From Education to Employment: A Deep Learning Approach to Understanding Job Market Trends in Africa

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***Abstract*—The research addresses the complex relationship between education and job outcomes in Africa, examining it through a deep learning approach using South Africa's most recent Quarterly Labour Force Survey (2024). In this study, we developed a Multilayer Perceptron (MLP) model to predict employment and long-term employment status, achieving an accuracy of 99.71% for employment prediction and 91% for long-term unemployed predictions. The use of Local Interpretable Model-Agnostic Explanations (LIME) also helped interpret the model, revealing education level, industry type, job-seeking behavior, and work experience as important predictors. We observed a discrepancy between educational attainment and job-market demands, noting that technical and vocational training plays a crucial role in addressing labor shortages. These findings have important implications for AI-generated employment predictions, supporting the use of data-driven research to inform labor-policy development and workforce planning. Key recommendations include expanding vocational training, aligning educational curricula with current labor-market demands, and developing upskilling programs for workers in transitional careers. Additionally, integrating Artificial Intelligence (AI) tools can improve national labor-market forecasting. This study contributes to promoting a more inclusive and data-driven transition from education to employment across Africa.**

***Keywords*—education-to-employment, deep learning, employment prediction, Africa, long-term unemployment, technical and vocational education, artificial intelligence**

I. Introduction

Rising youth populations, shifts in global labor markets, and structural inefficiencies within educational systems have made the transition from education to work increasingly difficult for young people in Africa. Despite improvements in educational access and quality across the continent, employment outcomes have not yet followed the same positive trajectory. As Sumberg *et al*. [1] observe, overly simplistic narratives portraying African youth as either a demographic dividend or a potential crisis have gained traction as convenient representations; however, they fail to capture the deeper structural barriers that continue to constrain employment opportunities for young people across the continent. As stated by Ayele *et al.* [2], although many young Africans successfully complete different levels of education, they continue to face significant barriers to securing viable employment. In addition, Baah-Boateng [3] argues that persistently high levels of youth unemployment in Africa are symptomatic of deeper structural and economic challenges, rather than individual failure to acquire or demonstrate adequate qualifications.

A key issue discussed in the literature is that education systems often do not align with labor market requirements. Merwe [4] and Teal [5] argue that educational qualifications are regarded as simply screening devices rather than indicators of true employability, a situation that ultimately leads to frustration among graduates. As labor markets evolve, Oketch [6] offers a compelling case for rethinking human capital theory by emphasizing relevance over mere access. Mbithi *et al*. [7] illustrate this lack of relevance in the Kenyan context, where institutions have struggled to meet evolving business needs, particularly regarding digital and soft skills.

Technical and Vocational Education and Training (TVET) has been put forward as a tool for bridging this gap. Tripney and Hombrados [8] provide evidence that, under favorable conditions, TVET can lead to positive employment outcomes and improved labor-market integration. Palmer [9] and Okojie [10] conclude that successful vocational training requires significantly broader changes, such as increased job investment and stronger governance. Nkunya and Mwila [11], as well as Paramole and Adeoye [12], emphasize the need for competency-based models of education and for productive partnerships between educators and industry stakeholders.

To address these challenges, emerging technologies such as Artificial Intelligence (AI) and Deep Learning (DL) hold significant potential for analyzing and leveraging education and employment data to inform policy and decision-making. Yoo *et al*. [13], Bommala *et al*. [14], and Andresen *et al.* [15] demonstrate how machine learning models can be developed to predict labor market outcomes through the analysis of complex, multidimensional datasets. Awujoola *et al*. [16] uniquely apply predictive modeling to assess employability using data sourced from academic institutions, while Senger *et al*. [17] employ a transformer-based model to extract and analyze data on workforce skills. However, Ahmed *et al.* [18] and Jacki *et al*. [19] raise concerns about adopting predictive or analytical models developed in non-African contexts without adequate adaptation and localization to the African environment.

Despite these advances, the existing literature continues to exhibit significant gaps and limitations. The absence of longitudinal data capturing shifts in educational attainment, employment stability, and transitions between education and work has received limited scholarly attention [20]. This gap is particularly evident in studies addressing intersectional inequalities [10], while the dynamics of informal-sector employment are seldom incorporated into predictive-modeling algorithms [9]. Furthermore, although several researchers have advocated for fair and interpretable AI systems, such standards are seldom applied in studies conducted within the African context [21, 22].

Building on these insights, this study investigates the

application of deep learning techniques to analyze and predict employment outcomes using education and demographic data across Africa. This research seeks to contribute to a more nuanced and data-informed approach to addressing youth unemployment and improving education-to-employment transitions in Africa. It does so through a synthesis of perspectives drawn from the reviewed studies, encompassing empirical evidence, emerging theoretical critiques, and methodological innovations. This research is guided by the following questions:

1) Can deep learning predict the likelihood of employment based on education and demographics?
2) What are the key predictors of long-term unemployment among different education groups?
3) How well do education levels and fields of study align with job market demands?
4) Which education levels are most associated with employment in high-demand sectors?

II. Literature Review

The relationship between education and employment in Africa is shaped by the combined effects of demographic changes, educational structures, economic conditions, and policy environments. The emergence of AI and DL is enabling the development of new analytical tools to better examine and understand this complexity. In this literature review, the selected studies are organized around key thematic areas, including (1) socioeconomic and structural barriers to employment; (2) educational attainment and labor market outcomes; (3) mismatches between education and industry needs; (4) the role and reform of Technical and Vocational Education and Training (TVET); (5) technological innovations and predictive modeling; and (6) equity, policy, and future directions.

A. Socioeconomic and Structural Barriers to Employment

Informal employment status coexists with persistent structural inequalities and weak economic transformation in numerous African nations. Sumberg *et al.* [1] and Ayele *et al.* [2] argue that the true crisis is not youth-specific unemployment, but rather the broader lack of job creation in the economy. Baah-Boateng [3] and Fox and Oviedo [20] further support this assertion by citing systemic constraints such as inadequate infrastructure and a weak investment climate. From a gender perspective, Okojie [10] identifies barriers such as discriminatory labor laws and cultural practices that disproportionately disadvantage young women. McGrath *et al.* [23] and Habiyaremye *et al.* [24] reinforce these findings and collectively argue that even well-targeted programs fail to generate sustainable employment outcomes when underlying structural issues remain unaddressed.

B. Educational Attainment and Labor Market Outcomes

Education does not automatically guarantee employment. As Merwe [4] and Bhorat *et al.* [25] argue, even formal qualifications may not substantially enhance an individual's employability in certain contexts. This disconnect between education and the labor market is further explored by Anowor *et al.* [26], who find that although primary and tertiary education levels are positively associated with employment, this does not imply that all levels of education uniformly lead to improved job prospects. Secondary education, on the other hand, does not appear to yield similarly positive outcomes in the labor market. Teal [5] demonstrates significant variation in the returns to education across relatively comparable African economies. The field of study, along with the quality of educational institutions, plays a critical role in shaping educational and employment outcomes. Mbithi *et al*. [7] and Hugo [21] highlight the importance of integrating soft skills development and experiential learning opportunities into academic programs to enhance graduate employability.

C. Mismatch between Education and Industry Needs

One of the most pervasive challenges is the persistent mismatch between the training provided by educational institutions and the expectations of employers. Oketch [6] examines shifts in educational planning ideologies and highlights developments associated with Human Capital Theory (HCT). Similarly, Mbithi *et al*. [7] and Paramole and Adeoye [12] observe that many African higher education institutions continue to operate with outdated curricula and pedagogical approaches. Employers increasingly seek flexible, technologically adept graduates who possess strong soft skills. However, the majority of students in African higher education institutions are not adequately exposed to such learning environments. Habiyaremye *et al.* [24] and Senger *et al.* [17] demonstrate that skills mismatches constitute a major contributing factor to youth unemployment in Africa. To address these challenges, McGrath *et al*. [23] argue that hybrid models of education that integrate general education with vocational and technical training may better prepare students for increasingly complex labor markets [27].

D. Role and Reform of Technical and Vocational Education and Training (TVET)

TVET remains a foundational component of skills-development strategies across Africa. A review by Tripney and Hombrados [8] finds that TVET has a positive impact on employment; however, the results are moderated by both program design and delivery mechanisms. Nkunya and Mwila [11] and McGrath *et al*. [23] describe how industry linkages, curriculum reforms, and infrastructure investments are all necessary for TVET to be effective. Palmer [9], Okojie [10], and Baah-Boateng [3] challenge the assumption that vocational training alone can resolve unemployment. They contend that broader systemic reforms and the creation of sustainable jobs are essential for training to serve as an effective intervention. In addition, gender inequalities in access and outcomes must be addressed through deliberate policies of inclusion [12, 28].

E. Technological Innovations and Predictive Modeling

Deep learning and machine learning have quickly become important and effective methods for analyzing occupational data. Recent work by Yoo *et al.* [13], Bommala *et al.* [14], and Ahmed *et al.* [18] indicates that supervised learning algorithms can be adapted to predict labor market trends. Awujoola *et al*. [16] and Andresen *et al.* [15] propose new frameworks for predicting employment probabilities using academic and demographic data, types of information that have been largely overlooked in previous analytical models. Senger *et al.* [17] use transformer models for skill

classification and emphasize that both structured data (education, demographics) and unstructured data (job postings) should be analyzed. Janiesch *et al.* [22] offer a perspective on the importance of context, scaling, and model interpretability. The future of predictive analytics for employment lies in developing models that integrate contextualized, multi-source datasets [19, 29, 30].

F. Equity, Policy, and Future Directions

A prominent theme emerging from the literature is the need for equitable education and employment policies. For instance, Anowor *et al.* [26] emphasize that governments should increase investment in both foundational and tertiary education. Supplementing this theme, Oketch [6] and Teal [5] note that without meaningful labor-market reforms, increased investment in education yields limited returns. Relatedly, the frameworks proposed by McGrath *et al.* [23] and Okojie [10] emphasize the importance of adopting gender-sensitive approaches in education and employment policy design. Baah-Boateng [3] reinforces this argument by emphasizing the need to focus not only on job training but also on sustainable job creation within the broader education–workforce nexus. With regard to investment, Fox and Oviedo [20] highlight the crucial role of institutional quality and macroeconomic stability in determining the effectiveness of education investments. Janiesch *et al*. [22] and Hugo [21] caution that predictive models based on artificial intelligence must be developed with a strong emphasis on fairness, accountability, and transparency. As Africa advances into the Fourth Industrial Revolution, education policies and systems must balance the pressures of global competitiveness with the preservation of locally grounded identities shaped by parental influence, community values, and cultural heritage [31, 32].

G. Identified Research Gaps

Despite the substantial number of studies reviewed, it is important to acknowledge the significant gaps that persist in this field. While the literature on the application of deep learning has advanced considerably in Western contexts, empirical evidence remains limited regarding its use within African labor markets. Few studies, such as Senger *et al.* [17] and Ahmed *et al*. [18], examine AI and education-to-employment transitions within African labor-market models. This highlights the need for more locally grounded research to address these gaps. Furthermore, longitudinal studies that follow students from education into employment across sectors and countries are virtually absent from the existing literature. Most of the available studies and datasets are cross-sectional, limiting understanding of long-term student outcomes and labor-market trajectories [33, 34]. In the absence of longitudinal and intervention-based studies that capture the dynamics of education-to-employment transitions, it remains difficult to establish causal relationships or to observe evolving labor market trends.

Third, although most studies acknowledge gender differences [10, 12], there is limited evidence of gender-disaggregated data systems or deep learning approaches that examine intersecting inequalities—particularly those affecting rural women, persons with disabilities, and individuals living in conflict-affected areas. Fourth, although research on technical and vocational education in Africa is growing, there remains little consensus on best practices for integrating soft skills, digital literacy, and entrepreneurial competencies into TVET programs. Moreover, the informal economy, which employs the majority of Africa's youth, remains almost entirely excluded from AI-based employability research [35].

This literature review synthesizes findings from diverse studies to provide a broader understanding of Africa's education-to-labor market ecosystem. It underscores the potential of deep learning models in predicting labor-market outcomes while emphasizing the need for contextually relevant data and inclusive analytical frameworks. Moving forward, interdisciplinary collaboration among educators, policymakers, and technology experts will be essential for developing predictive tools that can drive meaningful progress in labor-market planning and education reforms across the continent.

III. Materials and Methods

This study examines the relationship between education and employment trends in Africa through a deep learning framework. Specifically, it addresses key research questions related to predicting employment likelihood, identifying determinants of long-term unemployment, assessing the alignment between educational attainment and labor-market demands, and analyzing the association between educational levels and employment in high-demand sectors. A combination of data preprocessing, machine-learning modeling, explainability techniques, and visualization-based analysis, as depicted in Fig. 1, was employed to guide the methodological workflow.

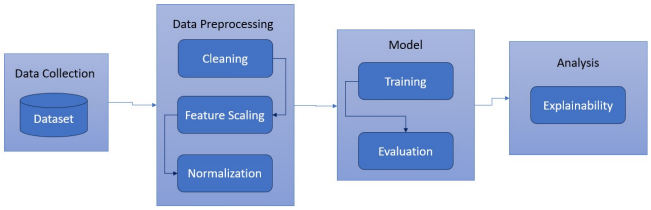

Fig. 1. Overview of the deep learning workflow for education–employment modeling.

A. Data Collection

The primary data for this study was obtained from the Quarterly Labor Force Survey (QLFS) 2024, which was downloaded from Kaggle. The dataset used contains 66,879 individual records and 161 variables, which provide employment, education, and demographic data for individuals in South Africa. The demographic data includes information on gender, age, population group, and marital status. The education data includes information on the highest level of education completed and the field of study for respondents with post-secondary qualifications, as shown in Table 1. Education levels range from the attainment of basic primary education to postgraduate degrees. The employment and job-market data include information on industry sectors, types of occupations, and whether the respondent was actively searching for a job. The workforce indicators, such as Not in Education, Employment, or Training (NEET) status, long-term unemployment, and access to social grants, capture key employment trends.

Table 1. A sample of the dataset

#	Variable	Value
1	Q13GENDER	Male
2	Q16MARITALSTATUS	Never Married
3	Q17EDUCATION	Bachelor's Degree
4	Q18FIELD	Computer Science
5	Q19ATTE	No
6	Q110EDUI	University
7	Status	Employed
8	Unempl_Status	Not Unemployed
9	Long_term_unempl	FALSE
10	Underempl	FALSE
11	Infempl	FALSE
12	NEET	FALSE
13	Q31ALOOKWRK	No
14	Q31BSTARTBUSNS	No
15	Q34WANTTOWRK	Yes
16	Q36TIMESEEK	Less than 3 months
17	Q37ACTPRIORJOBSEEK	Going to school
18	Province	Gauteng
19	age_grp1	20–29
20	Hrswrk	40

Although the QLFS 2024 dataset is nationally representative, certain biases may persist. Rural and informal-sector populations are often underrepresented, and the reliance on self-reported responses introduces the potential for recall or reporting bias.

B. Data Preprocessing

Prior to analysis, the dataset was subjected to thorough preparation to enhance data quality and model efficacy. Variables with an excessive number of missing values were dropped, while those with a moderate number of missing values were imputed using the mode. Categorical variables were encoded by assigning numerical values that reflected real-world order or category distinctions, such as education level, industry, and occupation. Continuous variables were normalized using min–max normalization to ensure consistent feature scaling. Because employment categories exhibited class imbalance, class-weighting techniques were applied to improve fairness in prediction outcomes.

C. Machine Learning Model

Two Multilayer Perceptron (MLP) deep learning models were implemented in Keras and TensorFlow to predict employment likelihood and identify key predictor variables. Each model was designed to address specific research questions and to adjust for the relevant hyperparameters, as shown in Table 2.

Table 2. Hyperparameters for each MLP model

Parameter	Employment Prediction (RQ1)	Long-Term Unemployment Prediction (RQ2)
Hidden Layers	2	2
Neurons	64, 32	128, 64
Activation	ReLU	ReLU
Dropout Rate	0.2	0.3
Optimizer	Adam	Adam
Learning Rate	0.0001	0.00005
Epochs	20	25
Loss Function	Sparse Categorical Crossentropy	Sparse Categorical Crossentropy

A Multilayer Perceptron (MLP) deep learning framework was constructed using Keras and TensorFlow to predict employment status and identify key predictor variables. The model architecture included an input layer, followed by two hidden layers with 64 and 32 neurons, respectively, and an output layer with three neurons corresponding to the employment categories (Employed, Unemployed, Discouraged). A Rectified Linear Unit (ReLU) activation function was applied to the hidden layers, and a softmax function was used in the output layer. Batch normalization and dropout were applied to enhance model performance and improve generalizability. The model was trained using the Adam optimizer with a learning rate of 0.0001 and a sparse categorical cross-entropy loss function, with training and validation sets split in an 80/20 ratio. The performance metrics used included accuracy, precision, recall, and the F1-score. The following is the pseudocode for the two models:

Pseudocode for MLP Model Implementation for Employment Prediction (Research Question 1)

```
BEGIN
    Define INPUT_LAYER with the number of input features from preprocessed data
    Add HIDDEN_LAYER_1 with 64 neurons, activation = ReLU
    Apply Batch Normalization to stabilize learning
    Apply Dropout (rate = 0.2) to prevent overfitting
    Add HIDDEN_LAYER_2 with 32 neurons, activation = ReLU
    Apply Batch Normalization to stabilize learning
    Apply Dropout (rate = 0.2) to prevent overfitting
    Define OUTPUT_LAYER with 3 neurons, activation = Softmax for multi-class classification
    Compile MLP using:
      - Loss function: Sparse Categorical Crossentropy
      - Optimizer: Adam (learning rate = 0.0001)
      Train MLP with:
      - Train-Test split (80%-20%)
      - Epochs = 20
      - Performance evaluation using Accuracy, Precision, Recall, and F1-Score
END
```

A sequential deep learning model was constructed, beginning with an input layer corresponding to the number of features in the dataset. The first hidden layer comprised 64 neurons with a Rectified Linear Unit (ReLU) activation function, followed by batch normalization and dropout to enhance generalization. The second hidden layer consisted of 32 neurons with ReLU activation, also followed by batch normalization and dropout. The output layer was defined with three neurons and a softMax activation function to facilitate multi-class classification. The model was compiled using the Adam optimizer and the sparse categorical cross-entropy loss function. Training was conducted with an 80%–20% train–validation split over 20 epochs (approximately nine hours). Model performance was subsequently evaluated using standard classification metrics, including accuracy and the F1-Score.

Pseudocode for MLP Model Implementation for Long-Term Unemployment Prediction (Research Question 2).

```
BEGIN
    Define INPUT_LAYER with the number of input features from preprocessed data
    Add HIDDEN_LAYER_1 with 128 neurons, activation = ReLU
    Apply Batch Normalization to stabilize learning
    Apply Dropout (rate = 0.3) to prevent overfitting
    Add HIDDEN_LAYER_2 with 64 neurons, activation = ReLU
    Apply Batch Normalization to stabilize learning
    Apply Dropout (rate = 0.3) to prevent overfitting
    Define OUTPUT_LAYER with 3 neurons, activation = Softmax for multi-class classification
    Compile MLP using:
```

- Loss function: Sparse Categorical Crossentropy
- Optimizer: Adam (learning rate = 0.00005)

Train MLP with:

- Train-Test split (80%-20%)
- Epochs = 25
- Performance evaluation using Accuracy, Precision, Recall, and F1-Score

END

D. Model Explainability (LIME Analysis)

To explain the predictions of the deep learning model, the Local Interpretable Model-Agnostic Explanations (LIME) technique was employed to identify key features affecting employment likelihood and to provide instance-level explanations. The LIME feature-importance charts highlighted key employment-related predictors such as job-search activity, education level, and industry. Data visualization played a crucial role in interpreting labor-market trends and assessing the alignment between education and employment. Heatmaps were employed to illustrate the distribution of educational attainment across different industries, while stacked bar charts were used to depict the relationship between fields of study and occupational categories. Scatter plots were used to examine the relationship between educational levels and unemployment rates, while LIME feature-importance plots enhanced the interpretability of the employment-prediction models.

The research adhered to ethical standards and maintained strict data privacy and anonymity. No identifiable information was included in the analysis. A key limitation of this study lies in its focus on South Africa, which may limit the generalizability of the findings to other African contexts. Although LIME enhanced the interpretability of the deep learning predictions, such models remain inherently complex, making full explainability challenging.

IV. Results and Discussion

This section presents and discusses the main findings of the study, structured around the research questions. The results integrate deep learning-based predictions, feature-importance analyses, and visualization-driven insights to enhance understanding of employment patterns in Africa. Each research question was examined independently to ensure a comprehensive analysis, thereby contributing to the broader knowledge base for policymakers, educators, and researchers.

Research Question 1: Can deep learning predict employment likelihood based on education and demographics?

To address this research question, a Multilayer Perceptron (MLP) model was developed and trained to classify individuals into distinct employment categories. The model achieved a test accuracy of 99.71%, indicating a high level of predictive performance for estimating employment likelihood using features such as educational attainment, demographic characteristics, and job-seeking behavior. The test loss of 0.0132 further reflects minimal misclassification and strong overall model performance. These results suggest that deep learning models can provide highly reliable employment predictions and serve as valuable tools for labor-market analysis and workforce planning. The model's predictive capability was assessed using standard classification metrics. The classification report, as shown in Table 3, presents the following metrics:

Table 3. Classification report on employment prediction based on education and demographics

Metric	Accuracy	Test Loss	Precision	Recall	F1-Score
Value	99.71%	0.0132	0.99	0.99	1.00

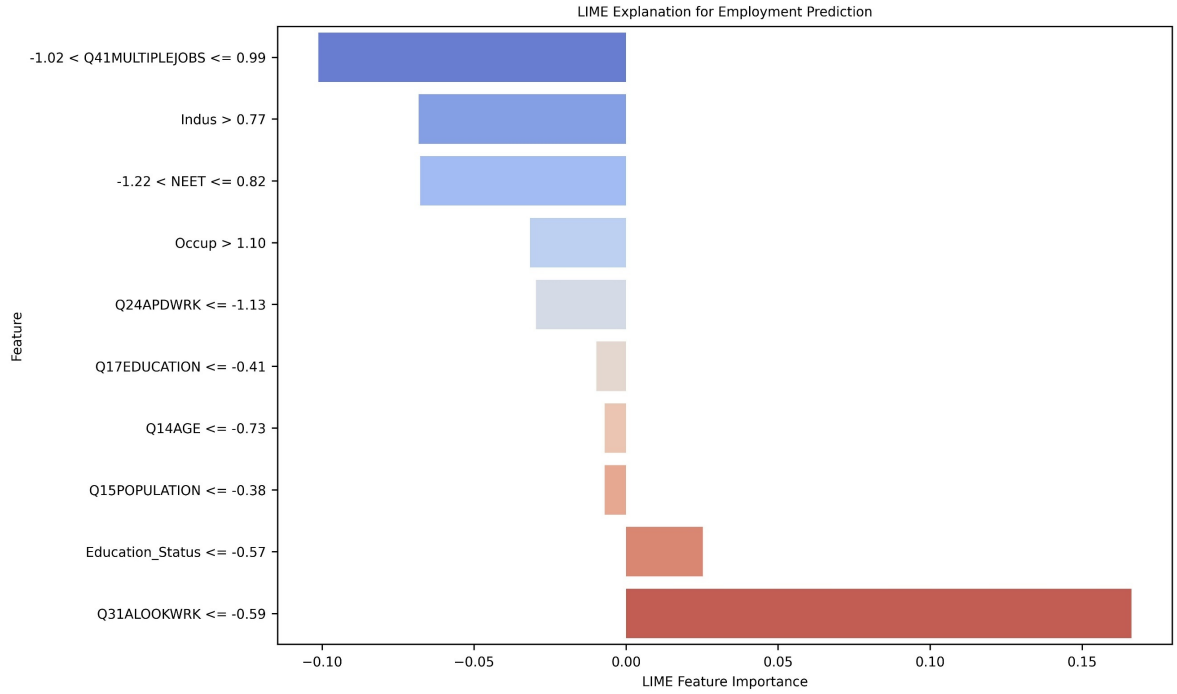

Fig. 2. LIME-based feature importance for employment prediction.

The interpretability analysis using LIME, as illustrated in Figs. 2 and 3, indicated that education level was the most influential predictor of employment likelihood, with individuals holding higher qualifications being significantly

more likely to be employed. The field of study was also a significant determinant of employment outcomes, with disciplines such as business, engineering, and healthcare exhibiting particularly strong employment prospects. Industry sector likewise emerged as a major determinant, with sectors such as finance and healthcare demonstrating higher employment rates. In addition, job-search activity was an important predictor, as individuals actively seeking employment exhibited significantly higher odds of securing work. In contrast, individuals classified as Not in Education, Employment, or Training (NEETs) were the least likely to obtain employment, underscoring the importance of sustained engagement in education or workforce participation.

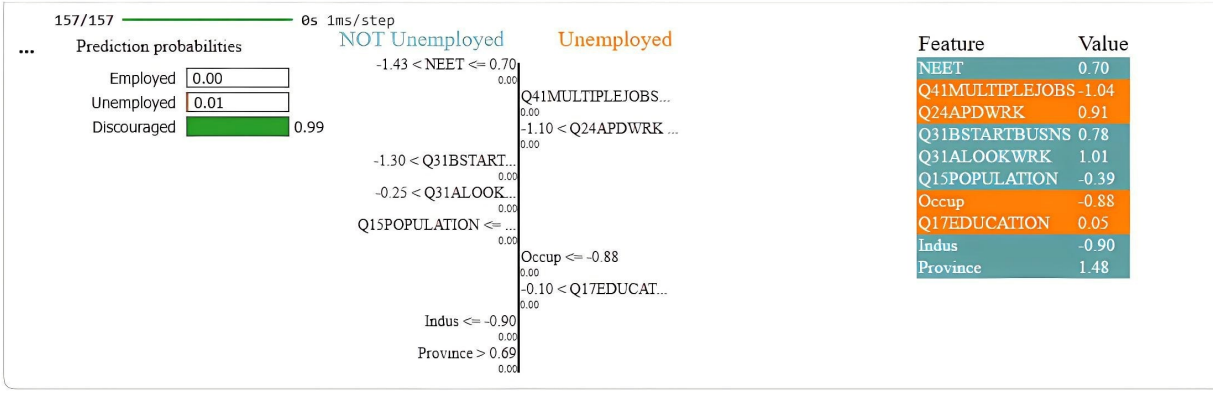

Fig. 3. Prediction and feature analysis from LIME on employment.

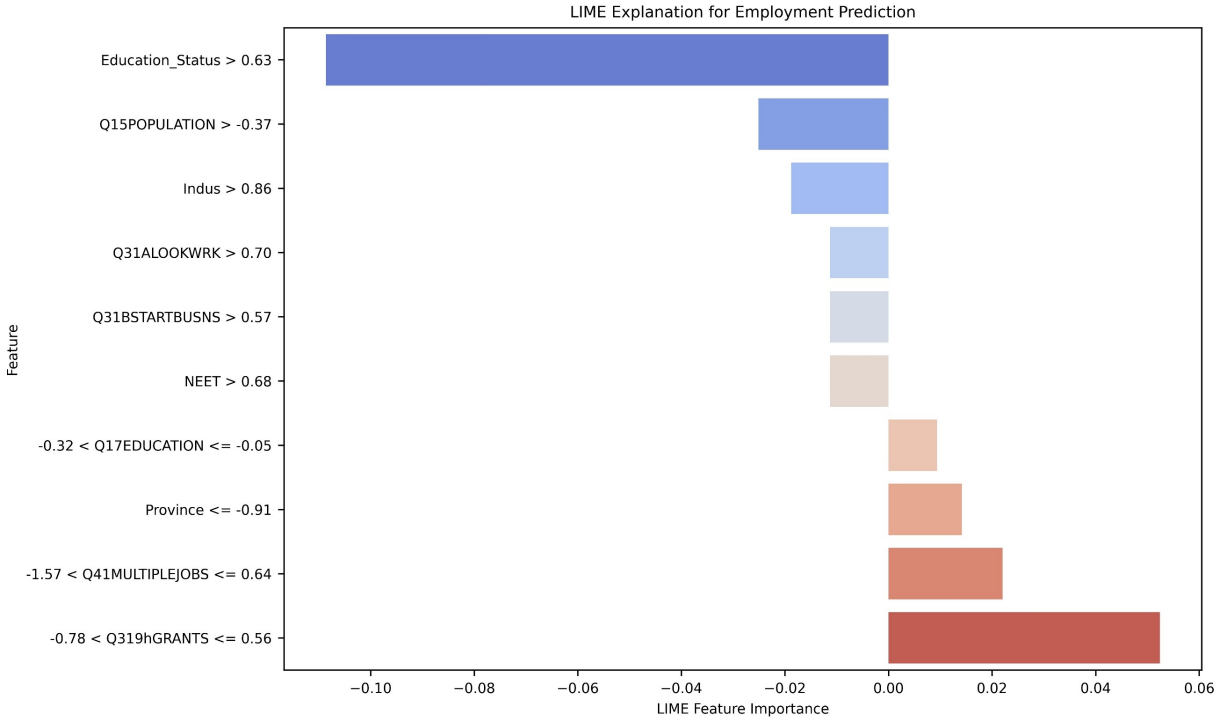

Fig. 4. LIME explanation for long-term unemployment prediction.

These findings reaffirm the critical role of education and proactive job-seeking behavior in shaping employment outcomes. The exceptionally high accuracy of the deep learning model demonstrates its potential as a decision-support tool for labor economists and policymakers. Given this potential, integrating Deep Learning (DL) approaches into national employment systems could support data-driven workforce development and evidence-based policy formulation. Nonetheless, real-world implementation should account for model explainability and bias mitigation to ensure the ethical use of AI in employment prediction.

Research Question 2: What are the key predictors of long-term unemployment among different education groups?

A second Multilayer Perceptron (MLP) model was developed to classify individuals as long-term unemployed based on their educational background and level of work involvement. The model achieved an accuracy of 91%, effectively distinguishing between short- and long-term unemployed individuals. A recall score of 96% indicated that the model successfully identified a high proportion of long-term unemployed individuals. The detailed classification report, including key performance metrics, is presented in Table 4.

Table 4. Classification report on long-term unemployment

Metric	Accuracy	Test Loss	Precision	Recall	F1-Score
Value	91%	0.2269	0.79	0.96	0.85

The LIME analysis, as illustrated in Figs. 4 and 5, identified the most significant factors associated with long-term unemployment. Education level emerged as one of

the strongest predictors, with individuals possessing lower levels of education experiencing significantly longer periods of unemployment. The variable representing the number of jobs held (Q41MULTIPLEJOBS) was also a strong indicator, suggesting that individuals with more diverse job experience were less likely to be long-term unemployed. The history of job starts (Q31BSTARTBUSNS) similarly emerged as an important factor, with individuals who had previously engaged in business activities or formal employment being less likely to remain unemployed for extended periods. Industry type also influenced long-term unemployment rates, with sectors such as construction and manufacturing exhibiting lower rates compared to the service industry. In contrast, social grant recipients (Q319hGRANTS) were found to be at greater risk of long-term unemployment, possibly due to financial dependence reducing the urgency to seek employment.

These insights underscore the critical influence of education, industry affiliation, and prior job-seeking behavior in mitigating long-term unemployment. Policy interventions such as targeted reskilling initiatives and incentives that promote the accumulation of work experience could play a vital role in reducing prolonged joblessness.

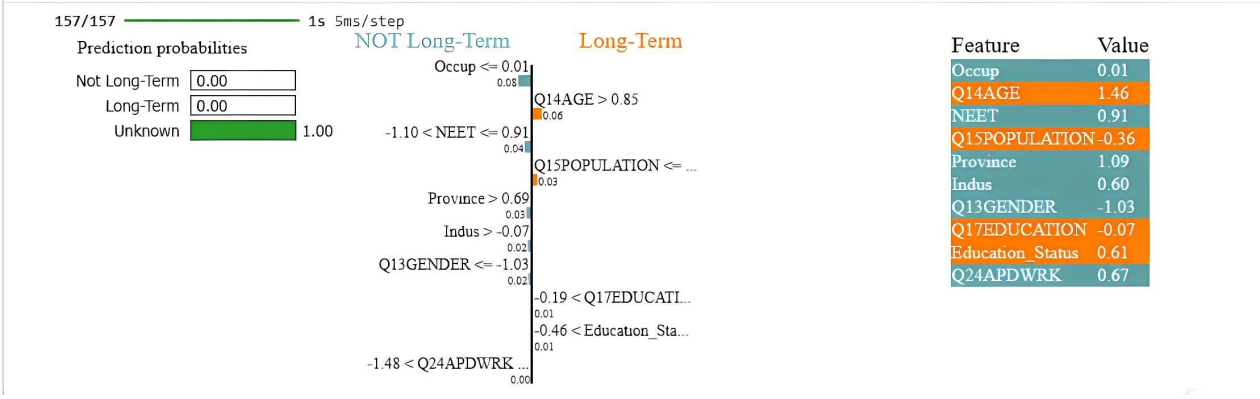

Fig. 5. Prediction and feature analysis from LIME on long term unemployment.

Research Question 3: How well do education levels and fields of study align with job market demands?

The objective of this analysis was to examine whether educational attainment and field of study aligned with the skill requirements of various industry sectors. As shown in Fig. 6, the finance, healthcare, and engineering industries employed a higher proportion of tertiary-educated workers, with more than 60% of employees in these sectors holding a university degree or diploma, confirming that these fields demand specialized skills. In contrast, the retail, manufacturing, and construction industries had a greater concentration of workers with secondary education, as more than 50% possessed only a Matric (Grade 12) qualification, indicating that these sectors often rely on labor that does not require university-level credentials.

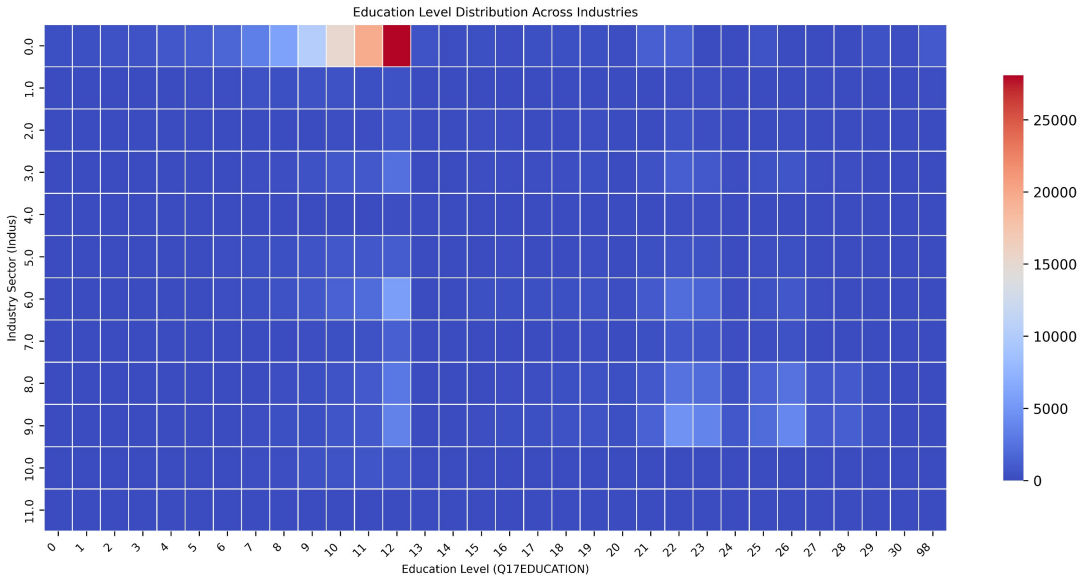

Fig. 6. Education level distribution across industries.

Further analysis of the relationship between field of study and field of occupation, as illustrated in Fig. 7, showed that approximately 70% of business and management graduates secured employment within their respective fields, whereas fewer than 40% of arts and social sciences graduates were employed in disciplines directly related to their studies. The alignment analysis also revealed that business and management graduates had access to a broad range of job opportunities across multiple industries, while engineering and computer science graduates were predominantly employed in technical roles. However, graduates from the arts and social sciences exhibited the lowest level of

employment alignment, suggesting a greater need for structured career planning within these disciplines, as illustrated in Fig. 8. The results presented in Fig. 9 indicate that some fields of study follow more prescriptive career trajectories, whereas others may require additional training or closer alignment with labor-market demands. Given the current structure of university curricula, policymakers should strengthen partnerships between academia and industry to better align educational outcomes with labor-market needs.

Research Question 4: Which education levels are most associated with employment in high-demand sectors?

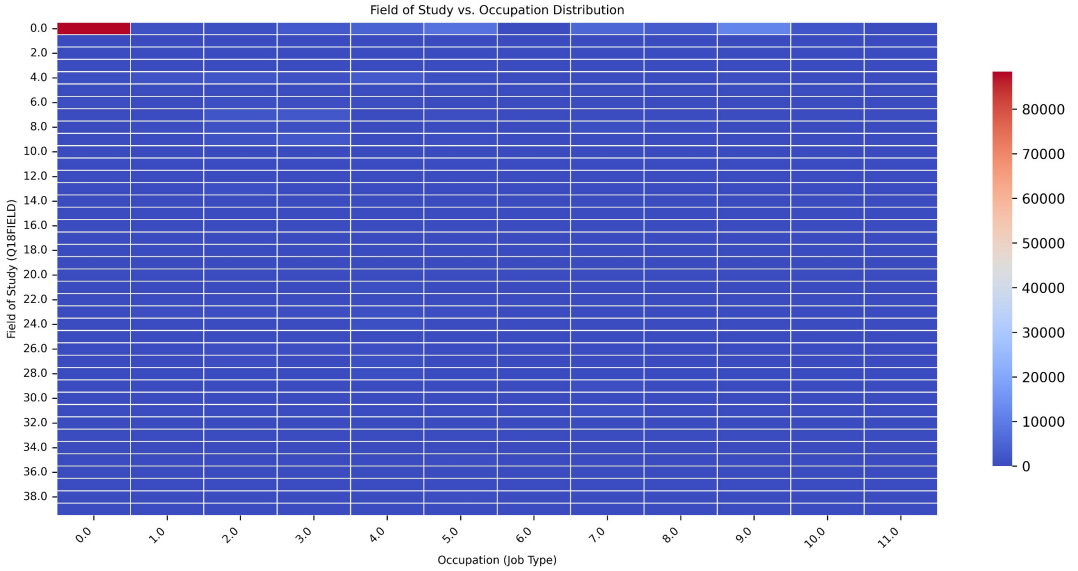

Fig. 7. Field of study versus occupation distribution.

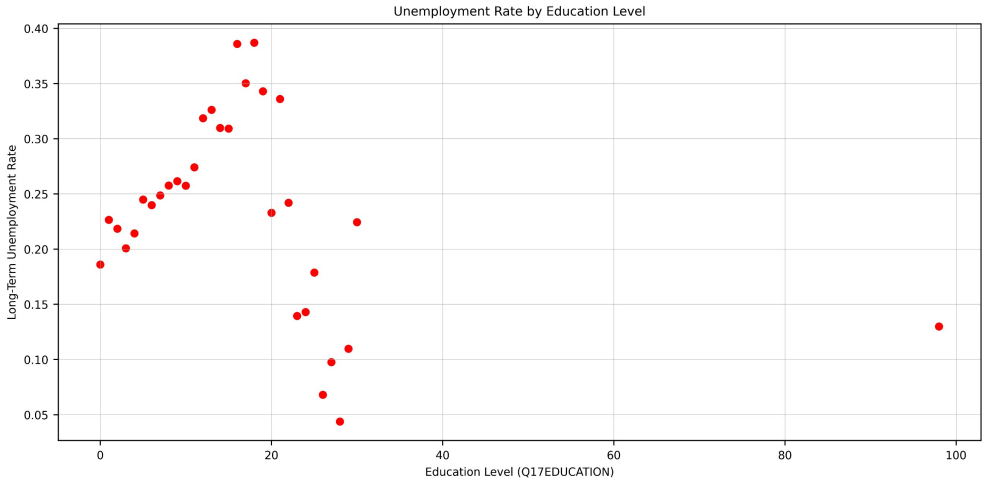

Fig. 8. Unemployment rate by education level.

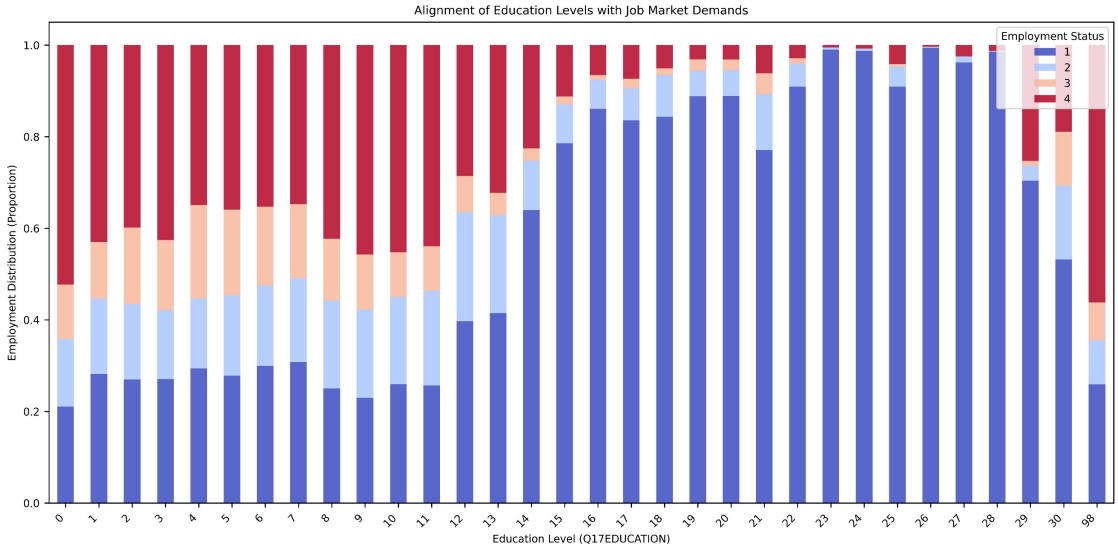

Fig. 9. Alignment of education levels with job market demands.

This research question aimed to identify the education levels associated with employment in industries characterized by high workforce demand. The analysis revealed that community and social services, retail and trade, financial services, and manufacturing were the sectors with the highest employment levels.

The analysis presented in Fig. 10 and Table 5 showed that the Matric (Grade 12) qualification was the most prevalent among employees in high-demand occupational sectors, accounting for 19.9% of the workforce. This finding underscores the importance of completing secondary education as a key threshold for labor-market accessibility. Tertiary diplomas and technical certificates together represented approximately 38.4% of employees in these sectors. Higher qualifications, including certificates with grade, diplomas with grade, post-higher diplomas (master's and doctoral levels), bachelor's degrees, and postgraduate diplomas, also made significant contributions to the workforce, particularly within the finance, healthcare, and technology industries.

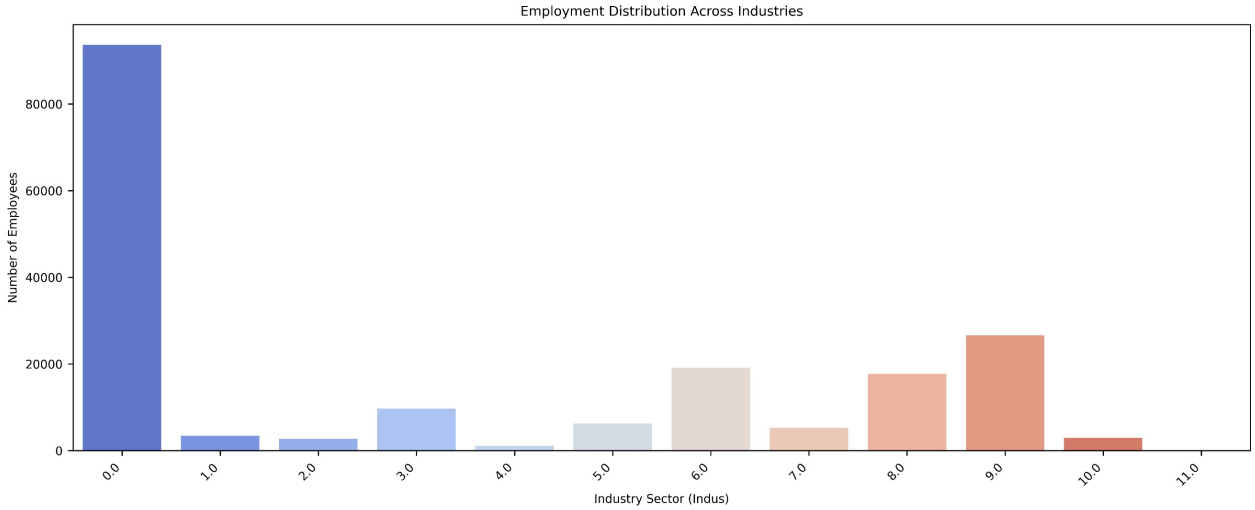

Fig. 10. Employment distribution across industries.

Table 5. Distribution of educational qualifications in high-demand occupation sectors

Education Level	Percentage (%)
Matric (Grade 12)	19.9
Tertiary Diplomas and Technical Certificates	38.4
University Qualifications	10.8

University qualifications accounted for approximately 10.8% of workers in high-demand industries, highlighting the significance of higher education in specialized sectors. At the same time, the findings emphasize the value of vocational programs and alternative training pathways as viable options for workforce preparation. Although this may not apply uniformly across all industries, it reinforces the notion that vocational education can serve as an effective alternative to traditional post-secondary education in many contexts.

In addition, individuals with no formal secondary education or only primary schooling were significantly underrepresented in sectors with high employment levels, as shown in Fig. 11. This finding highlights the critical importance of formal schooling in securing employment within the labor market. The results suggest a strong link between educational attainment and employment opportunities, indicating that secondary education and vocational training provide viable pathways into high-employment sectors. Consequently, investing in targeted skill-based learning and apprenticeship programs could play a vital role in improving employability and strengthening workforce readiness.

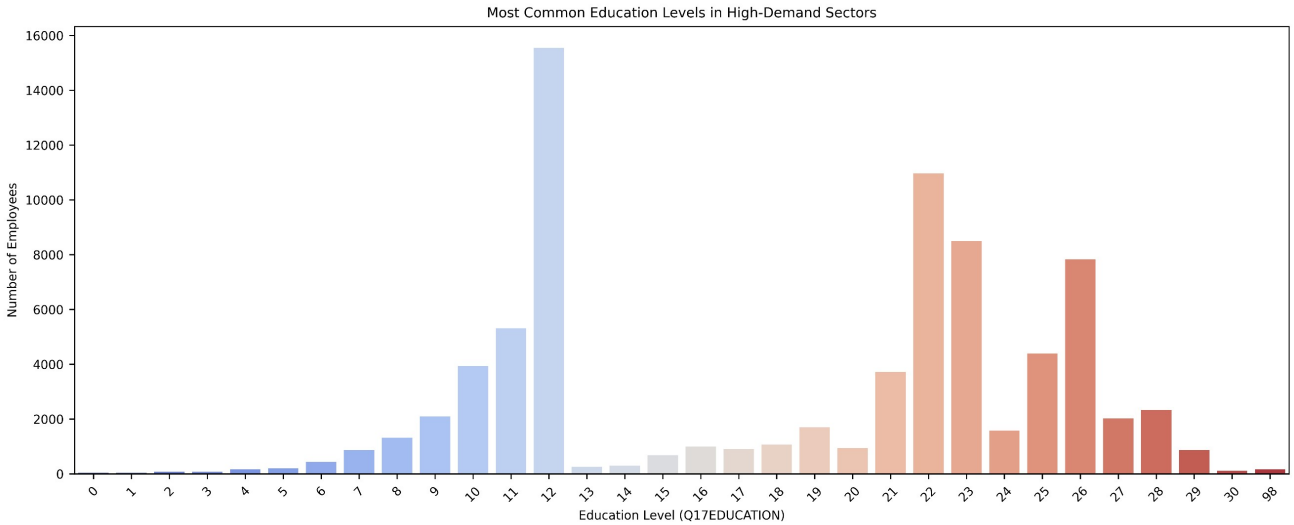

Fig. 11. Education levels in high-demand sectors.

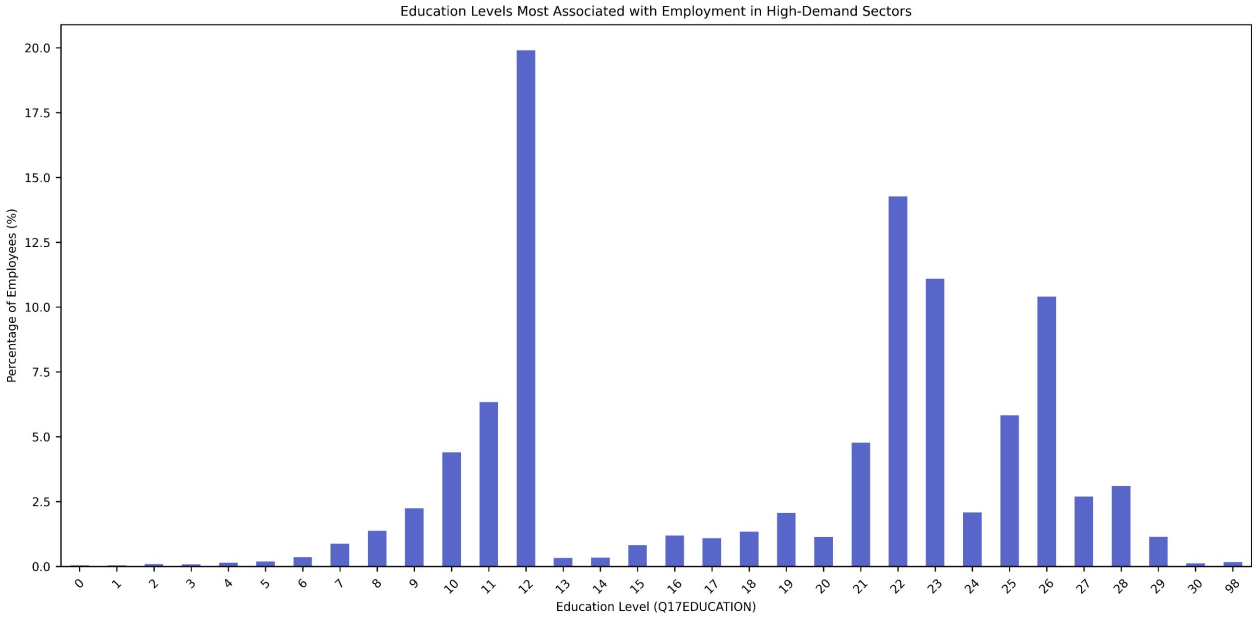

Fig. 12. Education levels are most closely associated with employment in high-demand sectors.

The findings of this study indicate that factors such as educational attainment, job-search activity, and industry type significantly influence an individual's likelihood of being employed. The deep learning models demonstrated strong predictive performance in distinguishing between employed and long-term unemployed individuals, while the use of LIME enhanced model interpretability and provided valuable insights into feature importance. Furthermore, the results revealed notable areas of mismatch between education and labor-market demands, underscoring the need for expanded workforce training and skills-development programs.

While education remains a vital stepping stone to employment success, not all degrees translate equally into labor-market opportunities, as illustrated in Fig. 12. Degrees in fields such as business and engineering offer promising career prospects when closely aligned with industry needs, whereas degrees in the social sciences may require deliberate career planning and additional skills development to enhance employability. The findings also indicate that long-term unemployment is influenced by prior job experience and industry of employment; therefore, training initiatives and policies that promote work experience and career mobility could serve as effective policy interventions.

These implications provide a data-driven foundation for policymakers, educators, and workforce planners to design strategies that strengthen education-to-employment pathways across Africa. To enhance employment prospects for future generations, greater emphasis should be placed on vocational education, targeted workforce reskilling, and industry-led curriculum development as key components of sustainable labor-market reform.

A. Employment Prediction Using Deep Learning

The employment prediction model achieved a high accuracy rate of 99.71%, demonstrating the strong potential of deep learning techniques for forecasting labor-market outcomes. The analysis revealed that education level, job-seeking behavior, and industry type were key determinants of employment status. These findings reinforce the well-established relationship between higher educational attainment and greater employability, particularly within professional and technical fields. This pattern aligns with the earlier findings of Mbithi *et al.* [7] and Habiyaremye *et al.* [24], who identified education and job-seeking behavior as key determinants of employability in African labor markets. Despite the strong empirical association between education and employment, individuals with lower levels of education or those classified as NEETs exhibited significantly lower probabilities of being employed. This finding raises important concerns about access to educational and economic mobility and underscores the role of formal education as a dominant predictor of labor-market success. Meaningful engagement with policymakers to promote workforce training and alternative skill-development programs for individuals without higher education would be an important approach to addressing these disparities.

B. Key Predictors of Long-Term Unemployment

The research revealed that educational attainment, prior work experience, and industry type were the most influential factors determining long-term unemployment. The model accurately classified individuals as short- or long-term unemployed with an accuracy rate of 91%, demonstrating its potential value as a tool for labor-market analysis and intelligence.

An important observation is that long-term unemployment is not solely driven by low educational attainment but is also influenced by the structure of the labor market and individuals' past work histories. Similar dynamics were reported by Baah-Boateng [3] and Okojie [10], who noted that structural constraints and prior work experience remain critical determinants of persistent unemployment. Individuals with diverse job-related experiences were found to be at lower risk of long-term unemployment, whereas those receiving social grants (Q319hGRANTS) faced a greater likelihood of remaining unemployed over extended periods. This finding suggests that while social assistance programs are vital for economic support, they may inadvertently contribute to labor-market detachment if not linked to

re-employment strategies. The results underscore the importance of implementing targeted job-training and internship programs for individuals seeking to re-enter the workforce. Policymakers should prioritize reducing structural barriers to employment, particularly within industries that exhibit high levels of long-term unemployment.

C. Education-Job Market Alignment

The research revealed a notable misalignment between levels of educational attainment and labor-market demand. More than 60% of employees in the finance, healthcare, and engineering sectors held tertiary-level qualifications, underscoring the relevance of higher education in these professional fields. In contrast, over 50% of workers in the retail, manufacturing, and construction sectors possessed only a Matric (Grade 12) qualification, indicating that advanced education is not a prerequisite for employment in certain industries. The disparity between business and engineering graduates (high alignment) and arts and social sciences graduates (low alignment) further demonstrates that not all degrees translate directly into employment opportunities. This observation aligns with Paramole and Adeoye [12] and Senger *et al*. [17], who highlighted persistent curriculum–industry mismatches and the need for flexible, skills-based learning environments across African universities. Addressing these disparities is essential to ensuring that industry needs are met through strengthened career counseling, industry-informed educational planning, and skills-based training programs that equip graduates with competencies relevant to labor-market demands.

D. High-Demand Education Levels

The study found that 19.9% of individuals employed in high-demand sectors held a Matric (Grade 12) qualification, while 38.4% possessed tertiary diplomas or technical certificates. In contrast, only 10.8% of employees in these sectors held university degrees. These findings highlight the critical role of vocational education and diploma programs in supporting workforce development. This aligns with the conclusions of Tripney and Hombrados [8] and Nkunya and Mwila [11], who reported that well-structured Technical and Vocational Education and Training (TVET) programs significantly improve employment outcomes when integrated with industry partnerships. The results challenge the notion that a university degree is the sole pathway to stable employment and instead emphasize the growing relevance of technical and vocational education in the modern labor-market landscape. Accordingly, both federal and provincial governments, in collaboration with educational institutions, should increase investment in apprenticeship programs, trade certifications, and training initiatives that align with industry needs. Such investments would help cultivate a more skilled and industry-ready workforce while simultaneously reducing the financial burden of student debt through accessible, tuition-free skills-development opportunities.

E. Policy Implications

The findings of this study hold significant implications for education policy and the design of labor-market reform. Given the demonstrated success of deep learning models in identifying employment and unemployment patterns, national employment agencies could leverage AI-driven forecasting tools to monitor labor-market dynamics in real time. Similar approaches have been proposed by Bommala [14] and Janiesch *et al*. [22], who advocate for the integration of explainable AI models into workforce-planning systems to enhance transparency, accountability, and contextual understanding.

1) Technical and Vocational Education and Training (TVET): Given that more than 38% of employees in high-demand sectors hold diplomas or technical certificates, increased investment in vocational and technical training is essential. Strengthening TVET systems will enhance workforce readiness, better align skills with industry needs, and expand employment opportunities for individuals without university degrees.
2) Job placement and career transition programs: Long-term unemployment requires sustained job-transition programs that connect unemployed individuals to skill-building opportunities and pathways into gainful employment.
3) Bridging the gap between education and employment: University degree requirements and curricula should be closely aligned with labor-market demands. For example, arts and social sciences programs could incorporate employability-skills components, internships, and experiential learning opportunities to enhance graduates' job readiness and overall employability.
4) Integration of predictive labor modeling into national planning: Predictive labor modeling should be incorporated into national employment and economic planning frameworks to anticipate labor-force dynamics, shifts in skill demand, and fluctuations in labor supply. Integrating AI-driven forecasting tools will enable policymakers to make data-informed decisions, assess economic impacts with greater accuracy, and design proactive workforce-development strategies.

The study reaffirmed that education remains a significant determinant of employment outcomes; however, not all degrees confer equal advantages in the labor market. Individuals who pursue vocational programs or obtain industry-relevant certifications possess a comparative advantage in securing employment, particularly within high-demand sectors. The application of deep learning models proved effective in analyzing labor-market dynamics and provides policymakers with data-driven insights to support evidence-based workforce planning. Future research could explore the effects of automation, the rise of remote work, and evolving industry demands on employment outcomes. Leveraging AI-driven analytics for education and employment policy will enable African countries to foster more inclusive, adaptive, and resilient labor markets. These findings reinforce the earlier arguments of Anowor *et al.* [26] and Oketch [6], who emphasized the need for stronger policy integration between educational reform and labor market analytics.

F. Limitations

This study focuses on South Africa, and the findings should therefore be interpreted within that specific national context. The Quarterly Labour Force Survey (QLFS) may not fully capture the experiences of rural populations or

informal-sector workers, and the reliance on self-reported responses introduces the potential for bias. Despite these limitations, the deep learning framework developed in this research can be adapted for similar studies across other African countries to support broader comparative analyses. While LIME provided valuable insights into feature importance and model behavior, it does not fully address the interpretability challenges inherent in deep learning models. The model's internal representations may not reflect direct causal relationships, and complex feature interactions can obscure certain outcomes. This is particularly important in African labor-market studies, where variations in data quality and collection methods can influence model performance. Future research should consider complementary approaches such as SHAP or counterfactual analysis to enhance the transparency, interpretability, and trustworthiness of AI-driven labor-market forecasting.

V. Conclusion

This research examined the relationship between education and employment outcomes in Africa through the application of deep learning techniques. Addressing four key research questions, the study provided insights into predicting employment status, identifying factors associated with long-term unemployment, mapping education to labor-market structures, and determining education levels linked to high-demand sectors. The results confirmed that education level, job-search behavior, and industry affiliation were significant determinants of an individual's likelihood of employment. The deep learning model achieved an accuracy rate of 99.71% in predicting employment outcomes, demonstrating its robustness as an analytical tool. Furthermore, long-term unemployment was more prevalent among individuals with lower levels of education, limited work experience, and employment in specific industries, underscoring the importance of targeted workforce-development initiatives across Africa.

The study also revealed a disconnect between higher education outcomes and labor-market demands for graduates. While more than 60% of the workforce in finance, healthcare, and engineering had completed post-secondary education, over 50% of employees in retail, manufacturing, and construction reported holding only a Matric (Grade 12) qualification. Notably, just 10.8% of the workforce in high-demand sectors had attained a university degree, underscoring the importance of strengthening vocational education and workforce participation. These findings highlight the urgent need for data-driven workforce planning and cost-effective policy interventions to ensure that vocational and technical education systems are responsive to the evolving needs of modern labor markets. Future initiatives should prioritize bridging the skills gap among graduates, expanding access to diversified vocational-training programs, and integrating artificial-intelligence–driven employment-forecasting tools to improve labor-market alignment and policy responsiveness.

African governments and educational institutions should increase investment in TVET. Given that 38.4% of employees in high-demand industries hold diplomas or technical certifications, policy frameworks should prioritize the expansion of apprenticeship programs, industry-linked certification schemes, and vocational-education pathways. Such initiatives would strengthen the alignment between education and labor-market needs, enhance employability, and support sustainable workforce development across the continent.

To reduce long-term unemployment, comprehensive career counseling and job-placement services should be integrated into both secondary and higher education institutions. Schools and universities should establish dedicated career-transition centers to help students align their educational pathways with labor-market opportunities and to equip them with practical job-search skills and employability training.

Higher education institutions should ensure that their degree programs are aligned with current labor-market demands. The study found that graduates in business, engineering, and healthcare demonstrated the highest levels of integration into the job market, whereas graduates in the arts and social sciences exhibited lower levels of employment alignment. Universities should therefore strengthen industry partnerships and embed internships, experiential learning, and employability-skills training within their curricula to improve graduate job-placement outcomes.

Employment agencies and government bodies should leverage AI-driven labor-market analytics to identify emerging job trends and skill shortages. The demonstrated capability of deep learning models shows that real-time employment forecasting can support evidence-based policy formulation and help address unemployment challenges and labor-market mismatches.

To enhance workforce adaptability, policymakers should develop structured reskilling pathways for unemployed individuals and workers in occupations experiencing declining demand. Promoting lifelong learning through targeted training programs in digital and technical skills can help mitigate job displacement caused by automation and contribute to long-term workforce sustainability.

Governments should implement structured re-employment programs to support individuals transitioning between jobs. Policy measures such as wage subsidies for employers who hire the long-term unemployed, targeted funding for entrepreneurship, and initiatives that promote labor-market mobility can help foster a more dynamic, inclusive, and resilient employment ecosystem.

The study underscores the critical role of education and training in shaping employment outcomes and demonstrates the potential of deep learning techniques for labor-market analysis and workforce planning. As African economies continue to evolve and diversify, cultivating a well-educated, skilled, and adaptable workforce will be essential for achieving sustained economic growth. Through strategic education reforms, AI-informed workforce planning, and employment-centered policies, governments and institutions can foster more inclusive and resilient labor markets. Ultimately, these efforts aim to expand employment opportunities, enhance economic stability, and promote equitable development across the continent.

Conflict of Interest

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

E.O. and S.A. worked on the introduction and the existing literature review on African employment market and education; D.K.D. and S.A. worked on the methodology, the results, and the conclusion. E.O. and D.K.D. both edited the content and reviewed the final work. All authors had approved the final version.

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