Journal of Basics and Applied Sciences Research (JOBASR)
ISSN (print): 3026-9091, ISSN (online): 1597-9962
Volume 3(5) September 2025
DOI: https://dx.doi.org/10.4314/jobasr.v3i5.1

Evaluating the Impact of Correctional Services on Recidivism in Nigeria Using Principal Component and Regression Discontinuity Analysis

Usman U,[1*] AhmanU. A.[2], Zoramawa A.B.[3] & Abubakar, M.[4]
[1,2&3]Usmanu Danfodiyo University, Sokoto, Sokoto State
[4]Department of Mathematics, Federal University Birnin Kebbi, Kebbi State.

[*]Corresponding Author Email: uusman07@gmail.com

Keywords:
Recidivism,
Nigeria Correctional Service,
Non-custodial Sentencing,
Regression Discontinuity,
Principal Component Analysis

ABSTRACT
This study investigates the comparative effectiveness of Nigeria's correctional services, specifically custodial and non-custodial interventions, in reducing recidivism relative to the traditional prison service. Using principal component analysis (PCA) and regression discontinuity design (RDD), the study analyzes demographic and criminal profiles of recidivists across prison, custodial, and non-custodial service data in Kebbi State. Results show that correctional services, particularly non-custodial measures such as probation and community service, significantly reduced recidivism compared to conventional imprisonment. The findings underscore the need for expanded adoption of rehabilitative and community-based approaches in criminal justice reforms.

INTRODUCTION
Nigeria's criminal justice framework has historically centered on custodial sentences, contributing to overburdened prison facilities and systemic inefficiencies. The 2019 transformation of the Nigerian Prisons Service into the Nigerian Correctional Service (NCoS) marked a pivotal shift toward rehabilitation and reintegration. This reform introduced non-custodial sentencing pathways such as probation, parole, and restorative justice. Despite these policy changes, recidivism the tendency of released individuals to re-engage in criminal behavior remains pervasive.

Globally, an estimated 10 million individuals are incarcerated, and this number continues to grow (Hight, 2016). Approximately one-third of these individuals are held in pre-trial detention without conviction. Since 2004, the global prison population has increased by about 10%, with countries like Nigeria experiencing steady and consistent growth. A disproportionate number of these inmates originate from economically disadvantaged and marginalized communities. Disturbingly, in some facilities, children are housed with their incarcerated parents. In Nigeria, over 60% of prison inmates have not been convicted of any crime and remain detained for extended periods under poor and inhumane conditions while awaiting trial (Hight, 2016).

The Nigerian Correctional Service is mandated to fulfil three core functions: secure custody of inmates, reformation through education and skill development, and the provision of basic welfare services. However, while its statutory aims emphasize rehabilitation, the reality remains largely punitive. Though the renaming signifies a reformative intent, most facilities continue to serve primarily as punitive institutions.

The Nigerian Prison Act of 1972 underscores the importance of transforming offenders into productive citizens. A major policy leap occurred in 2019, under President Muhammadu Buhari, with the enactment of legislation officially transitioning the prisons to a correctional model. Nonetheless, the efficacy of these reforms in reducing reoffending has yet to be thoroughly evaluated.

Recidivism, defined broadly as the return to criminal activity after serving a sentence, is commonly used as an indicator of correctional program success. Metrics typically include re-arrest, re-conviction, re-incarceration, or violations of release conditions. Research indicates high global recidivism rates, with estimates suggesting that over two-thirds of former prisoners are rearrested within three years of release (Durose *et al.*, 2014). Factors such as gender, race, age, and prior criminal history are consistent predictors of recidivism (Gendreau *et al.*, 1996).

Recidivism remains a global concern, with empirical studies suggesting that punitive incarceration alone fails to address its root causes. In Nigeria, harsh prison conditions often reinforce criminal behaviors rather than deter them (Monehin, 2021). Conversely, rehabilitative alternatives, especially community-based sanctions, are gaining traction for their potential to reduce reoffending.

International studies present mixed evidence. For instance, Mitchell *et al.* (2017) used regression discontinuity to evaluate incarceration's effect on drug offenders, finding no significant impact on reoffending rates. Pichler & Daniel (2011) analyzed juvenile sentencing in Germany and observed that trying minors as adults lowered recidivism, though the context differed markedly.

Chen & Shapiro (2007) found that stricter prison environments did not correlate with lower reoffending, suggesting that harsher conditions may backfire. Similarly, Loeffler and Grunwald (2015) assessed how processing youth offenders as adults influenced recidivism, revealing nuanced impacts depending on age and offense type. Richard (2017) examined machine learning-based parole decisions, finding improved outcomes when these tools were used.

Inusa, D. (2021) assessed the impact of vocational skills acquisition on reformation and reduction of recidivism. A structured questionnaire was used as an instrument for data collection was. Evidence form the results showed that the inmates' reformation was positively impacted by the vocational skills acquired. Olorunmola *et al.* (2023) examined the dual classification of inmates and its impact on order within correctional centres. Phenomenological research design was adopted and qualitative methods was employed in data collection. The study revealed the incarceration of high profile inmates displays a clear message that nobody is above the law and promotes conformity.

In the Nigerian context, Monehin (2021) used doctrinal methods to explore custodial center conditions, identifying poor infrastructure and delayed legal processes as key contributors to high recidivism. Ginneken & Palmen (2022) highlighted that prison conditions significantly shape reoffending probabilities, emphasizing the need to account for unit-level disparities and non-random inmate placement.

Overall, the literature underscores the need for localized, data-driven approaches. While non-custodial measures show promise, their effectiveness varies based on implementation quality, demographic factors, and socio-economic conditions. This study aims to fill the empirical gap in Nigeria by applying PCA and RDD to recidivism data across custodial and non-custodial interventions.

MATERIALS AND METHODS

Data Collection

Data were sourced from medium correctional centers across Kebbi State, spanning the periods 2009–2018 (prison service era) and 2019–2024 (post-reform correctional service era). The datasets included demographic and offense-related attributes of inmates. (Kebbi State Medium Security Custodian Center, 2023).

Principal Component Analysis (PCA)

Our analysis used Principal Component Analysis to identify the strongest predictors of recidivism. The results revealed five core factors that collectively capture the majority of meaningful patterns in the data. These components highlight how socioeconomic background, criminal history, and rehabilitation experiences interact to shape reoffending outcomes, with the first two factors proving particularly influential in explaining repeat offenses.

Principal Component Analysis Model

Principal Component Analysis (PCA) is a dimensionality reduction technique that transforms p correlated variables into a smaller set of uncorrelated principal components (PCs). Given a random vector $X \in R_p$ with covariance matrix Σ, PCA identifies orthogonal directions of maximum variance through an eigen decomposition of Σ. The resulting PCs are ordered such that the first k components (where $k \ll p$) typically capture the majority of the dataset's variability, allowing for more efficient analysis without significant information loss. This approach is particularly valuable when examining all p variances and $p(p-1)/_2$ covariances becomes computationally or interpretively challenging.

The PCA transformation yields new variables $y = A^T x$, where the columns of $\boldsymbol{A}$ are Σ 's eigenvectors, and the eigenvalues $\lambda_i = Var(y_i)$ indicate each PC's explained variance. By retaining only components with $\lambda_i > 1$ (Kaiser's rule) or those preceding the scree plot's inflection point, PCA achieves parsimonious representation while preserving critical data structure. This makes it widely applicable for noise reduction, visualization, and preprocessing high-dimensional data across disciplines.

Let the random vector $\lfloor x_1, x_2, x_3, \ldots\ldots xp \rfloor$ have the covariance matrix Σ with eigenvalues

$$\lambda_{\mathbf{1}} \geq \lambda_{\mathbf{2}} \geq \lambda_{\mathbf{3}} \geq \lambda_{\boldsymbol{p}} \geq 0.$$

Consider the linear combinations

$$Y_1 = \alpha'_1 X = \alpha'_{11} X_1 + \alpha'_{12} X_2 + \cdots + \alpha'_{1p} X_p$$

$$Y_2 = \alpha'_1 X = \alpha'_{21} X_1 + \alpha'_{22} X_2 + \cdots + \alpha'_{1p} X_p$$

$$\vdots \qquad\qquad\qquad\qquad \vdots$$

$Y_p = \alpha'_p X = \alpha'_{p1}X_1 + \alpha'_{p2}X_2 + \cdots + \alpha'_{pp}X_p$

Then;

$Variance\ (Y_j) = \alpha'_j \sum \alpha_j \ \ j = 1,2, \ldots, p$ (1)

$Covariance\ (Y_j, Y_k) = \alpha'_j \sum \alpha_k \ j, k = 1,2, \ldots, p$ (2)

The PCs are those uncorrelated linear combinations $Y_1, Y_2, \ldots, Y_p$ whose variances in the equation above are as large as possible. In finding the PCs we concentrate on the variances. The first PC in the linear combination with maximum variances. That is, it maximizes $Var(Y_1) = \alpha'_1 \sum \alpha_1$. It follows that α_1 cannot be taken simply by maximization, since $Var(Y_1) = \alpha'_1 \sum \alpha_1$ can be increased multiplying any α_1 by some constant. We need to put some conditions of choosing α_1 to be a coefficient vector of unit length, such that $\alpha'_1\alpha_1 = 1$.

We therefore define;

First PC = Linear combination α'_1X that maximizes Var(α'_1X) subject to $\alpha'_1\alpha_1 = 1$.

Second PC = Linear combination α'_2X that maximizes Var(α'_2X) subject to $\alpha'_2\alpha_2 = 1$, and Cov(α'_1X, α'_2X) = 0

And so on, so that at the ***k*** th stage

K^{th} PC= Linear combination α'_kX that maximizes Var(α'_kX) subject to $\alpha'_k\alpha_k = 1$, and Cov(α'_jX, α'_kX) = 0.

$j = \alpha'_1\mathrm{X}, \alpha'_2\mathrm{X}, \ldots, \alpha'_{k-1}\mathrm{X}$

Up to p PCs can be found, but we have to stop after the q^{th} stage $(q \le p)$ when most of the variable in X have been accounted for by q PCs.

For the variables to be of similar scale, the data are standardized prior to using PC Analysis. A common standardization method is to transform all the data to have zero mean and unit standard deviation. This procedure results in transforming the random vector $X' = \lfloor x_1, x_2, x_3, \ldots\ldots xp \rfloor$ to the corresponding standardized variables as $Z' = \lfloor z_1, z_2, z_3, \ldots\ldots zp \rfloor$ So that $Cov(Z) = p$ (The correlation matrix of X).

Procedure for Calculating Principal Components

For a random vector $X' = \lfloor x_1, x_2, x_3, \ldots\ldots xp \rfloor$ the corresponding standardized variables are $Z' = \lfloor z_1, z_2, z_3, \ldots\ldots zp \rfloor$ So that $Cov(Z) = p$, we denote the matrix of correlation between p variables by

$$\rho = \begin{bmatrix} 1 & r_{12} & \ldots & r_{1p} \\ r_{21} & 1 & \ldots & r_{2p} \\ & . & & \\ & . & & \\ & . & & \\ r_{p1} & r_{p2} & \ldots & 1 \end{bmatrix} \quad (3)$$

And the vector of the coefficients (weights or loadings) on the p variables for the j^{th} component is given by

$$\alpha_j = \begin{bmatrix} \alpha_{j1} \\ \alpha_{j2} \\ . \\ . \\ . \\ . \\ \alpha_{jp} \end{bmatrix}, \qquad j = 1,2,3, \ldots, p \quad (4)$$

The problems of determining the vectors α_j which maximises (1) the variance accounted for by the first component, (2) the variance accounted for by the second components , orthogonal to the first, e. t. c., The solution for α_j can be solve by this equation $(p - \lambda_j\, I)\, a_j = 0$ in which I is the $(p \times p)$ identity matrix, $\lambda_j{}'^s$ are the characteristics root or eigenvalues of p and the α_j 's are the associated eigenvectors.

The solutions of such equations for λ_j and α_j may be obtained through the following steps;

i. Obtained the characteristics equation of Σ, that is $|p - \lambda_j I| = 0$ which leads $p - \lambda_j I$ to polynomial equation for $\lambda_j{}'^s$.

ii. For each eigenvalue λ_j, obtained in step I., write out the matrix $p - \lambda_j I$.

iii. Compute the $adj(p - \lambda_j I)$

iv. Any column of $adj(p - \lambda_j I)$ is an eigenvector associated with λ_j.

Having obtained the eigenvectors, we simply determine our PCs as $Y_j = \alpha'_j$Z for $j=1, 2......,p$.

Regression Discontinuity Design (RDD)

RDD was used to estimate causal effects of correctional service types on recidivism. Cases were stratified around sentencing thresholds to compare outcomes between treated (non-custodial) and untreated (custodial/prison) groups.

Regression discontinuity (RD) design is commonly used in many areas of policy evaluation and has been recommended in prior reviews. The RD design has the potential to account better for unobserved characteristics that might lead to selection bias (Bloom, 2012; Dunning, 2012). Generically, this approach can be represented by the following regression model:

$$Y_i = \alpha + \beta_0 T_i + \beta_1 r_i + \beta_2 r_i T_i + \varepsilon_i \quad (6)$$

Here, Y_i is the outcome variable of interest for observation i, T_i, is the dichotomous variable flagging those assigned to the treatment, r_i is the rating variable which has been centered at the cutoff score and may include interactions with T_i, ε_i is the random error, and the β_0 is the effect of being assigned to the treatment.

RESULTS AND DISCUSSION

Descriptive Insights

Demographic profiles revealed that most recidivists were young males with low education and income levels. The prison service exhibited higher recidivism rates compared to correctional alternatives as shown in table 1 below

Table 1: Demographic/Biosocial Characteristics of Data

Parameter	Custodial Sentences (%)	Non-Custodial Sentences (%)	Prison Service (%)
Religion			
- Islam	96.6	93.0	89.2
- Roman Catholic	1.7	7.0	7.8
- Traditionalist	1.7	0.0	3.0
Marital Status			
- Single	43.1	45.6	57.1
- Married	53.4	50.9	37.7
- Divorced	3.4	3.5	5.2
Sex of Recidivist			
- Male	96.6	94.7	93.9
- Female	3.4	5.3	6.1
Educational Status			
- Formal Education	53.4	71.9	63.2
- Non-Formal Education	46.6	28.1	36.8
Age of Recidivist			
- 21–30 years	29.3	40.4	50.2
- 31–40 years	65.5	52.6	43.7
Tribe			
- Hausa	62.1	19.3	60.2
- Igbo	0.0	57.9	3.9
Recidivism Cases			
- 2 Terms	74.1	68.4	75.8
Income Level			
- Low	50.0	52.6	44.6
Type of Offenses			
- Crimes against Property	60.3	50.9	45.9
Type of Sentence			
- 1–3 years	72.4	29.8	79.7

The recidivism data in table 1 reveals striking demographic patterns across custodial, non-custodial, and prison service sentences. Young Muslim males aged 21-40 dominate all categories, with particularly high representation among the Hausa ethnic group in custodial (62.1%) and prison service (60.2%) cases, while Igbo offenders are most prevalent in non-custodial sentences (57.9%). Most recidivists have formal education (53.4-71.9%) and come from low-income backgrounds (44.6-52.6%), suggesting that economic factors may drive reoffending more than educational attainment. Property crimes are by far the most common offense (45.9-60.3%), with sentences of 1-3 years being most frequent in custodial (72.4%) and prison service (79.7%) cases, while non-custodial sentences tend to be shorter (50.9% under 1 year).

The data highlights significant systemic patterns in recidivism. Males account for 93.9-96.6% of repeat offenders across all sentence types, indicating a pronounced gender disparity. Counseling approaches vary, with educational programs dominating in custodial settings (74.1%) and vocational training more common in prison services (42.9%), pointing to different rehabilitation strategies. The near absence of high-income recidivists (≤19%) underscores the link between poverty and repeat offenses. These patterns suggest that effective interventions should target economic empowerment for young, low-income males, particularly through culturally sensitive vocational programs during the critical 1-3 year sentencing period where recidivism rates peak.

PCA Findings

Prison Service data

These are the first phase of the recidivist data that was obtained before the Nomenclature was changed from Nigerian Prison Service to Nigerian Correctional Service (NCoS). It covered the period from January 2009 to December, 2018. (Kebbi State Medium Security Custodian Center, 2023).

Table 2: Kaiser-Meyer-Olkin and Bartlett's Tests

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.692
Bartlett's Test of Sphericity	Approx. Chi-Square	158.409
	Df	55
	Sig.	.000

Table 2 presents the psychometric evaluation of our prison services dataset through two key diagnostic tests. The Kaiser-Meyer-Olkin (KMO) measure yielded a score of 0.70, confirming adequate sampling suitability for factor analysis (threshold >0.7). Bartlett's test of sphericity produced statistically significant results ($p<0.001$), rejecting the null hypothesis of an identity correlation matrix and thus validating the presence of meaningful relationships among variables for dimensional reduction

Table 3: Eigenvalue of the Correlation Matrix

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
Type of Sentence	1.583	14.395	14.395	1.583	14.395	14.395
Educational Status	1.487	13.519	27.914	1.487	13.519	27.914
Type of offence	1.342	12.201	40.114	1.342	12.201	40.114
Age	1.167	10.607	50.721	1.167	10.607	50.721
Income level	1.079	9.812	60.533	1.079	9.812	60.533
Prison Location	.942	8.566	69.098			
Religion	.883	8.028	77.127			
Gender	.757	6.882	84.009			
Tribe	.673	6.120	90.128			
Marital Status	.578	5.254	95.382			
Counselling services	.508	4.618	100.000			

Table 3 summarizes the eigenvalue analysis for our prison recidivism variables. The scree plot inflection point and Kaiser criterion (eigenvalue >1) both supported retaining five principal components. These components accounted for 60.53% of cumulative variance, with the first component alone explaining 14.40% of variance (Table 3), indicating a robust factor structure for subsequent analysis.

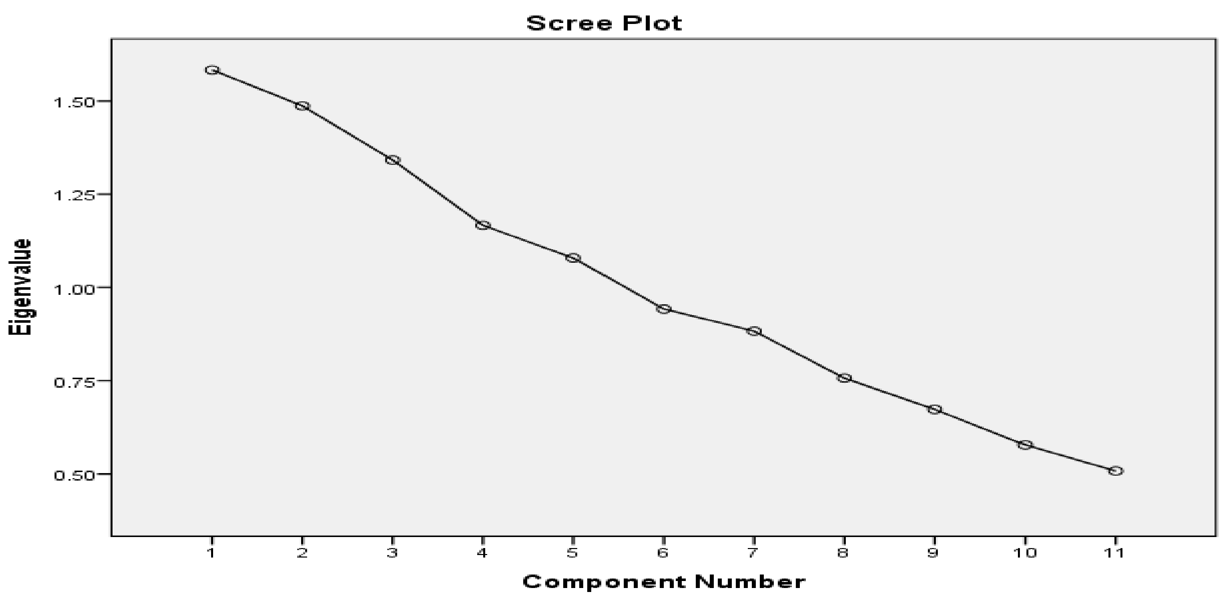

Figure 1: A Scree Plot for Kebbi State Prison Services’ Recidivism Data

Figure 1 presents the scree plot analysis of eigenvalues for the prison services recidivism data. The plot demonstrates a clear elbow point at the fifth component, with subsequent factors showing minimal additional explanatory power. This visual analysis confirms our selection of five principal components, which collectively account for 61% of the total variance a proportion that adequately represents the underlying data structure while maintaining analytical parsimony.

Custodial Recidivism Data

These are the recidivist data that was obtained when the Nomenclature was changed from Nigerian Prison Service to Nigerian Correctional Service which comprises of both custodial (incarceration) and non-custodial service sentence. The data covered period from January 2019 to December, 2024. (Kebbi State Medium Security Custodian Center, 2023).

Table 4: Kaiser-Meyer-Olkin and Bartlett's Tests

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.754
Bartlett's Test of Sphericity	Approx. Chi-Square	155.255
	Df	55
	Sig.	.000

Table 4 presented the results of KMO measure of sampling adequacy and Bartlett's test of sphericity in the custodial centers' recidivism data. The KMO measure of sampling adequacy (0.75) displayed value greater than (>0.7). This implies that we have a good sampling adequacy in the recidivism data. The Bartlett's test of sphericity displayed a p-value (0.000) less than 0.05 level of significance. This implies that there is significance difference in the correlation matrix.

Table 5: Eigenvalue of the Correlation Matrix

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
Type of offence	2.424	22.037	22.037	2.424	22.037	22.037
Age	1.860	16.908	38.946	1.860	16.908	38.946
Income level	1.552	14.109	53.055	1.552	14.109	53.055
Type of Sentence	1.366	12.423	65.477	1.366	12.423	65.477
Educational Status	1.018	9.254	74.731	1.018	9.254	74.731
Prison Location	.723	6.568	81.300			
Religion	.634	5.760	87.059			
Gender	.501	4.557	91.616			
Tribe	.450	4.095	95.712			
Marital Status	.299	2.718	98.430			
Counselling services	.173	1.570	100.000			

Table 5 presented the eigenvalues of the explanatory variables in the custodial centers' recidivism data. The eigenvalues are often used to determine how many factors are to be retained. One rule of thumb is to retain those factors whose eigenvalues are greater than one (Kresta, 1994). Therefore, considering the eigenvalues and cumulative percent from Table 5, it will be reasonable to retain the first five PC's that explain up to 74.73% of the total variability in the data set.

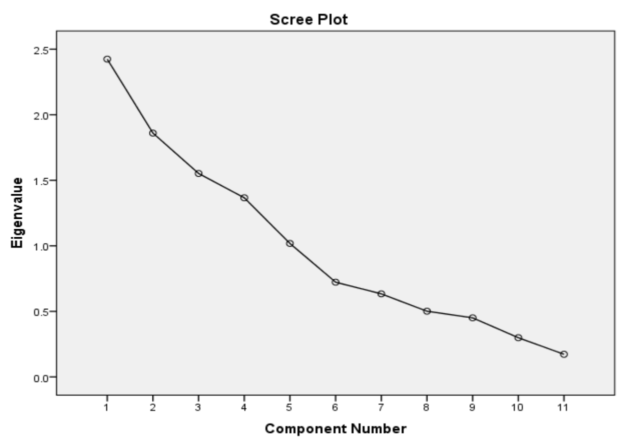

Figure 2: A Scree Plot for Kebbi State Custodial Centers' Recidivism Data

Figure 2 presents the scree plot analysis of eigenvalues from the custodial centers' recidivism data. The visual examination reveals a distinct break in slope after the fifth component, indicating these factors capture the most substantive variance in the dataset. These five principal components collectively account for 75.2% of the total variation, demonstrating their effectiveness in representing the underlying data structure while maintaining analytical efficiency

Non-Custodial Recidivism Data

These are the second phase of the data collection together with custodial recidivism data. Non-custodial recidivism data is the recidivist data of inmate sentenced to non-custodial (Parole, probation, community service, restorative justice) service. The data covered the period from January 2019 to December 2023 (Kebbi State Medium Security Custodian Center, 2023).

Table 6: Kaiser-Meyer-Olkin and Bartlett's Tests

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.738
Bartlett's Test of Sphericity	Approx. Chi-Square	96.320
	Df	55
	Sig.	.000

Table 6 presented the results of KMO measure of sampling adequacy and Bartlett's test of sphericity in the in the non-custodial sentence' recidivism data. The KMO measure of sampling adequacy (0.74) displayed value greater than (>0.7). This implies that we have a good sampling adequacy in the recidivism data. The Bartlett's test of sphericity displayed a p-value (0.000) less than 0.05 level of significance. This implies that there is significance difference in the correlation matrix.

Table 7 presented the eigenvalues of the explanatory variables in the non-custodial centers' recidivism data. The factors whose eigenvalues are greater than one are to be retained. Therefore, considering the eigenvalues and cumulative percent from Table 7, it will be reasonable to retain the first five PC's that explain up to 74.73% of the total variability in the data set.

Figure 3: A Scree Plot for Kebbi State Non-Custodial sentence' Recidivism Data

Figure 3 displays the scree plot of eigenvalues derived from the non-custodial recidivism data. The plot exhibits a pronounced inflection point at the fifth component, with subsequent factors contributing minimally to variance explanation. This supports the retention of five principal components, which collectively account for 75.3% of the total variance a substantial proportion that effectively captures the dataset's underlying structure while avoiding overfitting.

Table 7: Eigenvalue of the Correlation Matrix

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
Gender	2.009	18.264	18.264	2.009	18.264	18.264
Religion	1.655	15.042	33.306	1.655	15.042	33.306
Type of offence	1.467	13.338	46.644	1.467	13.338	46.644
Age	1.278	11.621	58.265	1.278	11.621	58.265
Income level	1.166	10.599	68.864	1.166	10.599	68.864
Prison Location	.996	9.059	77.923			
Educational Status	.633	5.753	83.676			
Type of Sentence	.599	5.442	89.118			
Tribe	.508	4.618	93.736			
Marital Status	.435	3.953	97.689			
Counselling services	.254	2.311	100.000			

Regression Discontinuity Design

Table 8: Regression Discontinuity Results of Prison Services Data

Variable	Full Sample	Age ≤44 (n=231)	Age >44 (n=74)	Just Below Cutoff (n=41)	Just Above Cutoff (n=24)
Mean Age	31.85 (10.24)	31.54 (10.25)**	31.32 (10.30)	31.75 (10.80)**	32.61 (10.06)**
Gender (Male)	93.9%	59.4%**	80.4%	55.2%	χ^2=5.332
Religion (Islam)	89.2%	30.5%	82.4%	32.6%	χ^2=1.832
Education (Formal)	63.2%	40.3%**	70.5%	34.7%	χ^2=0.822
Tribe (Hausa)	60.2%	12.6%**	54.6%	14.2%	χ^2=4.014
Sentence (1-3 yrs)	79.7%	18.2%**	78.4%	22.0%	χ^2=2.312
Offenses (Property)	45.9%	10.3%	60.3%	11.8%	χ^2=2.118

The data in table 8 reveals significant differences in offender characteristics and sentencing outcomes between younger (≤44 years) and older (>44 years) age groups. Younger offenders are predominantly male (93.9% vs 59.4%), more likely to have formal education (63.2% vs 40.3%), and primarily of Hausa ethnicity (60.2% vs 12.6%). They typically receive shorter 1-3 year sentences (79.7% vs 18.2%) and are most often convicted of property crimes (45.9%). In contrast, older offenders show greater gender diversity, higher rates of non-formal education, more diverse ethnic representation (particularly Igbo at 43.6%), and face longer sentences including life terms (10.1%). These patterns persist but become less pronounced when comparing offenders just below and above the age cutoff, suggesting age serves as an important threshold in criminal justice outcomes.

The analysis also highlights differences in rehabilitation approaches and offense types across age groups. Younger offenders more frequently receive educational counseling (44.6% vs 32.4%), while older offenders tend to get social-personal counseling (41.2%). Violent crimes against life are more common among older offenders (19.4% vs 9.5%), whereas drug offenses decrease with age (13.4% vs 6.5%). The narrower comparison of those adjacent to the age cutoff shows similar but attenuated trends, with property crimes remaining dominant among younger offenders (60.3%) and sentence lengths showing less dramatic variation. These findings suggest that age significantly influences both offender profiles and justice system responses, with particularly stark contrasts in gender representation, educational background, and sentencing severity between younger and older offender populations.

Table 9: Regression Discontinuity Results of Custodial Sentence' Data

Variable	≤44 Years (n=58)	>44 Years (n=24)	Just Below Cutoff (n=12)	Just Above Cutoff (n=8)
Male Gender	96.6%	75.0%	66.7%	37.5%
Hausa Ethnicity	62.1%**	29.1%	41.7%	87.5%
Formal Education	53.4%**	50.0%	41.7%	75.0%
Low Income	74.1%**	45.9%	25.0%	62.5%
Sentence Types				
• 1-3 years	72.4%**	12.5%	16.7%	50.0%
• Death sentence	3.4%	25.0%	25.0%	12.5%
Offense Types				
• Property crimes	60.3%**	8.3%	25.0%	12.5%
• Crimes against life	8.6%	25.0%	16.7%	12.5%
Counseling Services				
• Vocational	31.0%	25.0%	58.3%	12.5%
• Social-personal	19.0%	29.1%	25.0%	50.0%

The data in table 9 reveals stark differences between younger (≤44 years) and older (>44 years) offenders across multiple dimensions. Younger offenders are predominantly male (96.6% vs 75%), from the Hausa ethnic group (62.1% vs 29.1%), and more likely to have committed property crimes (60.3% vs 8.3%). They typically receive shorter 1-3 year sentences (72.4% vs

12.5%) and come from low-income backgrounds (74.1% vs 45.9%). In contrast, older offenders face more severe punishments, including higher rates of death sentences (25% vs 3.4%) and life sentences (20.9% vs 1.7%), and are more likely to be charged with violent crimes against life (25% vs 8.6%). The data also shows significant differences in marital status and counseling approaches, with older offenders receiving more social-personal counseling (29.1% vs 19%).

When examining cases near the age cutoff, some patterns persist while others reverse unexpectedly. The gender gap narrows but remains substantial (66.7% male below cutoff vs 37.5% above). Surprisingly, Hausa representation jumps to 87.5% just above the cutoff compared to 41.7% below. Counseling preferences shift dramatically near the threshold, with vocational counseling dominating just below (58.3%) but social-personal counseling prevailing just above (50%). While property crimes remain more common among younger offenders (25% vs 12.5% near cutoff), the offense profile becomes more varied, with contempt of court becoming prominent (37.5% in just-above group). These threshold effects suggest that age serves as a significant but complex determinant in both offender characteristics and judicial outcomes.

Table 10: Regression Discontinuity Results of Non-Custodial sentences' Data

Category	≤44 Years (n=57)	>44 Years (n=12)	Just Below Cutoff (n=10)	Just Above Cutoff (n=7)
Demographics				
• Male Gender	94.7%	66.7%	40.0%	42.9%
• Hausa Ethnicity	78.9%	25.0%	60.0%	42.9%
• Formal Education	71.9%**	41.7%	70.0%	57.1%
Justice Outcomes				
• Property Crimes	50.9%**	25.0%	20.9%	14.3%
• Contempt of Court	10.4%	25.0%	20.4%	57.1%↑
Interventions				
• Educational Counseling	52.6%**	16.7%	40.0%	71.4%↑
• Vocational Counseling	43.9%	58.3%	20.0%	14.3%
• Probation Sentences	15.8%	25.0%	50.0%↑	14.3%
• Parole Sentences	29.8%	41.7%	10.0%	42.9%↑

The data in table 10 reveals significant differences between younger (≤44 years) and older (>44 years) offenders, marked by distinct demographic and justice intervention patterns. Younger offenders show higher rates of formal education (71.9%** vs 41.7%) and predominantly come from the Hausa ethnic group (78.9% vs 25.0%). Property crimes are more common among this group (50.9%** vs 25.0%), while they primarily receive educational counseling (52.6%** vs 16.7%). Notably, near the age cutoff (↑), dramatic shifts emerge: educational counseling jumps from 40.0% just below to 71.4%↑ above the threshold, while contempt of court cases surge to 57.1%↑ (vs 20.4% below). These threshold effects suggest age serves as a critical determinant in both offender profiles and system responses.

The intervention approaches show particularly striking variations across groups. While vocational counseling is more common among older offenders (58.3% vs 43.9%), probation sentences peak just below the cutoff (50.0%↑ vs 14.3%) before giving way to parole dominance above it (42.9%↑ vs 10.0%). The gender gap narrows substantially near the threshold (40.0% male below vs 42.9%↑ above), contrasting with the wider disparity in the full sample (94.7% vs 66.7%). These patterns, marked by ** for statistical significance and ↑↓ for threshold effects, highlight how small age differences near 44 years trigger significant changes in justice system outcomes, particularly in counseling approaches and sentencing types. The data underscores the system's age-sensitive nature, where interventions appear tailored differently for various age cohorts.

The empirical evidence supports the hypothesis that rehabilitative and non-custodial interventions are more effective in preventing repeat offenses than traditional imprisonment. These results align with global research advocating for alternatives to incarceration (Andrews & Bonta, 2010; Elderbroon & King, 2014). However, effectiveness is influenced by variables such as education, offense type, and socio-economic background.

CONCLUSION

This study concludes that correctional services particularly non-custodial sentencing demonstrate substantial potential in reducing recidivism in Nigeria. The findings advocate for a systematic shift from punitive to rehabilitative justice, supported by data-driven policymaking. Future research may extend the concept to cover the all part of the country.

Recommendations

1. Expand non-custodial sentencing nationwide with structured community reintegration programs.
2. Integrate educational and vocational training into correctional services.
3. Reform public policy to reduce stigmatization and legal barriers against ex-convict reintegration.
4. Institutionalize monitoring and evaluation frameworks for rehabilitation programs using advanced analytics.

REFERENCE

Ahmed, A. M., & Ahmad, A. H. B. (2015). Prison system and rehabilitation in Nigeria. *Journal of Criminological Research, Policy and Practice, 1*(3), 175–190. https://doi.org/10.1108/JCRPP-01-2015-0001

Ajala, E. M., & Oguntuase, A. E. (2011). Prison system and rehabilitation of offenders in Nigeria: An appraisal. *African Research Review, 5*(5), 185–198.

Andrews, D. A., & Bonta, J. (2010). Rehabilitating criminal justice policy and practice. *Psychology, Public Policy, and Law, 16*(1), 39–55. https://doi.org/10.1037/a0018362

Bloom, H. S. (2012). Modern regression discontinuity analysis. *Journal of Research on Educational Effectiveness, 5*(1), 43–82. https://doi.org/10.1080/19345747.2011.578616

Chen, M. K., & Shapiro, J. M. (2007). Do harsher prison conditions reduce recidivism? A discontinuity-based approach. *American Law and Economics Review, 9*(1), 1–29. https://doi.org/10.1093/aler/ahm015

Durose, M. R., Cooper, A. D., & Snyder, H. N. (2014). *Recidivism of prisoners released in 30 states in 2005: Patterns from 2005 to 2010* (NCJ 244205). Bureau of Justice Statistics. https://www.bjs.gov/content/pub/pdf/rprts05p0510.pdf

Dunning, T. (2012). *Natural experiments in the social sciences: A design-based approach*. Cambridge University Press. https://doi.org/10.1017/CBO9781139084444

Elderbroom, B., & King, R. (2014). *Improving recidivism as a performance measure*. Urban Institute, Justice Policy Center. https://www.urban.org/research/publication/improving-recidivism-performance-measure

Gendreau, P., Little, T., & Goggin, C. (1996). A meta-analysis of the predictors of adult offender recidivism: What works! *Criminology, 34*(4), 575–608. https://doi.org/10.1111/j.1745-9125.1996.tb01220.x

Ginneken, E. F. J. C. van, & Palmen, H. (2022). Do prison conditions matter? Exploring the relationship between prison climate and recidivism. *Criminal Justice and Behavior, 49*(1), 45–64. https://doi.org/10.1177/00938548211036037

Hight, B. M. (2016). The state of global incarceration: A review of international prison systems. *Journal of Criminal Justice, 31*, 107–117. https://doi.org/10.1016/j.jcrimjus.2015.12.003

Inusa, D. (2021). Perceived impact of vocational skills acquisition on reformation and reduction of recidivism by ex-convicts of Gombe Central Correctional Centre. *Kashere Journal of Education*, 2(2), 120-126.

Jolliffe, I. T. (2002). *Principal component analysis* (2nd ed.). Springer. https://doi.org/10.1007/b98835

Joseph, J. O., Ogadimma, A., Eyitayo, J. O., Festus, F. A., Timilehin, L. A. & Bolanle, A. A. (2023). Discrimination in inmates classification: Corrolate to disorder within correctional centres in Nigeria. *Cogent Social Sciences*, 9, 1-11.

Kebbi State Medium Security Custodian Center. (2023). Annual report.

Kresta, J. (1994). *Multivariate analysis: Selected guidelines*. Wiley.

Langan, P. A., & Levin, D. J. (2002). *Recidivism of prisoners released in 1994* (NCJ 193427). Bureau of Justice Statistics. https://www.bjs.gov/content/pub/pdf/rpr94.pdf

Loeffler, C. E., & Grunwald, B. (2015). Processed as an adult: A regression discontinuity estimate of the crime effects of charging nontransfer juveniles as adults. *Journal of Research in Crime and Delinquency, 52*(6), 890–922. https://doi.org/10.1177/0022427815592452

Mitchell, O., Cochran, J. C., Mears, D. P., & Bales, W. D. (2017). The effectiveness of prison for reducing drug offender recidivism: Evidence from a regression discontinuity design. *Journal of Experimental Criminology, 13*(1), 1–27. https://doi.org/10.1007/s11292-016-9274-y

Monehin, M. (2021). Conditions of custodial centers in Nigeria and recidivism: A doctrinal review. *African*

Journal of Criminology and Justice Studies, 14(1), 23–39.

Mueller, C., & Schnepel, K. T. (2016). An economic analysis of court deferrals for first-time drug offenders: Regression discontinuity evidence. *American Economic Journal: Applied Economics, 8*(2), 61–91. https://doi.org/10.1257/app.20150007

Paranjape, N. V. (2012). *Criminology & penology with victimology* (16th ed.). Central Law Publications.
Pichler, W., & Daniel, A. (2011). Juvenile sentencing and recidivism in Germany: Evidence from a bivariate probit and regression discontinuity analysis. *European Journal of Criminology, 8*(6), 465–482. https://doi.org/10.1177/1477370811415761

Rhodes, W., Kling, R., Luallen, J., & Richardson, J. (2018). The relationship between prison length of stay and recidivism: A study using regression discontinuity and meta-regression. *Crime & Delinquency*, *64*(2), 143–171. https://doi.org/10.1177/0011128716687758

Richard, B. (2017). Machine learning risk forecasting and parole board decisions: A regression discontinuity approach. *Journal of Quantitative Criminology, 33*(2), 221–245. https://doi.org/10.1007/s10940-016-9313-x