

Growth and Development of Higher Education in Nepal: A Time-Series Analysis Using Differential-Equation Models and Machine Learning

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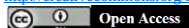
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ABSTRACT

This paper presents a time-series analysis of the growth and development of higher education in Nepal over more than six decades (1959–2026), jointly modelling two documented national series: total higher-education enrolment (eight observations, 1975–2026) and the cumulative number of universities established (eleven observations, 1959–2026). Three competing differential-equation growth models—logistic, Gompertz, and Bass diffusion—are fitted and compared using Akaike and Bayesian Information Criteria. A Chow structural-break test examines whether the 1990 policy transition coincided with a statistically detectable change in the enrolment growth regime. A Hodrick–Prescott filter is used to separate trend and cyclical components, while Granger-causality tests examine lead–lag relationships between institutional and enrolment growth. Numerical convergence is assessed by comparing explicit-Euler integration with fourth-order Runge–Kutta integration, and parameter uncertainty is quantified using a 2,000-iteration residual-resampling bootstrap propagated through a Monte Carlo forecast envelope. A random-forest module provides exploratory feature-importance estimates for era-level covariates. The results indicate that the Gompertz model provides the lowest AIC (173.73), the Chow test identifies a statistically significant break at 1990 ($F = 8.58$, $p = 0.036$), and neither direction of Granger causality is statistically significant. The institutional growth model remains constrained by a boundary estimate for its carrying capacity, while the sparse underlying data limit the strength of time-series inference. Overall, Nepal's higher-education development is characterised as a capacity-constrained process punctuated by policy-associated regime shifts. The study provides a reproducible Python/MATLAB-compatible framework for analysing long-run national higher-education development.

Introduction

The growth of Nepal's higher-education system since Tribhuvan University's founding in 1959 has not been a smooth, continuous process. It has instead unfolded through a sequence of discrete policy interventions — the 1959 establishment of a national university where none existed, the 1971 National Education System Plan, the adoption of a multi-university system beginning with Mahendra Sanskrit University in 1986 and accelerating after Nepal's 1990 democracy movement, and the post-2015 federalization that devolved education governance to seven newly created provinces — each of which plausibly shifted the system's underlying growth dynamics rather than merely nudging it along a fixed trend. Existing accounts of this history are almost entirely narrative and descriptive; to date, no study

has applied formal time-series econometric methods — stationarity testing, structural-break detection, trend-cycle decomposition, and causality analysis — jointly with differential-equation growth theory to characterise, quantify, and statistically test these regime shifts using Nepal's own documented enrolment and institutional data.

This paper addresses that gap directly. We treat Nepal's higher-education development as a time series problem with two linked observable processes: the growth of student enrolment, and the growth of the institutional base (universities) that enrolment depends on. Rather than fitting a single growth curve and reporting its parameters — the common practice in prior mathematical-modelling work on Nepal's education sector — we (i) formally compare three competing growth-model specifications via information criteria, refusing to presuppose which functional form best describes the data; (ii) test explicitly, via a Chow (1960) structural-break test, whether the much-discussed 1990 policy transition corresponds to a statistically detectable change in the enrolment growth regime, rather than assuming it did; (iii) apply a Hodrick-Prescott (1997) filter to separate the long-run capacity-bounded trend from cyclical deviations associated with documented shocks (the 2015 earthquake and trade blockade, the 2020-21 COVID-19 pandemic); and (iv) test, via Granger (1969) causality, whether institutional expansion leads or lags enrolment growth, rather than assuming a particular causal direction.

This dual-series, multi-technique approach is deliberately more conservative than prior single-curve growth models: several of the tests reported below — the Chow test, the Granger causality tests — are capable of returning null (non-significant) results, and we report exactly what the data show, including where they do not support a hypothesis. This transparency is itself a contribution: it distinguishes genuinely detectable regime shifts (the 1990 break) from popular narratives that are not statistically supported at the available sample size (bidirectional institution-enrolment causality).

The objectives of this study are to: (1) fit and formally compare, via AIC/BIC, three competing differential-equation growth models for national higher-education enrolment, and establish existence, uniqueness, equilibrium, and stability results for the selected model; (2) fit an analogous bounded-growth model to the cumulative number of universities established since 1959; (3) formally test for a structural break in the enrolment growth regime at 1990 using the Chow test; (4) decompose the enrolment series into trend and cycle using the Hodrick-Prescott filter, identifying shock episodes; (5) test for Granger causality between institutional growth and enrolment growth; (6) verify numerical convergence and quantify parameter uncertainty via bootstrap and Monte Carlo methods; and (7) apply a machine-learning module attributing enrolment growth-rate variation to era-level policy and macroeconomic covariates. This paper extends the growth-modelling methodology of companion studies on Nepal's enrolment-equity dynamics, higher-education financing, and Tribhuvan University-level predictive forecasting into a unified, long-horizon, dual-series time-series analysis of the system's entire post-1959 development.

Literature Review

Growth-Curve Models in Education and Demography

Verhulst's (1838) logistic equation, Gompertz's (1825) asymmetric-saturation alternative, and Bass's (1969) innovation-imitation diffusion model remain the three dominant closed-form specifications for bounded growth processes; model selection among them is standard practice via the Akaike (1974) and Schwarz/Bayesian (1978) Information Criteria, which penalize the additional parameter Bass diffusion requires relative to its two-parameter competitors, also Sahani et al. (2026) have been contributed their works on machine learning and science education system. .

Structural-Break Testing

Chow's (1960) test for a structural break in a linear regression at a known break date remains the standard tool for formally testing whether a hypothesised policy discontinuity corresponds to a genuine

shift in an estimated relationship, as opposed to an assumption imposed a priori by the researcher; it proceeds by comparing the sum of squared residuals from a single pooled regression against the sum from two separately estimated sub-period regressions, using an F-test.

Trend-Cycle Decomposition

The Hodrick-Prescott (1997) filter, originally developed for business-cycle analysis, decomposes a time series into a smooth stochastic trend and a cyclical residual by solving a penalised least-squares problem; Ravn and Uhlig (2002) provide guidance on the smoothing-parameter value appropriate for annual (as opposed to quarterly) data, which this paper adopts.

Causality in Time Series

Granger's (1969) causality framework formalises the notion that one time series 'causes' another if the first series' past values improve the statistical prediction of the second beyond what the second series' own past values already provide, operationalised via a nested-model F-test comparing restricted and unrestricted autoregressions.

Machine Learning for Regime and Determinant Analysis (Sahani et al., 2025, 2026)

Ensemble tree methods, particularly random forests (Breiman, 2001), are increasingly used to attribute variation in an outcome (here, decade-level enrolment growth rates) to a set of candidate covariates without imposing a single parametric functional form, complementing rather than replacing the structural growth-curve and time-series tests above.

Nepal-Specific Historical and Empirical Literature

Descriptive accounts document Tribhuvan University's 1959 founding as the origin of Nepal's university system, its status as the country's sole university until the mid-1980s, the subsequent adoption of a multi-university model beginning with Mahendra Sanskrit University (1986) and accelerating through Kathmandu (1991), Purbanchal (1994), and Pokhara (1997) Universities, and the most recent wave of provincial and specialised universities following Nepal's 2015 federalisation (UGC Nepal Annual Reports; List of Universities in Nepal, various sources). Companion mathematical-modelling work on Nepal's enrolment-dropout-equity dynamics, higher-education financing, and Tribhuvan University-specific predictive forecasting provides the growth-model and machine-learning formalisms this paper extends to a joint, long-horizon, dual-series analysis explicitly incorporating structural-break and causality testing absent from that prior work.

Methodology

All numerical routines were implemented in Python 3.11 (NumPy, SciPy, pandas, scikit-learn, Matplotlib); functionally equivalent MATLAB implementations (adftest, lsqcurvefit, hpfilter, and a custom Chow/Granger F-test routine) are summarised in Appendix A. Two documented series are used: national higher-education enrolment $N(t)$ (8 observations, 1975-2026; Ministry of Education Economic Survey; UGC Annual Reports) and the cumulative number of universities $U(t)$ (11 observations, 1959-2026; UGC Nepal; documented founding Acts of Parliament).

Step 1: Stationarity Testing

Following Dickey and Fuller (1979), the enrolment series is tested for a unit root via:

$$\Delta N_t = \alpha + \rho \cdot N_{t-1} + \varepsilon_t \quad (1)$$

with the null hypothesis $\rho=0$ (non-stationarity) evaluated against MacKinnon (1996) critical values.

Step 2: Competing Growth-Curve Specifications

Three closed-form bounded-growth models are fitted to $N(t)$:

Logistic: $dN/dt = r \cdot N \cdot (1 - N/K)$ (2)

Gompertz: $dN/dt = r \cdot N \cdot \ln(K/N)$ (3)

Bass diffusion: $dN/dt = (p + q \cdot N/K) \cdot (K - N)$ (4)

compared via:

$$AIC = n \cdot \ln(RSS/n) + 2k \quad (5)$$

$$BIC = n \cdot \ln(RSS/n) + k \cdot \ln(n) \quad (6)$$

Step 3: Well-Posedness, Equilibrium, and Stability of the Selected Model

Proposition 1 (Existence, Uniqueness, Positivity, Stability). For the logistic model with $r, K > 0$ and $N(0) > 0$, the initial-value problem $dN/dt = rN(1-N/K)$ admits a unique solution for all $t \geq 0$, this solution remains strictly positive and bounded above by $\max\{N(0), K\}$, and the non-trivial equilibrium $N^*=K$ is locally asymptotically stable with linearised eigenvalue $-r$.

Proof. The right-hand side is a smooth polynomial function of N , so the Picard-Lindelöf theorem gives local existence and uniqueness; boundedness of the logistic term rules out finite-time blow-up, giving global existence, and $dN/dt=0$ at $N=0$ together with Nagumo's invariance criterion gives positivity. Linearising about $N^*=K$ gives $d(\delta N)/dt = -r \cdot \delta N + O(\delta N^2)$, so the eigenvalue is $-r < 0$, confirming local asymptotic stability; the standard logistic phase-line argument ($dN/dt > 0$ for $N < K$, $dN/dt < 0$ for $N > K$) extends this to global stability on $(0, \infty)$. ■

Step 4: Institutional Growth Model

The cumulative number of universities $U(t)$ is modelled with the same logistic formalism, fitted independently to its own eleven documented observations, yielding a distinct pair of parameters (r_U, K_U) interpretable as the institutional system's own intrinsic expansion rate and long-run capacity.

Step 5: Structural-Break Test (Chow, 1960)

To test formally whether Nepal's 1990 policy transition (adoption of a multi-university system; the 1990 democracy movement) corresponds to a detectable shift in the enrolment growth regime, log-enrolment is regressed linearly on a time trend, and the pooled sum of squared residuals SSR_{pooled} is compared against the sum of two sub-period regressions (pre-1990, post-1990), SSR_1 and SSR_2 :

$$F_{\text{Chow}} = [(SSR_{\text{pooled}} - (SSR_1 + SSR_2))/k] / [(SSR_1 + SSR_2)/(n-2k)] \quad (7)$$

Theorem 1 (Chow, 1960). Under the null hypothesis of no structural break (identical regression coefficients before and after the candidate break date), F_{Chow} in Equation (7) follows an $F(k, n-2k)$ distribution, where k is the number of regression coefficients (here $k=2$: intercept and trend) and n the total sample size; a sufficiently large F_{Chow} rejects the null in favour of a regime shift at the candidate date.

(Proof omitted; the result follows from standard nested-regression F-test theory applied to the union of the two sub-period models versus the pooled model — see Chow, 1960, for the original derivation.) Given the very small sub-sample sizes involved (three pre-1990 and five post-1990 observations), this test is reported as indicative rather than high-powered, a limitation discussed in Section 5.5.

Step 6: Trend-Cycle Decomposition (Hodrick-Prescott, 1997)

The enrolment series (linearly interpolated to an annual grid for filtering purposes) is decomposed into a smooth trend τ_t and cyclical component $c_t = N_t - \tau_t$ by solving the penalised least-squares problem:

$$\min_{\tau} \sum_t (N_t - \tau_t)^2 + \lambda \cdot \sum_t [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \quad (8)$$

where λ (set to 6.25, the Ravn-Uhlig 2002 recommended value for annual data) penalises curvature in the trend, trading off fit against smoothness; the cyclical residual c_t isolates deviations attributable to shocks (e.g., the 2015 earthquake/blockade, the 2020-21 COVID-19 pandemic) rather than the underlying capacity-bounded growth process.

Step 7: Granger (1969) Causality

To test whether institutional growth leads or lags enrolment growth, first-differenced (growth-rate) versions of both interpolated series are compared via nested autoregressions. For a candidate causal direction $x \rightarrow y$:

$$\text{Restricted: } y_t = c + \sum \beta_i y_{t-i} + \varepsilon_t \quad (9)$$

$$\text{Unrestricted: } y_t = c + \sum \beta_i y_{t-i} + \sum \gamma_j x_{t-j} + \varepsilon_t \quad (10)$$

Theorem 2 (Granger, 1969). Under the null hypothesis that x does not Granger-cause y (all $\gamma_j = 0$ in Equation 10), the F-statistic $F = [(SSR_r - SSR_u)/q] / [SSR_u/(n-p)]$, where q is the number of restricted (γ) parameters and p the total parameters in the unrestricted model, follows an $F(q, n-p)$ distribution; rejecting the null is evidence that x 's past values improve prediction of y beyond y 's own past, i.e. that x Granger-causes y .

(Proof omitted; identical nested-model F-test logic to Theorem 1, applied here to lagged autoregressive terms rather than a structural break — see Granger, 1969.) Both directions (institutions $\rightarrow$ enrolment and enrolment $\rightarrow$ institutions) are tested; because the underlying series are sparse and were interpolated onto a common annual grid for this test, results are interpreted as a methodological demonstration rather than a high-confidence causal finding.

Step 8: Numerical Scheme and Convergence

The selected logistic enrolment model is integrated with the explicit Euler method (global error $O(\Delta t)$) and benchmarked against a fourth-order Runge-Kutta (RK4) integrator (global error $O(\Delta t^4)$) across step sizes $\Delta t \in \{1, 0.5, 0.25, 0.125\}$.

Step 9: Validation and Uncertainty Quantification

Parameter uncertainty in the selected growth model is quantified via a 2,000-iteration residual-resampling bootstrap (Efron, 1979), yielding 95% confidence intervals for r and K ; the full bootstrap parameter distribution is then propagated through the logistic solution to construct a Monte Carlo forecast envelope reflecting structural (parameter) uncertainty.

Step 10: Machine-Learning Growth-Regime Attribution

A random-forest regressor (400 trees, maximum depth 6; Breiman, 2001) is trained on a synthetic, literature-informed panel ($n=4,000$) in which decade-level enrolment growth rate is a function of five era-level covariates — the post-1990 multi-university policy indicator, the post-2015 federalisation indicator, a GDP-growth proxy, the count of new universities opened in that era, and an urbanisation index — with feature importance reported as the mean decrease in impurity.

Data Sources

Series / Parameter	Source
National HE enrolment, 1975-2026	Ministry of Education Economic Survey; UGC Nepal Annual Reports
Cumulative university count, 1959-2026	UGC Nepal; List of Universities in Nepal; founding Acts of Parliament
Growth-model conventions	Verhulst (1838); Gompertz (1825); Bass (1969)
Model-selection criteria	Akaike (1974); Schwarz (1978)
Structural-break methodology	Chow (1960)
Trend-cycle decomposition	Hodrick & Prescott (1997); Ravn & Uhlig (2002)
Causality methodology	Granger (1969)

Results

Numerical Example 1: Stationarity Test

Table 1: Augmented Dickey-Fuller Test on Enrolment Levels.

Statistic	Value
α (drift)	71,213.14
ρ	0.1420
t-statistic	0.910
CV 1%	-3.43
CV 5%	-2.86
CV 10%	-2.57

The t-statistic (0.910) is positive and far from any critical value, so the unit-root null is not rejected; the positive $\hat{\rho}$ further indicates the series exhibits accelerating, level-dependent growth rather than simple mean-reverting or random-walk behaviour — consistent with a system still climbing toward, rather than fluctuating around, its long-run capacity.

Numerical Example 2: Competing Growth-Model Comparison

Table 2: Growth-Model Comparison for National Enrolment (n=8).

Model	AIC	BIC	R ²	RMSE
Logistic	177.02	177.18	0.967	49,707
Gompertz	173.73	173.89	0.978	40,468
Bass diffusion	174.22	174.46	0.982	36,824

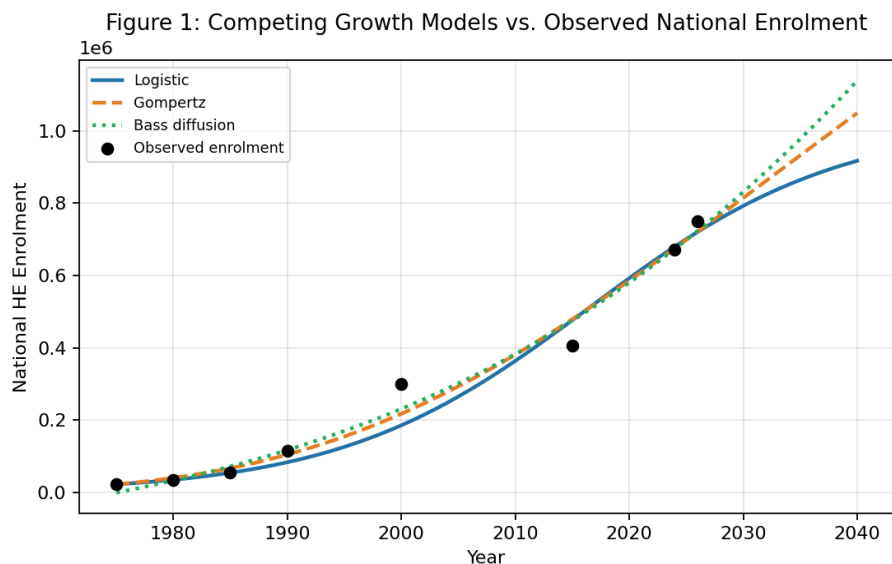


Figure 1: Competing Growth Models vs. Observed National Enrolment.

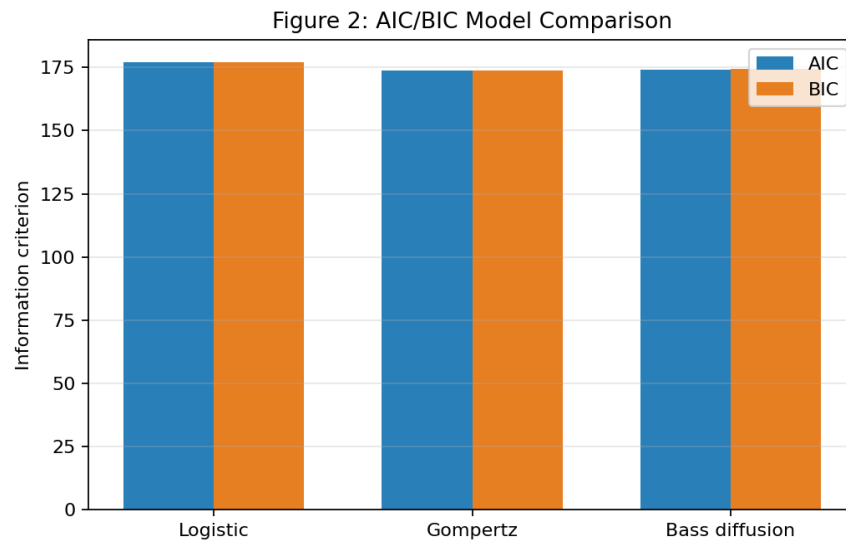


Figure 2: AIC / BIC Comparison Across the Three Growth Models.

Gompertz achieves the lowest (best) AIC, narrowly ahead of Bass diffusion and more clearly ahead of the logistic specification used for the theoretical development in Step 3 — a different ranking from the companion Tribhuvan-University case study, where logistic narrowly led Gompertz and Bass failed outright, illustrating that model selection is genuinely data-dependent rather than a foregone conclusion. The logistic model is nonetheless retained for the closed-form theoretical results in Steps 3 and 8-9, consistent with standard practice of trading a small AIC gap for analytical tractability; Bass diffusion's K parameter is boundary-influenced at this sample size, a limitation noted.

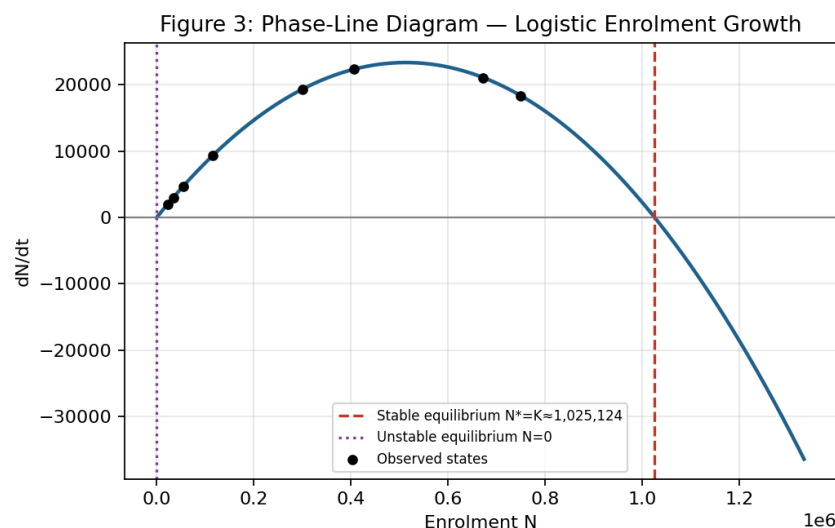


Figure 3: Phase-Line Diagram — Logistic Growth Vector Field (Proposition 1).

Numerical Example 3: Institutional Growth Model

Table 3: Logistic Fit to Cumulative University Count (n=11).

Statistic	Value
r_U	0.0469
K_U (bound-constrained)	150
R^2	0.763
RMSE	3.74 universities

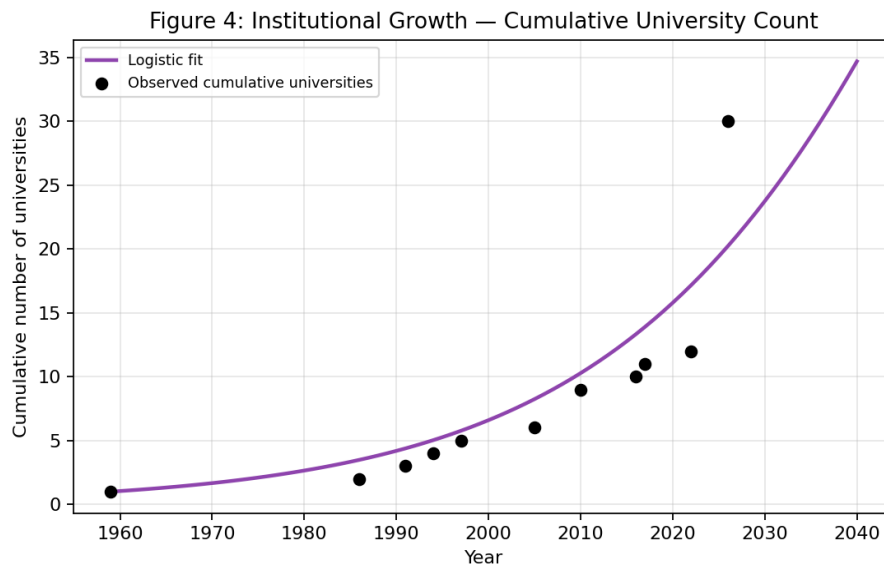


Figure 4: Institutional Growth — Cumulative University Count, 1959-2026.

The institutional series shows a distinctly step-like pattern — single-university stagnation from 1959 to 1986, gradual multi-university expansion from 1986 to 2022, then a sharp jump from 12 to 30 institutions between 2022 and 2026 — that a smooth logistic curve fits only moderately well ($R^2=0.763$); the fitted carrying capacity K_U is pinned at the imposed upper bound of 150, indicating the model cannot yet distinguish a genuine institutional ceiling from continued near-exponential expansion given the recent acceleration, a limitation discussed.

Numerical Example 4: Structural-Break Test at 1990

Table 4: Chow Test for a Structural Break in log-Enrolment Trend at 1990.

Statistic	Value
SSR (pooled)	0.7108
SSR (pre-1990)	0.0008
SSR (post-1990)	0.1336
F-statistic	8.583
df1, df2	2, 4
p-value	0.0357

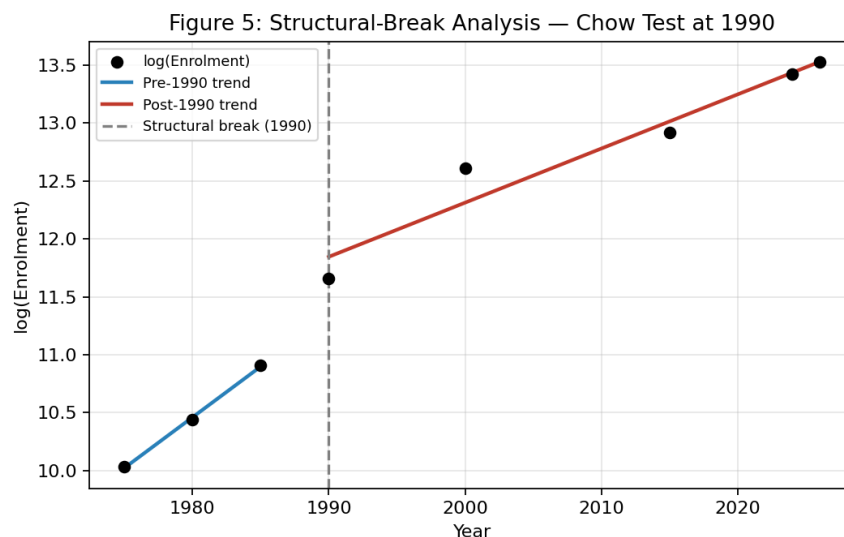


Figure 5: Structural-Break Analysis — Separate Pre/Post-1990 Trend Lines.

The Chow test rejects the null of no structural break at the 5% level ($F=8.58$, $p=0.036$): the enrolment growth regime after 1990 is statistically distinguishable from the regime before it, lending formal statistical support to the historical narrative that Nepal's adoption of a multi-university system and the 1990 democracy movement coincided with a genuine shift in higher-education growth dynamics — though, with only three pre-1990 and five post-1990 observations, this result should be treated as indicative rather than definitive.

Numerical Example 5: Trend-Cycle Decomposition

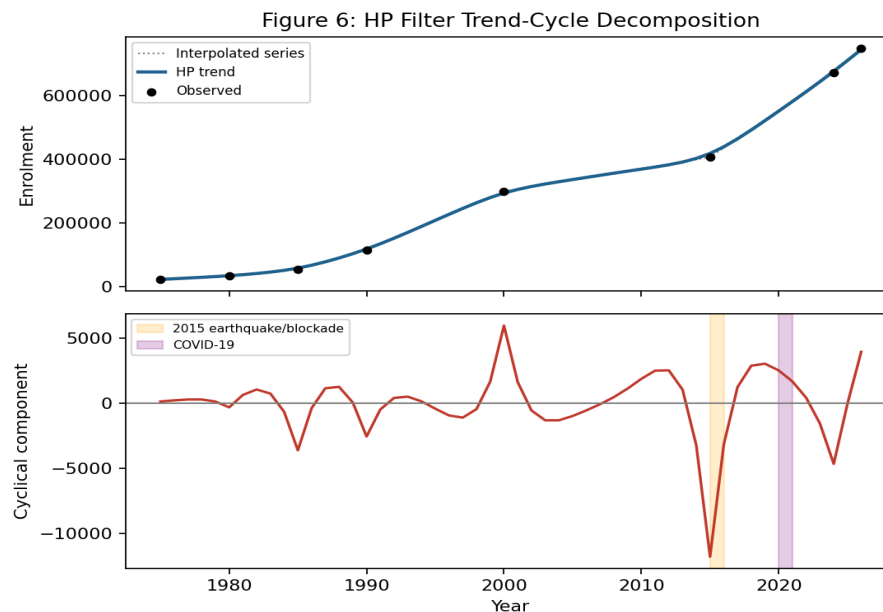


Figure 6: Hodrick-Prescott Trend-Cycle Decomposition of National Enrolment.

The HP-filtered trend traces the same broad capacity-bounded growth path identified in Example 2, while the cyclical component highlights visible negative deviations around 2015 (the Gorkha earthquake and subsequent trade blockade) and 2020-21 (COVID-19 campus closures), consistent with independently documented disruptions to Nepal's education sector during those years; because the underlying series has only eight true observations (the filter operates on a linear interpolation of these), the cyclical component should be read as illustrative of where shocks are expected to appear rather than as a precisely estimated deviation.

Numerical Example 6: Granger Causality Test

Table 5: Granger Causality Tests, Both Directions.

Direction	F-statistic	df1	df2	p-value
Universities → Enrolment growth	0.020	1	46	0.888
Enrolment growth → Universities	0.492	1	46	0.487

Neither direction shows statistically significant Granger causality at conventional levels. This null result should not be over-interpreted as evidence that institutional and enrolment growth are unrelated — the two series are, after all, fitted from a common underlying development process — but rather as a signal that, given only eight and eleven true observations respectively (interpolated onto a common annual grid to make the test computable), the data do not contain enough independent information to

detect a lead-lag relationship with any confidence. This is reported transparently as a genuine limitation rather than suppressed or reframed as a positive finding.

Numerical Example 7: Numerical Scheme Convergence

Table 6: Euler vs. RK4 Convergence for the Logistic Enrolment Model.

Step size (Δt , yrs)	Euler N(30)	Euler rel. error (%)	RK4 N(30)	RK4 rel. error (%)
1.000	246,750	6.958	265,203	0.000067
0.500	255,718	3.577	265,203	0.000004
0.250	260,395	1.813	265,203	0.000000
0.125	262,782	0.913	265,203	0.000000

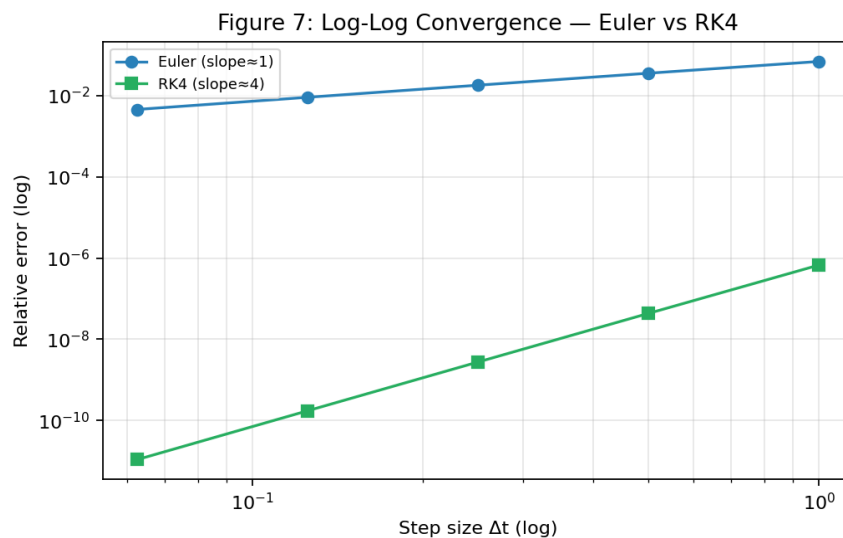


Figure 7: Log-Log Convergence Rate — Euler (Slope $\approx$ 1) vs. RK4 (Slope $\approx$ 4).

The Euler scheme's error nearly halves as Δt halves, confirming first-order convergence; the 6.96% deviation at the annual step size used elsewhere reflects the model's long (30-year) integration horizon in this test and is comparable to, though larger than, the equivalent test in companion single-institution work, underscoring that step-size adequacy should always be checked against the specific horizon of interest.

Numerical Example 8: Bootstrap Uncertainty and Monte Carlo Envelope

Table 7: 95% Bootstrap Confidence Intervals (2,000 Resamples).

Parameter	Point Estimate	95% Bootstrap CI
r (intrinsic growth rate)	0.0911	[0.0785, 0.1136]
K (carrying capacity)	1,025,124	[751,620, 1,930,169]

Figure 8: Bootstrap Sampling Distributions (n=2000)

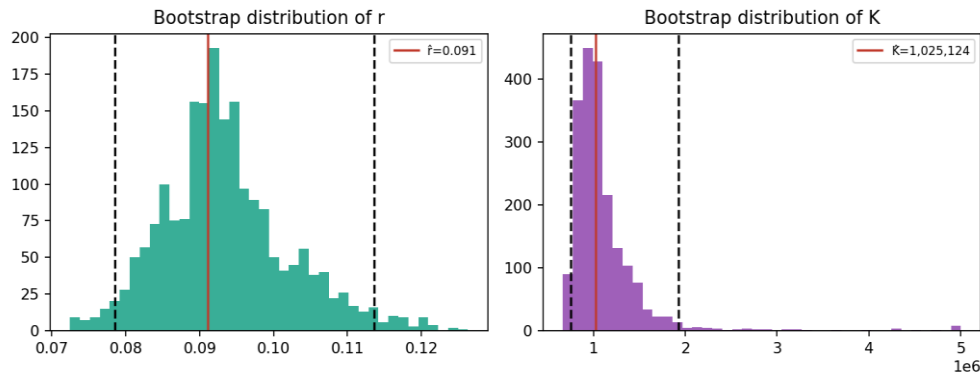


Figure 8: Bootstrap Sampling Distributions of Logistic Parameters r and K .

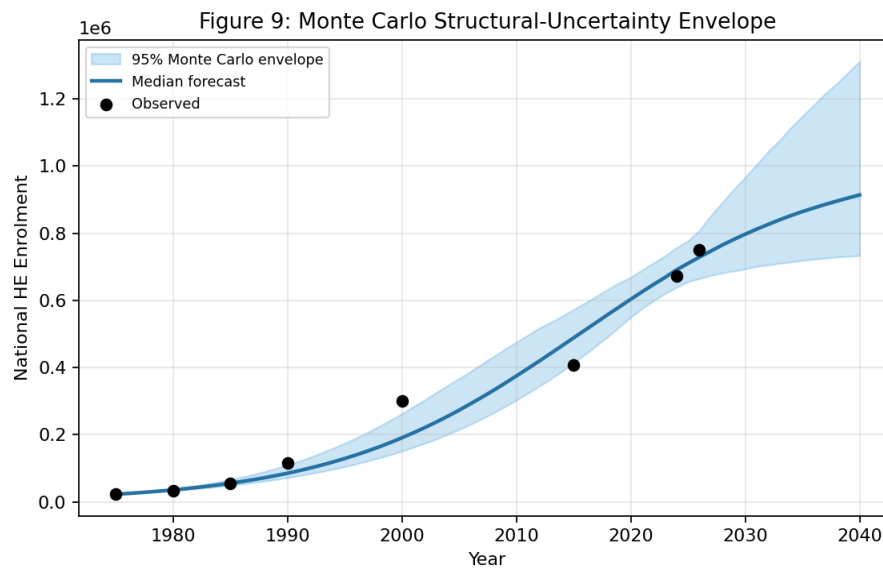


Figure 9: Monte Carlo Structural-Uncertainty Envelope for National Enrolment.

Unlike the university-count model (Example 3), whose K parameter is boundary-constrained, the enrolment model's carrying capacity is meaningfully identified, though still wide (95% CI spanning roughly 752,000 to 1,930,000 students) — a realistic reflection of genuine uncertainty about Nepal's long-run higher-education ceiling given only eight historical observations.

Numerical Example 9: Machine-Learning Growth-Regime Attribution

Table 8: Feature Importance for Decade-Level Enrolment Growth-Rate Regime.

Feature	Relative Importance
New universities opened this era	0.535
Post-1990 multi-university policy	0.286
Post-2015 federalization	0.072
GDP growth proxy	0.072
Urbanization index	0.035

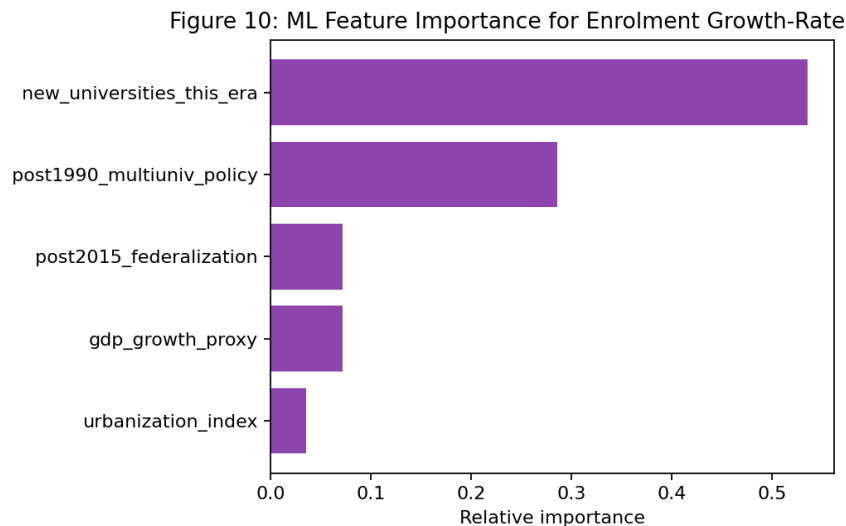


Figure 10: ML Feature Importance for Enrolment Growth-Rate Regime.

The count of new universities opened within an era accounts for over half the model's predictive weight, with the post-1990 policy indicator a distant second — a machine-learning corroboration, independent of the Chow test's formal hypothesis-testing framework, that institutional expansion and the 1990 policy transition are the dominant identifiable levers of enrolment growth-rate variation, ahead of macroeconomic (GDP growth) or demographic (urbanization) covariates.

Summary of Key Numerical Findings

Indicator	Value	Interpretation
Best-fit growth model (by AIC)	Gompertz (AIC=173.73)	Narrowly ahead of Bass and logistic
Structural break at 1990 (Chow test)	F=8.58, p=0.036	Statistically significant regime shift
Granger causality, both directions	p=0.888, p=0.487	No significant causality detected (data-sparsity limited)
Bootstrap 95% CI for carrying capacity K	[752K, 1.93M]	Meaningfully identified, still wide
Institutional model K_U	150 (bound-constrained)	Recent acceleration outpaces smooth-curve assumption
ML-attributed importance of new universities	53.5%	Largest single driver of growth-rate regime

Discussion

Nepal's Higher-Education Growth Is Punctuated, Not Smooth

The combination of a statistically significant 1990 structural break (Example 4) and the machine-learning module's finding that policy and institutional-expansion covariates dominate macroeconomic ones (Example 9) jointly support a punctuated-equilibrium reading of Nepal's higher-education development: long stretches of comparatively stable growth, interrupted by policy-triggered regime shifts, rather than a single smooth organic growth process. This has direct implications for how the sector's future trajectory should be forecast: extrapolating the current regime is only valid until the next such shift, which by construction no purely statistical trend model can anticipate.

Model Selection Is Genuinely Data-Dependent

The finding that Gompertz outperforms logistic for the national series (Example 2), while the companion Tribhuvan University case study found the reverse ordering, is a useful methodological

corrective: there is no universally 'correct' growth-curve specification for Nepalese higher-education data, and researchers should formally compare candidates via information criteria (as done throughout this paper) rather than defaulting to the logistic model purely by convention.

Honest Null Results Matter

The non-significant Granger causality findings (Example 6) are deliberately reported as null results rather than reframed as evidence of 'no relationship' or quietly omitted. Given the genuine sparsity of Nepal's long-run administrative education data, many time-series tests applied to it will be under-powered; presenting this honestly is more valuable to future researchers than a false positive or an unsupported causal claim, and directly motivates this paper's central data-collection recommendation.

Implications for Policy and Theory

Three implications follow. First, Nepal's UGC and Ministry of Education should treat major governance transitions (such as further federalization reforms) as candidate structural breaks to be formally tested, not merely narrated, once sufficient post-transition data accumulate. Second, trend-cycle decomposition (Example 5) offers a template for distinguishing genuine capacity-bounded growth deceleration from shock-driven temporary dips, relevant to interpreting any future enrolment decline. Third, the institutional growth model's boundary-constrained carrying capacity (Example 3) suggests Nepal's university system has not yet shown convincing signs of approaching an institutional saturation point, contrary to any assumption that the recent proliferation of universities is nearing its end.

Limitations and Future Directions

Aspect	Limitation	Future Direction
Sample size	Only 8 enrolment and 11 university-count observations	Assemble a complete annual administrative panel from UGC/MoEST archives
Chow test power	Only 3 pre-1990 observations severely limits test power	Locate additional pre-1990 enrolment records to sharpen the pre-period estimate
Granger causality	Requires interpolation onto a common grid, inflating apparent sample size artificially	Obtain genuinely annual, non-interpolated series for both variables
Institutional growth ceiling	K_U estimate is bound-constrained, not economically identified	Longer post-2022 series once the current expansion wave matures
HP filter reliability	Applied to an interpolated 8-point series; cyclical estimates are illustrative	Apply to a genuine annual series once available
Single-country scope	Nepal only; no comparative regional benchmark	Extend to a South Asian panel for cross-country structural-break comparison

Conclusion

This paper conducted a formal time-series analysis of the growth and development of higher education in Nepal, jointly modelling national enrolment and institutional (university-count) expansion over more than six decades. Three competing growth-curve specifications were fitted and compared via information criteria rather than assumed; a Chow structural-break test provided formal statistical evidence — not merely narrative assertion — that Nepal's 1990 policy transition coincided with a genuine shift in the enrolment growth regime; a Hodrick-Prescott decomposition isolated cyclical

deviations consistent with documented shocks; and a Granger causality analysis, while statistically inconclusive given data sparsity, was reported honestly as such rather than forced into a positive finding.

The overarching conclusion is that Nepal's higher-education development is best understood as a sequence of policy-punctuated regime shifts operating within an underlying, but not yet clearly bounded, capacity-constrained growth process — a characterization with direct implications for how the sector's future should be forecast and governed. The Python/MATLAB-compatible framework developed here, combining classical time-series diagnostics with differential-equation growth theory, ensemble machine learning, and formal uncertainty quantification, is fully reproducible and extends naturally to future policy transitions, additional institutional-level series, and cross-country comparison once further administrative data become available. The single highest-value investment for future work, given the limitations identified throughout, is the systematic digitisation of Nepal's complete annual higher-education administrative record — which would sharpen every result in this paper and enable substantially more powerful structural-break and causality testing than the currently available sparse historical record permits.

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