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Service Disruption, Recovery, and Financial-Operational Context in a Public Tertiary Hospital: A Longitudinal Study of AIIMS New Delhi, 2010-2025

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Abstract

Background

Public tertiary hospitals must sustain high-volume referral, teaching, and clinical services while managing constrained resources and external shocks. Longitudinal evidence integrating audited financial context, capacity, and multiple-service outputs is limited. This study examined long-term institutional expansion, the 2020–2021 service interruption, and subsequent service recovery at AIIMS New Delhi.

Methods

A retrospective longitudinal case study was conducted using publicly available annual reports from AIIMS New Delhi financial years 2010–2011 through 2024–2025. An institution-year series covered outpatient attendance, admissions, procedures, beds, occupancy, length of stay, and consolidated financial indicators; and a Center-year panel provided corroborative evidence. Long- linear trend models, exploratory segmented pulse-and-slope models, and Center fixed-effects models were estimated with robust uncertainty assessments and sensitivity analyses for approximate, missing, and definition-shift observations.

Results

Admissions increased by an estimated 3.71% per year (95% CI 1.21% to 6.27%) and reported bed capacity by 3.48% per year (95% CI 2.80% to 4.17%). In 2020–2021, outpatient attendance, admissions, and procedures were estimated to be 61.0%, 44.5%, and 62.1% below their fitted pre-shock trajectories, respectively, while bed occupancy was estimated to be 28.0 percentage points below its fitted trajectory. These are model-estimated deviations, not causal effects. By 2024–2025, outpatient attendance was 9.7%, admissions 34.7%, procedures 27.6%, and beds 31.0% above the observed 2019–2020 baseline, although occupancy remained 2.8 percentage points lower. Centre fixed-effects models provided within-source corroboration for outpatient and procedure disruption, whereas the admission estimate was imprecise. From 2019–2020 to 2024–2025, nominal income and expenditure increased by 70.1% and 68.4%, respectively.

Conclusions

AIIMS New Delhi experienced substantial but service-specific restoration of reported activity after a severe 2020–2021 interruption. Recovery is interpreted against both the observed 2019–2020 baseline and the fitted pre-shock trajectory, which are not equivalent benchmarks. The findings do not establish complete institutional resilience, technical efficiency, backlog resolution, or causal effects of the pandemic period, expenditure, or bed expansion on service restoration.

Highlights

• Admissions and bed capacity showed sustained growth over the 15-year study period.

• The COVID-19 period coincided with sharp, service-specific disruptions in 2020–2021.

• All major service volumes exceeded the observed 2019–2020 baseline by 2024–2025.

• Nominal financial growth accompanied service recovery but did not establish efficiency, real resource growth, or a causal contribution to recovery.

1. Introduction

Public tertiary hospitals hold a challenging role within health systems. They are tasked with delivering a large volume of outpatient, diagnostic, and procedural services while simultaneously fulfilling responsibilities related to specialist referrals, medical education, research, and public health. These functions are delivered under changing demand, finite budgets, workforce constraints, and periodic additions to physical capacity. Hospital performance is therefore not adequately represented by one financial ratio or one service indicator. It is better understood through the joint movement of resource inputs, service outputs, and operating conditions over time. Research on public hospitals has used financial ratios, data envelopment analysis, and econometric models to examine these dimensions, but findings vary with ownership, reimbursement arrangements, case mix, and the variables included in each model [20–28].

The distinction between financial and operational performance is especially important in a publicly funded tertiary institution. Expenditure growth may accompany capacity expansion, a new clinical centre, higher input prices, or more complex care; it does not by itself demonstrate inefficiency. Similarly, higher outpatient attendance, admissions, or procedures may indicate greater service reach, but these volumes do not directly measure quality or population need. Reviews of hospital finance show that accounting definitions and performance measures are not standardized, while evidence linking financial results to quality is mixed [21, 22]. Efficiency studies likewise demonstrate that input-output estimates are sensitive to variable selection and institutional context [23–25]. A defensible longitudinal analysis must therefore preserve the distinctions among financial indicators, capacity utilization, and performance measures before interpreting how they move together.

The COVID-19 pandemic made this analytical problem more urgent. A systematic review found extensive reductions in healthcare utilization during the early pandemic, although the size of the decline differed across services and settings [1]. Comparative analyses subsequently showed that disruptions occurred across national health systems but were not uniform in depth, duration or recovery [2, 3]. Hospital-based and administrative-data studies documented reductions in admissions, outpatient consultations and procedures in Kenya, the Philippines, Iran, Uganda, Bangladesh and other settings [4–12]. These studies collectively establish that the pandemic was a major service shock. They also show that a single percentage change is insufficient to describe its institutional consequences.

The period after the initial shock is equally important. Some service categories recovered quickly, whereas others remained below previous trajectories or changed in composition [4–13]. Longer follow-up in China and Bangladesh, for example, identified persistent or uneven effects beyond the first pandemic year [6, 9]. An Indian tertiary-hospital study observed sharp reductions during lockdown followed by a gradual recovery, but it involved a private corporate hospital and only a two-year comparison [13]. Such evidence points to the need for longer pre-shock baselines and explicit post-shock slopes. Without them, temporary interruption, delayed recovery, and a durable change in institutional trajectory can be difficult to distinguish. This study uses resilience as a bounded empirical concept. Recent reviews describe health-system and hospital resilience through preparedness, absorption of disruption, maintenance of essential functions, adaptation and recovery [17–19]. No single agreed hospital-resilience measure has emerged, and many underlying capabilities - such as coordination, workforce flexibility, supply management and organizational learning - are not directly observable in annual reports [15–19]. Accordingly, the present study does not claim to measure resilience as a complete latent organizational property. It examines the observable financial-operational pattern: the scale of the service disruption, the subsequent direction and rate of recovery, and the extent to which institute-wide findings are corroborated across hospital centres.

In a publicly funded tertiary hospital, financial resilience differs from conventional firm-level interpretations centred on profitability or revenue generation. Public hospitals operate within government appropriation processes, annual budget cycles, expenditure rules, and designated funding arrangements that may limit the speed with which resources can be redirected. During a major health shock, however, institutions may simultaneously need to maintain essential services, preserve workforce and infrastructure, strengthen infection-control and emergency functions, and reprioritize resources toward changing clinical needs. In this setting, financial resilience is best treated as a bounded contextual concept concerning continuity of resource availability and essential operations. For AIIMS New Delhi, grants and subsidies are the predominant reported income source; however, the annual financial statements do not directly reveal internal budget-reallocation decisions. Funding continuity and expenditure patterns are therefore interpreted as contextual indicators rather than direct evidence of specific adaptive financial mechanisms.

Evidence from India remains important but incomplete for this purpose. A systematic review documented wide effects of COVID-19 on the Indian healthcare system [14], and a large Delhi multispecialty hospital reported major reductions in non-COVID outpatient and surgical activity [13]. Earlier studies of public district hospitals in India and Bangladesh showed substantial variation in technical efficiency [27, 28]. These contributions provide useful national and regional context, yet they differ from a long-horizon study of a government-funded referral and teaching institution. They generally do not combine audited finance, institute-wide service indicators, recovery trajectories and centre-level corroboration across a fifteen-year period.

The choice of longitudinal method also requires caution. Interrupted time-series analysis can estimate changes in level and slope when a shock has a clearly defined date [29]. However, methodological reviews repeatedly identify inadequate treatment of autocorrelation, incomplete model reporting, limited sensitivity analysis and overstatement of causal interpretation [30–32]. Multicenter extensions further show that pooled effects can conceal stable differences and heterogeneous responses among centres [33]. These

considerations are especially relevant here because annual institutional data provide a small number of time points and because hospital reporting definitions and organizational boundaries can change. The pandemic model is therefore treated as an exploratory structural-break analysis, supported by conventional and heteroscedasticity-and-autocorrelation-consistent inference, diagnostics, sensitivity checks and a separate centre fixed-effects analysis.

Within this context, the present study develops a harmonized financial-operational dataset using the annual reports of AIIMS New Delhi for the period 2010-11 to 2024-25. The data consist of aggregated institutional indicators rather than individual patient-level records. It combines information on reported expenditure and grants, bed strength, workforce measures, outpatient attendance, admissions, procedures, bed occupancy, average length of stay and centre-specific workload. Particular attention is given to missing or approximate observations, changes in reporting definitions and the distinction between legacy AIIMS Main accounts and later consolidated financial statements. These source-related boundaries are explicitly preserved instead of being obscured through automatic data merging.

The study had three aims. The first aim was to evaluate trends in institutional capacity, service use, and performance indicators over the years. The second aim is to study the immediate effects observed in the years 2020-21 and the recovery observed later using annual models classified according to segments. The third aim is to check if the trends at the institute level follow the same trend once the differences that exist between the centers have been considered and the operational results are interpreted along with the financial ones available. The study does not specify how the experience of some institutions could be representative of all hospitals in India; however, it serves as an illustration of the possibility of changing the annual reports into materials for research regarding expansion, disruption, and recovery of institutions, appreciating at the same time the limits of the causal analysis and interpretation of patient information.

2. Related Literature

2.1 Public hospital financial and operational performance

Research on hospital performance commonly differentiates among resource inputs, service outputs, financial circumstances, and quality indicators. Data envelopment analysis studies frequently classify beds, personnel, and expenditure while outpatient visits, admissions, and procedures are considered outputs [23–25, 27, 28]. Although this approach is valuable for comparisons, estimates depend on variable selection, hospital similarity, and contextual adjustment. Reviews and empirical studies conducted in China, India, and Bangladesh reported substantial variations in specification and hospitals [23, 24, 27, 28]. Consequently, a single coefficient linking capacity to output should not be interpreted as a universally applicable production relationship.

Financial results are formed by funding rules, accounting possibilities, ownership, payment systems, and mandated functions [20, 22]. A positive balance may reflect timing or accounting treatment, whereas grant dependence is normal for many public providers. A scoping review found no simple or consistent relationship between stronger financial indicators and better care [21]. Therefore, financial measures

should be interpreted with service scale, capacity change, and reporting scope rather than used as isolated performance scores. Length of stay and bed occupancy can inform capacity planning; however, neither has a fixed interpretation. Length of stay responds to bed availability, case mix, discharge arrangements, and service configuration [26]. Occupancy may decline during disruptions, new bed ramp-ups or altered admission patterns. Therefore, longitudinal interpretation must account for changes in reporting and organizational expansion.

2.2 Disruption and recovery of hospital services during the Pandemic

The literature regularly identifies COVID-19 as a broad disruption of non-COVID and routine care. Moynihan et al. [1] synthesized evidence from multiple countries and reported substantial reductions in healthcare utilization. Arsenault et al. [2] and Ledesma et al. [3] extended this perspective by comparing several health systems and showing that disruptions differ across services and countries. These comparative studies are important because they shift attention from whether a disruption occurred to how severely each service was affected and how rapidly it returned. Hospital and administrative studies provide more detailed trajectories of these patients. A Kenyan interrupted time-series study found a fall in inpatient admissions across 204 hospitals with differences by ownership and an incomplete reversal within the available follow-up [4]. Studies in the Philippines, Iran and Uganda documented service-specific changes in admissions, procedures and case composition [5, 7, 8]. Recent studies from Bangladesh and Iranian governmental hospitals similarly show that outpatient, inpatient, occupancy, and procedural indicators did not move identically [9, 11, 12]. These results support the separate modelling of OPD attendance, admissions, and procedures rather than combining them into one activity index.

Indian evidence confirms substantial interruption but leaves room for a longer institutional analysis. Vaishya et al. [13] analyzed 6,77,237 records from a private Delhi tertiary hospital and reported sharp lockdown reductions followed by gradual improvement; the authors cautioned against generalizing to government institutions. Kapoor et al. [14] identified broader effects on access, infrastructure, workforce, and delivery. Neither study provides a fifteen-year audited financial-operational trajectory for a public tertiary referral institution.

2.3 Hospital resilience the interpretation of service recovery

Resilience is increasingly used to describe how hospitals prepare for, absorb, adapt to, and recover from disruptions. Fleming et al. [17] found wide variation in the metrics used to assess health system resilience, including service utilization, capacity, workforce, access, and recovery time. The hospital-focused reviews by Cavalieri et al. [18] and Carbonara et al. [19] similarly emphasize that resilience is multidimensional and depends on physical, human, informational, relational, and managerial capabilities. This literature review makes two points relevant to the present study: recovery should be measured over time, and observed service restoration cannot reveal every capability that produced it.

Qualitative and case study evidence identifies plausible recovery mechanisms. Hospital managers and frontline staff have emphasized governance, flexible deployment, communication, supplies, coordination,

and learning [15]. Commonwealth case studies describe digital adaptations, partnerships, and redesigned service pathways [16]. Annual reports can record the resulting volumes and resources, but they do not consistently measure these mechanisms. Consequently, the AIIMS study uses the term financial-operational resilience to describe an observed institutional pattern while reserving causal explanations about internal capabilities for cautious discussion.

2.4 Evidence from India and comparable low- and middle-Income countries

Public hospitals in South Asia experience high demand for their services due to insufficient resources and varying levels of institutional efficiency. In Madhya Pradesh and Bangladesh, the techniques of data envelopment analysis already pointed to significant differences in terms of operational efficiency in the case of public hospitals [27, 28]. Regardless of the fact that these studies show the established significance of aligning resource inputs and service outputs, district hospitals cannot be compared with AIIMS, a national teaching and referral center for advanced patients with specialized facilities and extended clinical, educational, and research functions. The research in Kenya, Uganda, Bangladesh, and India shows that service shocks are determined by access, referrals, priorities, and local capacity [4, 8, 9, 13, 14].

The Findings also vary according to the source of data. Patient-level records support analysis of case mix and clinical outcomes, claims data reflect reimbursed healthcare activity, and annual reports provide aggregated institutional information with comparatively limited clinical detail. The AIIMS dataset provides extensive longitudinal coverage and is linked to audited institutional reporting; however, it does not permit assessment of individual patient needs, disease severity, or equity in service access.

2.5 Longitudinal analysis of shocks and institutional heterogeneity

Interrupted time-series analysis is appropriate when a shock occurs at a defined point, and randomized comparisons are impossible [29]. Segmented Regression differentiates the previous trend in the data, the immediate level shift, and the slope post-shock. Reliability varies depending on the number and spacing of observations, the model nature, time correlation, and simultaneous changes. The review of the methodology confirms that practitioners do not always completely report the assumptions and diagnostics of the model [30–32]. The data from AIIMS necessitate a careful and uncomplicated approach when using this design of study. Annual observation eliminates the noise arising from seasonality; however, they offer only a single observation for the main shock year, allowing for limited power. Hence, the calculated deviation for 2020-21 can be considered only in an exploratory manner and not as a reliable effect. Although reporting both classical and HAC inference techniques and checking residuals can minimize this limitation, it cannot be completely removed.

Centre-level analysis offers additional evidence. Multicenter interrupted time-series approaches highlight the importance of accounting for both trends within individual centers and variations across centers [33]. The AIIMS centre-level panel is restricted to allow a sophisticated random-effects approach, either in

terms of shocks estimated through a simpler random-effects model or related to the complexity of the model used. Fixed effects estimates at the centre level can monitor differences in terms of institutional behavior that are constant across data groups. The consistency between the results from using time-series data and fixed effects estimates enhances the interpretation of the common shock impact. These differences reveal variations that should be examined rather than eliminated.

2.6 Research gap and positioning of the study

Although the literature in this area is substantial, it remains fragmented. Efficiency studies generally rely on cross-sectional comparisons among hospitals, whereas financial studies focus primarily on accounting performance and organizational viability. Pandemic-related research often examines only the initial shock period or concentrates on a single service area. Similarly, resilience studies rarely integrate continuous hospital-level financial and operational data over an extended period. Therefore, the gap is not an absence of hospital or COVID-19 research. The limited integration of audited finance, capacity, several service outputs, a long pre-pandemic baseline, an explicit recovery period, source-quality controls, and center-level corroboration in one public tertiary institution. The AIIMS study addresses this integration gap through a transparent case design while preserving the limits imposed by aggregation, reporting changes, a single institution, and observational data.

3. Data and Methods

3.1 Study design and setting

This study used a retrospective longitudinal case design to examine financial and operational changes at the All India Institute of Medical Sciences (AIIMS), New Delhi. The observation period extended from the financial year 2010-11 through 2024-25. The unit of analysis was an institution-year for the main longitudinal series and a hospital centre-year for the corroborative panel analysis. This study did not use patient records. All observations were aggregated statistics reported by the institutions. The design was intended to describe long-term expansion, estimate the magnitude of the 2020-21 service interruption, characterize the subsequent recovery trajectory, and examine whether the institute-wide pattern was also visible within centers after controlling for center differences.

3.2 Data sources and report selection

The source of data for the study primarily consisted of the annual report of AIIMS New Delhi for the duration of the study. Reports that contained “At a Glance” table comparative performance table and audited financial statements and workload tables for the center were included. In instances where both description and table data were available, data reported in table format were regarded as more accurate and trustworthy than any data appearing as estimates in the text. The operational file consisted of 15 fiscal-year observations. Budgetary data for 2012–2013 were only available in the form of estimates in the Director’s Reviews which were classified as estimates. The AIIMS report for 2016–2017 was missing hence, only the indicators of performance were reconstructed for that year making it a partial year. center-level panel data were compiled.

3.3 Data extraction and harmonization

Structured extraction templates facilitated the alignment of the years of reporting, institutional units, and measurements. OPD attendance, admissions, procedures, and beds were extracted from institute-wide summary tables wherever available. The names of the Centers were standardized in the reports, and general and private beds were combined to give the total number of beds wherever both were present. Ratios calculated were based on only those bought forward from the numerator and the denominator, and missing values were kept unattended; missing data were not replaced by interpolation, trend measurement, or narratives. In that report, values that had been presented cumulatively were not treated as annual values.

The process of harmonization was able to document the alterations in terms of the different measurements and reporting, unlike treating all observations as entirely similar. In 2015–2016, a significant alteration in he main hospital length of stay was identified and was not perceived as an operational effect. Similarly, in 2024–2025, the CDER procedure count was noted with a flag indicating its validation and was not allowed to influence the overall conclusion at the institutional level. With the development of specialized hospitals, reporting boundaries have been progressively extended. Thus, this study interpreted the time coefficients as relationships with time instead of a production function.

3.4 Financial scope and study variable

Data were collected from audited income and expenditure records. The early AIIMS Main financial accounts and the later consolidated or revised statements were considered as separate accounting series. The revised comparative data for 2019-20, which appeared in the 2020-21 statement, thus formed the base of the consolidated series up to 2024–2025. Because two sets of values were available for 2019–2020, they were retained to show the difference in accounting scope and were not merged into a single continuous series. All financial figures have been examined in current rupee value since the objective was to provide information about the institutional finance itself without aiming to assess real purchasing power.

The principal service metrics assessed were general OPD attendance, hospital admissions, and the total number of operations performed. Other indicators were the overall number of beds, average length of stay at the Main Hospital, bed occupancy, net death rate, and infection rate, according to data availability and consistency of definitions.

The financial measures comprised total revenue, total spending, grants and subsidies, establishment cost, administrative cost, expenditures on materials and supplies, financial surplus or deficit, operating margin, reliance on grant, expenditure distribution, and expenditure per service unit. Operating margin was determined by dividing surplus or deficit by total income, while grant dependency as grants and subsidies divided by total income; and unit expenditure as total expenditure in rupees divided by relevant service output. Workload indicators included ratio of OPD attendence, procedures per admission, OPD per bed, and admissions per bed. The study variables were organized into the domains and analytical roles summarized in Table 1.

Table 1
Data domains and operational use

Domain	Variables	Role in the analysis
Resource and finance inputs	Beds, faculty and non-faculty staffing, total income and expenditure, grants, establishment, administration and material expenditure	Describe institutional resources and financial intensity; finance scopes analyzed separately
Service outputs	OPD attendance; admissions; procedures	Primary longitudinal, interruption and center-panel outcomes
Performance indicators	Bed occupancy, length of stay, net death rate, infection rate	Secondary operational indicators, subject to definition stability
Derived workload indicators	Admissions/OPD, procedures/admission, OPD/bed, admissions/bed, unit expenditure	Transparent ratios for descriptive interpretation, not composite efficiency scores
Context and quality controls	Fiscal year; phase; hospital centre; source file/location; exact, approximate or partial status	Define time, institutional heterogeneity and evidence quality

3.5 Statistical analysis

3.5.1 Descriptive and long-term trend analysis

Annual distributions, period means, absolute changes, relative changes, and compound annual growth rates were calculated first. The pre-COVID period covered observations through 2019-20, 2020-21 represented the principal disruption year, 2021-22 was treated as a transition year, and 2022-23 through 2024-25 formed the later recovery period for descriptive comparison. Recovery was assessed using two complementary benchmarks. Observed-baseline recovery refers to restoration to or above the reported 2019-20 service level. Trajectory recovery refers to movement toward the fitted continuation of the pre-shock trend estimated by the segmented model. Exceeding the 2019-20 observed baseline therefore does not necessarily imply full return to the model-estimated pre-shock trajectory.

$$ln(Y_t) = \alpha + \beta_1 Time_t + \varepsilon_t. \quad (1)$$

The corresponding average annual percentage change was computed as $100[\exp(\beta_1)-1]$. Length of stay and percentage-point outcomes were modelled using their reported scales. Heteroscedasticity-and-autocorrelation-consistent standard errors with one lag [HAC (1)] were used for primary trend inference, with HC3 inference used as a robustness check. The approximate 2012-13 service row was from the excluded sensitivity models.

3.5.2 Pandemic interruption and recovery model

The pandemic analysis used an exploratory segmented pulse-and-slope model rather than a simple two-period comparison.

$g(Y_t) = \beta_0 + \beta_1 Time_t + \beta_2 Shock_t + \beta_3 Recovery_t + \varepsilon_t.$ (2)

Here, g(.) was the natural logarithm for OPD attendance, admissions, and procedures, and the identity function for bed occupancy. Time_t represents the underlying annual trend. Shock_t equals one only for 2020–2021 and zero otherwise, estimating the model-based deviation in the principal disruption year from the fitted continuation of the pre-shock trajectory. Recovery_t was zero through 2020–2021 and then increased annually thereafter to describe the post-shock slope. The fitted continuation is a model-based counterfactual rather than an independently observed comparison: no unaffected hospital, service, or external control series was available. Accordingly, the segmented coefficients are interpreted as exploratory deviations from a fitted pre-shock trajectory and not as causal effects of COVID-19. Because the analysis uses annual fiscal-year observations, within-year seasonality cannot be estimated separately and was not included as a seasonal component. Potential serial correlation across annual observations was assessed using HAC (1) inference and residual diagnostics, including the Durbin-Watson statistic and Breusch-Godfrey tests where estimable; given the small number of observations, these procedures are treated as robustness assessments rather than proof that all temporal dependence has been eliminated.

Conventional ordinary-least-squares confidence intervals were presented because of the very small annual sample, whereas HAC (1) p-values were used for sensitivity assessment. The model was described as exploratory structural-break evidence, not a causal estimate of the pandemic, because 2020-21 was a high-leverage observation and other contemporaneous operational changes could not be separated [29–32].

3.5.3 Center fixed-effects corroboration

A centre-year panel was used to assess whether the institute-wide disruption was visible within repeatedly reported hospital centres. The specification was:

$ln\,(Y_it + 1) = \alpha_i + \beta_1 Time_t + \beta_2 Shock_t + \beta_3 Recovery_t + \varepsilon_it.$ (3)

Here, α_i denotes centre fixed effects. Adding one permitted retention of legitimate zero-procedure counts. Standard errors were clustered by centre, with HC3 inference used as a secondary check. CDER and the National Cancer Institute were excluded from the primary panel model because their procedure definitions or reporting windows were not comparable with the repeatedly reported centre series. The centre panel is derived from the same institutional reporting system as the institute-level series and therefore provides within-source corroboration rather than independent external confirmation. With only ten centre clusters in the primary panel, cluster-robust inference may be imprecise; p-values and confidence intervals are therefore interpreted cautiously and alongside HC3 sensitivity results rather than as strong evidence of uniform centre-level effects [33].

3.6 Diagnostics, sensitivity analysis and interpretation

Model adequacy was evaluated using residual analysis, the Durbin-Watson statistic, Breusch-Godfrey tests where estimable, variance-inflation checks, and influence assessment. Sensitivity testing involved omitting the approximate observation for 2012-13, comparing conventional, HAC, and HC3 standard error

estimates, excluding centres with inconsistent reporting practices, and examining panel models adjusted for service capacity. The findings were reported mainly through regression coefficients, converted effect measures, and 95% confidence intervals. Two-tailed p-values below 0.05 were treated as statistically significant, values ranging from 0.05 to less than 0.10 were regarded as indicative, and values were interpreted as inconclusive. When interpretations varied among the uncertainty estimation methods, the finding was classified as method-sensitive. Capacity-related coefficients were not interpreted when they showed substantial variation in the sensitivity analysis.

3.7 Ethics and reproducibility

The analysis used publicly available annual reports containing aggregated institutional. No individual-level, identifiable, or confidential patient information was accessed, and individual consent was not required. No formal ethics approval number was obtained. The final ethics statement will be aligned with the selected journals and institutional requirements. Data preparation retained the source-file and report location fields, exact/approximate/partial status flags, transformation rules, and analysis outputs. The statistical workflow was implemented in Python using tabular data processing and regression procedures, and the linked workbooks preserved the extracted data, derived indicators, model specifications, diagnostics, and publication tables needed to reproduce the reported results.

4. Results

4.1 Analytical coverage and data quality

The institute-level operational data spanned 15 fiscal years from 2010-11 to 2024-25. The service volume trend analysis and interrupted time-series models were based on 14 observations because the 2016-17 report did not provide recoverable institute-wide totals for OPD attendance, admission, or procedure. The service figures from 2012-13 were approximate; these were included in the analysis and subsequently omitted in a sensitivity check. The centre-level panel initially comprised134 raw centre-year records. After accounting for outcome-specific missing data and removing centre series with comparable reporting, the primary fixed-effects models included either 123 or 124 observations. The consolidated financial datasets, restricted to comparable records covered six financial years from 2019-20 to 2024-25.

4.2 Long-term operational trends

Across the observation period, reported admissions increased by an estimated 3.71% per year (95% CI 1.21% to 6.27%; HAC $p = 0.003$), while reported bed capacity increased by 3.48% per year (95% CI 2.80% to 4.17%; $p < 0.001$). OPD attendance and procedures also showed upward point estimates of 2.78% and 3.18% per year, respectively; however, their confidence intervals included zero, and the evidence was classified as suggestive. The main Hospital length of stay increased by 0.44 days per year (95% CI 0.28 to 0.60; $p < 0.001$); however, this result must be read with the documented reporting-definition shift around 2015-16 and was not interpreted as a direct change in efficiency. The estimated annual changes, confidence intervals, sample sizes, and evidence classifications are summarized in Table 2.

Table 2
Long-term trend estimates

Outcome	Annual effect	95% CI	p (HAC)	N	Evidence
Total OPD	2.78%/year	-0.36 to 6.01	0.083	14	Suggestive
Total admissions	3.71%/year	1.21 to 6.27	0.003	14	Supported
Total procedures	3.18%/year	-0.39 to 6.87	0.082	14	Suggestive
Total beds	3.48%/year	2.80 to 4.17	< 0.001	14	Supported
Main Hospital LOS	+ 0.44 days/year	0.28 to 0.60	< 0.001	15	Supported; definition caution

4.3 Observed service disruption and subsequent recovery

In 2019-20, the immediate pre-COVID baseline comprised 44,14,490 OPD attendances, 2,68,144 admissions, 2,01,707 procedures and 2,792 reported beds. In 2020-21, OPD attendance fell by 65.1%, admissions by 47.4% and procedures by 63.9% relative to the baseline. Reported beds increased by 14.4%, but the Main Hospital bed occupancy fell from 85.9% to 56.2%, a reduction of 29.7 percentage points. The length of stay increased from 9.9 to 10.4 days.

Recovery was progressive rather than immediate. OPD attendance remained 42.6% below the baseline in 2021-22 and was 3.6% below it in 2022-23. Admissions exceeded the 2019-20 level by 4.7% in 2022-23, while procedures exceeded it by 23.4%. By 2024-25, OPD attendance was 9.7% above the baseline, admissions were 34.7% higher, and procedures were 27.6% higher. Bed capacity was 31.0% higher than in 2019-20, whereas occupancy was 83.1%, still 2.8 percentage points below the baseline value. The 2024-25 procedure total was lower than in 2023-24 but remained above the pre-COVID level. The year-by-year service volumes and percentage changes relative to the 2019-20 baseline are presented in Table 3. Figure 1 illustrate the corresponding indexed trends in service activity and reported capacity.

Table 3
Service activity relative to the 2019-20 baseline

Year	OPD	Δ	Admissions	Δ	Procedures	Δ	Beds	Occupancy
2019-20	44,14,490	+ 0.0%	268,144	+ 0.0%	201,707	+ 0.0%	2,792	85.9%
2020-21	15,42,854	-65.1%	140,962	-47.4%	72,737	-63.9%	3,194	56.2%
2021-22	25,33,814	-42.6%	202,831	-24.4%	144,471	-28.4%	3,279	69.8%
2022-23	42,55,801	-3.6%	2,80,770	+ 4.7%	2,48,826	+ 23.4%	3,325	83.1%
2023-24	47,94,497	+ 8.6%	321,847	+ 20.0%	279,296	+ 38.5%	3,391	85.3%
2024-25	48,43,572	+ 9.7%	361,236	+ 34.7%	257,451	+ 27.6%	3,657	83.1%

Note: **Δ** means Percentage change from baseline (2019–2020)

4.4 Segmented estimates of the 2020-21 interruption and recovery slope

The segmented models indicated a large model-estimated deviation in 2020-21 after accounting for the preceding annual trends. OPD attendance was estimated to be 61.0% below the fitted pre-shock trajectory (95% CI 75.8% to 37.2% lower; OLS p = 0.001). The corresponding deviations were 44.5% below the fitted trajectory for admissions (95% CI 59.2% to 24.4% lower; p = 0.002) and 62.1% below for procedures. Bed occupancy showed a model-estimated deviation of 28.0 percentage points below the fitted trajectory. These quantities are distinct from observed year-to-year or baseline changes and should not be interpreted as causal effects of the pandemic.

The estimated post-shock slope for OPD attendance was positive, at 3.72% per year, but it was not statistically significant under conventional OLS inference or HAC (1) inference the estimated immediate deviations in 2020-21and the post-shock slopes for each outcome are reported in Table 4.

Table 4
Immediate disruption and post-shock slope estimates

Outcome	Immediate effect	95% CI	p (OLS)	Post-shock slope	p (OLS)	p (HAC)
OPD	-61.0%	-75.8 to -37.2	0.001	+ 3.72%/year	0.482	0.438
Admissions	-44.5%	-59.2 to -24.4	0.002	+ 7.25%/year	0.056	0.030
Procedures	-62.1%	-73.8 to -45.1	< 0.001	+ 8.83%/year	0.055	0.021
Bed occupancy	-28.0 pp	-40.8 to -15.2	< 0.001	-0.58 pp/year	0.674	0.598

4.5 Centre-level corroboration

The Centre fixed-effects models provided within-source corroboration of broad service disruption. After controlling for stable differences among centres, OPD activity was estimated to be 61.9% below the fitted centre-level trajectory in 2020-21 (95% CI 80.9% to 24.0% lower; cluster-robust p = 0.006), and procedures were 47.5% lower (95% CI 70.4% to 6.9% lower; p = 0.027). The admission estimate was negative but statistically imprecise. These estimates represent average within-centre deviations; they do not imply that every centre experienced an identical disruption. Because the panel contains only ten centre clusters and is derived from the same institutional reporting system, the results are treated as corroborative and uncertainty is interpreted cautiously. The center fixed-effects estimates and their uncertainty are reported in Table 5. Figure 2 compares the institute-level and center-level estimates of the immediate service disruption.

Table 5
Centre fixed-effects estimates for the immediate 2020–2021 disruption

Outcome	Effect	95% CI	p (cluster)	p (HC3)	N	Evidence
OPD	-61.9%	-80.9 to -24.0	0.006	0.005	124	Supported
Admissions	-34.6%	-67.0 to + 29.6	0.224	0.206	123	Uncertain
Procedures	-47.5%	-70.4 to -6.9	0.027	0.015	124	Supported

4.6 Financial-operational findings

Within the comparable consolidated/restated series, the nominal total income increased from Rs 2,815.03 crore in 2019–2020 to Rs 4,787.04 crore in 2024–2025, a rise of 70.1%. Nominal expenditure increased from Rs 2,705.50 crore to Rs 4,555.96 crore, a rise of 68.4%. Grants and subsidies remained the principal income source, accounting for approximately 92.0% of the total income in 2019–2020 and 92.8% in 2024–2025. The reported operating margin was positive in the three anchor years shown, although it narrowed to 1.98% in 2020–2021 before reaching 4.83% in 2024–2025.

Expenditure per OPD attendance increased from Rs 6,129 in 2019-20 to Rs 17,954 during the 2020-21 service contraction. It subsequently declined to Rs 9,406 in 2024-25, which was 47.6% below the pandemic-year value but 53.5% above the 2019-20 baseline. This indicator reflects the interaction between nominal expenditure and service volume and is not interpreted as a direct measure of cost efficiency. Available grant-budget data showed 99.4% utilization in 2024-25. The selected comparable financial and operational indicators are summarized in Table 6. Figure 3 presents an indexed comparison of nominal expenditure and service outputs for the pre-shock, and latest observation years.

Table 6
Selected consolidated financial-operational indicators

Year	Income (Rs Cr)	Expenditure (Rs Cr)	Grants (Rs Cr)	Surplus (Rs Cr)	Operating margin	Expenditure/OPD (Rs)
2019-20	2,815.03	2,705.50	2,588.90	109.54	3.89%	6,129
2020-21	2,824.65	2,769.98	2,735.26	54.67	1.98%	17,954
2024-25	4,787.04	4,555.96	4,442.00	231.08	4.83%	9,406

4.7 Diagnostics and sensitivity analyses

Excluding the approximate 2012–2013 service totals produced only small changes in the long-term trend estimates. The immediate disruption findings remained negative after the incompatible centre series were removed. Residual and heteroscedasticity checks did not overturn the main findings. The principal qualification concerned recovery slope inference: conventional and HAC p-values differed for admissions and procedures. Capacity-adjusted panel models were less stable, and the bed coefficients changed in sign or magnitude across specifications. Accordingly, the results support reported capacity expansion and service recovery but do not support the causal claim that bed additions generate proportional increases in activity. The sensitivity checks and the corresponding boundaries on interpretation are summarized in Table 7.

Table 7
Sensitivity and claim-boundary summary

Issue	Sensitivity result	Result interpretation
Approximate 2012-13 service totals	Trend estimates changed minimally after exclusion.	Core long-term direction was stable.
Conventional vs HAC inference	Admissions and procedures recovery slopes crossed the 0.05 threshold across estimators.	Report as positive but method-sensitive.
Centre exclusions	Immediate centre effects remained broadly negative after excluding incompatible series.	Supports disruption, not universal centre equivalence.
Capacity-adjusted panel	Bed coefficients changed sign or magnitude across models.	Do not claim proportional service growth caused by bed additions.
Financial scope	Legacy and consolidated accounts differed materially.	Do not present one uninterrupted 15-year financial series.

5. Discussion

5.1 Principal findings

This longitudinal case analysis revealed a cautiously interpreted pattern of institutional expansion, substantial disruption in reported healthcare activity, and progressive service recovery at AIIMS New Delhi. Across the observed period, inpatient admissions increased at an estimated yearly rate of 3.71%, and reported bed capacity increased by approximately 3.48% per year. The 2020–2021 financial year represented a clear interruption in the institutional series. Relative to the fitted continuation of the preceding trend, segmented regression estimated deviations of 61.0% for outpatient attendance, 44.5% for admissions, and 62.1% for procedures, together with a 28.0-percentage-point deviation in bed occupancy. These are exploratory model-based deviations and not causal effects of COVID-19. Centre fixed-effects models provided within-source corroboration for outpatient and procedural disruption, whereas centre-level admission estimates remained statistically inconclusive.

The recovery trajectory was gradual and differed by across service category. By 2022–2023, hospital admissions and procedural activity exceeded their corresponding 2019–2020 levels, whereas outpatient attendance remained slightly lower than the pre-pandemic baseline. By 2024–2025, outpatient attendance had risen to 9.7% above the baseline, while admissions and procedures increased by 34.7% and 27.6%, respectively. The reported bed capacity expanded by 31.0%; however, bed occupancy remained 2.8 percentage points lower than that recorded in 2019–2020. Financial measures also showed nominal increases in total income, expenditures, and grants during the recovery period. Overall, the findings indicate a marked financial and operational recovery. However, the analysis was based on aggregated institutional data; and did not establish a direct causal association between higher expenditure or expanded bed capacity and the observed expansion in service volumes.

5.2 Long-term expansion and operational change

The sustained increase in inpatient admissions and recorded bed capacity reflects the gradual expansion of the institution service infrastructure. However, this growth was simplified to a simple input-output relationship. Over time, AIIMS established and reorganized several specialized centers, while service boundaries evolved, and center functions varied in terms of referral volume, clinical workload and care pathways. Studies on Public-hospital performance research similarly shows that observed associations depend on the variables, the comparability of institutional units and the treatment way contextual factors are incorporated into the analysis [23–25, 27, 28]. In the present study, the capacity-adjusted coefficients changed materially across the different models. Such variation does not imply that capacity should be excluded; rather, it indicates that bed numbers alone is an insufficient measure of effective clinical capacity.

The relatively stable long-term admission pattern, compared with the less consistent outpatient and procedure trends, may indicate variations in referral practices, center development, case mix, reporting definitions, or annual variations. Inpatient did not improve. whereas outpatient or procedural performance did not. Similarly, the observed increase in the Main Hospital length of stay cannot be understood as a decline in efficiency. Length of stay is affected by factors such as clinical complexity, availability of inpatient beds, discharge planning and service organization [26]. In addition, the annual reports document a change in definition around 2015–16. Therefore, this study treats the published length-of-stay series as a descriptive measure with a reporting discontinuity, rather than a fully consistent measure of clinical performance.

5.3 Pandemic disruption in relation to previous evidence

The magnitude and breadth of the 2020-21 decline are consistent with international evidence that the COVID-19 period coincided with major disruptions to routine, elective, and referral care. Systematic and cross-country studies reported widespread reductions in healthcare use, with large differences across services and health systems [1–3]. Hospital and administrative-data studies in multiple settings similarly documented substantial reductions [4–12]. In the present study, however, the segmented model provides only a fitted pre-shock counterfactual trajectory; without an unaffected comparison hospital or external control series, the estimated 2020-21 deviations cannot be interpreted as causal pandemic effects.

The study also extends the available Indian evidence. A private multispecialty hospital in Delhi reported sharp reductions in non-COVID outpatient, inpatient and surgical activity followed by gradual improvement [13], while a systematic review described wider effects on access, infrastructure, workforce and service delivery in India [14]. The present study differs by using a long pre-shock baseline, a government-funded tertiary referral setting, several operational outcomes, audited financial context and follow-up through 2024–25. Agreement between institute-level and centre fixed-effects estimates for outpatient activity and procedures makes it less likely that the aggregate decline was generated by one dominant centre. However, the uncertain centre-level admission effect confirms that the shock was not statistically identical across every service dimension.

5.4 Recovery as an observable dimension of resilience

The post-2020 pattern supports describing AIIMS as having achieved substantial restoration of reported service activity, while recovery depends on the benchmark used. Relative to the observed 2019-20 baseline, outpatient activity remained 42.6% lower in 2021-22 and 3.6% lower in 2022-23, whereas admissions and procedures returned above that baseline earlier. By 2024-25, all three principal service volumes exceeded the observed 2019-20 level. This baseline recovery does not necessarily mean that each service fully returned to the fitted continuation of its pre-shock trajectory. The segmented post-shock slopes provide a second, model-based perspective on trajectory recovery, but the estimates are imprecise and method-sensitive for some outcomes. Recovery is therefore reported separately as observed-baseline restoration and movement toward the fitted pre-shock trajectory.

Resilience remains a bounded interpretive concept in this study rather than the primary empirical outcome. Reviews describe health-system and hospital resilience through preparedness, absorption, adaptation, maintenance of essential functions, recovery, and organizational capabilities [15–19]. Annual reports do not measure these mechanisms consistently. They reveal reported service volumes, financial inputs, and capacity indicators, but not the full organizational processes, workforce flexibility, coordination, learning, patient safety, or quality that produced them. Accordingly, the study demonstrates disruption and service restoration and discusses their relevance to resilience without claiming a comprehensive resilience measure.

5.5 Financial-operational interpretation

The comparable consolidated/restated financial series shows that nominal income increased from Rs 2,815.03 crore in 2019-20 to Rs 4,787.04 crore in 2024-25, while nominal expenditure increased from Rs 2,705.50 crore to Rs 4,555.96 crore. Grants and subsidies remained the major reported source of income. During the 2020-21 service contraction, expenditure per outpatient visit increased from Rs 6,129 to Rs 17,954 because expenditure did not decline in proportion to patient volume. By 2024-25 the indicator had declined to Rs 9,406, although it remained above the 2019-20 nominal value. This pattern should not be interpreted as a direct measure of efficiency. Public hospitals must maintain workforce, infrastructure, emergency readiness, infection-control functions, and other semi-fixed obligations even when patient volumes fall.

Changes in case mix may also have influenced the relationship between expenditure and service volume during the recovery period. A tertiary referral institution may experience changes in clinical complexity, referral patterns, or resource intensity following a major health-system disruption. However, the annual reports do not provide a consistent longitudinal measure of patient acuity, diagnosis-related case mix, or severity. The 68.4% increase in nominal expenditure between 2019-20 and 2024-25 therefore cannot be attributed to a post-pandemic increase in higher-acuity patients. It may reflect a combination of capacity expansion, input-price changes, staffing and infrastructure costs, service restoration, changes in clinical complexity, and other institutional factors that cannot be separately identified from the available aggregated data. For the same reason, technical efficiency cannot be inferred: the study does not estimate

a production frontier or a causal input-output relationship, and key determinants of effective production and quality are incompletely observed.

The centre-level results should be interpreted as within-source corroboration of the institute-wide pattern rather than independent confirmation. The fixed-effects specification controls for stable differences among centres but does not eliminate time-varying changes in staffing, case mix, policy, referral patterns, or centre-specific events. It also estimates average within-centre deviations rather than a separate shock effect for every centre. With only ten clusters, cluster-robust inference is inherently limited; therefore, the centre estimates are used to assess consistency of direction and broad heterogeneity rather than to support strong claims of uniform effects across all centres.

5.6 Centre heterogeneity and institutional learning

Based on the center-level results, one can conclude that the total amounts on the institutional level should be supported by evidence obtained from the center. As such, the centers at AIIMS differ in terms of specificity, and age, other characteristics. Nevertheless, the fixed effects that determine the stable characteristics of institutions cannot eliminate the challenge of various time-related changes such as staffing, case mix, policies or events affecting the target center.

The heterogeneity discussed earlier has real world implications. Targeting a single institution-wide recovery target might hide the continued pressure within specialty areas that recuperate slowly or have small service components. Procedures in outpatient service areas or in patient-heavy centers may have different benchmarks regarding disruptions, staffing structures and other measures of success. Prospectively monitoring many indicators at the center level, including deviation from an established baseline, length of time required for restoration, amount of backlog, capacity utilization and other quality indicators will allow for converting retrospective results into a more operational learning system. It is important to ensure that all differences among centers are preserved in the analysis instead of arriving at one common efficiency score for all service components.

5.7 Study contributions and interpretation boundaries

The study makes four main contributions. First, it reconstructs a harmonized fifteen-year financial-operational record from dispersed annual reports while retaining missingness, approximation, source location, and accounting-scope flags. Second, it moves beyond a simple pre/post comparison by estimating the immediate 2020–21 deviation and the subsequent recovery slope. Third, it triangulates institute-wide findings with a centre fixed-effects panel, separating broad common patterns from centre heterogeneity. Fourth, it applies a claim-bounded interpretation of resilience: service restoration is quantified, but latent organizational mechanisms, patient outcomes and causal effects of expenditure or bed expansion are not inferred from data that cannot support them. The combination of documentary transparency, longitudinal modelling, sensitivity analysis and explicit claim limits is the central methodological contribution. Table 8 presents the principal findings, their interpretation, the related literature and the boundaries of the claims supported by the data.

Table 8
Interpretation of principal findings and claim boundaries

Finding	Interpretation	Literature alignment	Claim boundary
Long-term admissions and bed growth	The reported institutional service platform expanded over time.	[23–28]	No stable causal bed-output relationship was established.
Large 2020–21 service decline	COVID-19 coincided with a major interruption across several service pathways.	[1–14]	Segmented estimates are exploratory, not definitive causal effects.
Service-specific recovery	Admissions and procedures restored earlier than outpatient activity; all exceeded baseline by 2024–25.	[4–12]	Above-baseline volume does not prove that unmet need or backlogs were fully resolved.
Centre-level corroboration	Outpatient and procedure disruption was not confined to one large centre.	[33]	Admission effects remained heterogeneous and statistically uncertain.
Nominal financial growth	Resource availability accompanied capacity expansion and service recovery.	[20–22]	Expenditure, grants and operating margin are not direct efficiency or quality measures.
Observed operational resilience	The institution absorbed a severe shock and restored reported service activity.	[15–19]	Annual reports do not measure all preparedness, adaptation or learning mechanisms.

6. Policy and Management Implications

The findings have implications for institutional reporting, surge planning and recovery management. The first priority is an integrated longitudinal dashboard that links finance, capacity and service activity while preserving definitions, source locations and reporting boundaries. The difficulty of reconstructing historical indicators from annual reports shows that data consistency is itself an institutional resilience resource. A dashboard should therefore distinguish exact, approximate, partial and definition-shift observations; retain both current and revised values; and prevent incompatible accounting scopes from being combined automatically.

Second, disruption monitoring should remain service-specific. The present study found different interruption and recovery patterns for outpatient attendance, admissions, procedures and occupancy. A single composite workload indicator would have hidden those differences. Operational monitoring should compare each service with both its immediate pre-shock baseline and its expected trajectory. This matters because a large year-on-year increase after a disruption may still leave activity below the level implied by the earlier trend. Thresholds for escalation should therefore be defined separately for outpatient, inpatient and procedure-intensive pathways.

Third, capacity planning should move beyond bed counts. Beds become usable service capacity only when aligned with staffing, diagnostics, theatres, supplies, referral coordination and discharge pathways. The instability of capacity-adjusted coefficients in the centre models reinforces this point. Expansion decisions should be assessed through a balanced set of indicators that includes staffed beds, service throughput, occupancy, waiting time, procedure backlog and centre-specific constraints. During a shock, available physical capacity may rise while effective utilization falls because other components of the care pathway are disrupted.

From a broader health-systems perspective, the AIIMS experience also has implications for Universal Health Coverage (UHC) in post-shock settings. Resilient tertiary service delivery contributes to UHC by preserving and restoring access to essential and specialized care during and after major disruptions. The service-specific recovery observed here suggests that post-shock management should monitor whether different care pathways recover at comparable rates rather than relying only on aggregate hospital activity. For publicly funded referral institutions, continuity of financing, usable capacity, and service-specific recovery monitoring may support the service-delivery dimension of UHC. However, the present dataset does not measure financial protection, unmet need, waiting times, or equity of access; the findings therefore inform UHC-oriented service-delivery planning rather than demonstrate achievement of UHC itself.

Fourth, financial monitoring during disruption should separate unavoidable fixed-cost intensity from preventable operational inefficiency. A sudden increase in expenditure per visit during a service contraction does not necessarily indicate waste, particularly when the institution must maintain workforce, infrastructure, infection control and emergency functions. The Review should therefore examine the composition of expenditure, budget execution, service restoration and quality indicators together. Nominal financial growth should also be distinguished from real resource growth through inflation-adjusted analysis when consistent data become available.

Finally, institute-wide recovery should be accompanied by centre-level accountability and learning. Aggregate restoration can coexist with unresolved bottlenecks in specialized units. Regular centre reviews should examine deviation from baseline, restoration time, backlog, staffing pressure and data quality, while avoiding rankings that ignore differences in centre mandate and case mix. The findings are directly relevant to AIIMS New Delhi and may inform other large public referral hospitals, but transfer requires attention to differences in funding, institutional scope and reporting systems.

Box 1. Practical management priorities arising from the analysis

Priority	Recommended institutional action	Minimum monitoring evidence
Data continuity	Maintain a version-controlled finance-capacity-service dashboard with explicit definition and scope flags.	Source file, table/page location, revision status, exact/approximate flag.
Service-specific shock detection	Set separate disruption and restoration thresholds for OPD, admissions, procedures and occupancy.	Baseline, expected trajectory, observed deviation and time to restoration.
Usable capacity	Assess beds together with staffing, diagnostics, theatre access, supplies and discharge pathways.	Staffed beds, occupancy, throughput, backlog and pathway constraints.
Financial interpretation	Review expenditure composition and service restoration jointly rather than treating unit expenditure as a standalone efficiency score.	Nominal and real expenditure, budget utilization, fixed-cost components and service outputs.
Centre learning	Conduct centre-level recovery reviews without imposing one uniform target across heterogeneous services.	Centre deviation, recovery time, backlog, staffing pressure and selected quality indicators.

7. Strengths, Limitations, and Future Research

7.1 Strengths

The second major constraint is annual aggregation. The principal institute-level models use 14 usable annual observations because institute-wide service totals were unavailable for 2016-17. This leaves nine usable pre-shock observations, one principal disruption-year observation, and four post-shock observations for estimating the post-shock trajectory. Such a short annual series provides limited support for causal attribution and makes recovery-slope estimates imprecise and method-sensitive. Annual data cannot distinguish pandemic waves, lockdown stages, within-year seasonality, or phased restoration. The 2020-21 shock also coincided with multiple policy, organizational, and service changes. Accordingly, the segmented coefficients are interpreted as exploratory deviations from a fitted pre-shock trajectory rather than causal effects of COVID-19.

Another advantage the analytical triangulation. Long-term trend models, segmented impact analysis, baseline comparisons, and center-fixed effects enable answering related questions without making any single model to be accepted as the "final" one. Traditional, HAC, HC3, and cluster robust uncertainty estimates are included in the paper whenever needed, while the sensitivity analysis aims to show the influence of the 2012-13 approximate figures as well as incompatible series belonging to the centers. The boundaries of the claims are clearly defined in this study, which is particularly important when a limited annual time series is used to discuss a significant system shock.

7.2 Limitations

The available variables also limit interpretation. Institutional totals cannot measure unmet need, waiting time, patient severity, case mix, equity, readmissions, outcomes, patient safety, or the quality of restored

services. Financial values are nominal rather than inflation-adjusted, and the broader consolidated scope used in later statements prevents construction of a single directly comparable fifteen-year financial series. Nominal expenditure growth therefore does not establish real resource growth, financial resilience, technical efficiency, quality, or a causal contribution to service recovery. Centre fixed-effects models control only for time-invariant centre differences, not for time-varying staffing, policy, referral, or case-mix changes, and they rely on only ten centre clusters, fewer than preferred for precise cluster-robust inference. Finally, activity above the observed 2019-20 baseline does not establish full return to the fitted pre-shock trajectory or complete resolution of accumulated backlogs and deferred care.

The second major constraint is annual aggregation. The models use 14 data points to analyze key results long-run trends due the lack of overall institute-specific information in the 2016–17 data. The data of one year have the main event of the year 2020-21 and the models have no means of differentiating between pandemic waves, lockdown stages, seasonal variations, and intra-period restoration trends. The shock also coincided with multiple policy, organizational, and service changes; thus, the obtained coefficients are partially causal due to being structural break estimates. The positive trends for admissions and procedures crossed the typical 0.05 benchmark depending on the method of uncertainty estimation, thus the data is at least directionally supportive but method-dependent.

The quality and comparability of the data present additional limitations. The service totals for the 2012-13 period were estimated, the data from 2016-17 are unfinished since some results were not presented, and some parameters underwent changes regarding definition or reporting boundaries. The main hospital length of stay changed around 2015-16. Although the sensitivity analyses reduced the possibility of the above findings influencing the major conclusions, no analytical adjustments could substitute for unrealized information.

7.3 Future research

This study reconstructed fifteen years of reported operational activity and available financial context at AIIMS New Delhi to examine institutional expansion, the 2020-21 disruption, and subsequent service recovery. Admissions and reported bed capacity showed long-term growth, while outpatient attendance and procedures displayed positive but less statistically certain trends. The pandemic period coincided with pronounced reductions in outpatient attendance, admissions, procedures, and bed occupancy. Segmented estimates describe exploratory deviations from a fitted pre-shock trajectory rather than causal COVID-19 effects. Centre fixed-effects analysis provided within-source corroboration for broad outpatient and procedure disruption, although the admission estimate remained heterogeneous and statistically uncertain.

Recovery was progressive and service-specific, and its interpretation depends on the benchmark. Admissions and procedures exceeded their observed 2019-20 levels before outpatient activity did, and by 2024-25 all three principal service volumes were above that observed baseline. This does not necessarily establish full return to the fitted pre-shock trajectory. Nominal income, expenditure, and grants also increased, but these financial measures provide institutional context rather than evidence of real resource growth, technical efficiency, financial resilience, quality, or a causal contribution to service restoration. The

rise and later decline in expenditure per outpatient attendance primarily reflects the interaction between relatively persistent institutional costs and changing service volume, not a standalone efficiency measure.

8. Conclusion

The most defensible conclusion is therefore one of substantial, service-specific restoration of reported activity, with resilience retained only as a bounded interpretive concept. Annual reports do not reveal all preparedness, adaptation, organizational learning, patient outcomes, unmet need, equity effects, or service quality, and the small annual time series limits causal interpretation. The contribution of the study lies in its transparent integration of audited financial context, capacity, multiple service outcomes, exploratory structural-break analysis, centre-level corroboration, sensitivity analysis, and explicit claim boundaries. This approach provides a reproducible basis for institutional learning and for more consistent, service-specific monitoring in future health-system disruptions.

This study reconstructed fifteen years of reported financial and operational activity at AIIMS New Delhi and used that record to examine institutional expansion, the 2020–21 disruption and subsequent recovery. Admissions and reported bed capacity supported long-term growth, while outpatient attendance and procedures displayed positive but less statistically certain trends. The pandemic year coincided with pronounced reductions in outpatient attendance, admissions, procedures and bed occupancy. Centre fixed-effects analysis corroborated broad outpatient and procedure disruption, although the admission effect remained heterogeneous and statistically uncertain.

Recovery was progressive and service-specific. Admissions and procedures exceeded their 2019–20 levels before outpatient activity did, and by 2024–25 all three principal service volumes were above the pre-pandemic baseline. Nominal income, expenditure and grants also increased, but the evidence does not show that financial growth or bed expansion caused service restoration. The rise and later decline in expenditure per outpatient attendance primarily reflects the interaction between relatively persistent institutional costs and the collapse and recovery of service volume, not a standalone measure of efficiency.

Declarations

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Consent for publication

Not applicable

Conflict of interests

The authors declare that they have no competing financial, professional, or personal interests that could have influenced the research, analysis, presentation, and interpretation of the findings reported in the manuscript.

Ethics Statement

Ethics approval and consent to participate did not apply to this study. The research was based exclusively on publicly available AIIMS New Delhi annual reports containing aggregated institutional, financial, capacity, and healthcare-service statistics. No individual-level patient records, identifiable personal information, or confidential clinical data.

Author Contribution

All authors contributed to the conceptualization and design of the study. The authors jointly identified and reviewed the relevant AIIMS New Delhi annual reports and contributed to data extraction, harmonization, verification, and preparation of the analytical dataset. All authors participated in the development of the methodological framework, statistical analysis, interpretation of the findings, and assessment of the study limitations.

The original manuscript was prepared collaboratively by the authors. All authors critically reviewed and revised the manuscript, approved the final version, and agreed to be accountable for the accuracy and integrity of the work.

Data Availability Statement

The AIIMS New Delhi annual reports used as the primary data sources for this study are publicly available on the official AIIMS New Delhi website. The harmonized data-extraction sheets, derived indicators, analytical dataset, and supporting analysis materials are available from the corresponding author upon reasonable request.

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Figures

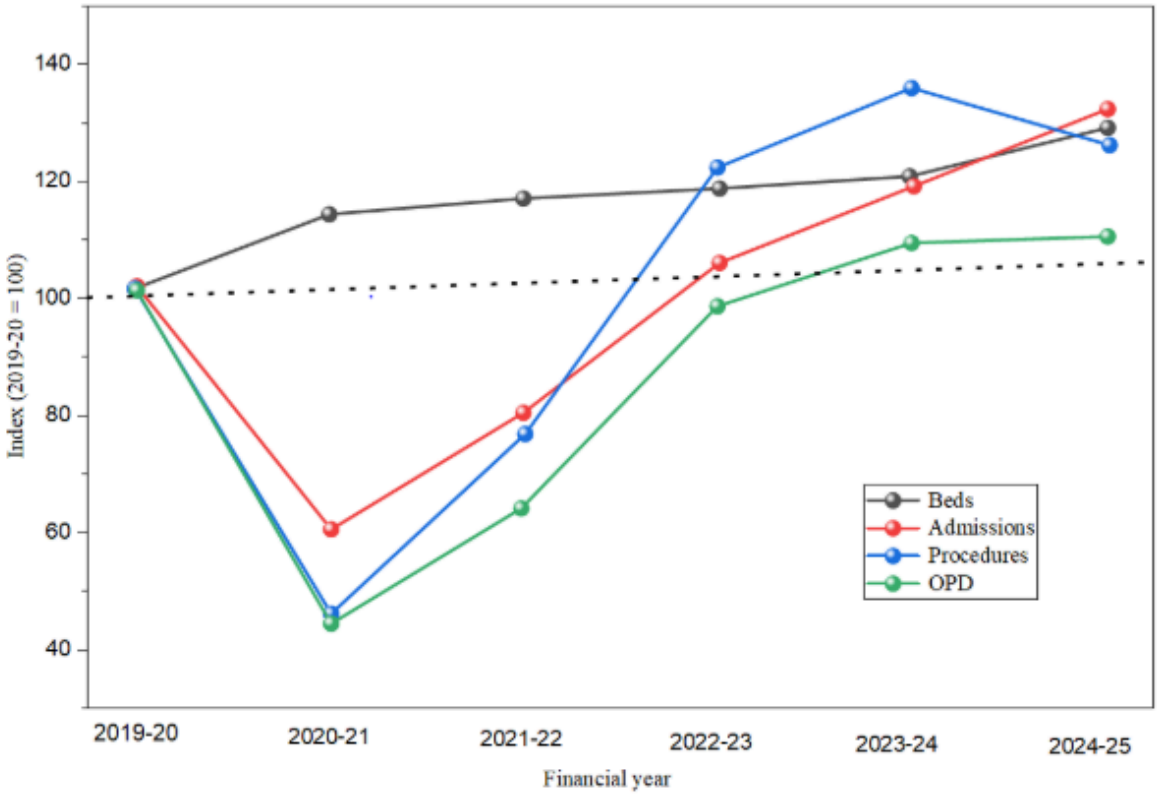

Figure 1

Observed service activity and reported bed capacity indexed to 2019-20 (=100).

Figure 1. Alt text: Line chart showing OPD attendance, admissions, procedures, and reported bed capacity indexed to the 2019–20 baseline of 100. OPD attendance, admissions, and procedures decline sharply in 2020–21 and then recover. By 2024–25, all three service-volume indices are above the 2019–20 baseline, while reported bed capacity remains above baseline throughout the post-shock period.

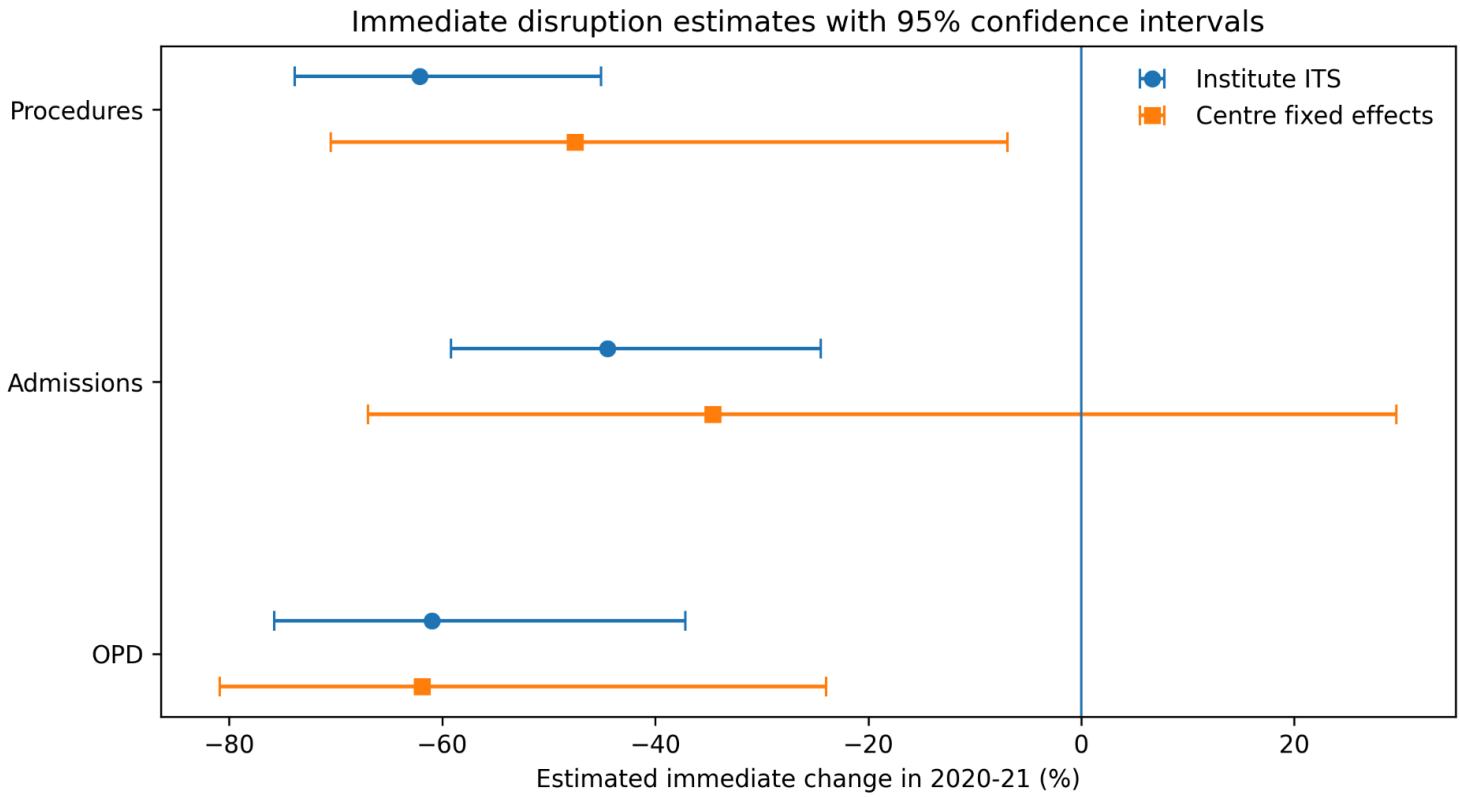

Figure 2

Institute-level and centre fixed-effects estimates of the immediate 2020-2021 service disruption.

Figure 2. Alt text: Plot comparing institute-level interrupted time-series estimates and centre fixed-effects estimates of the immediate 2020–21 change in OPD attendance, admissions, and procedures, with 95% confidence intervals. All point estimates indicate declines; centre-level confidence intervals are wider, particularly for admissions.

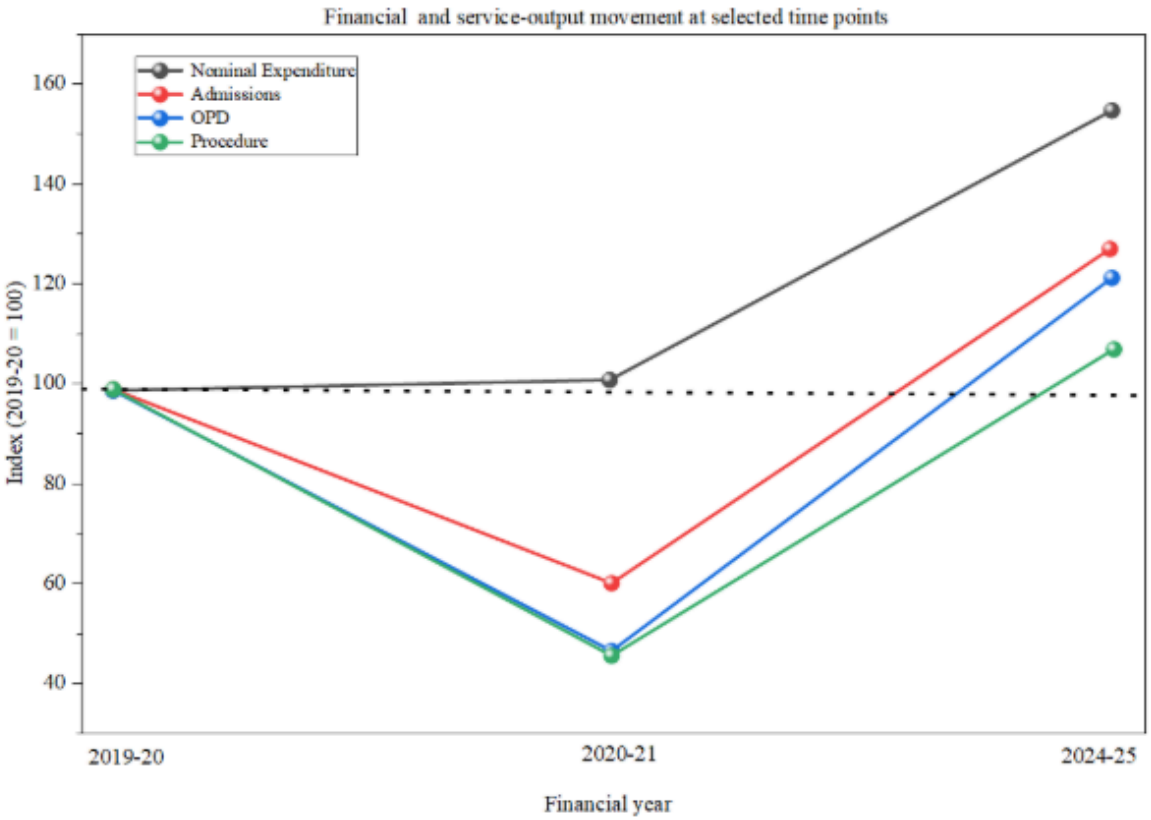

Figure 3

Indexed nominal expenditure and service outputs at the pre-shock, shock, and latest observation points.

Figure 3. Alt text: Line chart showing nominal expenditure, OPD attendance, admissions, and procedures indexed to the 2019–20 baseline of 100 for 2019–20, 2020–21, and 2024–25. Service outputs decline sharply in 2020–21 and rise above baseline by 2024–25, while nominal expenditure remains close to baseline in 2020–21 and increases substantially by 2024–25.