion that AI can serve as a valuable tool in recruiting for non-specific job categories.

D. Better Work-Life Balance

The findings of the research propose that AI has the potential to enhance the work-life balance of TAP professionals, marking a newly emerging theme. According to research participants, AI's ability to streamline and automate tasks such as sourcing, pre-screening, and candidate engagement can significantly reduce workloads and free up time.

This notion finds support in a study by [40], who identified that AI can enable HR professionals to work more efficiently, allowing them to focus on higher-value tasks and ultimately leading to an improved work-life balance. Similarly, [41] discovered that AI can alleviate the workload of recruitment professionals, resulting in lower stress levels and an enhanced work-life balance. They suggest that AI contributes to achieving a better work-life balance by enabling professionals to allocate more time to crucial tasks like strategic planning, building candidate relationships, and skill development.

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VI. CONCLUSION

Professionals express a strong interest in leveraging AI during the sourcing, pre-selection, and candidate engagement stages, particularly for high-volume recruitment and generic job categories. Their objectives include workload reduction, improved work-life balance, and broadening the candidate pool. However, enthusiasm for AI diminishes when considering the interview phase, irrespective of hiring volume or job category. Professionals harbor concerns about delivering an enhanced candidate experience and perceive using AI as the initial interaction as potentially indicating a lack of commitment to candidates. HR leaders should thoughtfully select the recruitment stages for AI integration and address the apprehensions raised by TAP professionals.

The research employed a conceptual model integrating the recruitment phase into the UTAUT theoretical framework to unveil these insights, rendering them contextually pertinent to AI adoption in recruitment and selection. By incorporating the recruitment phase into the UTAUT, the study provides a unique perspective, emphasizing the necessity for specialized and contextualized theoretical frameworks to comprehend intricate phenomena like AI. The researcher suggests that the same conceptual framework could be applied to explore other emerging technologies, including the metaverse, robotic process automation, augmented reality, and analogous innovations within the recruitment and selection process. The Conclusions section should clearly explain the main findings and implications of the work, highlighting its importance and relevance.

VII. CONFLICT OF INTEREST

The author declares no conflicts of interest regarding the publication of this paper.

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Anushree Srivastava contributed equally to this paper.

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