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Substance abuse and Human Capital Development in Nigeria: An Endogenous Growth Model

IJIE, Ikhayere Jossy (PhD)
Deputy Commander of Narcotics (Rtd)
NDLEA, Lagos State
ijieikhayere65@yahoo.com (0703-1644-353)

Abstract

Substance abuse has a detrimental impact on human capital development by eroding the physical, mental and educational foundation of the workforce. This study aims to interrogate the long-run relationship between Human Capital Development (HCD) and Substance Abuse Prevalence (SAP) in Nigeria economy. The data for substance abuse prevalence are extrapolated from the National Drug Law Enforcement Agency (NDLEA) Annual Report from 1993 to 2025. Human Capital Development is indexed by secondary school enrolment for the same period. Results from the Vector Auto Regressive Distributed Lag (VAR) techniques show that SAP has a significant Negative Impact on Human Capital Development in the short run, while the variable Capital Expenditure (CE) on substance abuse prevention shows a negative but significant impact on HCD. The results of the long-run analysis also show that SAP has a significant negative impact on HCD at the 1% level. Contrary to our a priori expectation, Capital Expenditure (CE) on substance abuse prevention has a negative but significant effect on HCD at the 5% level. Based on these findings, the study recommended that a massive preventive substance abuse education and enlightenment programme that emphasises a healthy lifestyle should be embarked upon in our educational institutions.

Keywords: Capital Expenditure, Human Capital Development, Substance Abuse Prevention

Jel code: H54, J24, O15, I18

1. INTRODUCTION

Human Capital is the stock of knowledge or unique features a worker possesses (either innate or acquired) that contribute to his/her potential productivity. It is not only the years of schooling or its quality, and previous training that are the important determinants of individual human capital, but also other non-cognitive attributes such as personal creativity, initiative, self-esteem, attitudes towards work and personal abilities in relation to people (OECD, 2022). Thus, Economists treat human capital as the economic value of a worker's experience, skills and

health. It represents the intangible assets an individual possesses – such as education, technical knowledge and problem-solving abilities that increase their productivity and drive economic growth (Germana, 2008). In this sense, human capital is treated as an intangible factor of production.

This study is most interested in utilising human capital theory at a much more macro level to understand how trends in substance abuse prevalence can affect Human Capital Stock. Substance abuse shock can have devastating effects on the national economy through the channel of human capital depletion, loss of lives, livelihood, nutrition, the interruption of essential health care and education (Ijie, 2019). Such shocks will likely reverberate in individuals' life spans, limiting their productivity. The erosion of health, knowledge, skills, school dropouts, and opportunities due to the pandemic and substance abuse prevalence could undermine economic gains and advancement both in the present and in the future (Ijie et al., 2020). The quality of human capital has become of special importance to Economists as a key component of the health and wealth of an individual. Researchers have used several ways, such as educational level, job skills, school enrolment, years of schooling, return to education, human capital index, health, public expenditure on education, and cognitive tests as standardised proxies for human capital (See Elektronik (2002), Schultz (2010), and Yohana (2023)). The most appropriate way used will depend on the specific context, data availability and purpose of analysis.

There are global efforts by the World Bank to accelerate more and better investment in people for greater quality and economic growth. According to World Bank HCI (2020), the Human Capital Index data shows that Singapore ranks highest with a score of 0.88, followed by Hong Kong at 0.81 and Japan at 0.81.

Sub-Saharan Africa is still the poorest region and lags behind other regions in key indicators such as learning, out-of-school children, adult survival rates and stunting proportion of children. Despite significant potential, Nigeria ranks low globally, placing itself 168th out of 174 Countries in the human capital development index (Rukaiya, 2015).

2.0 LITERATURE REVIEW

2.1 Conceptual Review.

The term 'Substance' is employed to refer to a certain range of illicit drugs which include narcotics of various types, marijuana and hashish, cocaine, methaqualone, inhalants, and illicitly used prescription drugs including a wide range of tranquillisers, barbiturates, amphetamines and similar compounds. Its

prevalence refers to the proportion of a specific population that engages in the harmful or hazardous use of a psychoactive substance over a defined period of time.

2.2 Theoretical Framework

The international guidelines for studies involving substance abuse and HIV/AIDS are largely categorised under Cost –of –Illness (COI) and socio–economic impact studies Eric et al., 2003). COI studies, like most forms of economic analysis, require a more extensive and demanding economic framework, such as general equilibrium modelling. For instance, Cuddington and Hemcock (1995) used a Neoclassical One-sector, Two-factor growth model in Tanzania and Malawi upon HIV/AIDS prevalence. Cuddington categorised the effects of a disease such as substance abuse/HIV AIDS on economic growth into those associated with rising morbidity and those associated with rising mortality rates. According to them, the rise in morbidity will have two immediate effects – a negative labour productivity effect and a positive health care expenditure effect. These effects, in turn, alter savings behaviour as well as investment in education. The negative labour productivity effect will arise because the sick or diminished health status of affected workers will bring less productivity than a healthy, happy worker. On the other hand, the positive health care expenditure refers to an increase by households and public or private health care systems to assist substance abusers and their families in coping with their deteriorating health condition and resource costs on abuse prevention and law enforcement activities.

Romer's (1986) endogenous growth model assumes that knowledge is a capital good with an increasing marginal product. In endogenous growth theory, human capital is the main focus and substance abuse operates as a factor that endogenously reduces the stock of human capital, thereby impeding technological change and economic growth. In this perspective, substance abuse is not an external (Exogenous) shock but a detrimental factor generated within the economic system that directly reduces the necessary investment in human capital. Romer's theory of endogenous technological change ties the development of new ideas of economic growth to the number of people working in the knowledge sector, which could be enhanced by training, skills acquisition, education and good health. Though Romer's foundational theory (1986) did not explicitly model substance abuse, it emphasised that human capital accumulation is voluntary and relies on time allocation, making it highly sensitive to internal social, health and policy factors. Substance abuse can be viewed as an endogenous choice or

consequence that reduces the time and efficiency dedicated to skill acquisition and the reversal of knowledge and innovation, and thus decreases the overall output of the economy. Substance abuse shocks are endogenous through the mechanism of human capital depletion by eroding skills and abilities, reducing the effective labour force and the quality of human capital.

2.3 Empirical Review

Far-reaching econometric models have also been developed and employed in estimating the impact of substance abuse on macroeconomic outcomes such as human capital, educational attainment, productivity, employment status, poverty, labour supply and wages (Brettany et al., 2020; Bamgbade et al., 2018; Ijie, 2018; Sarki et al., 2011). Giorgio et al. (2012) carried out a study on the impact of alcohol, tobacco, marijuana and cocaine use on educational attainment. They estimated a simple Ordinary Least Squares (OLS) and Difference-In-Differences (DID) approach model to estimate the endogeneity bias. They used the Double Difference and Triple Difference models that rely on the observation of agents' educational outcomes before and after the treatment, defined as consumption of addictive substances. The results obtained from their most reliable specification bring new evidence supporting the lack of a causal relationship between alcohol and tobacco consumption and educational performance in the short run. However, they found a significant negative effect when considering a heavy measure of cocaine and marijuana use. David et al. (2002), using a data of 21years longitudinal study of the health development and adjustment of a birth cohort of 1,256 New Zealand children, employed method of fixed effect regression model to examine the association between frequency of cannabis use and psycho-social outcomes in adolescence/young adulthood. The study concludes that there is an association between cannabis use, particularly regular or heavy use, were associated with increase rates of a range of adjustment problems in adolescence. The study further reports a strong association between other illicit drug use and crime, depression and suicidal behaviour, with these adverse effects being most evident for school-aged regular users.

It is believed that preferences towards drugs may differ over geographic areas. Many studies use geographic locations in some ways as an independent control variable. Some use geographic location to mean the difference between urban and rural areas. Desimone and Farrelly (2003) cautioned against interpreting results when geographic fixed effects are not included because studies have shown that the magnitude of price responsiveness is overestimated when fixed effects are not included. Kaestner (1994) used two-equation models

to estimate the effect of the drug. Using the 1984 and 1988 waves of the National Longitudinal Survey of Youth, he used a two-equation model to estimate the effect of illicit drug use on wages. The cross-sectional results, which are generally consistent with the findings of previous research, suggest that illicit drug use has a large positive effect on wages. The longitudinal estimates, which control for unobserved heterogeneity in the sample, are mixed among men; the estimated wage effects of both Marijuana and Cocaine use are negative. Among women, the effect of Cocaine use remains large and positive. Kaestner (1996), using a reduced form regression model, provided a descriptive and multivariate analysis of the relationship between drug use and poverty for two national samples of young adults. One sample was obtained from the National Household Survey on Drug Abuse (NHSDA). The other was from the National Longitudinal Survey of Youth (NLSY). The result of the analysis indicates that for both samples, drug use is associated with greater poverty and that drug use and poverty are related because drug use affect the determinations of poverty, education, human capital, investment, marriages and fertility and he concluded that personal specific factors such as ability, preferences and family background affect drug use as well as educational achievements, skill accumulation, marriage and fertility.

Wura et al. (2023), using a cross-sectional survey of non-institutionalised individuals, examined the nexus between substance abuse and four domains of human capital development among Black youth, using the nationally representative annual cross-sectional data for black adolescents (12- 17 years). They analysed the National Survey on Drug Use and Health (2015-2019) to determine the influence of human capital factors (cognitive development, social and emotional development, physical health and mental health) on exclusive and concurrent Tobacco and Cannabis use (TCU). The results indicate that investment in cognitive development decreased the odds of tobacco and Cannabis use. Similarly, investment in social and emotional development reduced the odds of Tobacco and Cannabis use. Good physical health reduced the odds of cannabis and tobacco use. A major depressive episode increased the likelihood of cannabis use. The study concluded that investment in cognitive, social and emotional aspects of human capital development and physical health among Black Youth is protective against substance use.

Pierre and Michael (2008) interrogated drug use and employment status in metropolitan Miami. They collected data from 1996 – 1997 in low-income and high-income neighbourhoods in

Miami to analyse the effect of chronic drug use on employment. Given the significant gender differences in substance use patterns and labour market behaviour, they designed separate models for males and females. The analysis estimated univariate probit models of employment and a bivariate probit model that allows for possible correlation among missing or unobserved determinants of drug use and employment. The key finding was that regardless of gender and specification, chronic drug use significantly reduced the probability of being employed. The study provides new evidence on the labour market effect of drug addiction.

Kenneth et al. (2018), using Instrumental Variable and correlational analysis designs implemented in large population –based Swedish samples, investigated the association between poor academic achievement and risk of drug abuse influenced by causal processes. Their study revealed that low academic achievement in childhood and adolescence is associated with increased substance use. These results provide empirical support for efforts to improve academic achievement as a means to reduce the risk of drug abuse. Ijie and Babalola (2020), using time series data of substance abuse prevalence (1993-2017) from the National Drug Law Enforcement Agency (NDLEA), employed Auto Regressive Distributed Lag models (ARDL) to investigate the nexus between labour force, economic growth and substance abuse prevalence. Their findings revealed that substance abuse prevalence has a long-run negative impact on the labour force and is significant in the short run. The study also revealed that rehabilitated substance abuse addicts have a short-run positive impact on the labour force in Nigeria economy. Musa et al. (2022), using simple survey research with a sample size of 398 questionnaires in some selected secondary schools in Bauchi State of Nigeria, analysed the effect of drug abuse on human capital development. Their study revealed several impacts of substance abuse on human capital, especially in the areas of school dropouts and brain disorders.

Torkel et al. (2020) used structured interviews with 1970 young people enrolled at outpatient clinics in 11 Swedish cities to investigate mental health problems among the young people. The data were analysed through frequency and average calculations, Chi-Square tests and multivariate logistic regression analysis. The results of their findings indicate that a relatively large percentage of the total group (34-54%) reported problems such as concentration difficulties, anxiety and depression. Epkan et al. (2015), while investigating the relationship between drug abuse and psychological behaviour among adolescents in Senior Secondary

Schools in Cross River State, Nigeria, employed Pearson Product Moment Correlation analysis to determine the relationship between cocaine sniffing and students' psychological behaviour. He found that cocaine and heroin sniffing has a significant relationship with students' psychological behaviours. Amos (2024), using a sample of 400 students from selected tertiary institutions in Lagos, Nigeria, employed a descriptive survey to examine the effects of drug abuse on students' academic performance. A structured questionnaire with a five (5) point Likert scale was used to analyse the data. The result indicates that 78.9% of the total respondents attributed loss of memory to drug abuse, while 86.1% and 77.8% favoured absenteeism/ declining grades, respectively, to drug abuse. Substance abuse can cause severe and irreversible depletion of human capital. The skills, knowledge, experience and health that individuals invest in to remain productive members of society will be eroded. There is no doubt that the investment in higher education is lost when trained individuals leave jobs and do not return to them due to the effects of substance abuse.

3.0 METHODOLOGY

3.1 Model Specification

Methodology is one of the main sources of difference in results. The methods followed in the conduct of a study form the basic determinant of the difference in results among related studies in a particular field. To capture the impact of Substance Abuse Prevalence (SAP) on Human Capital Development (HCD) - proxied by Secondary school enrollment, the study made HCD the dependent variable and placed SAP as the focus variable. A controlled variable, Government Capital (CE) expenditure on substance abuse prevention, which could have an impact on human capital, was introduced. Adapting the model of Cuddington (1995), this study specifies the model as

$$HCD = f(SAP, CE) \text{ ....(1)}$$

Empirically, the regression equation for estimating the impact of substance abuse prevalence on human capital is thus;

$$HCD = \alpha 0 + \alpha 1 SAP + \alpha 2 CE \text{ .....(2)}$$

This is further specified as,

$$HCD = \alpha 0 + \alpha 1SAP + \alpha 2CE + \varepsilon \quad \ldots\ldots\ldots(3)$$

To equalise the variables in the model, the natural log of CE was taken to give equation 4 as

$$HCD = \alpha 0 + \alpha 1SAP + \alpha 2lCE + \varepsilon \quad \ldots\ldots\ldots\ldots(4)$$

Where

HCD~ Human Capital Development proxied by Secondary school enrollment

SAP~ Substance Abuse Prevalence

lCE~The natural log of Capital Expenditure

$\alpha 0$~ Constant

$\alpha 1 - \alpha 2\ represent$ the marginal effects of the independent variables

$\varepsilon -$ error term

a priori **expectation**

When SAP is low, the HCD becomes high since more of the workforce will be active at work. Therefore, the impact is expected to be inverse, as

$\frac{\partial HCD}{\partial SAP} = \alpha 1 < 0$

The Capital Expenditure (CE) is expected to have a positive impact on HCD. Because when the economy spends more on capital, such as the construction of more rehabilitation centres, building of more schools and hospitals, among others, the human capital development will improve.

i.e. $\frac{\partial HCD}{\partial lCE} = \alpha 2 > 0$

3.2 Measurement of variables

Human Capital Development (HCD): This is indexed by the secondary school enrollment, which covers enrollment from Junior Secondary School 1 to Senior Secondary School 3.

Substance Abuse Prevalence: This is simply the proportion of the Nigerian population that actively misuses and is dependent on psychoactive substances. It measures the prevalence of

drug abuse in the Nigerian economy at the time. Capital Expenditure (CE): Capital Expenditure by the government on substance abuse prevention is included in the model because increases in healthcare and substance abuse preventive expenditure are some of the macroeconomic consequences of substance abuse.

3.3 Estimation Technique

The study used the relevant pre-estimation techniques such as Descriptive Statistics, Correlation Matrix and Unit root tests. The main estimation technique was the Vector Auto-Regressive Distributed Lags (VAR) technique, while the post-estimation techniques were the tests for Heteroscedasticity and serial correlation.

3.4 Source of Data

Human Capital Development was indexed by Secondary school enrolment. Data for 1993-2025. The data were obtained from the World Development Indicators (2023). The data for substance abuse prevalence were extrapolated from the NDLEA annual report from 1993 to 2025. The data for capital expenditure on substance abuse prevention were obtained from the Federal Ministry of Finance. Results of Analysis

4.0 Descriptive Statistics

The descriptive statistics are presented in Table 1 with 31 observations. It shows that Human Capital Development (HCD) has the highest mean of 36.05501, followed by Capital Expenditure (LCE) and Substance Abuse Prevalence (SAP) with a mean of 20.28786 and 0.006753, respectively. The distribution also shows that variables HCD and SAP show a kurtosis less than 3 (Platykurtic or platykurtotic distribution), meaning that the distribution is flat relative to the normal, while LCE shows that the distribution is peaked (Leptokurtic distribution). The Jarque-Bera test shows the normal distribution of the data. The probability as reported is the probability that the Jarque-Bera statistic exceeds, in absolute terms, the observed value under the null hypothesis. The probability shows that LCE is not normally distributed, as it is less than 0.05, while HCD and SAP are normally distributed, as their probabilities are more than 0.05.

Table 1: Results of Descriptive Statistics

	HCD	SAP	LCE
Mean	36.05501	0.006753	20.28786
Median	35.11211	0.008162	18.89068
Maximum	54.88000	0.011461	28.42087
Minimum	19.66000	0.000286	15.90865
Std. Dev.	10.12028	0.003250	3.702614
Skewness	0.109723	-0.446565	1.463281
Kurtosis	1.738895	1.833003	3.599287
Jarque-Bera	2.116450	2.789435	11.52672
Probability	0.347071	0.247903	0.003141
Sum	1117.705	0.209354	628.9237
Sum Sq. Dev.	3072.600	0.000317	411.2806
Observations	31	31	31

Source: Author's Computation, 2025

The standard deviation shows the rate of disparity from the mean. Here, the volatility of the variable LCE has been reduced because its logarithm was taken, except that the rate of volatility of other variables is not too far from their respective mean.

Skewness is a measure of the asymmetry of the distribution of the series around its mean. The positivity of all the Skewness figures of the variables, except variable SAP, simply implies that the distribution has a long right tail.

4.1 Correlation Matrix

Table 2 shows the correlation matrix of the relationship between the variables. The two independent variables, SAP and LCE, all show a positive relationship with HCD. All the variables show a strong positive relationship. The importance of this correlation matrix is to test for the presence of multicollinearity in the model. From the results in Table 2, none of the variables has any presence of multicollinearity since all the independent variables have coefficients less than a threshold of 0.8.

Table 2: Results of Correlation Matrix

	HCD	**SAP**	**LCE**
HCD	1		
SAP	0.7511	1	
LCE	0.6004	0.4655	1

Source: Author's Computation, 2025

4.2 Test of Stationarity.

Since the dataset was a time series and is more often associated with the presence of a trend, the study carried out a unit root test to diagnose and remove the trend in the series. Table 3 presents this result for two test statistics: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP).

Table 3: Results of the Unit Root Test

ADF @Level		**ADF @ 1st Diff**		**PP @ Level**		**PP @ 1st Diff**		**Remark**
Series	Prob.	Series	Prob.	Series	Prob.	Series	Prob.	
HCD	0.2921	HCD	0.3797	D(HCD)	0.00	D(HCD)	0.0001	I(1)
SAP	0.4181	SAP	0.3669	D(SAP)	0.00	D(SAP)	0.00	I(1)
LCE	0.4829	LCE	0.5285	D(LCE)	0.00	D(LCE)	0.00	I(1)

Source: Author's Computation, 2025

The two test statistics used are Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP). It was discovered that variables HCD, SAP and LCE are stationary at 1st difference from the two test statistics used in Table 3. Hence, the result is an indication that the VAR technique should be more appropriate for the analysis.

4.3 Results of the Lag Selection Order

Table 4 presents the results of the lag selection order for the vector autoregressive model employed in this study. From the results, it shows that, out of the five test criteria used, four (LR, FPE, AIC and HQ) chose lag 4, while SC alone selected lag 1. Therefore, the study concludes that lag 4 would be employed in the analysis.

Table 4: Lag Selection Order

Lag	LogL	LR	FPE	AIC	SC	HQ
0	58.38893	NA	3.32e-06	-4.102884	-3.958902	-4.060070
1	101.1536	72.85827	2.74e-07	-6.603968	-6.028040*	-6.432714
2	109.1849	11.89823	3.03e-07	-6.532213	-5.524340	-6.232519
3	114.1443	6.245261	4.40e-07	-6.232914	-4.793096	-5.804781
4	135.8778	22.53837*	1.99e-07*	-7.176131*	-5.304366	-6.619557*

Source: Author's Computation, 2025

To examine whether the model can influence Human Capital development (HCD) in the long run, the Johansen Cointegration technique was employed using the Trace and Maximum Eigenvalue statistics to test for the existence of any long-run connection. Table 5 presents the results of the test, which is meant to test for the presence of long-run association in the model.

Table 5a: Johansen Cointegration Test (Trace)

Hypothesized		Trace	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.500479	30.76642	29.79707	0.0386
At most 1	0.235882	12.02555	15.49471	0.1557
At most 2 *	0.161682	4.761658	3.841466	0.0291

Source: Author's Computation, 2025

From the results in Table 5a, the Trace test indicates that there exist two cointegrating equations in the model since their probability values (0.0386 and 0.0291) are less than 0.05.

However, using the Maximum Eigenvalue test in Table 5b, it suggests only one cointegrating equation, which is enough to run the long-run analysis. Therefore, the null hypothesis is rejected and hence the acceptance of the fact that there is a long-run association in the model.

Table 5b: Johansen Cointegration Test (Maximum Eigenvalue)

Hypothesized		Max-Eigen	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None	0.500479	18.74088	21.13162	0.1046
At most 1	0.235882	7.263887	14.26460	0.4584
At most 2 *	0.161682	4.761658	3.841466	0.0291

Source: Author's Computation, 2025

This result informed the study to employ the vector error correction mechanism (VECM), which spreads out the short-run, long-run, and the speed of adjustment coefficient.

4.4 Results of Short Run and ECM Coefficient

Table 6 presents the results of the VECM model in the short run and the error correction. From the results, it is evident that substance abuse prevalence (SAP) has a significant negative impact on Human Capital Development (HCD) in the short-run, as its probability values (0.0172 and 0.0091) are less than the 5% threshold at lag 1 and 3, while the control variable CE shows a negative but insignificant impact on HCD with the probability values mostly more than 5%.

Table 6: Short Run and ECM Coefficient Analysis

Error Correction:	D(HCD)	Standard Error	t-Statistics	Probability
ECM(-1)	-1.668263	0.44290	-3.76669	0.0013
D(HCD(-1))	0.920866	0.36907	2.49510	0.0141
D(HCD(-2))	0.687647	0.32476	2.11739	0.0279
D(HCD(-3))	1.098835	0.38183	2.87782	0.0069
D(HCD(-4))	-0.166748	0.43431	-0.38394	0.35421
D(SAP(-1))	-3227.231	1352.52	-2.38609	0.0172
D(SAP(-2))	-1000.859	1370.13	-0.73048	0.2397
D(SAP(-3))	-3125.482	1144.02	-2.73202	0.0091
D(SAP(-4))	-1855.119	1066.77	-1.73901	0.0538
D(LCE(-1))	-0.643747	0.92505	-0.69591	0.2501
D(LCE(-2))	-0.608080	0.83578	-0.72756	0.2406
D(LCE(-3))	-2.309430	0.81237	-2.84284	0.0074
D(LCE(-4))	-0.773174	0.97000	-0.79709	0.2205
C	3.241541	1.51629	2.13781	0.0269
R-squared	0.808422			
Adj. R-squared	0.600879			
F-statistic	3.895199			

Source: Author's Computation, 2025

The SAP result is in line with the study's *a priori* expectation, which shows a negative and significant impact on HCD. Also, in Table 6, the ECM (-1) coefficient shows the correct negative sign (-1.6682), meaning that 166.8% of the disequilibrium in the model is corrected annually. The result also indicates that the error correction model (ECM) is significant at the 1% level. The ECM measures the speed of adjustment from the short run to the long run. The

speed is said to be very high. The coefficient of determination (R^2) indicates that 80.8% of the variation in HCD is explained by the model, which is a viable result. However, the R^2 Adjusted (60.09%) indicate a significant redundancy of some variables in the model in the short run.

4.5 Long-Run Analysis of the ARDL Model

Table 7 shows the long-run effects of SAP, among others, on HCD. In the long run, SAP has a significant negative impact on HCD at the 1% level, as shown by its p-value (0.00001). In the same vein, CE has a negative but insignificant (*p-value*: 0.1270) effect on HCD at the 5% level.

Table 7: Analysis of the Long-Run Effect

Variable	Coefficient	Standard Error	t-Statistics	Probability
HCD(-1)	1.000000			
SAP(-1)	-2569.778	281.237	-9.13739	0.00001
LCE(-1)	-0.653540	0.54516	-1.19880	0.1270
C	-4.946954			

Source: Author's Computation, 2025

4.6 Results of Forecasted Variance Decomposition

Table 8 showcases the results of the forecasted variance decomposition analysis, which explains the composition of the shocks to HCD within a period of 10 years. In Table 8, period 1 shows that changes in HCD are based on self-innovation (100.00), while other variables are not contributing anything. From period 3 through 10, the contribution of SAP is quite significant.

Table 8: Results of Forecasted Variance Decomposition

Period	S.E.	HCD	SAP	LCE
1	4.781970	100.0000	0.000000	0.000000
2	5.297268	92.66636	5.981227	1.352411
3	6.746551	58.04206	40.61293	1.345007
4	7.287320	50.27763	37.09397	12.62841
5	7.848721	52.31335	36.70315	10.98351
6	8.954404	40.26472	44.07844	15.65684
7	9.785080	40.51287	44.20412	15.28301
8	10.39802	36.22518	50.18962	13.58519
9	10.56107	36.81552	49.24092	13.94356
10	10.86221	38.34442	48.30330	13.35228

Source: Author's Computation, 2025

4.6 Results of Diagnostic Test

More so, the Breusch-Godfrey test employing the LM test indicates that the probability value (0.587) of the F-statistic (0.3819) is greater than 5%, meaning that we accept that there is no

serial correlation and heteroscedasticity in the model.

Table 9: Results of Diagnostic Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	1.766528	Prob. F(5,24)	0.51580
Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	0.381942	Prob. F(2,22)	0.5870

Source: Author's Computation, 2025

5.0 Discussion of Results and Implications of Findings

The Study investigated the impact of substance use on Human Capital Development in Nigeria. While HDC stood as the response variable, Substance Abuse Prevalence was used as the focus variable and government Capital Expenditure on Substance Abuse Prevalence was controlled for. The main objective of the study was to determine the effect of substance abuse prevalence (SAP) on Human Capital Development.

The correlation matrix shows a positive relationship between the two independent variables, SAP/LCE and Human Capital Development. The importance of this correlation matrix is to detect multicollinearity in the model and prepare for further analysis. None of the variables has any presence of multicollinearity in the model since both coefficients of SAP/LCE are less than a threshold of 0.8. Since the data set was time series data and such is often more associated with the presence of trend, the study carried out a unit root test to diagnose and remove the trend, using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP). It was discovered that the variables HCD, SAP and LCE are stationary at the 1st difference. Hence, the result is an indication that VAR techniques should be more appropriate for the analysis to check whether the model can influence Human Capital Development in the long run. The Johansen Co-integration technique was employed using the trace and maximum eigenvalue statistics. The Trace test indicates that there exist two co-integrating equations in the model since their probability values (0.0386 & 0.0291) are less than 0.05. Hence, the rejection of the Null hypothesis and acceptance of the fact that there exists a long-run association in the model.

The main objective of the investigation was to determine the impact of the model on Human Capital Development. From the result of the Vector Error Correction Model (VECM) containing the short run and Error Correction, it is evident that SAP has a significant negative

impact on Human Capital Development in the short run, as its probability value (0.0172) is less than the 5% threshold. This result aligns with the a priori expectation and is also consistent with the study carried out by Musa et al. (2020) and Epkan et al. (2015), which revealed that substance abuse prevalence has a negative effect on Human Capital Development in Nigeria, especially in areas of school dropouts, mental health and academic performance of students.

5.2 Conclusion and Recommendations

The study examined the impact of substance abuse prevalence on Human Capital Development in Nigeria. The results show that substance abuse is endogenous and has a significant negative impact on human capital both in the short and long run. Contrary to our a priori expectation, the result also revealed that capital expenditure by the government on substance abuse prevention has a negative but significant impact on human capital development.

Based on the findings of this study, the following recommendations are made:

1. A massive preventive drug abuse education and enlightenment programme that emphasises a healthy lifestyle should be embarked upon frequently in our educational institutions due to the increasing number of youths getting involved in drug abuse.

2. Combating the menace of substance abuse prevalence needs the cooperation of all. To that extent, government and non-government organisations at both the local and international levels must network to ensure effective control. Hence, adequate funds should be made available to government Agencies involved in drug demand reduction activities.

3. The sale of drugs and alcohol should be prohibited within and around our educational Institutions.

4. It is also recommended that drug abuse tests should be carried out on candidates in our higher institutions before admissions are granted. This is to identify those who are involved in substance abuse and refer them to the appropriate authority for counselling.

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