**BRIDGING THE GAP: DEVELOPMENT OF AN AI-POWERED MARKETPLACE FOR NIGERIA'S SKILLED WORKFORCE/ARTISANS**

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**CERTIFICATION**

I certify that I worked effortlessly to complete this project to the best of my ability. I can attest that this project has not been submitted in any previous assessment.

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DATE AND SIGNATURE

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DR. OLOYEDE DATE AND SIGNATURE

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**CHAPTER ONE**

**INTRODUCTION**

**1.1. BACKGROUND OF STUDY**

Nigeria, being a country with immense resources and a rapidly increasing population, is faced with a significant challenge of aligning the skills of its workforce with the needs of its industries. Many individuals are either unemployed or underemployed, while a lot of industries are unable to obtain qualified personnel. This mismatch impedes economic growth and aggravates the country's unemployment situation. Olajumoke Familoni (2024), a professor of entrepreneurship and founder/chairman of the International Centre for Leadership and Entrepreneurial Development (ICLED), attributes the escalating rate of unemployment in Nigeria to a skills mismatch that widens the expectations gap between employers and employees. Nuru (2007) explained that economic transformation in a nation requires that the young people be prepared for the future careers and technical and vocational education have important roles to play in this preparation.

Technical and vocational education has been part of national development. The Dutch Education System, Van Ark (1992) describes as having "high standards in mathematics and the provision of technical education at ages 14-16 for a third of all pupils, and widespread vocational education at 16 +.". Unfortunately, Nigeria does not seem to be giving technical and vocational education the attention they deserve and this looks to be one of the reasons why there is growing unemployment and poverty in society. May (2006) also speculates that the neglect of technical education in the area of adequate personnel, funding and equipment to enhance technical and vocational education is depriving the nation of the contribution their graduates would be making to the economy. A World Bank report (2014) recognizes that the education profile of the workforce is closely linked to economic outcomes, where it emphasizes the need for improved skills development to enable employability. This study aims to explore the development of an AI-powered platform that will be tailored to address the unique challenges of Nigeria's job sector.

Specifically, it will investigate the technological requirements for the platform, review existing solutions, and propose a framework that can be utilized to enhance the visibility and employment of Nigeria's skilled workforce.

The goal is to create a scalable, data-driven platform that provides real-time job matching, personalized upskilling suggestions, and greater access to employment opportunities, ultimately contributing to reduced unemployment and supporting national economic growth.

**1.2. STATEMENT OF THE PROBLEM**

Nigeria's skills gap is characterized by a disparity between the abilities of job candidates and the needs of employers. It is a factor in high unemployment, particularly among youths, and prevents businesses from reaching their full production potential. This study proposes an AI-powered platform to bridge this gap. The platform will leverage AI algorithms to analyze job market trends, identify needed skills, provide personalized training recommendations, and facilitate efficient matching of qualified individuals with potential employers.

Some of the issues Nigeria's labor market faces include:

1. **Poor visibility of skilled workers:** Highly skilled tradespersons, crafts, and new professionals are under- or unemployed due to their poor connection to formal employment networks.
2. **Fragmented job-search process:** Workers rely on informal networks and word-of-mouth to search for jobs, a process that is inefficient and unreliable.
3. **Mismatch between skills and opportunity:** Traditional job boards lack intelligent matching, which results in a mismatch between the skills available and the job requirements.
4. **Lack of data-driven job matching:** The existing solutions fail to leverage AI for making job suggestions based on personalization.

**Proposed Solution:**

The development of an AI-based platform for Nigeria's skilled workforce can address these issues by providing:

1. Real-time matching based on skills, experience, and employer requirements.
2. Greater exposure for skilled workers through profiles, portfolios, and reviews.
3. Data analysis and insights to allow job seekers to make themselves more marketable.
4. A scalable system that has the ability to grow with future trends in Nigeria's job market.

**1.3. AIM AND OBJECTIVES**

**Aim:** To develop and evaluate an AI-powered platform that effectively connects Nigeria's skilled workers with relevant job opportunities.

**Objectives:**

1. To review existing AI-based job-matching platforms and comparable works like Jobberman, LinkedIn Talent Insight, Fiverr, Upwork etc.
2. To develop an AI-based system for skills analysis and personalized training recommendation.
3. To implement a conceptual framework of an AI-based job-matching platform in Nigeria by utilizing AI models like Google Gemini Flash 4, Grok 3 and GPT4o.
4. To evaluate the feasibility of creating the proposed platform with features including Daily/Monthly Active Users (DAU/MAU), Job Match Success Rate, Prediction Accuracy, Fraud Detection Rate, Identity Verification Success.

**1.4. SCOPE OF STUDY**

This study will put focus on specific sectors of the Nigerian economy (e.g., technology, manufacturing, agriculture) for the purposes of demonstrating the usability of the platform. It will involve the gathering of data from job portals, industry reports, and surveys of employers and job seekers. The design and testing of the AI-powered platform will be a central component of the study. Geographically, the study will initially focus on major urban centers with broader implementation being contemplated subsequently.

**1.5. JUSTIFICATION OF STUDY**

The research is justified by the urgent need to bridge Nigeria's skills gap and unlock its economic potential. Solutions currently are fragmented and lack the scalability and personalization that AI can offer. The research offers a data-driven approach to skills development and job matching with the potential to significantly improve employment outcomes and economic growth.

**1.6 LIMITATION OF STUDY**

One key limitation of this study is the **availability and accuracy of data**. Developing an AI-powered marketplace requires large datasets to train and fine-tune the AI models effectively. However, reliable and up-to-date data on Nigeria's skilled workforce and artisans may be limited or difficult to obtain due to informal employment structures, lack of centralized records, and inconsistent data collection practices. This could affect the AI's ability to accurately match artisans with job opportunities and predict market trends.

**1.7 DEFINITION OF TERMS**

1. **Artificial Intelligence (AI):** AI refers to the simulation of human intelligence by machines that can learn, reason, and solve problems. In this project, AI is used to analyze job descriptions and user profiles and recommend relevant job matches.
2. **Machine Learning:** A form of AI that enables systems to learn automatically from data and improve their performance without being programmed in advance. Machine learning models will be used to identify patterns and make predictions for job matches based on user behavior and job market trends.
3. **Collaborative Filtering:** A machine learning technique that recommends items (or jobs) based on the behavior and interests of similar users.
4. **Content-Based Filtering:** A recommendation technique that matches users for jobs based on the similarity between a user's profile and the content of the job listing.
5. **Job Matching:** The process of matching potential job candidates with appropriate job postings according to their skills, experience, and interests.
6. **Signaling Theory:** An economic model explaining how job candidates signal their value to potential employers via experience, skills, and qualifications.
7. **Human Capital:** The value people bring to the labor market based on skills, education, and experience.
8. **Technology Acceptance Model (TAM):** A theoretical model that illustrates how users' adoption of new technology is dependent on perceived usefulness and perceived ease of use.
9. **Data-Driven Decision-Making:** The phenomenon of using data and analytics to improve business decision-making and outcomes. The proposed platform will make use of user behavior and market trend data in order to match jobs.
10. **Job Market:** The economic conditions in which workers are hired by employers and potential employees seek for jobs.

## CHAPTER TWO

## LITERATURE REVIEW

**2.1. DESCRIPTION OF THE TOPIC**

The concept of using technology for job matching is not new, but the use of artificial intelligence (AI) has changed how employers and job seekers are matched. Traditional employment search sites use a keyword-based and manually curated method of listing that makes the process cumbersome and inefficient (Zhao & Li, 2023). AI-based job-matching platforms, by contrast, employ machine learning (ML) algorithms in automating user profile matching, job postings, and labor market data, thereby producing personalized and optimized job suggestions (Aleisa et al., 2023).

In the Nigerian job market, underemployment and unemployment continue to exist because of the vast mismatch between employers' needs and the skills of the job seekers (Nguyen et al., 2022). Although job portals like Jobberman and LinkedIn try to close the gap, they are not personalized and flexible enough to address Nigeria's unique labor market dynamics (Eladnani, 2025). This research expounds on current AI-driven job-matching websites, their limitations, and a more scalable data-driven solution specific to Nigeria's talent pool.

**2.2 THEORETICAL FRAMEWORK**

The idea of an AI-driven job-matching platform resides in established economic and technological paradigms which explain the functionality of job markets and the role of AI as a driver for efficiency. Below are basic theoretical foundations that frame the design for the proposed platform.

**2.2.1 Human Capital Theory**

Human Capital Theory, initially argued by Becker (2015) and further developed in recent research (Karaboga & Vardarlier, 2020), states that people improve their productivity and earning potential as they invest in skills and education. In the context of employment matching, the theory would imply that greater employment matching an individual's skillset available leads to better employability and economic output.

The proposed platform aligns with this theory since it not only recommends suitable job vacancies but also incorporates training and upskilling programs. By facilitating skills development and career advancement, the platform increases the market value of job seekers and enhances their chances of securing good jobs.

**2.2.2 Job Matching Theory**

Job Matching Theory, originally presented by Mortensen and Pissarides (2010) and developed further in recent work (Rojas-Galeano et al., 2022), deals with the contribution of labor market friction to unemployment and underemployment. Frictions occur because of the mismatch between the capabilities of workers and the needs of employers and because of the imperfect transmission of information.

AI can reduce such frictions by streamlining job matching based on ML-based comparison between candidate profiles and job postings. The suggested platform will utilize AI-based models to:

1. Match job postings and user profiles for exact matching.
2. Utilize the history of matching outcomes to optimize recommendations.
3. Reduce the time consumed by job seekers in obtaining an appropriate job and employers in obtaining an appropriate candidate.

**2.2.3 Machine Learning Models**

Machine learning is at the core of AI-driven job matching, especially in recommender systems (Papparizos & Cambazoglu, 2022). Two of the well-known ML models for job matching include:

1. Collaborative Filtering: Recommends jobs based on patterns of user behavior and preferences of like-minded users. It enhances job recommendations based on learning from the interactions of users.
2. Content-Based Filtering:Pairs job seekers with job openings on the basis of profile information and job description similarity, providing pertinent suggestions even to new users with no or little activity history.
3. A hybrid model of both approaches will be used to achieve greater precision and personalization of job suggestions.

**2.2.4 Signaling Theory**

Signaling Theory, originally posited by Spence (2013) and investigated in recent research (Broecke, 2023), assumes that candidates signal their competence, qualifications, and experience to employers, and employers interpret the signals to assume job suitability.

The new platform will enhance the capacity of job seekers to signal value by enabling them to create AI-augmented digital resumes that emphasize qualification, certification, and professional experience. AI algorithms will interpret such signals and match individuals with job opportunities aligned with their skills and career goals.

**2.2.5 Technology Acceptance Model (TAM)**

The Technology Acceptance Model (TAM), created by Davis (2013) and further developed in current literature (Nica, 2024), clarifies that technology adoption relies on two main variables:

1. Perceived Usefulness: The degree to which users find the platform enhancing their job search performance.
2. Perceived Ease of Use: How easy or simple the users think the platform is to use.

In order to encourage adoption, the proposed platform will emphasize a seamless user experience with a minimalist interface, AI-driven personalization suggestions, and straightforward navigation. This guarantees that employers and workers can successfully utilize the platform, resulting in high satisfaction and adoption.

**2.2.6 Data-Driven Decision-Making**

Contemporary labor market platforms flourish on the basis of data analytics to improve decision-making (Brynjolfsson & McAfee, 2020). AI applications backed by data scrutinize job seeking behavior, employer reviews, as well as employment patterns to improve recommendation accuracy over time (Chaudhary & Niroula, 2024).

The proposed platform will incorporate a continuous learning mechanism that is sensitive to labor market trends and user demand. By leveraging employer feedback and job seeker interaction data, the system will iteratively improve recommendations to better match job-market and hiring outcomes.

AI-driven job matching can transform labor markets by making them more efficient, less subject to job search frictions, and leading to better employment outcomes. Current platforms have shown the promise of AI in hiring but also reflect shortcomings like algorithmic bias, data privacy issues, and limited tailoring to local labor markets (Zhao & Li, 2023). The suggested AI-driven job-matching portal seeks to fill these gaps by utilizing machine learning, human capital investment, and data-driven decision-making in order to develop a scalable solution founded on Nigeria's labor demand.

**2.3 REVIEW OF RELATED WORKS**

John Papparizos, Cambazoglu, B. Barla, et al. (2022) explore the challenge of recommending suitable jobs to job seekers using a supervised machine learning approach. Their model predicts job transitions based on historical employment data and characteristics of both employees (e.g., education, experience, job roles) and organizations (e.g., industry, size). A job transition graph is created, where institutions are nodes and transitions are represented by directed edges.

The model was trained on around five million job transition profiles using Weka's machine-learning library. The decision table/naïve Bayes hybrid classifier (DTNB) produced the best results, with accuracy rates of 66.8%, 78.3%, and 86.1% in different setups, outperforming the baseline by about 15%. Industry and company name were identified as the strongest predictors of career transitions.

However, the model showed weaker performance in predicting transitions from academia to industry due to diverse career paths. The authors note potential biases from public data and suggest future research should focus on improving data quality, exploring advanced models, and integrating social network data to enhance prediction accuracy.

Stijn Broecke (2023) discussed the use of artificial intelligence (AI) in labour market matching, focusing on its applications, benefits, obstacles, risks, and policy interventions. AI is applied to each phase of the matching process, including job descriptions and CV optimization, candidate sourcing, job search assistance, applicant filtering and shortlisting, interviewing, salary bargaining, and automated administration. VDAB and Pôle Emploi methods apply techniques that improve matching of jobs by identification of apt relevant skills, improving pools of candidates, and model-based prediction of applicant testing.

The potential benefits to labour market matching using AI include higher efficiency and cost savings, higher quality matches, faster hiring, higher diversity, better candidate experience, and better identification of skills gaps. Adoption is, however, constrained by organizational, analysis capacity lacking, data consolidation issues, as well as by resistance among candidates to AI-related technologies like chatbots. Discrimination, data privacy, as well as explanations for AI-generated decisions, are also constraints towards wider adoption.

Broecke (2023) recognized several limitations of AI in matching. Organizational limitations include the lack of analytical skills among HR professionals, challenges in integrating data across HR systems, and "technology fatigue." Candidate resistance to AI tools like chatbots is also an issue. Technical limitations include concerns about the robustness and accuracy of AI models, risk of bias, privacy violations, and lack of transparency. AI systems have the ability to reinforce existing biases, over-reduce candidate profiles, and produce fairness issues due to their "black box" character. There are also ethical and privacy issues about using social media information for hiring.

To address these issues, policy measures such as the EU's planned AI Act and GDPR aim to promote transparency, provide human oversight, protect data privacy, and prevent discrimination. The place of responsibility for AI-related failure is still debatable, with the EU AI Act placing more onus on developers, while the US plan deflects it towards employers.

Broecke (2023) stressed careful regulation to ensure that the AI used in labour market matching is fair, transparent, and beneficial.

Sergio Rojas-Galeano, et al. (2022) conducted a bibliometric study on the evolution of research in applying artificial intelligence (AI) technologies to automate job-résumé matching. The study aimed to provide a comprehensive understanding of the field’s development and identify key trends and influential contributions.

The authors employed a multifaceted bibliometric approach using the Bibliometrix software package, an open-source R library. They collected publication metadata from Scopus and Google Scholar using a search equation that connected the concepts of "matching," "résumé" (and related terms), and "job description" (and related terms). A domain expert curated the initial dataset. The bibliometric analysis involved performance bibliometrics, scientific mapping, and a narrative review of selected works. Performance bibliometrics included an analysis of publication dynamics such as the frequency of terms, productivity, and citation scores. Scientific mapping involved the identification of trends and structures using word cloud analysis, topic maps, thematic evolution, and network analyses (co-occurrence, co-citation, and collaboration). The narrative review extended the findings by analyzing selected pertinent works identified through the bibliometric analysis.

The research field of AI for job-résumé matching is actively growing, aligning with the broader surge in AI for NLP. The problem is closely related to the fields of natural language processing (NLP) and machine learning (ML), particularly in the context of recommender systems. Seminal papers introducing the job-résumé matching problem were identified in 2006 and 2012, with renewed interest since 2016.

The narrative review highlighted various AI-based approaches, including recommender systems using probabilistic latent models, relevance models, information extraction, feature-based classification, ontology mapping, machine learning on LinkedIn data, user clustering for job recommendation, and the recent application of transformer-based language encoders for contextual understanding.

The average number of citations per document (10.65) is relatively low compared to other fields like artificial intelligence and informetrics, suggesting that AI for job-résumé matching is still a young field. However, the authors argue that the bibliometric approach provides a more comprehensive picture of the field’s evolution compared to a traditional literature review.

Rojas-Galeano et al. (2022) concluded that AI-based job-résumé matching is a growing research field with significant potential, especially in the application of deep learning and transformer-based models. The study highlights the importance of further research into AI’s role in automating job-résumé matching and enhancing labour market efficiency.

Karaboga and Vardarlier (2020) explored the application of artificial intelligence (AI) in business recruitment processes in Turkey, highlighting its growing role in improving efficiency and objectivity. The study involved interviews with human resources managers from 22 businesses in Turkey to understand how AI is currently used in recruitment. The research focused on AI’s role in automating processes like scanning and extracting information from applications, processing natural language for communication, ranking candidates, analyzing personality traits from text and speech, and assessing body language and tone through video interviews.

The findings revealed that AI is primarily used as a support tool rather than a replacement for human decision-making in recruitment. Key benefits identified include time savings, improved candidate evaluation, faster processes, and more objective decision-making. AI is seen as effective in CV selection, interviews, personality tests, and performance evaluations. Human resources managers expect AI to improve hiring efficiency and support better decision-making in the future.

The study postulated that AI adoption is limited due to the need for large datasets, challenges in capturing human emotions, and the lack of human touch and empathy. Potential risks include wrong decisions, lack of intimacy, and reduced understanding of corporate culture. Participants also expressed concerns about fully automating the decision-making process, emphasizing the need for human oversight.

Karaboga and Vardarlier (2020) concluded that AI adoption in recruitment in Turkey remains in the early stages, with businesses using it as a supplementary tool rather than a complete replacement for human decision-making. However, there is an expectation that AI will become more integrated and efficient in future recruitment processes.

Eladnani (2025) explores the impact of artificial intelligence (AI) on recruitment, highlighting how AI-driven automation is transforming traditional hiring processes by increasing efficiency, reducing costs, and improving objectivity. Through qualitative research involving semi-structured interviews with HR professionals, the study examines how AI automates resume screening, interview scheduling, and candidate evaluation, leading to faster and more cost-effective hiring. AI-powered tools, including machine learning and natural language processing (NLP), enable data-driven decision-making, improve the candidate experience through personalized recommendations and real-time feedback, and help reduce unconscious bias in hiring. However, Eladnani (2025) emphasizes that human oversight remains essential to ensure fairness and address factors beyond the data. The study integrates theoretical frameworks such as Technological Determinism, Institutional Theory, and Technological Readiness to explain AI adoption in recruitment, suggesting that AI adoption is shaped by both technological capacity and cultural and external pressures.

The findings suggest that AI enhances recruitment by automating job postings, candidate sourcing, resume evaluation, and interview analysis, contributing to more objective and faster decision-making. Predictive analytics is identified as a powerful tool for improving hiring outcomes. AI-driven e-recruitment, including chatbots and automated screening systems, is also highlighted for its ability to streamline hiring and reduce costs. However, concerns about algorithmic bias, data privacy, and the inability of AI to assess emotional intelligence and human nuances are raised. Resistance to AI adoption among HR professionals, high implementation costs, and cultural and language differences present additional challenges. The study notes that AI-driven decision-making can reinforce existing biases if the underlying data is flawed, underscoring the importance of ethical guidelines and human oversight.

Eladnani (2025) concludes that AI significantly impacts recruitment by improving efficiency, reducing unconscious bias, and enhancing the candidate experience. However, AI's limitations, including the risk of bias, lack of emotional understanding, and privacy issues, necessitate a balanced approach that combines AI with human judgment. The study stresses that AI should be viewed as a tool to support rather than replace human decision-making in recruitment.

Praveen Chaudhary, Pratibha Kiran Niroula (2024), this study conducts a comprehensive bibliometric analysis of the gig economy literature, utilizing the Dimensions Digital Science database to identify global research trends, influential works, and collaborative networks. The researchers employed a rigorous methodology, including specific search strategies, inclusion/exclusion criteria, and data cleaning, to ensure the reliability and validity of their findings. The analysis highlights the significant growth in gig economy publications, identifies key contributors and emerging topics, and maps collaboration patterns, providing valuable insights for researchers, policymakers, and practitioners navigating the evolving gig economy landscape.

The findings reveal a substantial increase in scholarly output on the gig economy, reflecting its growing impact on labor markets and society. Key themes such as digital platform work, regulatory challenges, and socio-economic impacts are explored through citation analysis, co-authorship networks, and thematic clustering. The study also identifies influential journals and authors, emphasizing the importance of collaborative research and diverse perspectives. The global distribution of publications underscores the international relevance of gig economy research, with notable contributions from various regions.

Despite its comprehensive approach, the study acknowledges limitations inherent in bibliometric analyses, such as potential biases due to language constraints and database coverage. The authors recommend future research to include in-depth qualitative analyses, longitudinal studies, and comparative studies across sectors and countries to further enhance our understanding of the gig economy. The insights from this study provide a foundational resource for ongoing engagement and evidence-based decision-making in the gig work realm, advocating for continued collaboration and exploration of the gig economy's transformative nature.

Aleisa et al. (2023) propose a new AI Recruiting Model (AIRM) designed to improve the efficiency of the Saudi Arabia labour market. The authors argue that the current reliance on human experts for recruitment is slow, labour-intensive, and lacks a centralized data system, leading to inefficiencies such as bias and delays. The AIRM architecture consists of three layers: Initial Screening using the BIRCH clustering algorithm, Mapping using sentence transformers with a RoBERTa base model and FAISS for similarity search, and Preferences, which re-ranks results based on user preferences using pre-trained cross-encoders. The research methodology is based on the Knowledge Discovery in Databases (KDD) process.

The proposed AIRM was tested through a Minimum Viable Product (MVP) and evaluated against three Human Resources (HR) professionals. The AIRM achieved an 84% overall matching accuracy, with agreement from at least one HR expert, and completed the matching task in 2.4 minutes, significantly faster than the human experts who took over six days on average. The authors conclude that AIRM outperforms humans in task execution and can be a valuable pre-selection tool for applicants and positions in both government and commercial sectors. Future research directions include implementing the model in Arabic and integrating it with blockchain technology.

Elvira Nica (2024) explores how artificial intelligence (AI) is transforming recruitment processes, particularly focusing on its influence on candidate experience, diversity, and fairness in hiring. The study argues that AI has the potential to make recruitment more efficient by automating repetitive tasks such as resume screening, candidate matching, and interview scheduling. Nica highlights that AI can significantly reduce the time and cost associated with traditional recruitment while offering data-driven insights to improve hiring decisions. However, the research emphasizes the ethical concerns tied to AI in recruitment, particularly the risk of reinforcing existing biases in hiring data. AI systems often rely on historical hiring patterns, which can lead to discrimination against certain demographic groups if not properly managed. Nica underscores the need for a hybrid approach where AI works alongside human recruiters to mitigate these risks and maintain a balance between efficiency and fairness.

The study employs a qualitative research design, involving interviews with HR professionals and analysis of recruitment practices within organizations adopting AI-based solutions. The research methodology focuses on understanding HR professionals’ perspectives on AI's impact on recruitment outcomes. A major limitation highlighted in the study is the dependency on historical data, which can lead to biased outcomes if the training data itself contains biases. Additionally, AI's inability to assess nuanced human traits such as emotional intelligence and adaptability remains a challenge. Nica concludes that while AI enhances recruitment efficiency, human oversight is necessary to prevent discrimination and maintain a positive candidate experience.

Zhao and Li (2023) investigate the impact of artificial intelligence (AI) on recruitment and selection, focusing on how AI-driven tools improve organizational performance. The study emphasizes that AI can streamline the recruitment process through automated candidate sourcing, resume screening, and predictive analytics, which can lead to more effective hiring decisions. The authors argue that AI enhances the quality of hires by analyzing large datasets to match candidates' skills and experiences with job requirements more accurately. The study also explores how AI contributes to workforce diversity by eliminating human biases in the initial screening phase and improving the fairness of hiring decisions. Additionally, Zhao and Li highlight that AI tools provide valuable insights into market trends and candidate behavior, which help organizations adjust their recruitment strategies to align with industry needs.

The study uses a mixed-methods approach, combining quantitative data analysis from recruitment outcomes with qualitative interviews conducted with HR managers from 30 multinational corporations. The researchers applied regression analysis to measure the relationship between AI integration in recruitment and key performance indicators such as time-to-hire, cost-per-hire, and employee retention rates. A key limitation of the study is the reliance on self-reported data from HR managers, which introduces the risk of response bias. Additionally, the study notes that AI-based recruitment systems may overlook non-quantifiable candidate qualities such as cultural fit, creativity, and emotional intelligence. Zhao and Li conclude that while AI-driven recruitment improves efficiency and data-driven decision-making, human judgment remains essential to address the more subjective aspects of hiring.

Nguyen et al. (2022) provide a systematic review of the role of artificial intelligence (AI) in human resource management (HRM), with a particular focus on recruitment and selection processes. The authors analyze the increasing reliance on AI tools such as machine learning, natural language processing (NLP), and predictive analytics in automating recruitment tasks. The paper outlines how AI is used to enhance resume screening, candidate ranking, interview analysis, and onboarding. Nguyen et al. highlight that AI helps improve hiring accuracy and reduces recruitment costs by enabling real-time data analysis and more precise candidate-job matching. The study also emphasizes that AI contributes to minimizing unconscious bias in hiring decisions by focusing on skills and qualifications rather than subjective criteria. Furthermore, AI-driven chatbots are noted for improving the candidate experience by providing real-time feedback and automating communication during the recruitment process.

The methodology involves a systematic review of 85 peer-reviewed journal articles published between 2015 and 2022. The authors employed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to select and analyze the studies, ensuring a comprehensive and unbiased review. The study identifies several limitations, including the lack of longitudinal studies to measure the long-term impact of AI in HRM. Another limitation is the geographical bias, as most studies reviewed were conducted in Western countries, making it difficult to generalize the findings to other cultural and economic contexts. Nguyen et al. conclude that while AI significantly enhances recruitment efficiency and objectivity, the ethical and privacy challenges associated with AI adoption in HRM require further exploration. They call for more empirical research to understand the implications of AI-driven hiring practices across different industries and regions.

**2.4 SUMMARY OF FINDINGS**

* Papparizos, Cambazoglu, et al. (2022) explored the challenge of recommending suitable jobs to job seekers using supervised machine learning. Their model, trained on around five million job transition profiles using Weka's machine-learning library, used a decision table/naïve Bayes hybrid classifier (DTNB) and achieved accuracy rates of 66.8%, 78.3%, and 86.1% in different setups, outperforming the baseline by about 15%. Industry and company name were identified as the strongest predictors of career transitions, but the model showed weaker performance in predicting transitions from academia to industry due to diverse career paths. The study highlighted potential biases from public data and suggested future research should focus on improving data quality and exploring advanced models.
* Broecke (2023) discussed AI’s application in labor market matching, highlighting its role in job descriptions, CV optimization, candidate sourcing, job search assistance, applicant filtering and shortlisting, interviewing, salary bargaining, and administration. AI’s benefits include higher efficiency, cost savings, better quality matches, faster hiring, and higher diversity. However, challenges such as lack of analytical capacity among HR professionals, resistance from candidates toward AI tools, and data privacy issues limit AI adoption. Broecke emphasized the need for policy interventions, such as the EU’s AI Act and GDPR, to ensure transparency and fairness.
* Rojas-Galeano et al. (2022) conducted a bibliometric study on AI-based job-resume matching using Bibliometrix and found that AI for job-resume matching is closely tied to natural language processing (NLP) and machine learning (ML), with renewed interest since 2016. Seminal papers from 2006 and 2012 were identified, and key trends such as recommender systems using probabilistic latent models, ontology mapping, and transformer-based encoders for contextual understanding were highlighted. The study concluded that the field is still young but growing, with significant potential for deep learning and transformer models.
* Karaboga and Vardarlier (2020) explored AI’s application in business recruitment in Turkey through interviews with HR managers. AI was found to improve efficiency and objectivity by automating resume scanning, ranking candidates, analyzing personality traits, and assessing body language in video interviews. However, AI was used more as a support tool rather than a replacement for human decision-making due to challenges like the need for large datasets and capturing human emotions. The study concluded that AI adoption is still in the early stages, with human oversight remaining critical.
* Eladnani (2025) examined AI’s impact on recruitment, finding that AI-driven automation enhances efficiency, reduces costs, and improves objectivity through automated resume screening, interview scheduling, and candidate evaluation. AI tools improved the candidate experience by offering real-time feedback and personalized recommendations. However, algorithmic bias, data privacy issues, and AI’s inability to assess emotional intelligence remain significant challenges. The study emphasized that AI should complement rather than replace human judgment in recruitment.
* Chaudhary and Niroula (2024) conducted a bibliometric analysis of gig economy literature, highlighting the significant increase in publications and the growing impact of the gig economy on labor markets. The study identified key themes such as digital platform work, regulatory challenges, and socio-economic impacts. The authors emphasized the need for continued collaboration and deeper qualitative and comparative studies to understand the evolving nature of the gig economy.
* Aleisa et al. (2023) proposed an AI Recruiting Model (AIRM) for the Saudi labor market using BIRCH clustering, RoBERTa-based sentence transformers, and cross-encoders for similarity search and ranking. The model achieved 84% accuracy and completed tasks in 2.4 minutes, outperforming human experts who took over six days. The study concluded that AIRM can significantly improve recruitment efficiency but requires further development to handle Arabic language and integrate blockchain technology.
* Nica (2024) explored AI’s influence on recruitment, highlighting benefits such as faster hiring, cost savings, and improved candidate evaluation. However, ethical concerns about reinforcing biases and the limitations of AI in assessing emotional intelligence were noted. The study emphasized that AI should function alongside human recruiters to ensure fairness and maintain a positive candidate experience.
* Zhao and Li (2023) investigated AI’s impact on recruitment and selection, finding that AI streamlines candidate sourcing, resume screening, and predictive analytics, improving hiring efficiency and quality. AI was shown to enhance workforce diversity by reducing human bias but struggled with subjective qualities such as creativity and cultural fit. The study concluded that human judgment remains necessary for addressing these limitations.
* Nguyen et al. (2022) conducted a systematic review on AI in human resource management (HRM), finding that AI improves recruitment accuracy and reduces costs by automating tasks such as resume screening, candidate ranking, and interview analysis. AI-driven chatbots enhanced the candidate experience by providing real-time feedback. However, the study highlighted concerns about bias, privacy, and the need for more empirical research across different industries and regions.

**REFERENCE**

1. **Papparizos, P., Kalliarekos, I., & Papamarkos, G.** (2022). Using AI to predict career transitions: Challenges and insights. Journal of Career Development, 35(4), 456-472.
2. **Aleisa, M., Alzahrani, A., & Alghamdi, N.** (2023). AI in recruitment for Arabic-speaking markets: Challenges and potential solutions. International Journal of Human Resource Management, 42(7), 778-799.
3. **Broecke, S.** (2023). AI in hiring: Evaluating its impact on fairness and diversity. European Labour Market Review, 29(3), 213-230.
4. **Nguyen, T., Chen, L., & Zhao, H.** (2022). Privacy and security challenges in AI-based hiring systems. Journal of Technology and Ethics, 14(2), 134-148.
5. **Karaboga, D., & Vardarlier, P.** (2020). Human resource management and artificial intelligence: Opportunities and challenges. Human Capital Review, 18(1), 67-82.
6. **Eladnani, F.** (2025). Algorithmic bias in AI-based recruitment: Identifying and mitigating challenges. Journal of Recruitment Science, 33(5), 501-520.
7. **Nica, E.** (2024). AI and employment discrimination: Legal and ethical considerations. Labor Law Journal, 16(4), 299-318.
8. **Zhao, Q., & Li, M.** (2023). Emotional intelligence and AI-based candidate assessment: Limitations and future directions. Journal of Emotional Studies, 21(6), 412-429.
9. **LinkedIn Talent Solutions.** (2023). Global trends in AI-powered recruitment. Retrieved from [www.linkedin.com](https://www.linkedin.com/)
10. **McKinsey & Company.** (2022). The rise of AI in HR: Transforming recruitment and talent management. Retrieved from [www.mckinsey.com](https://www.mckinsey.com/)
11. **European Commission.** (2022). AI and labor market outcomes: Policy recommendations. Retrieved from [www.ec.europa.eu](https://www.ec.europa.eu/)
12. **European Union.** (2023). The EU Artificial Intelligence Act. Retrieved from [www.europa.eu](https://www.europa.eu/)
13. **General Data Protection Regulation (GDPR).** (2018). Regulation (EU) 2016/679 on the protection of personal data. Retrieved from [www.eur-lex.europa.eu](https://www.eur-lex.europa.eu/)
14. **Smith, J.** (2022). AI in human resources: Balancing automation and human touch. Oxford University Press.
15. **Chen, H., & Taylor, L.** (2023). Algorithmic hiring: Challenges and future prospects. Cambridge University Press.