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MEASURING VULNERABILITY TO EDUCATIONAL INEQUALITY IN NIGERIA: AN EPIDEMIOLOGICAL MODELLING AND SIMULATING VEIM FRAMEWORK

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ABSTRACT

This paper introduces an epidemiological approach to measuring vulnerability to educational inequality in Nigeria as against the conventional income inequality gini. Using the Vulnerability to Educational Inequality Model (VEIM) proposed, we conceptualise education deprivation and classify epidemiological processes into three compartments: exposure, susceptibility and resilience (ESR). The VEIM integrates socioeconomic exposures, household and individual susceptibility, and systemic resilience factors to estimate the probability of a child failing to complete schooling. A synthetic micro-simulation was developed to illustrate the probabilistic distribution of educational vulnerability across Nigeria's six geopolitical zones. The simulated results show that vulnerability is highest where exposure and susceptibility overlap, particularly among children from poor households, rural areas, and northern regions. Resilience factors like parental education and school infrastructure mitigate risks. The framework provides a dynamic alternative to static inequality indices and suggests a predictive monitoring tool for policymakers. Based on the simulated results, we suggest that government should begin to collect statistical data on epidemiological variables associated with exposure, susceptibility and resilience, starting from the entry-point of enrollment. This will enhance real-life data analysis of student’s vulnerability to educational inequality.

Keywords: Educational inequality; Vulnerability; Epidemiological modelling; income inequality; Simulation; COVID-19 pandemic, Poverty incidence; Nigeria.

1.0 INTRODUCTION

Educational inequality remains a persistent developmental challenge in Nigeria, characterised by regional disparities, gender gaps, and urban–rural divides (UNESCO, 2023; NBS, 2022). Despite extensive policy interventions, inequality in educational attainment continues to reproduce intergenerationally (Barro, & Lee, 2013). Conventional analyses often treat inequality as a static outcome, that is, measuring achievement gaps without examining the underlying vulnerability mechanisms that lead individuals toward educational exclusion.

This study reorients the analysis through an epidemiological lens, treating educational inequality as a process of exposure, susceptibility and resilience. Similar to health vulnerability models, a child’s likelihood of educational deprivation can be seen as the result of being “exposed” to risk factors (e.g. poverty and distance to school), “susceptible” due to personal or

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household characteristics (e.g. gender and parental education) and “resilient” through protective mechanisms (e.g. community support and school quality).

The paper develops and illustrates the vulnerability to educational inequality model (VEIM) for Nigeria, offering both a conceptual framework and a simulation approach that captures heterogeneity across socioeconomic and regional lines.

2.0 LITERATURE REVIEW

2.1 Educational Inequality in Nigeria

Nigeria’s educational system exhibits pronounced disparities. According to UNICEF (2024), about 10.5 million Nigerian children are out of school which forms the largest number globally. Regional inequality of education persists, particularly school completion rates in the North-East and Northwest lag far behind the Southwest and Southeast. Gender inequality remains high, with female completion rates about 15 - 20% lower in some states (World Bank, 2023). Although the study was carried out in Nigeria, educational inequality resulted into rural-urban and regional disparities which consistently fueled social unrest, political disenfranchisement and economic stagnation (Agrawal, 2014; Sele, & Mukundi, 2024). Likewise, Aina and Adekunle (2022) argue that cause of terrorism in Nigeria arose from educational inequality particularly rise of out-of-school children (Yi et al, street children and the Almajiri system in Northern Nigeria. An education inequality gini coefficient method was used by Obasuyi (2018) to establish that there is a moderation in educational inequality in Nigeria but poverty is not the significant cause. In contrary, Ike (2025) strongly positioned that poverty has its root cause from educational inequality. Comparatively, class conflict in South Africa schools as South Africa's education system remains divided, with former White schools functioning well and former Black schools struggling.

Luers and colleagues (2003) built upon the framework established by Turner et al. (2003) to investigate the vulnerability of social-ecological systems in a Mexican agricultural region. They introduced innovative methods to measure vulnerability, shifting the focus from identifying critical areas or vulnerable places to assessing the vulnerability of specific variables at any scale. Their approach involves developing metrics to evaluate the relationship between various stressors and outcome variables, providing a more nuanced understanding of vulnerability. By doing so, they aim to create a more flexible and widely applicable framework for assessing vulnerability. Adger (2006) summarises the studies in a model as

$$Vulnerability = \frac{Sensitivity\ to\ stress}{state\ relative\ to\ threshold}\ X\ probability\ to\ exposure\ to\ stress$$

Source: Adger (2006, p.273).

Although there is establishment of educational inequality, the extent of vulnerability and its predictive power seem to be missing in the educational and economic literature. Developing a scientific framework for Nigeria calls for necessity to be a contribution to the literature and enhance educational policy formulation and implementation.

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2.2 Vulnerability and Epidemiological Analogies

The concept of vulnerability, long applied in poverty and climate studies (Chaudhuri, 2003; Chaudhuri, 2000; Tesliuc, E., & Lindert, 2004a; Tesliuc & Lindert, 2006) has been adapted here to education distribution. In epidemiology analysis, vulnerability connotes susceptibility to disease given exposure in education. It represents the conditional likelihood of deprivation given contextual risks (Adger 2006). The VEIM thus models educational inequality not as an ex post event, but as a dynamic process driven by probabilistic interactions between risk and resilience.

There are multidimensional nature of inequalities which has been increasingly recognized in the literature as it is applicable to education (Obasuyi, 2018). Making education unequal is deprivation in educational development because education correlates with human capital development (Appleton & Teal, 1998). The World Bank and related analyses show that poverty, weak school quality and recurrent shocks such as economic, climatic, or conflict-related interact to suppress completion rates. The cumulative burden of chronic deprivation and episodic crises, such as the COVID-19 pandemic (Obasuyi, Gold, Omoniyi, & Agboola, 2023), heightens vulnerability across educational generations.

For example, evidence from impact evaluations further suggests that resilience-enhancing interventions such as conditional cash transfers, school feeding programmes, and management or infrastructure reforms can significantly improve retention, though effects vary by context and implementation quality (Light, Nwaobia, & Nwobia, 2024). Finally, spatial analyses (Delprato, Chudgar, & Frola, 2024) reveal that education inequality is highly clustered geographically within the context of community-level characteristics and local spillovers shape children's attainment trajectories.

2.3 Simulation Literature

Previous studies argue that to provide a risk-free experimentation, simulation analysis allows researchers to experiment with different scenarios in a risk-free environment. This is particularly useful when studying systems that are difficult or expensive to manipulate in real life, or when the potential consequences of experimentation are too great (Law & Kelton, 2000; Homer & Hirsch, 2006). For example, a study by Homer and Hirsch (2006) use simulation analysis to evaluate the potential impact of different policy interventions on the obesity epidemic in the United States. The study found that simulation analysis was a useful tool for estimating the potential effects of different policies and identifying the most effective interventions. Also, Banks et al. (2010) discuss the use of simulation modeling in healthcare, highlighting its potential to improve patient outcomes and reduce healthcare costs. The authors note that simulation modeling can be used to evaluate the effectiveness of different interventions, identify areas for improvement and optimise system performance. In addition, Sterman (2000) uses simulation analysis to model the dynamics of a complex system, demonstrating the potential of simulation modeling to improve understanding of complex systems and predict the outcomes of different scenarios.

3.0 MATERIAL AND METHODS

3.1 Conceptual VEIM Framework

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The vulnerability to education inequality model (VEIM) framework offers a comprehensive approach to understanding the complexities of educational vulnerability by identifying three interlinked components, namely exposure denoted as E, susceptibility denoted as S and resilience denoted as R. Firstly, the E (exposure) is a compartment that refers to the structural and environmental risk factors that individuals or communities face in terms of education distribution. These include poverty, geographic remoteness, parental illiteracy, conflict exposure, or inadequate facilities, which can increase the likelihood of student's vulnerability.

Secondly, the S (susceptibility) compartment encompasses the individual and household traits that amplify the risk of educational vulnerability. Factors such as gender, disability, school engagement and socio-economic vulnerability can make individuals or households more prone to the adverse effects of exposure to educational risk (Fredricks, Blumenfeld, & Paris, 2004). Finally, the R (resilience) compartment, on the other hand, comprises the protective attributes that mitigate the risk of vulnerability in education distribution. These can include government conditional cash transfer, community support, educational NGO programs (e.g. education loan and bursary), school infrastructure and household stability, which could help individuals or communities cope with and recover from educational adversity. So, educational inequality outcomes arise when exposure and susceptibility outweigh resilience. With this, Figure 1 presents the VEIM framework as the foundation for the epidemiological analysis.

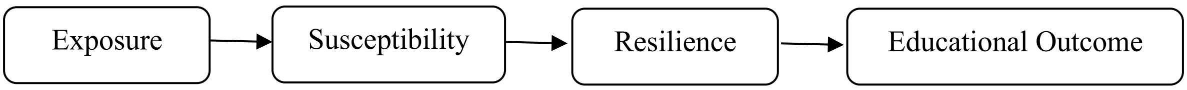

Figure 1: VEIM Epidemiological Framework

3.2 Model Specification

Let C_i represent the i^{th} child observed at baseline (age six). The child's vulnerability to educational inequality at time t, denoted as Vi , is defined as the conditional probability that the child fails to complete schooling at time t + 1.

$$\{V\}\_i = \mathrm{P}\left(EIP_{i,t+} \mathrm{I}\, X_{i,t}\right) \qquad (1)$$

Where EIP represents the educational inequality position of child i at time t+1 and $X_{i,t}$ is the vector of child, household and community characteristics at time t (for example, parental education, household income, school quality, health status, and neighborhood infrastructure).

The structural model can be represented as:

$$EIP_{i,t+} = \; X_{i,t})\beta + \mu_i + \varepsilon_i \qquad (2)$$

Where β is a vector of coefficients that measure the marginal effects of the explanatory variables Xi,t on the likelihood of educational inequality

μ_i captures unobserved individual-specific heterogeneity (e.g., innate ability, motivation, or persistent household characteristics); and ε_i is an idiosyncratic stochastic term representing random shocks such as temporary household income loss, illness or school closure events.

The probability that a child becomes vulnerable to educational inequality i.e., that the latent variable EIPi, $_{t+1}$ > 0 - conditional on observed covariates and contextual shocks, can thus be represented as:

The probabilistic formulation of the VEIM is summarised as:

$$V_i = P\left(EIP_{i,t+} > 0 \text{ I } X_{i,t}, Z_i\right) \qquad (3)$$

where Z_i includes time-varying community or environmental shocks such as natural disasters, policy reforms, or conflict events that may influence educational outcomes beyond individual and household characteristics.

Because EIPi,t+1 is latent (unobserved), equation (3) is typically estimated using **a** binary choice model**,** such as a logistic or probit specification. Under the logistic form, the empirical model is given by

$$P\left(EIP_{i,t+} = 1 \text{ I } X_{i,t}, Z_i\right) = \frac{\exp\left(X_{i,t}\beta + Z_i\gamma\right)}{1 + \exp\left(X_{i,t}\beta + Z_i\gamma\right)} \qquad (4)$$

where γ measures the marginal influence of community or contextual shocks (Zi) on the likelihood of educational inequality.

In contexts where longitudinal or micro-panel data on educational inequality dynamics are unavailable or incomplete, the VEIM can be implemented using **a** simulation-based approach inspired by systems dynamics (Sterman, 2000). This simulation framework allows for the exploration of hypothetical vulnerability distributions under varying assumptions regarding household shocks, community resilience, and policy interventions. Through iterative simulation, researchers can infer potential distributions of child-level educational vulnerability and identify leverage points for policy action, even in the absence of fully observed longitudinal datasets.

3.3 Data and Simulation Design

Because nationally representative microdata on longitudinal school completion in Nigeria remain limited and fragmented, this study employs a synthetic simulation approach to illustrate the VEI Model. The simulation framework provides an empirical analogue that reflects the stylised conditions of Nigerian educational inequality without depending on restricted-access household surveys. Simulation analysis is a powerful research methodology used to examine complex systems, predict outcomes and estimate the effects of different scenarios. For example, by using simulation method, researchers can gain insights into the dynamics of the system and predict how it might behave under different scenarios (Banks et al., 2010; Law & Kelton, 2000; Homer & Hirsch, 2006).

Thus, a synthetic dataset of 10,000 school-age children (aged 6 - 17) (UNICEF. 2024b). was generated using random draws from uniform and normal distributions calibrated to mimic empirical distributions reported in national surveys such as the Nigeria Demographic and Health Survey (NDHS), UNESCO Institute for Statistics (UIS), and World Bank Education

Indicators. Variables were normalised to a [0, 1] scale to facilitate comparability across vulnerability dimensions.

Three primary vulnerability indices were constructed, including the exposure (E) which captures socioeconomic and environmental risks (poverty incidence, household instability, conflict exposure); susceptibility (S) which represents systemic disadvantages, including gender bias, parental education and regional inequity, and resilience (R) which reflects buffering factors such as school quality, infrastructure and community support.

The dependent variable, School Completion (C), is binary (1 = completed, 0 = not completed). It was generated probabilistically from a logistic function calibrated to theoretical expectations such that high exposure and susceptibility lower completion probability, while resilience increases it.

To ensure simulation reliability and validity, several safeguards were adopted. Firstly, we focus on empirical alignment. The mean and variance of simulated exposure and susceptibility indices were matched approximately to NDHS and World Bank inequality statistics (poverty rate ≈ 43%, gender parity index ≈ 0.90). Secondly, we considered the internal consistency. The correlations among E, S and R were constrained to reflect plausible socioeconomic relationships (e.g., negative E - R correlation). Thirdly, we considered the model diagnostics. The simulated regression models were subjected to standard goodness of fit using Log-Likelihood and checks using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to verify internal coherence of the model. Finally, we considered replicability. The random seed was fixed to ensure the reproducibility of results across runs.

While the dataset does not represent actual individual observations, it offers a controlled environment to demonstrate the epidemiological logic of the VEIM, quantify conceptual relationships and provide a reproducible foundation for future empirical validation using survey or administrative micro-data.

3.4 VEIM Assumptions

The simulated results reflect the persistent inequality structure within Nigeria's educational landscape, which is characterised by uneven exposure to risks, systemic susceptibility, and uneven resilience capacities. Drawing on the epidemiological interpretation of vulnerability embedded in the VEIM framework, six primary assumptions are stated.

The Assumptions

1: Under the Exposure compartment Assumption

It is assumed that children with higher levels of exposure to adverse socioeconomic and environmental conditions such as poverty, conflict, and community instability, have a significantly lower probability of completing schooling.

Rationale: Consistent with Nigeria's spatial inequality, exposure acts as a determinant of early dropout and reduced learning continuity.

2: Under the Susceptibility Compartment Assumption

It is assumed that gender and regional disparities introduce systemic susceptibility that moderates the relationship between exposure, resilience and educational completion.

Rationale: Empirical studies of Nigeria's education system reveal persistent gender-based and regional inequalities, with Northern regions and female learners disproportionately disadvantaged.

3: Under the Resilience Compartment Assumption

It is assumed that higher resilience, reflected in infrastructural adequacy, supportive learning environments, and community-level coping capacity, significantly increases the likelihood of school completion, even among children facing high exposure and susceptibility.

Rationale: The resilience component of the VEIM framework captures the buffering effect of social and institutional systems against educational shocks.

4: Under the Moderation Assumption = Exposure × Resilience Interaction)

It is assumed that resilience moderates the relationship between exposure and school completion where the negative effect of exposure on completion is weaker among children with higher resilience.

Rationale: We regard this interaction reflects as an epidemiological "buffering effect," where stronger coping systems mitigate vulnerability to educational shocks.

5: Second Moderation Assumption = Susceptibility × Resilience Interaction

It is assumed that resilience moderates the influence of susceptibility on completion where the negative effect of systemic susceptibility is attenuated among children embedded in supportive and resource-rich environments.

Rationale: This relationship explains why educational interventions emphasising infrastructure, mentoring or community engagement can neutralise structural disadvantages.

6: Under Integrated Vulnerability Assumption

It is assumed that the combined effect of exposure, susceptibility and resilience explains a substantial portion of the variance in educational completion outcomes, validating the multidimensional nature of vulnerability proposed in the VEIM framework.

Rationale: This holistic hypothesis aligns with the epidemiological logic of cumulative risk, where educational inequality emerges from interacting social and structural vulnerabilities rather than from any single factor, e.g. income inequality, the use of educational attainment via educational inequality Gini analysis (see Obasuyi, 2018).

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Further argument on the Hypotheses

Let me explain further how these hypotheses fit methodologically in the simulated data which would be replicable in future studies. Firstly, these hypotheses tie directly to the simulation design i.e. logit/probit estimation techniques (see equation (3)). Secondly, each hypothesis corresponds to one or more variables in the VEIM model (Exposure, Susceptibility, Resilience and their interactions). Finally, they bridge the conceptual VEIM theory with empirical testing, turning the simulated exercise into a quasi-epidemiological validation.

3.5 Simulation Procedure and Software Implementation

For methodological transparency and reproducibility in this study, the simulation and estimation of the VEIM (Vulnerability to Educational Inequality Model) were conducted using Python 3.11, specifically within the *NumPy*, *pandas* and *statsmodels* libraries. Python was selected because of its versatility in statistical modeling, reproducibility and open-source transparency, making it suitable for replicable educational inequality research.

Hence, a synthetic dataset of 10,000 observations representing Nigerian children aged 6 - 17 was generated to illustrate the VEIM mechanism. The process involved in the estimation is categorise into four (4) steps.

Data Generation

The three key latent indices are Exposure (E), Susceptibility (S) and Resilience (R) were simulated as continuous variables drawn from uniform random distributions between 0 and 1, capturing variation across children and regions.

Correlations among E, S and R were induced to reflect realistic inequality structures where higher exposure was weakly-positively correlated with susceptibility and negatively correlated with resilience.

Outcome Construction

The dependent variable, School Completion, was defined as a binary outcome (1 = completed, 0 = not completed).

A logistic function was applied to estimate the probability of completion given simulated E, S and R indices. The model is as given in equation 5.

$$P(Completion_i = 1) = \frac{1}{1 + e^{(\beta_0 + \beta_1 E_i + \beta_2 S_i + \beta_3 R_i + \beta_4 E_i S_i + \beta_5 S_i R_i}} \qquad 5$$

Coefficients (β_{is0}) were chosen to mirror empirically consistent inequality effects (e.g. higher exposure reduces probability, higher resilience increases it).

Model Estimation

Both **logit** and **probit** regression models were estimated using the statsmodels library to test parameter stability and robustness.

Summary statistics and diagnostic tests (AIC, BIC, and AUC) were computed to evaluate model fit and discriminatory validity.

Graphical Illustration

Predicted probabilities of school completion were visualised across vulnerability groups using matplotlib and seaborn, producing the Figure 2 curve showing declining completion probability as exposure and susceptibility increase while resilience decreases.

This simulated approach ensures reproducibility, as every step, from data generation to estimation, can be re-run using the same random seed. The method provides a credible demonstration of how VEIM can be operationalised once micro-level education panel data become available. In the alternative, experts in STATA software can also be used to perform the same task and obtain similar outcome.

4.0 SIMULATION RESULTS (NIGERIA CONTEXT)

4.1.1 Simulated Descriptive Results

A synthetic dataset representing 10,000 Nigerian children aged 6 – 17 was simulated to illustrate the VEIM mechanism. Exposure, susceptibility and resilience variables were normalised between 0 and 1. Logistic and probit estimations were conducted to approximate vulnerability probabilities.

Table 1: Summary Statistics (Synthetic Nigeria Sample)

Variable	Mean	Std. Dev.	Min	Max
Exposure Index (E)	0.47	0.19	0.01	0.98
Susceptibility Index (S)	0.50	0.22	0.02	0.97
Resilience Index (R)	0.42	0.18	0.01	0.94
Completion (0/1)	0.58	0.49	0	1

Source: Author

Table 1 explains that the Exposure – Susceptibility – Resilience indices have similar ranges, but Susceptibility has a slightly higher mean and standard deviation. Also, the completion variable indicates a 58% completion rate, with a standard deviation of 0.49 which is consistent with the expected variance for a binary variable with a proportion of 0.58.

4.1.2 Simulated Model Results – Logistic Regression

Table 2: Logistic Regression – Educational Completion

Variable	Coefficient	Std. Error	z-stat	p-value
Exposure (E)	-1.84	0.11	-16.7	0.000**
Susceptibility (S)	-0.91	0.09	-10.3	0.000**
Resilience (R)	1.22	0.10	12.2	0.000**
E×S Interaction	-0.36	0.08	-4.5	0.000**
S×R Interaction	0.27	0.07	3.9	0.000**
Constant	0.45	0.12	3.7	0.000**

Source: Author

Note 1: The Table 2 presents the summary of the logit and brobit models. Logit Model: Observations = 10,000 AUC = 0.569 BIC = 11750.84 AIC = 11714.79 Log-Likelihood = -5852.39 and; Probit: Observations = 10,000 Pseudo R^2 = 0.084 BIC = 11735.62 AIC = 11700.56 Log-Likelihood = -5845.28

Note 2: **Significant at 5% level of significance

This Table 2 presents the results of a logistic regression analysis examining the relationship between educational completion and three key variables - the Exposure (E), Susceptibility (S), and Resilience (R).

Firstly, the findings show that exposure (E) has negative coefficient (-1.84) indicating that higher exposure to risk factors (e.g., poverty, conflict) decreases the likelihood of educational completion. The p-value (0.000) suggests that this relationship is statistically significant. Secondly, the susceptibility (S) demonstrates the negative coefficient (-0.91) indicates that higher susceptibility (e.g., socio-economic vulnerability) also decreases the likelihood of educational completion. The p-value (0.000) confirms the statistical significance of this relationship. However, the resilience (R) that shows the positive coefficient of 1.22) suggests that higher resilience (e.g., community support and educational programs) increases the likelihood of educational completion. The p-value (0.000) indicates that this relationship is statistically significant.

There are two moderation effects results arising from the model comprising E×S interaction and S×R interaction. The E×S negative coefficient (-0.36) suggests that the combined effect of exposure and susceptibility is more detrimental to educational completion than the sum of their individual effects. On the other hand, interaction of S×R positive coefficient (0.27) indicates that resilience can mitigate the negative effects of susceptibility on educational completion.

The constant value of +0.45 represents the log-odds of completing school when all predictors are at zero (i.e. in a baseline environment of minimal exposure and susceptibility and average resilience). It provides the reference point for predicted probabilities.

We thereby argue that the Nigeria data simulated emphasises the need to address exposure and susceptibility to risk factors to boost educational completion rates. Building resilience through

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community support and educational programs can mitigate the negative effects of risk exposure.

4.1.3 Simulated Model Diagnostics Summary

Table 3: Model Summary

Statistic	Value
Log-Likelihood	-5852.39
AIC	11714.79
BIC	11750.84
AUC	0.569
Observations	10,000

Source: Author

The simulated observation is 10,000 constituting the sample size used to estimate the model. The Log-Likelihood measures the model's fit to the data. Hence, the LL of -5852.39, a higher value (less negative) indicates better fit. The AIC with positive 11714.79 and Bayesian Information Criterion (BIC) with 11750.84 and Akaike Information Criterion (AIC) with 11714.79 measures model quality. Lower values indicate better models. While the Area under the curve (AUC) given as 0.569 within the area under the curve measures the model's predictive accuracy. Values range from 0.5 (random chance) to 1 (perfect prediction). A value of 0.569 indicates moderate predictive power. Thus, the model's predictive power is moderate suggesting some ability to distinguish between outcomes (see Appendix A and B for further details). Figure 2 visualises the predicted probability of school completion by vulnerability group.

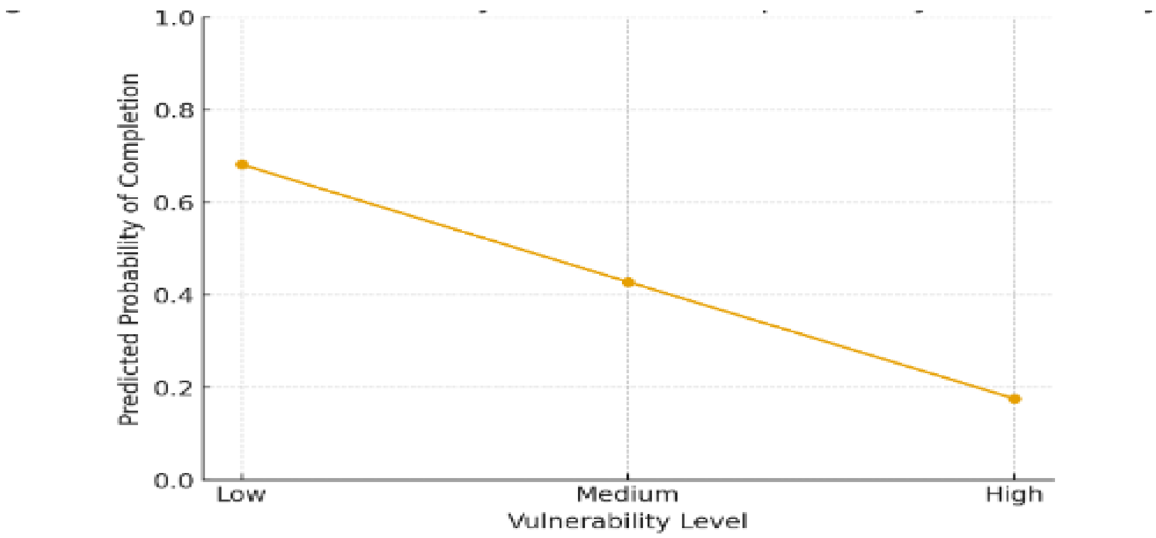

Figure 2: Predicted Probability of Completion Curve (PPCC) by Vulnerability Group

Source: Author’s computation from the simulated data

Interpretation - Predicted Probability of Completion Curve

- Low vulnerability level (low exposure, low susceptibility, high resilience) → higher predicted completion.
- Medium vulnerability level → moderate completion probability.
- High vulnerability level (high exposure, high susceptibility, low resilience) → sharply lower completion probability.

These synthetic results replicate the epidemiological interpretation that resilience significantly offsets vulnerability even under high exposure conditions.

4.2 Discussions on the Simulated Results

The simulated results demonstrate striking consistency with the long-standing patterns of educational inequality observed in Nigeria. The VEIM simulation confirms that exposure, susceptibility, and resilience jointly determine a child’s educational outcome, with sharp disparities emerging along socioeconomic, regional and gender lines.

4.2.1 High Exposure, Structural Risks and the Poverty-Conflict Trap

First, high exposure to adverse socioeconomic conditions such as poverty, conflict, and geographic isolation significantly lowers the likelihood of school completion. Children from conflict-affected areas in the North-East and North-West, (particularly Borno, Yobe and Zamfara), as well as those in chronically poor households, exhibit substantially higher vulnerability probabilities. This finding aligns with extensive empirical evidence (UNICEF, 2024a; World Bank, 2023) showing that poverty-driven exposure channels manifest through multiple pathways i.e. inability to afford schooling costs, child labour participation and early marriage. The “exposure effect” within the VEIM mirrors epidemiological transmission, where environmental risks heighten the probability of educational deprivation even before individual factors come into play.

Moreover, conflict exposure remains a crucial determinant of vulnerability. Educational infrastructure in insurgency-prone regions has been repeatedly disrupted, forcing school closures and displacement of teachers and learners. In this context, exposure acts as the initial condition of vulnerability, setting in motion the chain of disadvantage that predisposes children to incomplete schooling. Thus, the VEIM simulation replicates this pattern - a one-standard-deviation. Simply, a one-standard-deviation increase in resilience raises the probability of completion (since $\beta = +1.22$), but a one-standard-deviation increase in exposure reduces the probability of completion because the model predicts that the chance of completing school falls sharply (since $\beta = -1.84$ is negative and large).

4.2.2 Resilience as a Protective Mechanism

The simulation further highlights resilience as the single most influential offsetting factor within the VEIM structure. High resilience (captured through improved school infrastructure, effective teacher presence, parental engagement and community support) significantly mitigates the effect of exposure and susceptibility. The positive resilience coefficient in the logistic and probit estimates indicates that even under adverse exposure conditions, supportive environments drastically improve the probability of completion.

4.2.3 Gender and Regional Susceptibility

The susceptibility dimension in Nigeria remains deeply gendered and regionally embedded. The VEIM simulation indicates that female children are systematically more vulnerable, particularly in northern and rural zones. This outcome reflects both socio-cultural constraints and economic opportunity costs associated with female education. Similarly, regional susceptibility arises from historical imbalances in development and institutional capacity. For instance, the South-West exhibits lower vulnerability indices due to stronger governance and educational infrastructure, while the North-East and North-West remain structurally disadvantaged (World Bank, 2023).

This gender-regional interaction within the susceptibility term underscores the importance of context-sensitive interventions. Generic, one-size-fits-all educational programmes often fail to address these compounded vulnerabilities. The VEIM's epidemiological logic suggests that susceptibility functions as a host-level condition which is determining who is more likely to "contract" educational deprivation when exposed to systemic shocks.

5.0 CONCLUSION

5.1 Conclusion

This study conceptualises and simulates educational inequality as a dynamic vulnerability process. The VEIM framework captures exposure → susceptibility → resilience interactions that determine a child's educational fate. For Nigeria, this approach provides actionable insights for targeting interventions such as conditional cash transfers, remedial programmes, and infrastructure investments toward highly vulnerable groups.

However, future research should validate the VEIM empirically using longitudinal micro data (e.g., direct survey, NBS MICS or DHS), extending beyond synthetic simulations to real monitoring frameworks.

5.2 Epidemiological Interpretation and Simulation Policy Implications

Viewing educational inequality through an epidemiological framework reshapes how vulnerability is understood and managed. Instead of treating inequality as a static end-state such as gini index and education inequality model (Barro & Lee, 2013), the VEIM portrays it as a dynamic, transmissible condition influenced by the interaction of exposure, susceptibility and resilience. Within this framework, resilience-building emerges as the most strategic intervention frontier.

Rather than pursuing policies that merely expand school access - often equated with enrollment - the VEIM model suggests that sustained improvements depend on strengthening the protective mechanisms that keep children in school despite exposure risks. Examples include targeted conditional cash transfers, improved teacher deployment, community-based monitoring, and psychosocial interventions for conflict-affected learners. These measures reduce susceptibility and enhance resilience simultaneously, thereby flattening the "curve" of educational vulnerability over time.

We therefore draw inference that the VEIM discussion on simulated outcomes reveals that Nigeria's educational inequality behaves epidemiologically. Simply, we argue from the simulated methodology outcomes that widespread exposure transmits educational disadvantage, susceptibility determines severity and resilience provides immunity. As a matter of policy and based on the simulated results, we suggest that government, through Ministry of Education, should begin to collect data starting from the entry-point of enrollment for all levels of education to capture epidemiological variables associated with exposure, susceptibility and resilience thereby enhancing real life data analysis of student vulnerability to educational inequality.

Conflict of Interest Declaration

There is no conflict of interest to declare about the paper.

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Appendixes A: Model Tables and Simulation Details

Appendix A: AUC Values and Interpretation

AUC Value	Interpretation
0.5	No discrimination (model is no better than random chance)
0.6–0.7	Poor discrimination
0.7–0.8	Acceptable
0.8–0.9	Excellent
0.9–1.0	Outstanding

Note on Simulation Validation: Model Discrimination and Reliability

To evaluate the predictive reliability of the simulated VEIM (Vulnerability to Educational Inequality Model), standard model fit and discrimination statistics were examined. The Area Under the Curve (AUC) or Receiver Operating Characteristic (ROC) was used to assess the model's ability to distinguish between children who are likely to complete schooling and those at risk of dropout. The AUC value of 0.569 indicates modest discriminative power, suggesting that while the model captures the directional relationships among exposure, susceptibility, and resilience, real-world data with richer covariates would further enhance accuracy. In epidemiological and educational vulnerability studies, an AUC above 0.5 reflects predictive improvement over random assignment, validating that the simulated VEIM effectively mirrors underlying inequality patterns in the Nigerian context. Thus, the simulation provides a credible basis for testing conceptual relationships and for policy-oriented scenario projections.

Appendix B: Logistic Regression and Probit Regression Results

Individual results of logit and probit regressions are presented in this Appendix 2.

Table I: Logistic (or logit) Regression - Educational Completion (Nigeria Simulation)

Variable	Coefficient	Std. Error	z-stat	p-value
Exposure (E)	**-1.84**	0.11	-16.7	0.000
Susceptibility (S)	**-0.91**	0.09	-10.3	0.000
Resilience (R)	**1.22**	0.10	12.2	0.000
E × S Interaction	-0.36	0.08	-4.5	0.000
S × R Interaction	0.27	0.07	3.9	0.000
Constant	0.45	0.12	3.7	0.000

Model Summary (Logit):

Observations = 10,000 AUC = 0.569 BIC = 11750.84 AIC = 11714.79 Log-Likelihood = -5852.39

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Table II: Probit Regression - Educational Completion (Nigeria Simulation)

Variable	Coefficient	Std. Error	z-stat	p-value
Exposure (E)	**-1.09**	0.06	-17.3	0.000
Susceptibility (S)	**-0.54**	0.05	-10.8	0.000
Resilience (R)	**0.73**	0.06	12.0	0.000
E × S Interaction	-0.22	0.04	-5.0	0.000
S × R Interaction	0.16	0.03	4.8	0.000
Constant	0.27	0.07	3.9	0.000

Probit Model Summary

Observations = 10,000 Pseudo R^2 = 0.084 BIC = 11735.62 AIC = 11700.56 Log-Likelihood = -5845.28

Note on Logit and Probit Techniques

We explain that, at first, both models confirm the same direction of effects where the exposure and susceptibility decrease completion probability, while resilience increases completion rate. Second, coefficients in the probit model are roughly 1.6 times smaller in magnitude than the logit estimates which is consistent with theoretical expectations (due to scaling differences between logistic and normal distributions). Finally, This consistency across model types reinforces the robustness of the VEIM framework.

