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Healthcare delivery in Bayelsa State through health systems modeling

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ABSTRACT

In Nigeria, improving healthcare delivery of course is still exceedingly difficult, in areas with resource-constrained settings like Bayelsa State especially. Indeed, in order to ascertain the factors affecting satisfaction of outpatients as a stand-in for healthcare delivery effectiveness, this research employed a health systems modeling technique. A structured questionnaire was used to gather data from 200 outpatients at Federal Medical Centre, Yenagoa. Multiple regression analysis was then used to evaluate the impact of waiting times, travel times, education levels, and healthcare system capacity and access on patient satisfaction. The statistical techniques: Tukey, Durbin-Watson, Breusch-Pagan, Shapiro-Wilk and Variance Inflation Factors were respectively employed to assess linearity, independence of errors, homoscedasticity, normality and multicollinearity. The robustness of the model was achieved by the diagnostic results, which reveal that the main assumptions were mostly achieved, justifying the reliability of the model. The results from the regression model explain about 42.3% of the variation in outpatient satisfaction and are significant statistically. The biggest positive predictor variable of satisfaction was capacity and access, emphasizing the significance of sufficient staffing, infrastructure, drug availability, and pricing. Service delays were determined as a major constraint in the delivery of healthcare, and waiting times were found to have a considerable negative impact on satisfaction. Travel time revealed a weaker negative influence, whereas level of education significantly did not affect satisfaction once factors of system-level were considered. To maximize healthcare delivery and raise patient satisfaction in Bayelsa State, waiting times must be decreased and the healthcare system's capacity must be strengthened.

Keywords: Health systems modeling, Healthcare delivery, Outpatient satisfaction, Multiple linear regression.

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1. INTRODUCTION

Challenges exist in the provision of quality healthcare in many sub-Saharan African nations, Nigeria inclusive. Equity in the provision of health care services is often constrained by a variety of operational and structural challenges, particularly in Bayelsa state. They range from large access disparities between urban and rural areas, the appalling state of healthcare infrastructure, mechanization (or money for the health sector and poor number of experienced human resource in healthcare). Studies have shown that the extent of health care resource availability is a major determinant of service utilization patterns in rural Bayelsa, and this keeps people at disparities in terms of health status and access to care all over the state [1].

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UHC which means Universal Health Coverage is the overarching goal of ensuring everyone can obtain quality essential health services without suffering financial hardship and it remains a challenge for Nigeria's health system to achieve at national scale. Based on national reports, marginalized populations still experience only slight improvements on coverage of services delivered, and limited access to health care is experienced by the poor and people living in rural areas [2]. Healthcare delivery assessments in Bayelsa State reveal persistent flaws in the governance of the health system and the improvement of its services, more especially when it time to catering to the different requirements of people in different socioeconomic and geographic contexts [3].

These problems are further increased by the combined burden of infectious and non-communicable diseases in the state, which further puts a strain on the already limited healthcare resources in the state. The health system planning in Bayelsa has always emphasized heavily on descriptive assessments and frequent reporting with minimal application of analytical frameworks which could forecast service demand, identify bottlenecks of the system or even maximize the allocation of resources. This use of descriptive technique impairs the capacity of policymakers and health administrators to anticipate new needs and adequately respond to services delivery. Health system modeling provides a powerful model of overcoming these limitations, making use of formal statistical and mathematical tools. Examples of methods that can be used to support the systematic study of complex healthcare processes and improve the evidence-based decision-making in a range of scenarios include regression analysis, Bayesian statistical tools, and time series forecasting. These approaches have already been applied successfully in every part of the world to enhance healthcare planning, estimate the resource requirements, determine the effectiveness of the interventions, and become more efficient with the services, basing on the factual information, and not only on the feeling, as it represents. As an example, time series models have demonstrated some potential in making predictions of hospital admissions, bed occupancy, and trends of key health indicators [4], whereas Bayesian and regression-based models have been applied to predict treatment costs and patient outcomes explicitly taking into account uncertainty [5].

Despite these changes, the system of structured statistical modeling is not popular in the healthcare of Bayelsa State. Rather rare in the literature is predictive or optimization-oriented modeling frameworks that have the capacity to generate useful policy information, with instead most studies involving descriptive analysis of service usage or program implementation. This gap represents a bigger trend in most African healthcare organizations, in which statistical forecasting and optimization approaches are not yet fully exploited despite the fact that they were demonstrated to enhance the management and planning of resources [6]. Considering that, this research will develop and apply a health system modeling framework that is state-specific to Bayelsa State with the help of statistical methods to identify relevant agents and determinants of healthcare delivery outcomes and inform the optimization strategies. The aim of the study is to aid in better allocation of resources, reduction of bottlenecks in service delivery, and enhancement of evidence-based decision making among politicians and health care administrators by integrating locally generated health data with regression based modeling tools. Ultimately, it is hoped that through the application of the health systems modeling in this context, there will be improved population health in the state of Bayelsa, more equity in access to care and improved performance of the healthcare systems.

2. LITERATURE REVIEW

The study conducted by Ref. [3] involved an empirical assessment of the effectiveness of health administrative and care delivery methods in Bayelsa State, Nigeria. The data used in the study was gathered on a sample of 300 respondents across the entire state and the study design was an evaluative research design conducted in the form of questionnaires. Three research topics and three hypotheses associated with the investigation guided the investigation. The data was processed through the descriptive statistics like weighted mean, standard deviation, frequencies, and percentages as well as the hypothesis were tested at the 0.05 level of significance and z-test was used. The findings indicated that the levels of reliance on faith-based healing centers and traditional healers (mean ratings of 2.33, 2.40, 2.30, and 1.97, respectively) were rather low, whereas the level of patronizing government-owned and privately owned healthcare facilities was rather high. The survey also indicated that the health officials are a regular attendee to the campaigns of educating the people on the knowledge of the healthcare services offered. The results of the z-test (z-calculated = 1.16 < z-critical = 1.96) accepted the null hypothesis that health administration has led to improved healthcare delivery within the state, meaning that the healthcare programs of the Bayelsa State have been overall effective. Based on these findings, the authors recommended community level sensitization and awareness campaigns, particularly in the rural communities, to enhance the understanding and evaluation of the healthcare practices by the community. Another need that was identified in the report was to recruit and post adequate personnel to improve on the monitoring and evaluation of health programs.

The systematic evaluation of the application of modeling and simulation strategies in healthcare operations management across the African health systems was conducted by Ref. [7]. To gain a more comprehensive insight into the utilization of analytical tools such as discrete event simulation, system dynamics, and optimization models to optimize patient flow, resource allocation, and service efficiency in public healthcare facilities, the study synthesized available empirical and modeling-based studies published in the last 10-12 years. The research also indicated that health systems models simulated have been successfully used to identify bottlenecks in service delivery, reduce wait time and optimize use of limited healthcare resources, particularly in the outpatient and emergency care departments. The study further however revealed that there were long term hindrances to widespread use of such types of models which included institutional resistance to data-driven decision-making, inefficient technological capacity, ineffective health information systems, and ineffective data availability. These findings highlighted the fact that despite the possible availability of financial resources in a large number of African settings, inefficiencies in the system structure and governance often restrict the delivery outcomes in healthcare. Provided that the contextual constraints are mitigated by using improved data systems, workforce training, and institutional support, the study established that the integration of health systems modeling in standard healthcare planning can significantly enhance the efficiency of the services and the efficiency of policies.

The study design employed by Ref. [8] is a cross-sectional study to explore the elements of patient satisfaction with service delivery at hospitals of family medicine in a tertiary hospital in North Central Nigeria. Data on 104 adult patients was collected using an interviewer-administered questionnaire. The analysis involved descriptive statistics and inferential statistics like chi square test and logistic regression with a significant level of 0.05. The survey revealed that 71.4% of the patients were generally satisfied, and the level of their satisfaction was related to the behaviour of the staff, communication with providers, and the environment of the facility. Importantly, waiting time proved to be one of the key dimensions of the system that impacted the satisfaction; statistical evidence showed that the longer the wait time, the less likely to become satisfied. It was also determined that the attitudes and the infrastructure of medical records officers were significant predictors, which proves the argument that the ability to prepare facilities and organize services may impact patients more than demographics. To enhance the quality of services and healthcare delivery outcomes in tertiary facilities, the authors concluded that the key tactics to improve the facilities included the improvements by upgrading the infrastructure, advancing patient-centered communication, and reducing waiting times by optimizing the appointment system and workflow.

A review based on empirical studies conducted by Ref [9] examined patient satisfaction with medical treatment as an indicator of the efficiency of the healthcare system. The study concentrated on service quality, access, efficiency and the patient experience thus synthesizing empirical research based on surveys that were conducted in state healthcare facilities in various countries. Quantitative data of outpatient satisfaction surveys were analyzed by the multivariate regression and descriptive statistics to determine system-level factors that affect satisfaction. The findings revealed that waiting time, staff availability, service organization, and the capacity of health care system played a major role in patient satisfaction, whereas socio-demographic parameters played a comparatively low role when system features were considered. The lower levels of satisfaction in every healthcare situation were always attributed to the inefficient service processes, to the waits of long duration, and poor infrastructure. The research found that, as opposed to just relying on increased funds, a system-based approach, the sole way to improve healthcare delivery outcomes, is through improved capacity, reduction of service delays, and improved operational efficiency. The writers emphasized that the level of patient satisfaction can provide a useful empirical perspective on measuring the efficiency of the healthcare system and guide the legislative reforms to make the most of the provided services.

To determine the patient satisfaction with primary health care (PHC) services in Saudi Arabia, Ref. [10] carried out a systematic review and meta-analysis, examining the level of patient satisfaction and its determinants. The authors examined the studies related to many regions and found out that the accessibility concerns (waiting time and access to the facility) were associated with lower satisfaction whereas the overall level of satisfaction was moderate with the communication and continuity of care as important positive predictors. The meta-analytic findings have noted that although the system level factors, which considered service organization, provider behavior, and operational efficiency, were more substantial determinants of the degree of satisfaction, demographic variables such as age and education were mediated in a moderate manner. The review covers the factors affecting happiness in a middle-class healthcare environment in a comprehensive empirical synthesis through the application of rigorous quality evaluation methods and heterogeneity analysis. To enhance the patient experience and outcome, the authors proposed that the PHC centers must enact quality improvement and continuous assessment measures.

To explore the significant issues that affect patient satisfaction with the healthcare service delivery, Ref. [11] conducted an intensive literature review with a focus on the quality of the delivered services, communication, the physical environment, digital transformation, and accessibility. The authors reviewed 54 peer-reviewed articles of Scopus-indexed journals published within 2019-23 according to PRISMA guidelines. They synthesized reliability, responsiveness and empathy, which were frequent, important determinants of patient satisfaction in diverse healthcare facilities. Another aspect of the review that attracted attention is the role of patient-provider communication that is becoming very important and how polite, patient-centered, and transparent communication significantly enhances trust and satisfaction. Moreover, it was found that digital transformation, which encompasses telemedicine, electronic health record systems, enhances the effectiveness of services, reduces the waiting time, and expands access to care that have a positive effect on patient satisfaction. The waiting time and physical environment were also discovered to be the factors that had a major influence on the patient happiness and experience. Based on the findings, the authors argued that to meet patient expectations and improve the outcomes of healthcare delivery, continuous service enhancement, use of technology and patient-centered care strategies are essential. To sustain patient satisfaction improvement, the conclusions of the review also comprised several recommendations regarding the need to conduct more research and practice in the future and emphasized the importance of constant evaluation of new changes in healthcare service delivery.

3. METHODOLOGY

3.1. RESEARCH DESIGN

This study uses health systems modeling in conjunction with a cross-sectional survey research design. The design is suitable for investigating connections between patient satisfaction at a particular moment in time and elements of the healthcare system. Multiple linear regression is used to model and optimize healthcare delivery outcomes from quantitative data collected via a structured questionnaire.

3.2. STUDY AREA

The Federal Medical Centre in Yenagoa, Bayelsa State, Nigeria, was the site of the study. Residents of Bayelsa State and the surrounding states can receive referral, inpatient, and outpatient treatments from this significant tertiary healthcare facility. Because FMC Yenagoa serves a diverse population from both urban and rural areas, it is a good place to research patient satisfaction and the dynamics of healthcare delivery.

3.3. STUDY POPULATION

Outpatients who visited Federal Medical Centre in Yenagoa during the data collecting period make up the study population.

3.3.1. Criteria for inclusion

- Adult outpatients who are at least eighteen years old
- On the day of the survey, patients who had finished their outpatient consultation
- Patients who gave their informed permission

3.3.2. Exclusion standards

- Emergency situations and inpatients
- Patients who couldn't finish the questionnaire or were in serious condition

3.4. SAMPLE SIZE AND SAMPLING TECHNIQUE

During outpatient clinic hours, a convenience/systematic sampling technique was used to pick a sample of outpatients. After completing their clinic visits, consenting respondents were given questionnaires to make sure they had gone through the entire outpatient care procedure. In all a sample of 200 volunteered participants were used for this study.

3.5. INSTRUMENT FOR DATA COLLECTION

A structured questionnaire with four sections was used to gather data:

- Section A covers socio-demographic traits, such as age and educational attainment.
- Section B: Indicators of healthcare access and capability
- Section C: Indicators of the service procedure (travel time, waiting time)
- Section D: Measures of patient satisfaction

Waiting time and travel time were recorded in minutes, and responses to Sections B and D were scored on a four-point Likert scale.

3.6. MEASUREMENT OF VARIABLES

3.6.1. Response variable

Score for Patient Satisfaction (Z). Five factors (indicators) were used to gauge patient satisfaction:

1. Waiting period satisfaction
2. Satisfaction with the professionalism and attitude of the staff
3. Satisfaction with the standard of care
4. Satisfaction with the accessibility of prescription medications
5. General satisfaction with outpatient care

Every item was scored using a four-point Likert scale, where 1 represented "very dissatisfied" and 4 represented "very satisfied." Each respondent's raw satisfaction score was calculated as:

$$\text{Raw Score} = \sum_{i=1}^{5} \text{Item}_i. \tag{1}$$

A 0–100 scale was used to normalize the score as follows:

$$Z = \frac{\text{Raw Score} - 5}{20 - 5} \times 100. \tag{2}$$

3.6.2. Predictor variables

The following predictor/independent variables were looked at in this study:

1. Score for Capacity/Access (W_1): Five access indicators were combined to create a composite index:
   - facilities' accessibility,
   - staff availability,
   - accessibility of medications,
   - equipment accessibility,
   - service affordability.

   A four-point Likert scale was used to quantify each indication, which was then summed and normalized to a scale from 0 to 100.
2. Waiting Time (W_2): The self-reported wait time (measured in minutes) before getting medical help.
3. Travel Time (W_3): The respondent's self-reported travel time (in minutes) from home to FMC Yenagoa.
4. Level of Education (W_4): Assessed as an ordinal variable with the following code:
   - 0 = No formal schooling
   - 1 = Elementary schooling
   - 2 = Secondary schooling
   - 3 = Higher education

3.7. RELIABILITY OF COMPOSITE MEASURES

The internal consistency of the multi-item constructs used in this study was tested via Cronbach's Alpha coefficient. This technique evaluates the degree at which items measuring the same underlying construct produce consistent results. Reliability analysis was performed for the two composite indices (Patient Satisfaction and Capacity/Access to Healthcare Services); each measured using five Likert-scale items. The results of the analysis revealed that the Patient Satisfaction scale had a Cronbach's Alpha coefficient of 0.85, while the Capacity/Access scale recorded a Cronbach's Alpha value of 0.83, which according to established thresholds; both values exceed the minimum acceptable level of 0.70, indicating good internal consistency. These findings suggest that the items used to construct the composite variables are reliable and suitable for subsequent statistical analysis.

3.8. MODEL SPECIFICATION

The following multiple linear regression model was created in order to investigate the impact of healthcare system characteristics on patient satisfaction:

$$Z = \beta_0 + \beta_1 W_1 + \beta_2 W_2 + \beta_3 W_3 + \beta_4 W_4 + \varepsilon, \tag{3}$$

where Z and W_i have been defined earlier, β_0 is the intercept, β_i are the coefficients of the regression, ε is the error term.

3.9. METHOD OF DATA ANALYSIS

Both descriptive and inferential statistical methods were used to analyze the data. The characteristics of the respondents were summed up using descriptive statistics (means, frequencies, and percentages). Multiple linear regression was used for inferential analysis in order to estimate the association between healthcare system characteristics and patient happiness.

3.9.1. Multiple linear regression

If a regression model involves more than one independent variable, it is called a multiple regression model and is of the form as displayed in Eq. (3). Due to the nature of numerous explanatory variables, the study employed the general linear model that is making use of matrix form.

3.9.2. The general linear regression model

The general linear regression model expresses a linear relationship between the dependent variable Z, and p explanatory variables, where p can be 1, 2, 3, ... etc. In fact, when p is more than two as it is in this study, estimation of the parameters of the model becomes extremely tedious. However, this difficulty can be greatly reduced by the use of matrix algebra. Matrix algebra provides a compact method of handling regression model.

Suppose we postulate that there is a linear relationship between the dependent variable, Z and p explanatory variables $W_1, W_2, \ldots, W_p$ for a population of size N observations on Z and the W's, we may write:

$$Z_i = \beta_0 + \beta_1 W_{1i} + \beta_2 W_{2i} + \cdots + \beta_p W_{pi} + \varepsilon_i, \quad i = 1, 2, \ldots, N. \tag{4}$$

Re-writing Eq. (4) as a set of N simultaneous equation, we get:

$$\begin{aligned} Z_1 &= \beta_0 + \beta_1 W_{11} + \beta_2 W_{21} + \cdots + \beta_p W_{p1} + \varepsilon_1, \\ Z_2 &= \beta_0 + \beta_1 W_{12} + \beta_2 W_{22} + \cdots + \beta_p W_{p2} + \varepsilon_2, \\ &\vdots \\ Z_N &= \beta_0 + \beta_1 W_{1N} + \beta_2 W_{2N} + \cdots + \beta_p W_{pN} + \varepsilon_N. \end{aligned} \tag{5}$$

Eq. (3) can be re-written more compactly in matrix form as:

$$\mathbf{Z} = \mathbf{W}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{6}$$

Table 1. Anova table for regression analysis.

Source of variation	Df	SS	MS
Regression	p	SSR	MSR
Error	$n - p - 1$	SSE	MSE
Total	$n - 1$	SST	

where

$$\mathbf{Z} = \begin{bmatrix} Z_1 \\ Z_2 \\ \vdots \\ Z_N \end{bmatrix}, \quad \mathbf{W} = \begin{bmatrix} 1 & W_{11} & W_{21} & \ldots & W_{p1} \\ 1 & W_{12} & W_{22} & \ldots & W_{p2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & W_{1N} & W_{2N} & \ldots & W_{pN} \end{bmatrix},$$
$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_p \end{bmatrix}, \quad \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_N \end{bmatrix}. \tag{7}$$

$$F = \frac{\text{MSR}}{\text{MSE}} = \frac{\text{SSR}/p}{\text{SSE}/(n-p-1)}. \tag{8}$$

The decision rule is to reject H_0 if $F > F_{\alpha,p,n-p-1}$ otherwise we do not reject H_0. Alternatively, the decision rule is to reject H_0 if p-value is less than or equal to the significance level ($\alpha = 5\%$ in this study).

3.9.3. Coefficient of determination

The (multiple) coefficient of determination is given by:

$$R^2 = \frac{\text{SSR}}{\text{SST}} = 1 - \frac{\text{SSE}}{\text{SST}}, \tag{9}$$

where $Z_i, \hat{Z}_i, \bar{Z}$ are in deviation form. The adjusted R^2 written as $\bar{R}^2$ is defined by:

$$\bar{R}^2 = 1 - (1 - R^2)\frac{n-1}{n-p-1}. \tag{10}$$

3.9.4. Test of hypotheses

The model in this study $Z = \beta_0 + \beta_1 W_1 + \beta_2 W_2 + \beta_3 W_3 + \beta_4 W_4 + \varepsilon$ involves four explanatory variables. Hence two types of tests about the parameters of the model can be conducted, namely; individual tests and joint tests.

Individual test

Individual test involves testing whether an explanatory variable has any influence on the dependent variable when the other explanatory variable is held constant.

Under the assumption that each ε_i is $N(0, \delta^2)$, the test statistic is given as:

$$t = \frac{\hat{\beta}_i}{\text{SE}(\hat{\beta}_i)}. \tag{11}$$

The decision rule is to reject H_0 at the α level of significance if $|t| > t_{\alpha/2,n-p-1}$ (and hence conclude that a relationship exists between z and w_i) and do not accept H_0 otherwise. Alternatively, the decision rule is to reject H_0 if p-value is less than or equal to the significance level.

Joint test

This involves testing whether W_i, $i = 1, 2, 3$ and 4 are jointly related to Z. Thus, a joint test can be conducted using the Analysis of variance techniques as follows:

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$$
$$H_1 : \text{At least one } \beta_i \neq 0.$$

ESS = TSS - RSS.

4. RESULTS

The result of multiple linear regression model in Table 2 satisfies the assumptions of linearity, independence of errors, homoscedasticity, and lack of multicollinearity, according to diagnostic tests. The validity of the regression estimates is unaffected even though the Shapiro–Wilk test indicates a slight departure from normality of residuals, which is typical in cross-sectional healthcare survey data. All things considered, the model is appropriate for inference and statistically sound. Hence, the test of hypothesis for the regression analysis is presented thus:

4.1. HYPOTHESIS FOR JOINT TEST

H_0: At Federal Medical Centre, Yenagoa, there is no statistically significant correlation between outpatient satisfaction and waiting time, travel time, capacity/access, or educational attainment.

H_1: At the Federal Medical Centre in Yenagoa, there is a statistically significant correlation between outpatient satisfaction and at least one of the following: waiting time, travel time, capacity/access, and educational attainment.

The null hypothesis is rejected since the p-value in Table 3 is 0.000, which is less than the level of significance of 0.05, which becomes necessary to carry out individual tests.

4.2. TEST FOR INDIVIDUAL PARAMETERS

To investigate the impact of W_1, W_2, W_3, and W_4 on the dependent variable Z, a multiple linear regression model was developed whose results are summarized in Table 4. The findings show that the model fits the data quite well. According to the coefficient of determination, the explanatory variables in the model account for about 42.3% of the variation in Z. The modified/adjusted coefficient of determination shows that 41.1% of the variation in Z is still explained after controlling for the number of predictors, indicating a sufficient explanatory power for cross-sectional healthcare survey data. The F-statistic, which is statistically significant at the one percent level (F = 35.67, p = 0.000), further supports the model's overall relevance by showing that the explanatory variables collectively have a significant impact on the dependent variable.

By analyzing the calculated coefficients, it is found that the positive and statistically significant effect of W_1 on Z is present. Specifically, other things being equal, a one unit increase in W_1 will produce an average increase of 0.54 units in Z. The implication of this outcome is that significant improvements in the dependent variable have a strong relationship with the improvement of W_1. W_2 and Z, on the other hand, are negatively associated and statistically significant in the relation of which an average result in a decrease of 0.23 units of Z is experienced with 1 unit increase in W_2. This underlines the importance of W_2 as a significant constraint that affects the result variable. W_3 has fairly moderate effect despite the fact that it tends to lower Z and this can be seen through the coefficient of W_3 which is negative but insignificant. The model concludes that W_4 does not play a significant role in explaining W_4 changes as the coefficient of W_4 is positive though not statistically significant.

The findings reveal in overall that W_1 is the most powerful positive driver of the response variable, suggesting that interventions targeted at enhancing this component are probably going to provide improvements significantly. W_2's large adverse impact on the other hand indicates that it is a serious barrier to better results and needs specific policy attention. More so, W_4 does not seem to be a crucial factor influencing the result in this model, but W_3 has a negative impact, though minor. These results when taken as a whole, give recommendations for healthcare delivery outcomes improvement, as well as empirical insight into the relative significance of the predictor variables in influencing the response variable.

4.3. DISCUSSION OF RESULTS

The multiple linear regression results provide useful data as regards the variables that affect the patient satisfaction and outcomes of healthcare delivery in the study. The explanatory variables, in combination, account a considerable portion of the variation in the dependent variable, which indicates that the influence of the aspects related to the healthcare system and service procedures on patient experiences is significant. The overall statistical significance of the model justifies the use of health systems modeling as a decision-support tool to improve healthcare delivery and justifies the relevance of the variables in the analysis of outpatient satisfaction variations.

The number and the availability of the healthcare system play a critical role in improving patient outcomes as the positive statistically significant effect of (W_1) indicates. This result means that the patient satisfaction will significantly improve because of the investments made to make the facility better prepared with adequate staffing, medication, equipment, and affordability. Policy-wise, significant advantages to patient satisfaction and service quality can first be achieved through investing resources on these capacity-enhancing aspects, particularly in state-owned healthcare organizations. Conversely, the waiting time is highlighted as a significant obstacle to the delivery of healthcare because of the adverse and significant impact of (W_2). Patient satisfaction is reduced significantly by longer wait times, which may probably imply inefficiencies in patient flow, staffing distribution, or appointment scheduling. Service responsiveness improvement and reducing delays needs policy measures which improve service points, queue management and also outpatient procedures optimization.

Although (W_3) is negative, the impact is quite minor and it is only marginally significant which indicates that the travel related barriers influence patient satisfaction in the area of the research secondarily. The findings imply that the positive changes at the facility, in particular, the service efficiency and service-capacity aspects, can contribute more to patient experience immediately than the geographic variables, though the proximity and accessibility remain important. Nevertheless, accessibility may further increase with the long-term improvement of the transportation in-

Table 2. Synopsis of diagnostic findings and multiple linear regression assumptions.

	Assumption				
	Linearity	Independence of errors	Homoscedasticity	Normality	Multicollinearity
Technique	Tukey	Durbin-Watson	Breusch-Pagan	Shapiro-Wilk	Variance inflation factor
Test statistic	0.3717	2.159	6.9671	0.9629	Range of 1.03 – 1.23
p-value	0.7101	0.292	0.1376	<0.001	–
Decision	NS	NS	NS	S	Acceptable
Interpretation	The association between Z & W_1, W_2, W_3, W_4 is linear adequately	Autocorrelation is not evident, and errors are independent.	The homoscedasticity requirement is met since the residuals' variance is constant across fitted values.	Given the sample size, residuals' minor deviation from normalcy does not invalidate inference.	There is no issue with multicollinearity among the independent variables.

Note: NS = Not significant, S = Significant

Table 3. Result of anova table for multiple regression model.

Model	SS	df	MS	F	Sig.
Regression	37495.316	4	9373.829	35.670	0.000
Error	51240.000	195	262.764		
Total	88735.316	199			

Table 4. Result summary of individual coefficients.

	Estimate	SE	T	p-value
Intercept	39.516	6.413	6.161	0.000
W_1	0.540	0.060	8.970	0.000
W_2	-0.227	0.062	-3.696	0.000
W_3	-0.062	0.037	-1.678	0.095
W_4	0.432	1.294	0.334	0.739
$R^2 = 0.423, \bar{R}^2 = 0.411, F = 35.670$				

frastructure and decentralization of services among the patients who travel greater distances. When the relationship between healthcare system and service processes variables are taken into consideration, the fact that the effect of (W_4) was not statistically significant shows that educational attainment variation is not a determining factor of patient satisfaction; hence, this indicates that patient characteristics are not the key reason behind unhappiness, but more so systemic factors, which points to the fact that the solution should be in supply-side reforms instead of demand-side reforms.

Put together, these findings reveal that to make healthcare provision better, a concerted effort is required to raise the capacity of the systems and reduce operational inefficiencies, in particular, waiting times. Policymakers and health administrators can apply these results to identify the areas of interventions of the utmost priority, allocate their resources more efficiently, and develop evidence-based interventions aimed at improving patient satisfaction and the work of the healthcare system in general. Consequently, the study demonstrates the usefulness of health systems modeling in facilitating policy decisions and the adoption of more effective and flexible healthcare delivery.

5. CONCLUSION

In considering the outpatient satisfaction in a government hospital context, this paper has explored the potential of the health systems modeling in the optimization of healthcare delivery in the state of Bayelsa. The data of outpatients was collected using a structured questionnaire and multiple linear regression analysis was conducted to examine how waiting time, travel time, education level, and capacity and access of the healthcare system affect the satisfaction with the healthcare system. The analytical method was driven by the school of thought to provide evidence based information that can be used to plan and make policies towards efficient healthcare delivery. Even the slight variations outside the normalcy were deemed not critical considering the sample size and the diagnostic tests confirmed that the regression model satisfied the key assumptions of multiple linear regression including linearity, error independence, homoscedasticity and non-existence of multicollinearity. On the whole, the findings reveal the effectiveness of statistical modeling as an instrument to understand the dynamics of the healthcare delivery and outline the most critical spheres to focus on.

The findings indicate that the explanatory variables as a whole remarkably explain the variation in outpatient satisfaction, which illustrates the significance of both system-level and service-process factors in the patient experience. Capacity and access were identified to be the highest positive source of satisfaction, and this highlights the importance of adequate staffing, infrastructure, medication supply, and costs in supporting healthcare service quality. Conversely, the waiting time was observed to reduce the satisfaction substantially, which shows a lack of operational efficiency leading to the quality of services offered in the health facilities of the people. The education level did not have a significant impact on satisfaction; the negative effect of travel time was weaker, which means that dissatisfaction with the patients is caused by the systemic issues, rather than individual characteristics.

In general, the research demonstrates that to enhance healthcare provision in the state of Bayelsa, specific efforts are required to expand the capabilities of the healthcare system and reduce the rates of service inefficiency, particularly, waiting times. The application of health systems modeling in this study proves that it is a helpful tool in identifying bottlenecks, allocating resources, and helping to make decisions based on data. By integrating the statistics modeling into the planning processes in healthcare, policymakers and health administrators can enhance the responsiveness, effectiveness, and equity of healthcare services and, therefore, the public health outcomes of the state.

6. RECOMMENDATIONS

1. Fund the access and ability of the healthcare system first: The capacity and access turned out to be the largest positive inducers of outpatient satisfaction, so policy makers are to focus on improving the infrastructure of facilities, increase the supply of medical personnel, ensure a constant stream of drugs, and upgrade the equipment needed. The enhancement of these core aspects will directly enhance patient satisfaction and the quality of services.
2. Implement special strategies to reduce outpatient waiting durations: Healthcare administrators ought to adopt measures that include more efficient appointment scheduling, more efficient patient flow, allocation of chores among healthcare workers, and increasing service points during peak hours since waiting time has been established to cause a great reduction in patient satisfaction. Such measures will be able to improve the performance of services and significantly reduce delays.
3. Normalize the use of health systems modeling as a decision-making tool: The research demonstrates how statistical modeling can be applied to identify significant factors that determine the outcome of healthcare delivery. Health authorities should formalize the use of data-driven health systems models in healthcare service planning, monitoring, and evaluation to help them better allocate resources and make evidence-based policymaking.
4. Give more consideration to plans and transformations than patient demographics: As the level of education did not show any significant effect on outpatient satisfaction, the healthcare delivery should be the center of healthcare provision improvement efforts and not patient characteristics. Healthcare services will be egalitarian and responsive to the requirements of all patient groups if supply-side reforms are prioritized.

7. LIMITATIONS OF THE STUDY

Despite the robustness of the analytical technique and the significance of the findings, this study has a few limitations which are worth mentioning. Firstly, this study employed a cross-sectional research design, which enables a dataset to be collected over a single time point. Therefore, this analysis is restricted to determining relationships, but not causality, between different variables.

Secondly, this study employed a convenience/systematic sampling technique in selecting respondents from the Federal Medical Centre, Yenagoa, which may limit the generalizability of this analysis. Although this dataset is sufficient for analysis, this may not represent other patient populations, especially in other facilities with different operational characteristics. Thirdly, although this analysis employed a dataset based on self-reported information collected through structured questionnaires, this dataset is vulnerable to potential biases, which may affect the accuracy of responses, especially in determining patient satisfaction and perceptions of healthcare services.

Fourthly, while composite indices were developed for patient satisfaction and healthcare system capacity/access using Likert scales, in terms of determining reliability, internal consistency measures such as Cronbach's alpha were used, although the results showed a good level of reliability, a lack of other validation techniques, such as factor analysis, may not allow for a thorough level of construct validation. Fifthly, the number of independent variables was limited to waiting time, travel time, education level, and capacity/access. Other factors, such as income level, health status, quality of communication, and facility environment, which could affect patient satisfaction, were not included in the model, which could have led to the variation in the dependent variable.

Lastly, the study was conducted in a single tertiary care facility. While such a study provides valuable insights into the delivery of healthcare in a particular context, such findings cannot be extrapolated to other levels of care, such as primary or secondary care, or to different regions with different structures of healthcare systems.

DATA AVAILABILITY

The data will be available on request from the corresponding author.

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