Dhaka Univ. J. Sci. 74(2): 295–300, 2026 (July)
ISSN 1022-2502, E-ISSN 2408-8528
DOI: https://doi.org/10.3329/dujs.v74i2.85408

Difference Equation Simulation of the Effect of Education Support on Youth Employment

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(Received: 2 November 2025; Accepted: 17 January 2026)

Abstract

Unemployment is a global issue affecting many nations, and various factors contribute to the increase in unemployment rates, particularly among young people. This article examines how access to educational support can impact youth employment rates over time. A discrete-time difference equation is developed and analysed for stability. A simulated numerical experiment demonstrates that educational interventions, such as educational support, can improve youth employment. Thus, policy recommendations are proposed to facilitate the successful implementation of educational supports for youths.

Keywords: Mathematical Model; Educational Support; Youth; Employment.

I. Introduction

Youth employment remains one of the most critical challenges facing developed and developing economies. Globally, approximately 13% of the youth are not in Education, Employment, or Training (EET)[1]. However, despite various skill development programs being initiated by governments of countries, there are still significant economic and social consequences resulting from high unemployment rates globally. In many nations, particularly those with rapidly growing populations, the gap between educational outcomes and labor market requirements continues to widen. For instance, in Nigeria, as a developing nation, the problem is exacerbated by limited access to quality education, curricula mismatches in schools, insufficient skill development programs, and labor market needs[2]. Education support through policies such as vocational training, scholarships, skill development programs, and curriculum reforms plays a vital role in improving the employability and productivity of young people. Thus, understanding the quantitative impact of such support on employment outcomes is essential for effective policy formulation[3-7].

In recent years, numerical simulation has emerged as a powerful tool for analyzing the dynamic relationship between variables. Simulation techniques have been a valuable tool for policymakers and researchers to predict potential outcomes under various policy scenarios by modeling the relationships between variables. Hence, this approach helps in identifying the most effective education strategies for reducing youth unemployment and enhancing human capital development. This study, therefore, employs a numerical simulation framework to examine the impact of educational support on youth employment. This is to understand the measurable impact of education support and youth employment, which such researchers and policymakers are increasingly embracing (numerical simulation). This method allows the modeling of complex economic and social relationships to predict outcomes under different policy scenarios[5, 8, 9].

By simulating the effect of education support on youth employment, decision-makers can assess which investments produce the most significant impact and sustainability. The analysis aims to quantify the impact of varying levels of educational investment and skill-based initiatives on youth employment rates over time. The findings will provide valuable insights into the extent to which educational support can catalyze youth employment, which tends to lead to sustainable economic growth in countries.

II. Literature Review and Theoretical Basis

Youth unemployment is a pressing global and national problem. In Nigeria, despite initiatives in education and vocational training, many youths remain unemployed or underemployed[10]. One hypothesis is that education support, such as scholarships, learning materials, mentoring, and stipends, can significantly improve

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employability. But how significant are these effects, and over what timeframe?

A review of marginalized youth's journey to work[11] emphasizes that young people face complex, contextual barriers, such as a lack of networks, discrimination, transport, and a soft-skills gap that education support alone may not address. Theories that support this include the human capital theory, which posits that investing in education enhances skills, thereby increasing employability and wages. This implies that early intervention in youth may alter trajectories. Additionally, according to social capital and network theory, educational support often includes mentoring or linkage to firms, which provides access to job networks, referrals, and valuable information. Behavioral motivational theory suggests that support can reduce dropout rates, increase persistence and confidence, especially among disadvantaged groups. The labor market matching job search theory suggests that the skills acquired must align with market demand; otherwise, educational support may not translate into employment opportunities. These theories suggest that the effect of educational support on employment is mediated by factors such as retention, skill relevance, market absorption, and networks, in addition to raw capacity building et al.[11].

Various empirical studies have shown positive correlations between educational investment (such as scholarships, subsidized materials, and conditional cash transfers) and improved employment outcomes (e.g., higher wages, more stable jobs). Research on youth employment, academic performance, and labor market outcomes suggests that extra time spent working during schooling may lower school performance and ultimately impact labor market outcomes[12].Another study in Kenya on cognitive and non-cognitive skills reveals that both types of skills influence employability[13].In higher education, simulations (and serious games) are used to enhance learning outcomes, although not directly to improve employment outcomes. A systematic review of simulation in education reveals generally favorable effects on learning when well-integrated.

However, most of that literature focuses on pedagogical simulation rather than policy-level simulation, which links education to the labor market. In Sri Lanka, a Decision Support Tool for Inferring the Further Education Desires of Youth was developed through statistical modeling, utilizing national youth survey data to predict educational choices[14]. While not an employment simulation, it provides a model-based link between education support and youth decisions. According to[15], various simulation and forecasting models are used to estimate the effects of education or training policies on employment. However, such studies are more common in macro settings (e.g., national labor force models) than in micro youth-level studies.

System dynamics and agent-based models are increasingly used in development and policy research to simulate complex social dynamics over time, including education, health, migration, and employment flows[16]. These methods allow you to test "what-if" scenarios under varying policy parameters. The challenge lies in parameter calibration, validation, and sensitivity analysis[17]. The more your simulation is grounded in empirical data, the more credible its predictions will be. In view of [18], a systematic review of NEET (Not in Employment, Education, or Training) interventions in the UK and similar contexts found that high-contact, multi-component programs combining classroom training, work placements, and personalized support produce modest but significant improvements in employment (a 4% increase) over baseline comparisons. However, many interventions yield small effect sizes, and their success depends heavily on context, intensity, and duration.

In vocational or job training literature, the Model Programs Guide (USA) reviews job training programs for at-risk youth, noting that effectiveness is mixed, with some positive outcomes but often modest, possibly due to short program durations, weak follow-up, or poor alignment with labor market demands[19]. The Model Programs Guide on Academic Skills Enhancement highlights that effective interventions share features such as personalized attention, long-term support, experiential learning, and integration of community institutional linkages.

System dynamics, agent-based modeling, and Monte Carlo simulations are increasingly used to estimate policy impacts when long-term empirical data are unavailable[20]. For example, in education evaluation, researchers build dynamic simulation models to gauge long-run effects (Research on the Construction of Computer-Aided Dynamic Simulation Model of Labor Education Evaluation" as an analogous approach). A review of marginalized youth's journey to work [11] emphasizes that young people face complex, contextual barriers, such as a lack of networks, discrimination, transport, and a soft-skills gap that education support alone may not address. Lack of sensitivity and robustness testing in many models, i.e., how sensitive are results to dropout rates, variation in support intensity, and absorption rates? A calibration of parameters using the best available empirical data from Nigeria or similar contexts, and validating them through a cross-check with sensitivity analysis, can address this.Thus, by combining empirical parameter estimates with simulation, one can test "what-if" scenarios of education support.

III. Model Development and Analysis

This section states the discrete equation adopted and its definitions. It also lists the assumptions and derives the steady state and monotonicity conditions.

The discrete-time dynamical model, as defined in Equation (1) below, is implemented.

$$e_{t+1} = e_t + \alpha\tau_t(1-e_t) - \delta e_t \tag{1}$$

where $e_t \in \square$ denote the employment fraction at time $t = 0,1,2,\ldots$. The parameters and control are interpreted as follows:

1. e_t represents the employment-to-population ratio at time t with $e_t \in [0,1]$.
2. τ_t represents the training intensity during time period t with $\tau_t \geq 0$ being a fraction of the whole population trained.
3. α represents the effectiveness of training programs computed as a fraction of trained eligible people who cross over to being employed with $\alpha \geq 0$.
4. δ represents the fraction of the employed who cross over to becoming unemployed with $\delta \geq 0$.

Proposition 1 (Steady State): Consider a constant policy $\tau_t \equiv \tau \geq 0$, therefore, any fixed point $e*$ of Equation 1 satisfies

$$e* = \frac{\alpha\tau}{\alpha\tau + \delta}, \tag{2}$$

provided $\alpha\tau + \delta > 0$. If $\alpha\tau = \delta = 0$, every e is a fixed point.

Proof:

From Equation 1, $e* = e* + \alpha\tau\left(1-e*\right) - \delta e*$.

This implies $\alpha\tau\left(1-e*\right) = \delta e*$, and for $\alpha\tau + \delta > 0$,

$$e*(\alpha\tau + \delta) = \alpha\tau \quad \Rightarrow \quad e* = \frac{\alpha\tau}{\alpha\tau + \delta}. \tag{3}$$

If $\alpha\tau = \delta = 0$, then the update $e_{t+1} = e_t$. Thus, every e is fixed.

Proposition 2 (Monotonicity around the Steady State): For constant τ and parameters $\alpha, \delta \geq 0$, the sign of the increment

$$\Delta e_t := e_{t+1} - e_t = \alpha\tau\left(1-e_t\right) - \delta e_t, \tag{4}$$

is determined by comparison with $e*: \Delta e_t > 0$ iff $e_t < e*$, $\Delta e_t = 0$ iff $e_t = e*$, and $\Delta e_t < 0$ iff $e_t > e*$.

Proof:

Rearranging $\Delta e_t > 0$ gives $\alpha\tau\left(1-e_t\right) > \delta e_t$, equivalently

$$e_t < \frac{\alpha\tau}{\alpha\tau + \delta} = e*. \tag{5}$$

This implies that employment increases whenever it is below its equilibrium level.

For $\Delta e_t = 0$, $\alpha\tau\left(1-e_t\right) = \delta e_t$, and

$$e_t = \frac{\alpha\tau}{\alpha\tau + \delta} = e*. \tag{6}$$

Showing that the system is stationary at equilibrium.

Similarly, at $\Delta e_t < 0$, $\alpha\tau\left(1-e_t\right) < \delta e_t$, and

$$e_t > \frac{\alpha\tau}{\alpha\tau + \delta} = e*. \tag{7}$$

So, when employment exceeds equilibrium, attrition dominates, and e_t decreases toward $e*$.

Thus, the iteration is monotone toward the unique steady state $e*$, given that the parameters are constant and stability holds.

IV. Numerical Experiments and Discussion of Results

Using the discrete-time model of youth employment dynamics defined in Equation (1), this article simulates a youth population of size $N = 10,000$ with an initial employment rate of $e_0 = 0.30$ representing that 30% of the population is employed at baseline. The baseline assumes that a steady 5% of the youth population receives education support every year. Other parameters are assumed as $\alpha = [0.02, 0.05, 0.08]$, $\delta = 0.02$, and $\tau_t = 0.05$, with analysis computed over a 50-year period. The baseline assumes that a steady 5% of the youth population receives education or vocational training each year.

Computing the numerical simulation of youth employment dynamics gives the graph in Figure 1.

Numerical Simulation of Education Support of Youth Employment

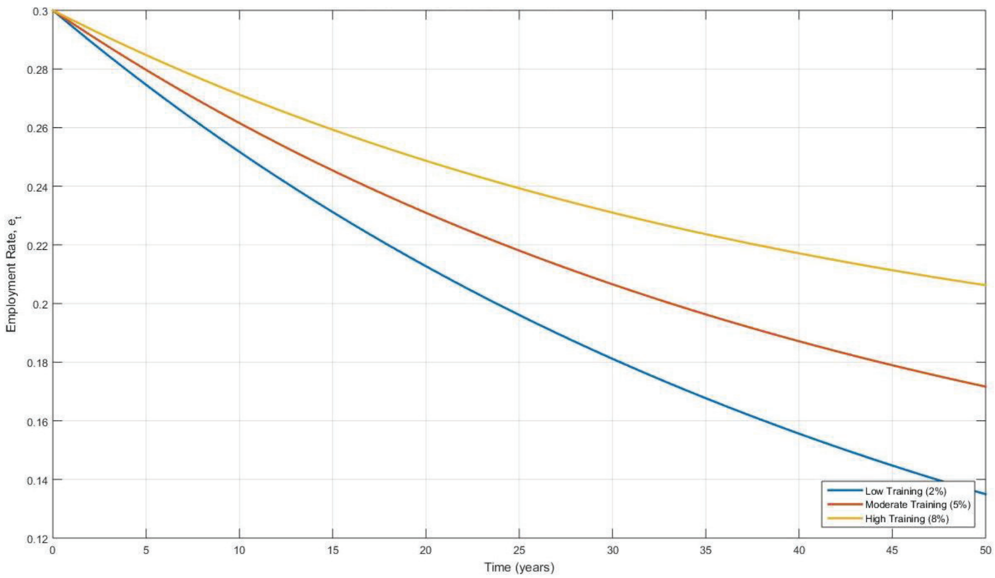

Fig. 1. Numerical Simulation of Education Support on Youth Employment

The figure shows how the employment rate of a youth population changes over time under three levels of education support: low (2%), moderate (5%), and high (8%). At $\alpha = 0.02$, as depicted by the blue curve, it is seen that education support is weak. Thus, employment declines steadily, with a small number of youths gaining employable skills while job losses continue. At $\alpha = 0.05$, as depicted by the orange curve, it is seen that a more substantial policy support leads to a slower decline, implying that the labour market absorbs trained youths more effectively. For the yellow curve with $\alpha = 0.08$, it is observed that high investment in education support mitigates job losses. Although there is still a decline in the employment rate, training support helps sustain youth employability over time. The simulation shows monotonic convergence of e_t towards the equilibrium of Equation 3. With higher training support (τ), the equilibrium employment rate e^* increases.

From a socioeconomic perspective, the gap between the curves represents the benefits of increasing educational support or training. In real-life scenarios, such as those in Nigeria or similar contexts, Figure 1 illustrates that policy-driven educational empowerment can significantly contribute to a decline in youth unemployment. Such countries would require consistent, high-level training intervention to stabilize youth employment.

To quantify sensitivity, α and τ are varied within realist bounds to compute the steady employment rate, which is graphed in the sensitivity surface shown in Figure 2 below.

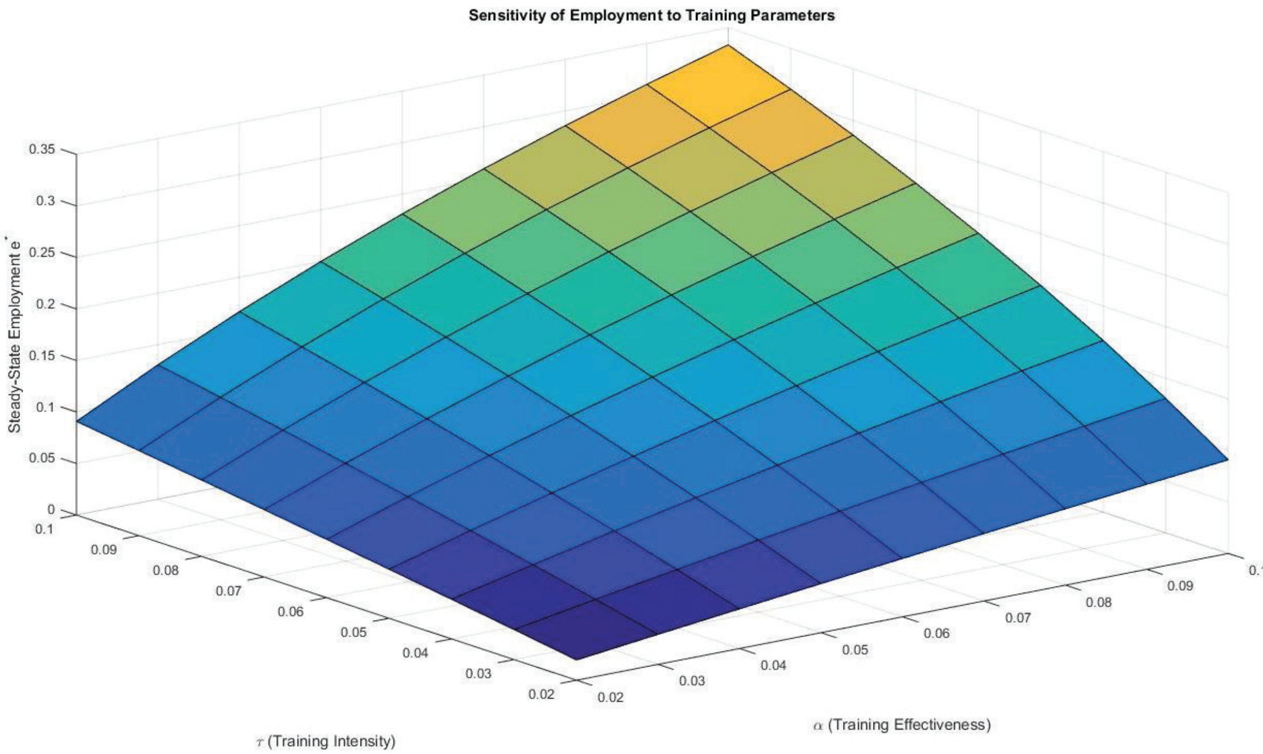

Fig. 2. 3D Surface Plot Showing Steady-State Employment Rate

As shown in Figure 2, the surface rises steadily towards the top right corner, where both α and τ are high. This implies that employment improves synergistically when both the quality and intensity of training programs increase. Conversely, when either α or τ is small, $e*$ approaches zero, which implies that poor or infrequent training fails to offset attrition losses. Mathematically, the surface is monotonic in both parameters, as $\frac{\partial e*}{\partial \alpha} > 0$, $\frac{\partial e*}{\partial \tau} > 0$. Interpreting to say that employment always increases with effective and/or intensive training.

From a policy perspective with an economic interpretation, the results provide a quantitative justification for multidimensional education and employment policies. High training effectiveness is characterized by improved curriculum quality, enhanced teaching standards, and increased skill relevance. Thus, helping each trained youth to become more employable. Similarly, a high training intensity represents frequent or broad-based access to training, which will help reach more youths or maintain employability over time. When both training effectiveness and training intensity are increased simultaneously, employment outcomes increase the most. This is consistent with how real-world training systems must strike a balance between quality and reach to achievea sustainable impact.

V. Conclusion

This article has developed a discrete-time model with simulations showing a numerically stable, data-linkable, and interpretable framework for quantifying how educational support affects youth employment. It bridges the fields of numerical mathematics, economics, and social policyto offer a model for forecasting impact evaluation. The results show that educational interventions, such as scholarships and vocational training, translate to long-term, measurable advantages in employment, given that their effectiveness is high. Additionally, the marginal return on training diminishes as the employment rate approaches its ceiling. This aligns with the human capital saturation effects. Furthermore, continuous retraining is necessary to offset labour-market attrition. Practically, modest increases in annual training participation can yield significant cumulative employment gains over time. Policymakers should thus focus on expanding education support, which will increase long-term youth employment. This will also help avoid poor-quality programs, as these will not compensate for low coverage. Additionally, introducing policies that reduce attrition, such as incentives for job stability, will amplify the benefits of training interventions. Future study of this work can incorporate time-varying or stochastic training rates with multiple subpopulations.

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