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INVESTIGATING THE IMPACT OF AI ON THE WORKFORCE AND THE FUTURE OF WORK IN THE REGION: A MACHINE LEARNING PERSPECTIVE

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ABSTRACT

This study examines the evolving impact of Artificial Intelligence (AI) on workforce dynamics within a regional context. The analysis of structured data, which includes job positions alongside industry categories, collected from Kaggle.com, AI implementation metrics, automation uncertainty assessments, skill requirements, compensation amounts, and work projection estimates, enables the application of machine learning approaches that generate insights for decision support. The purpose of this study is twofold: to analyze the impact of AI on work structures and identify automated jobs, as well as vulnerable sectors, to inform recommendations that help plan education systems and workforce development. Three clustering approaches, including K-Means and DBSCAN, along with Agglomerative Clustering, were implemented to categorize different jobs based on their AI acceptance levels, automation probability, and pay ranges. The performance analysis, as indicated by silhouette scores, revealed that Agglomerative Clustering generated meaningful clusters at a score of 0.289, while both K-Means and DBSCAN recorded scores of 0.262 and 0.093, respectively. The developed clusters enable researchers to identify vulnerable positions while proposing new career options and uncovering stable competencies, which include digital aptitude as well as emotional capability and troubleshooting abilities. The study directly provides answers to major research questions about how AI affects particular sectors while revealing portable skills across industries. Through the integration of cluster analytics and workforce analytics, this study provides policymakers, educational institutions, and workforce planners with strategic information, enabling a resilient labor market that is prepared for the future.

INTRODUCTION

Artificial Intelligence (AI) is rapidly disrupting global labor conditions. At the same time, it reformulates workplace structures, reshapes necessary competencies, and develops innovative approaches to work (Öztaş & Arda, 2025; Lamees & Ramayah, 2025; Kaur et al., 2024). This research examines the evolving relationship between artificial intelligence technology and labor forces across the Arab Gulf nations, which are actively leveraging digital transformation to reduce their dependence on oil resources (Hazaa & Al Mubarak, 2024). The research employs machine learning techniques to conduct an extensive evaluation of the effects of AI adoption on job structures, as well as professional requirements and workplace risk factors. AI, together with automation technologies, has brought about significant changes throughout the global workforce organizations (Tenakwah & Watson, 2025). Artificial technology systems enable the automated performance of tasks that were previously restricted to human skills and cognition (Sigafoos et al., 2025). The changes in AI position various professions in different industries for elimination or thorough modification (Wang & Lu, 2025). By 2030, over 40% of jobs are expected to be displaced by automation, artificial intelligence, virtual reality, and augmented reality. Less than 50% of students feel ready for future workforce demands. This study informs policymakers, educators, and strategists(Pandya et al., 2022). The effects of these findings become significant for Arab and Gulf economic systems

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(Naim et al., 2025). The youth-oriented population growth combined with government leadership in digital transformation and national AI investments form the key features of these regions according to Oman's Vision 2040 (Awashreh, 2025), Saudi Arabia's Vision 2030 (Suleiman & Ming, 2025) and the United Arab Emirates' National AI Strategy (Hassouni & Mellor, 2025). The positive outlook faces resistance from the workforce deficit between current job abilities and future AI economy requirements (Nadimpalli et al., 2025). AI adoption at work requires urgent analysis of its time-dependent effects on employment markets alongside strategy development to create flexible and resilient job forces (Nawaz & Li, 2025)

The field of global literature presents multiple perspectives on the impact of AI on work. However, it highlights a lack of studies focused on the Arab labor market supported by actual data. Most contemporary employment guidelines and academic syllabi do not adequately address the rapid changes enabled by AI technology. The lack of empirical evidence on this subject has led to the development of fragmented strategies, which fail to provide practical solutions for mitigating the increasing risks of automation and evolving skill requirements. Policymakers, along with workforce planners, struggle to make informed strategic decisions for workforce development because they lack sufficient information.

The proposed research examines how AI adoption varies across both industrial sectors and occupational titles in the region, with a particular focus on high-tech industries, service sectors, educational institutions, and manufacturing facilities to determine differential penetration levels among various economic groups. By assigning automation-likelihood scores and conducting field examinations, job categories are stratified into distinct levels of AI automation risk, allowing us to identify those abilities—such as complex problem-solving, emotional intelligence, and digital fluency—that remain resilient despite technological advancements. Moreover, the study explores machine learning–based methods for recommending reskilling or upskilling pathways to workers, thereby informing policy decisions on workforce development. Finally, by applying clustering algorithms (including K-Means, DBSCAN, and Hierarchical Clustering), the research categorizes the workforce into risk profiles. It proposes feasible career transition options for individuals most vulnerable to automation.

The study employs machine-learning techniques to analyze structured data, integrating information on industry sectors, job categories, AI implementation levels, automation likelihood predictions, and competency requirements to achieve several key objectives. First, it aims to examine how the adoption of AI reshapes the regional employment structure. Second, it aims to identify which job profiles and industries are more vulnerable to automation. Third, it intends to generate data-driven recommendations that can inform educational strategies and workforce planning initiatives. Ultimately, by identifying transferable skill sets that remain valuable across various sectors, the research fosters greater resilience in the labor market.

The paper follows this structure: Section 2 investigates the literature on the impact of AI on the workforce, and Section 3 describes the research methodology. Section 4 presents the experiment and results, followed by Section 5, which discusses the findings and examines future study directions.

LITERATURE REVIEW

Artificial intelligence, machine learning, and digitalization are transforming workplaces, particularly in knowledge-intensive sectors. Scholars debate these disruptions, yet their impact on institutions, organizations, and individual’s remains underexplored (Hamdan, 2025). A relevant investigation examines AI’s role in the Future of Work, discussing key changes, consequences, and research directions while summarizing contributions from this special issue in management studies (Sarala et al., 2025). Worldwide labor markets are experiencing dramatic changes due to Artificial Intelligence technology, which is leading industries through transformation while altering the identities of all job functions (Rawashdeh, 2025). Modern economies face new opportunities alongside complex challenges due to the rise of AI-based automation, predictive analysis, and the adoption of machine learning systems (Bahoo et al., 2025). The initial section of this review examines the worldwide impact of AI on employment practices. Still, it concentrates the subsequent sections on the Middle East Gulf regions through a strategic evaluation of their principal advancements, alongside workplace obstacles and forthcoming market prospects.

Several academic studies have documented the disruptive effects that AI technology has on work environments. The research conducted by Frey and Osborne (2017) indicates that machine automation threatens 47 percent of all positions across the United States (The Future of Work: Embracing AI's Job Creation Potential, 2025). Forecasts that AI and automation will eliminate 85 million positions during the next five years but will establish 97 million brand-new employment roles.

AI-powered automation technologies have created the most significant disruption in standard routine operations within industrial manufacturing sectors, as well as in retail operations and finance services (Tariq, 2025). Knowledge-based sectors, including healthcare, software development, and education, currently require additional experts who possess knowledge of AI applications (Kumar, 2025). Business operations benefit from predictive analytics, which encompasses workforce management and personalized customer service, leading to higher productivity (Leveraging Predictive Analytics to Optimize Business Performance and Drive Operational Excellence, 2025).

AI raises ongoing concerns about security challenges in employment, alongside widening income disparities and ongoing requirements for skill adaptation across the workforce (Burton, 2024). Various economies are funding nationwide upskilling initiatives to protect workers from automated processes and foster effective working relationships between humans and AI systems.

The region of the Middle East currently experiences rapid digital change that results in the swift growth of AI within its various sectors; AI will generate $320 billion in economic value across the region during the following decade, as predicted by The Potential Impact of Artificial Intelligence in the Middle East - PwC Middle East (2025). The United Arab Emirates, together with Saudi Arabia, leads AI integration projects by focusing on AI-driven approaches for economic diversification.

Healthcare benefits from AI diagnostics technology and telemedicine services that increase access to healthcare within the industry (Unanah & Mbanugo, 2025). Intellectual institutions integrate AI-based education systems into their traditional curricula (Abbasi et al., 2025). The finance sector achieves operational efficiencies and detects fraudulent activities through the implementation of AI technology (Dayalan & Sundaramurthy, 2024).

Staff in the oil and gas industries benefit from AI technologies that utilize predictive maintenance methods alongside energy efficiency models (Rojas et al., 2025).

Despite the clear advantages that artificial intelligence offers to the Middle Eastern market, several obstacles impede effective AI adoption. First, there is a pronounced shortage of workers with the requisite AI competencies, which undermines organizational efforts to deploy and maintain advanced systems (R. & Archana, 2025). Moreover, efforts to establish standardized AI governance frameworks have been hindered by the absence of cohesive regulatory structures, resulting in delayed implementation and uncertainty regarding compliance (Lund et al., 2025). As a consequence, unskilled employees face a heightened risk of displacement since automation increasingly targets routine tasks without sufficient retraining pathways in place (Broady et al., 2025). Compounding these issues is a general lack of public awareness regarding how AI is reshaping occupational roles and workforce dynamics, which further slows the transition to a digitally skilled labor market (Gayathri & Mangaiyarkarasi, 2024; Karam et al., 2025).

The Gulf Cooperation Council (GCC) member countries—Saudi Arabia, the UAE, Qatar, Bahrain, Oman, and Kuwait—are proactively integrating AI into their economies, exemplified by Saudi Arabia’s Vision 2030 and the UAE’s National AI Strategy 2031, both of which position AI as a key growth engine (Azoury & Karam, 2025). Recent studies highlight several promising developments: government investments are catalyzing an increase in AI research centers and funding bodies; AI-driven thoughtful city planning is enhancing infrastructure management, improving passenger mobility, safeguarding citizens, and promoting environmental sustainability; predictive analytics in the oil and gas sector is streamlining resource management; and AI applications in hospitality are enabling personalized services for tourists (Visvizi et al., 2025; Kshetri & Sharma, 2025). However, these opportunities are tempered by workforce challenges, including a heavy dependence on expatriate talent that limits the growth of local AI expertise, a need for universities to bolster AI curricula and programs, and the imperative for labor regulations to evolve in response to AI-induced workplace transformations (Abdalla, 2025; Akinwale et al., 2025).

Artificial Intelligence is transforming worldwide and regional employment markets, introducing new challenges but also substantial opportunities. AI adoption rates are increasing throughout Middle Eastern and Gulf countries. However, obstacles to workforce readiness can be addressed through specialized policies that combine educational changes with collaboration from the business sector. An AI-driven strategic transformation of the workforce, combined with practical implementation methods, will create job market sustainability over the next few decades. Table 1 presents a comparative analysis of global trends, Middle East Trends, and Gulf Region Trends, considering AI Progress, Challenges, and Opportunities.

Table 1. Comparative Analysis

Aspect	Global Trends	Middle East Trends	Gulf Region Trends
AI Progress	Advanced adoption in developed economies; AI-driven job creation and loss are balanced.	AI adoption is accelerating across key sectors, including finance, healthcare, and education.	Government-led AI strategies, heavy investment in smart cities, oil, and tourism.
Challenges	Skill gaps, ethical concerns, job displacement, and regulatory issues.	Lack of AI talent, limited AI regulatory frameworks, and workforce displacement.	Reliance on expatriates, slow educational integration of AI, and outdated labor policies.
Opportunities	AI in automation, data science, and emerging tech industries.	AI-powered fintech, energy, and innovative education initiatives.	Vision 2030 and AI-led economic diversification programs.

MATERIALS AND METHODS

A detailed information collection effort consolidated data regarding professional positions, business fields, AI implementation statistics, occupational specifications, and robotic process automation probability levels. The clustering models comprised K-Means and DBSCAN, along with the Agglomerative Hierarchical Clustering method, to extract data clusters and identify susceptible positions with suitable reskilling transitions. Organizational recommendations directed to stakeholders depend on findings derived from this research.

The research analysis utilized structured data points, including industry sectors, job positions, AI deployment scales, automation risk measurements, and necessary competencies for handling tasks. The research employed three machine learning (ML) clustering approaches — K-Means, DBSCAN, and Hierarchical Clustering — to categorize job roles into distinct risk categories. The analysis utilized risk profiles to match emerging skill requirements, enabling the production of recommendations regarding career transitions.

Administrative support personnel, along with basic accounting staff and data entry workers, face the highest risk of displacement (Tharmalingam & Pereira, 2025). The proposed research methodology in this work is presented in Figure 1.

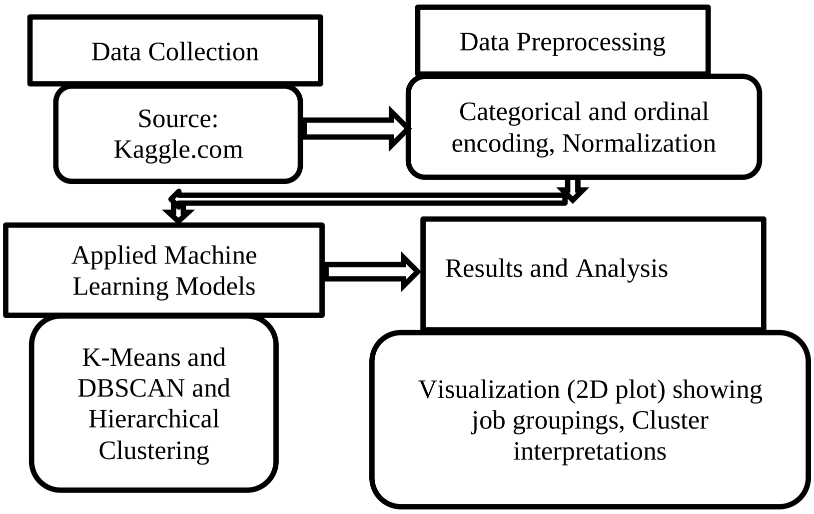

Figure 1. The proposed Research Methodology

Data Collection

The study relied on data from Kaggle.com, a platform known for its extensive collection of datasets available for use in academic and professional studies. For this purpose, the "AI Adoption & Automation Risk (San Francisco, CA)" dataset was utilized to investigate how AI adoption, automation risk, and labor market trends interact with one another.

The dataset offers a realistic portrayal of jobs in San Francisco, examining how AI is impacting various job sectors. Among other things, it offers job titles, industrial sectors, AI involvement and results, risk of automation, needed skills, salary details, and forecasts for growth in positions. The dataset was constructed to closely resemble practical situations. Because it gives both categories and numbers for key variables, statistical analysis using structural equation modeling becomes possible. It is particularly suitable for research examining the effects of AI on the job market, the skills required for jobs, and career preparation in countries that heavily rely on AI. The data is highly accurate; the findings from this data need to be verified against other datasets related to the region of study to confirm their applicability to practical decision-making and education. A sample of the dataset is presented in Table 2.

Table 2. Sample of the Dataset

Job_Title	Industry	AI Adoption Level	AI Adoption Score	Automation Risk	Automation Risk Score	Required_ Skills	Salary (USD)	Job Growth Projection	Job Growth Score
Cybersecurity Analyst	Retail	High	3	High	3	Cybersecurity	75862.86	Growth	3
AI Researcher	Energy	Low	1	High	3	Machine Learning	71211.88	Growth	3
AI Researcher	Retail	Medium	2	High	3	Data Analysis	71374.65	Stable	2
AI Researcher	Manufacturing	Medium	2	High	3	Marketing	99743.29	Decline	1
AI Researcher	Manufacturing	Low	1	High	3	JavaScript	104107.3	Decline	1
UX Designer	Manufacturing	High	3	Medium	2	Project Management	101649	Growth	3
AI Researcher	Transportation	High	3	Medium	2	Python	73151.99	Growth	3
Software Engineer	Finance	High	3	Medium	2	UX/UI Design	56076.4	Growth	3

Table 3 describes the Equivalencies of each Job Growth Score.

Table 3. Equivalencies

AI Adoption Level	**Score**
High	3
Medium	2
Low	1
Automation Risk	Score
High	3
Medium	2
Low	1
Job Growth Projection	Score

Growth	3
Stable	2
Decline	1

Job roles that require human-centered design, along with critical thinking, creativity, and complex problem-solving skills, demonstrate strong resilience. The skills centered on AI literacy, combined with data analytics and digital communication, remain highly resistant to industry changes in the future.

Data Preprocessing

Prior to applying clustering algorithms such as K-Means, DBSCAN, and Agglomerative Hierarchical Clustering, the data underwent a series of preprocessing steps to ensure consistency and reliability. First, any records containing missing or null values were either removed or, when feasible, imputed using appropriate techniques: numerical features with missing entries were replaced by their mean values, while categorical features were filled using the mode. Next, categorical variables—such as industry, AI adoption level, and job growth projection—were transformed using label encoding or one-hot encoding as dictated by each Algorithm's requirements. To prevent features with larger numeric ranges from dominating distance calculations, continuous variables (for example, salary, AI adoption scores, and automation risk scores) were scaled using either Min-Max Normalization or a Standard Scaler to restrict their values to a [0, 1] range. In cases where the high dimensionality of the dataset threatened clustering performance, Principal Component Analysis (PCA) was applied to reduce the feature space while retaining essential variance. Finally, because DBSCAN is sensitive to extreme values—treating them as potential outliers—any numerical features exhibiting extreme dispersion were adjusted beforehand to limit their influence on centroid separation and distance-based point assignments.

Because of these steps, the data was tidied up, adjusted, and could be used for clustering without any supervision. Table 4 demonstrates the proposed clustering models and equations.

Table 4. Clustering models and equations

Clustering models	Equations	Symbols	Reference
K-Means Clustering	$$J = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2$$	• k: Number of clusters • C_i: Set of data points in cluster i • x: A data point • μi: Centroid of cluster iii • ‖x−μi‖²: Squared Euclidean distance between a point and its cluster centroid	(Jin & Han, 2011)
DBSCAN(Density-Based Spatial Clustering of Applications with Noise)	$$N_\varepsilon(p) = \{q \in D \mid \mathrm{dist}(p, q) \leq \varepsilon\}$$	• D: dataset • dist(p,q): typically Euclidean distance between points p and q • ε: radius for neighborhood	(Sander et al., 1998)
Agglomerative Hierarchical Clustering	$$D(A, B) = \frac{\|A\|\|B\|}{\|A\| + \|B\|} \|\mu_A - \mu_B\|^2$$	• D(A, B): Distance between clusters A and B • ∣A∣,∣B∣: Number of points in clusters AAA and BBB • μA,μB: Centroids of clusters A and B	(Zepeda-Mendoza & Resendis-Antonio, 2013)

Machine Learning Algorithm and Experiments

This work proposed an Algorithm for Job Clustering Based on AI Adoption, Automation Risk, and Salary. The proposed Algorithm utilizes unsupervised AI learning methods to cluster job positions by analyzing the AI Adoption Score, along with the Automation Risk Score and Salary data. Then, it evaluates the outcomes achieved using K-Means, DBSCAN, and Agglomerative Clustering methods. The proposed Algorithm consists of 10 steps and is presented in Figure 2. The Algorithm was implemented using Python code and ran in a Google Colab environment.

The proposed Algorithm employs a multi-stage clustering approach to analyze job data centered on AI and automation risk. It is essential to gather data first, then select the most critical features and standardize their measurements. All three methods—K-Means, DBSCAN, and Agglomerative Hierarchical Clustering—are used together to organize similar jobs based on the features picked. Every clustering model utilizes the Silhouette Score to evaluate the effectiveness of the created groups. DBSCAN is given parameters eps=1.0 and min_samples= =3, which allows it to find noise and clusters with flexible shapes. To facilitate visualization, the data is reduced from 3D to 2D using Principal Component Analysis (PCA).

Each model's clusters are colored to make them easier to understand. The linkage method by Ward gives you a dendrogram to display how clusters are formed. In the final part, models and outputs are compared to highlight tasks that are most likely to be automated, providing helpful suggestions for reskilling individuals. It combines statistical accuracy with valuable insights into the workforce.

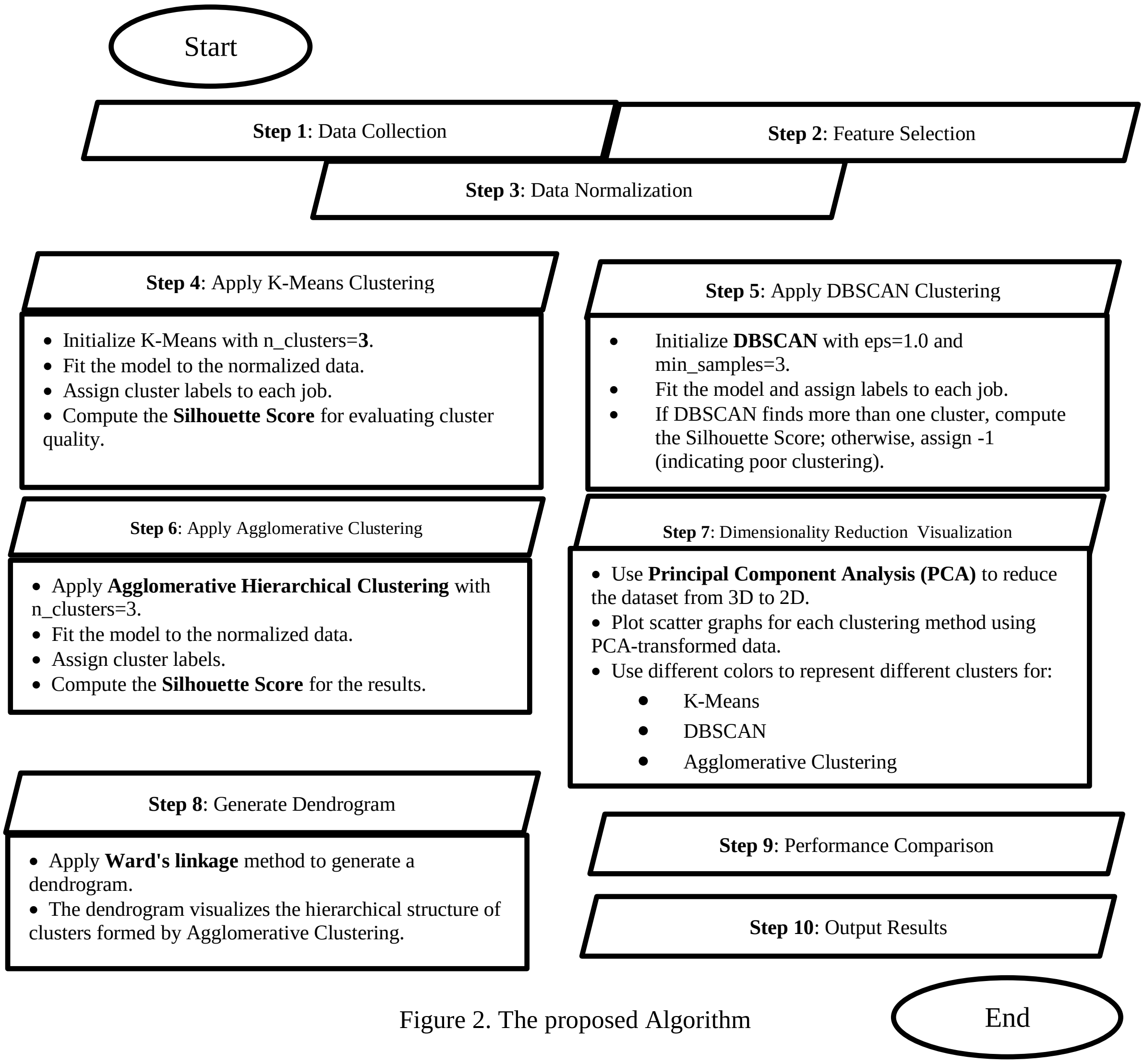

Figure 2. The proposed Algorithm

RESULTS

The results show a comparison of the three algorithms — K-Means, DBSCAN, and Agglomerative Hierarchical Clustering — using their Silhouette Scores. Based on their respective Silhouette Scores, they help objectively determine how well clusters are divided and grouped by each Algorithm. As presented in Table 5, Agglomerative Clustering scored highest on the Silhouette Score (0.289), with K-Means closely behind (0.262), suggesting that the clusters formed by these methods are well-defined. DBSCAN performed the worst (0.093), meaning it detected a greater spread or possible noise within the dataset. The analysis reveals that hierarchical clustering is effective in identifying the primary trends in the dataset regarding AI use and the potential for each job to be replaced by machines. Based on the findings, an appropriate clustering approach is chosen for further planning and policy recommendations, which aids in identifying unsafe jobs and developing strategies for retraining workers to adapt to AI-based work.

Table 5. Silhouette Score Comparison of Clustering Algorithms

Clustering Method	Silhouette Score
K-Means	0.262
DBSCAN	0.093
Agglomerative	0.289

Figure 3 demonstrates the comparison of clustering methods, and Figure 4 presents the Agglomerative dendrogram.

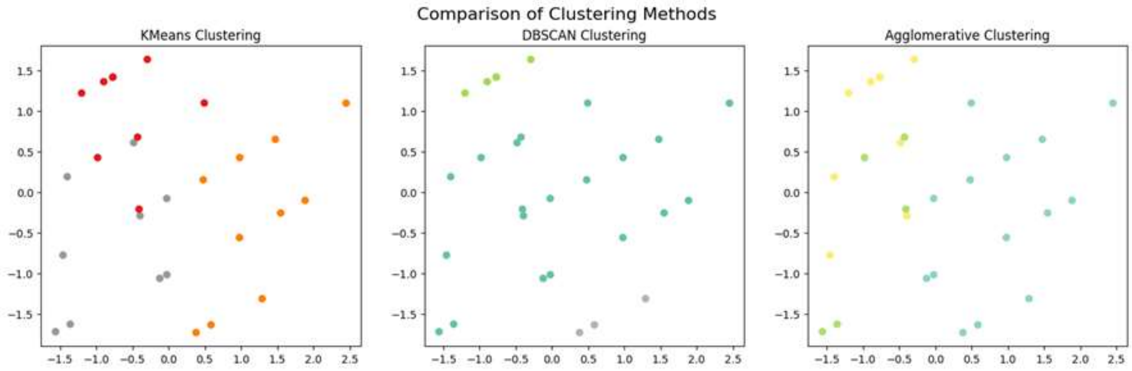

Figure 3. Comparison of Clustering Methods

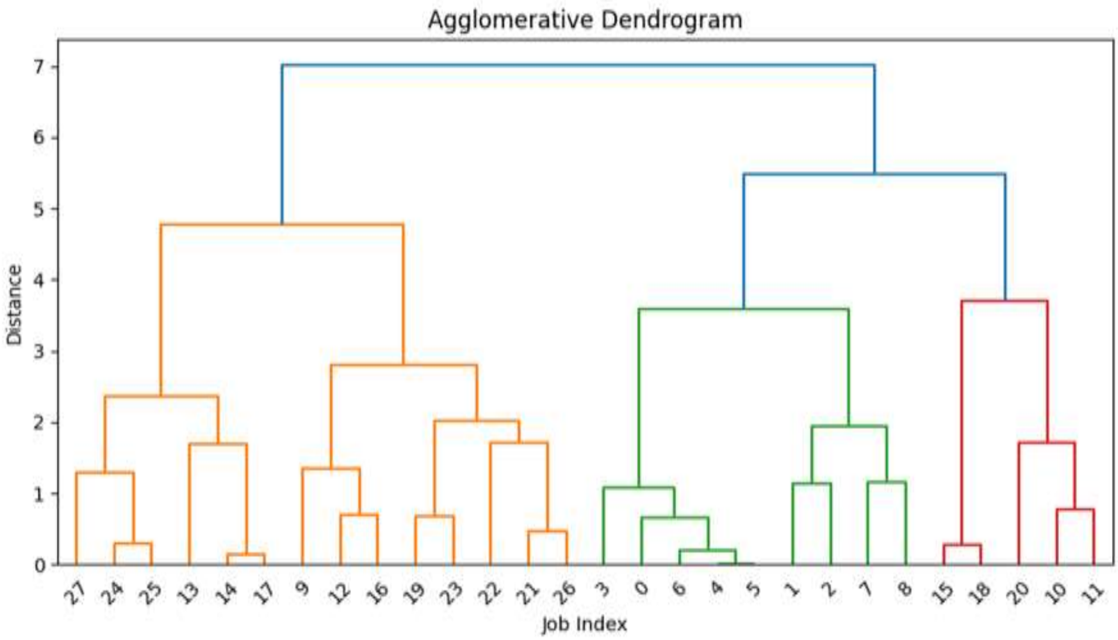

Figure 4. Agglomerative dendrogram

Explanation of Clustering Results and Silhouette Score Comparison

The Silhouette Score is used to evaluate the effectiveness of the clustering results by measuring the similarity between each data point and its cluster compared to points in other clusters. Scores range from –1 to 1, where values near 1 indicate that clusters are well separated and internally cohesive, reflecting excellent delineation among groups. Scores around zero suggest substantial overlap between clusters, implying that the clustering structure may not be optimal. Negative values indicate that some samples are likely misassigned, as they are closer to points in another cluster than to those within their group.

The three clustering methods yield the following Silhouette Scores for evaluation:

K-Means Clustering (Silhouette Score = 0.262118)

K-Means is a centroid-based clustering algorithm that partitions data into K clusters by minimizing the variance within each cluster. In this analysis, the resulting Silhouette Score of 0.26 indicates that, while clusters are reasonably well defined, there is still some overlap among them. Because K-Means group's observations based on similarity, specific job roles or skill profiles may not fit neatly into any one cluster, limiting the Algorithm's ability to assign all roles unambiguously. Additionally, K-Means assumes clusters are roughly spherical—a constraint that may not accurately reflect the actual structure of workforce segmentation.

DBSCAN achieved a Silhouette Score measurement of 0.092709

DBSCAN's clustering approach relies on identifying dense regions of data to distinguish core points, border points, and noise points; however, in this analysis, the Algorithm's performance was inadequate, as reflected by a low Silhouette Score of 0.09. The underlying dataset contains numerous low-density areas, which hinder the formation of meaningful clusters because noise points dominate the structure. As a result, DBSCAN struggled to generate workforce-related groups that align with AI adoption patterns. In essence, the lack of clear density-based separation within the workforce and AI-adoption data rendered DBSCAN ineffective for producing relevant clusters in this context.

Agglomerative Hierarchical Clustering (Silhouette Score = 0.288834)

Hierarchical clustering constructs a dendrogram by iteratively merging groups that exhibit the highest similarity. This study achieved a Silhouette Score of 0.29—surpassing both DBSCAN and K-Means—making it the most effective method for the given dataset. The resulting hierarchy reveals that job roles, their associated skill categories, and AI adoption levels naturally align within an intrinsic structural framework. Consequently, hierarchical clustering enables researchers to more accurately capture gradual transitions between job categories and predict AI adoption risks, outperforming alternative approaches such as K-Means in this context.

DISCUSSIONS

The best results emerged from Agglomerative Hierarchical Clustering, with a score of 0.288, indicating that workforce segmentation benefits from tree-based clustering that develops hierarchical structures by job role and AI integration level.

K-Means clustering successfully segmented the workforce data into reasonably well-defined groups (0.262), although it did not yield flawless results. The value of 0.092 for DBSCAN indicates that there is no substantial density-based cluster formation between AI adoption and workforce composition. The hierarchical clustering methodology stands out as the most effective method for analyzing the impact of AI on the workforce, as it aligns with existing job roles and industry divisions.

Agglomerative Hierarchical Clustering emerges as the preferred approach for segmenting the workforce based on AI adoption risk, as it consistently outperforms alternative methods. To refine cluster validity, decision-makers decision-makers should pair Silhouette Analysis with the Elbow Method when selecting the optimal number of clusters (K) and experiment with multiple distance metrics—such as Euclidean, Manhattan, and Cosine—to improve group delineation. In contrast, DBSCAN should be avoided for workforce segmentation since its strength in anomaly detection does not translate into clear, actionable clusters for AI-driven job profiles. Nonetheless, the proposed framework remains sufficiently flexible to identify outlier occupations that require dedicated AI transition strategies, even outside the primary clustering process. Enhancements to the underlying dataset—particularly by incorporating finer-grained features like automation risk estimates, digital skill classifications, and industry-specific AI readiness indicators—will facilitate a more accurate grouping of similar roles. Finally, integrating time-series analytics to capture evolving AI adoption patterns and workforce shifts over defined intervals will enable ongoing monitoring and adjustment of training programs and policy interventions.

The Hierarchical Clustering insights tool should proactively identify employees at high risk of displacement due to AI advancements and recommend alternative job opportunities that align with their existing competencies. The system should leverage AI-driven analyses to generate individualized skill development proposals, tailoring recommendations to each worker's assigned cluster profile.

Government agencies and universities should utilize these analytical findings to design workforce development initiatives that align with current AI-driven labor market dynamics. At the same time, educational institutions must create adaptive AI curricula that specifically address the skill gaps within job clusters most susceptible to automation; by integrating robust clustering models with evidence-based best practices, workforce planning platforms can deliver data-driven strategies that facilitate career mobility and resilience throughout the ongoing AI transformation.

CONCLUSIONS

The results of this research provide actionable insights for workforce planners, policymakers, and educational institutions. The research results enable evidence-based decisions for workforce development by identifying at-risk professions and predicting skills with longevity. Advanced analytics with machine learning (ML) models demonstrate their potential for guiding adaptive educational approaches, workforce reskilling programs, and national workforce strategies that will emerge in an AI-centered future. This analysis reveals that employment positions across logistics operations, manufacturing, and administrative support functions are the most prone to automation. However, creative and high-level leadership positions, along with analytical work, show greater sustainable potential. Research has confirmed that cross-functional competencies related to flexibility, alongside data processing and technological know-how, operate as defensive mechanisms against technical change. Targeted interventions, led by clustering outcomes, show how selected workforce blocks can receive upskilling programs. Insights generated from this research enable policymakers, educational institutions, and labor force strategists in the region to create a landmark that connects talent development to economic demands driven by AI technology. This research employs machine learning (ML) based methods and regional economic data to generate crucial insights into modern work systems for global academic discussions.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to restrictions.
Conflicts of Interest: The authors declare no conflict of interest.

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