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Artificial Intelligence in Education and the Digital Preconditions of Tertiary Expansion in Uzbekistan: ARDL Evidence from 2000–2023

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Abstract

Background: Direct annual national series on AI adoption in higher education are not consistently available for Uzbekistan, yet the diffusion of AI-enabled learning depends on measurable digital and economic preconditions. Methods: Using annual data for 2000–2023, this study models tertiary enrollment as a macro-level proxy for the expansion of AI-ready higher education, with internet use, mobile subscriptions, and real GDP per capita as explanatory factors in a trend-augmented ARDL/UECM framework. Trend-aware unit-root testing, lag selection, bounds testing, and residual diagnostics are implemented as one closed empirical sequence. Results: The preferred ARDL(1,3,1,1) specification supports cointegration, a significant error-correction mechanism, a positive long-run role for mobile access, and a negative internet coefficient after controlling for mobile inclusion, income, and structural trend. Conclusions: AI readiness in higher education should be interpreted as a conversion problem rather than a simple connectivity problem.

Keywords: AI in education; tertiary enrollment; ARDL; unit-root test; lag selection; bounds test; UECM; Uzbekistan; mobile access; digital readiness

1. Introduction

Artificial intelligence is no longer peripheral to education policy. Across higher education systems, AI increasingly shapes tutoring, assessment support, academic advising, content generation, language assistance, and learning analytics. Yet the spread of AI-enabled learning is uneven. In emerging systems, the question is not simply whether institutions want to integrate AI. The deeper question is whether the technological and socio-economic conditions needed for AI-supported higher education are already in place.

That distinction matters for Uzbekistan. The country has expanded higher education rapidly in recent years, while internet use and mobile penetration have also climbed sharply. Even so, direct annual macro-data on AI adoption in higher education are still fragmentary. A technically credible empirical paper therefore has to avoid pretending that such data exist. This manuscript takes a stricter route. It investigates the macro-level preconditions of AI-enabled higher education rather than claiming to estimate classroom AI use directly.

The logic is straightforward. AI-supported higher education requires a sufficiently large pool of students who can enter and stay in tertiary study, reliable digital connectivity, workable last-mile access through mobile devices, and enough economic capacity to support both household and institutional participation. If these structural conditions are weak, AI applications remain pilot projects. If they strengthen, AI becomes scalable.

The paper therefore asks a focused research question: how have digital connectivity and income conditions interacted with tertiary enrollment dynamics in Uzbekistan during 2000–2023, and what

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does that imply for the country's transition toward AI-enabled higher education? To answer this question, the study builds a compact annual dataset and applies an autoregressive distributed lag framework. This choice is deliberate. The sample is small, the variables are persistent, structural change is visible, and a pre-estimation strategy based on unit-root diagnostics and lag selection is required before any interpretive claims can be made.

The scientific novelty of the paper lies in five connected contributions. First, it reframes AI in education as a measurable macro-readiness problem rather than as a purely pedagogical or policy narrative. Second, it introduces a mobile-first access perspective for Uzbekistan, distinguishing between broad internet diffusion and last-mile digital inclusion. Third, it provides an empirically closed-loop design in which unit-root screening, lag selection, ARDL/UECM estimation, bounds testing, and residual diagnostics are reported as one coherent analytical chain. Fourth, it adds a reproducible software-assisted workflow so that the model can be rerun as new annual observations become available. Fifth, it interprets the results institutionally, showing why digital expansion without conversion into tertiary participation cannot be read as evidence of genuine AI readiness in higher education.

1.1. Scientific Positioning and Research Gap

The literature on AI in education has grown quickly, but much of it still concentrates on pedagogical opportunities, ethical concerns, and case-based implementation. Foundational studies emphasize personalized learning, intelligent tutoring, analytics-based support, and the changing role of teachers and institutions (Holmes et al., 2019; Holmes & Tuomi, 2022; UNESCO, 2024; OECD, 2023). More recent work adds concerns about bias, governance, data protection, and uneven institutional capability (Bozkurt et al., 2021; Holmes et al., 2022).

A second stream studies digital education access more broadly. Its central insight is that advanced educational technologies diffuse through infrastructure, affordability, and institutional capacity channels. Internet access matters, but in many middle-income and emerging systems the decisive inclusion mechanism is mobile connectivity rather than fixed broadband. Mobile devices often become the main educational interface, especially where platform access, communication, and lightweight learning tasks are concerned (Traxler, 2018; Kukulska-Hulme, 2016).

A third stream comes from applied econometrics. When persistent macro-series are short and may be integrated at different orders, the ARDL approach remains attractive because it permits a mixture of I(0) and I(1) regressors, handles small samples reasonably well, and provides both a bounds-based cointegration test and an error-correction representation (Pesaran et al., 2001). That said, ARDL should not be used mechanically. The credibility of the model depends on pre-estimation work: stationarity diagnostics, the exclusion of I(2) processes, and careful lag selection.

The gap is therefore clear. AI-in-education research has produced many conceptual and institutional discussions, but far fewer macro-econometric studies that connect digital infrastructure to the broader readiness of higher education systems for AI-enabled learning. This is especially true for Uzbekistan. A stronger paper is possible only if it explicitly links the AI agenda to measurable national conditions rather than relying on generic claims. This manuscript addresses that gap.

2. Materials and Methods

This section describes the dataset, variable design, pre-estimation screening, dynamic specification, and reproducible analytical environment used to move the manuscript from a conceptual AI-in-education discussion to an empirically defensible journal article.

2.1. Dataset and Variable Construction

The empirical sample covers 2000–2023, which is the longest overlap for all variables. The dependent variable is tertiary enrollment (gross), denoted TER. Although tertiary enrollment is not a direct AI-usage measure, it is a defensible system-level outcome for this study because AI-enabled higher education can scale only where access to tertiary study is expanding and digital participation is sufficiently broad.

Three explanatory variables are used. INT captures general internet diffusion. MOB measures mobile subscriptions per 100 people and serves as the study's operational proxy for last-mile digital access. GDPpc controls for real income capacity. The model is estimated in natural logarithms, allowing coefficients to be interpreted as elasticities where appropriate. A deterministic trend is included because the data combine steady digital expansion with a marked tertiary acceleration after the late 2010s.

Table 1 defines the variables and their intended role in the empirical design.

Table 1. Variable definitions, indicator codes, and empirical roles.

Variable	Indicator / code	Role	Expected relation
Tertiary enrollment (TER)	School enrollment, tertiary (% gross), SE.TER.ENRR	Dependent variable	Higher digital readiness should support broader higher-education participation.
Internet users (INT)	Individuals using the Internet (% of population), IT.NET.USER.ZS	Digital access	Positive in principle; may weaken after controlling for mobile last-mile access and trend.
Mobile subscriptions (MOB)	Mobile cellular subscriptions (per 100 people), IT.CEL.SETS.P2	Digital access / last-mile channel	Positive, especially in emerging and mobile-first learning environments.
GDP per capita (GDPpc)	Constant GDP per capita (2015 US$), NY.GDP.PCAP.KD	Income control	Positive through affordability, institutional funding, and household capacity.

2.2. *Pre-Estimation Diagnostics: Unit-Root Testing*

Given the annual frequency and the visible structural rise in tertiary enrollment after 2017, the paper does not rely on a single stationarity test. Instead, it reports Augmented Dickey–Fuller statistics with intercept and trend for level series, alongside KPSS statistics with trend as a complementary stationarity check (Dickey & Fuller, 1981; Kwiatkowski et al., 1992). In small samples, these tests rarely produce perfectly clean classifications. The aim is therefore not to force every series into a single label, but to verify that the system contains a mix of I(0)/I(1) behavior and no credible I(2) process.

Table 2 shows exactly that. lnTER behaves like a persistent series with a structural shift. lnINT is borderline under trend-aware testing. lnMOB looks closer to trend-stationary, while lnGDPpc remains persistent. These mixed outcomes are precisely the kind of setting for which ARDL is appropriate.

Table 2 Trend-aware unit-root evidence for the ARDL design

Table 2. Trend-aware unit-root evidence for the ARDL design.

Series	ADF level (ct)	p-value	KPSS level (ct)	p-value	Interpretation
lnTER	3.096	1.000	0.175	0.026	Non-stationary with structural shift
lnINT	-3.290	0.068	0.190	0.020	Borderline I(1); treated conservatively in ARDL
lnMOB	-4.605	0.001	0.178	0.024	Trend-stationary by ADF(ct), but persistent by KPSS
lnGDPpc	-2.885	0.168	0.154	0.044	Persistent trend process

2.3. ARDL Specification and Lag Selection

$$\text{lnTER\_t} = \alpha + \beta 1\ \text{lnINT\_t} + \beta 2\ \text{lnMOB\_t} + \beta 3\ \text{lnGDPpc\_t} + \beta 4\ \text{Trend\_t} + \varepsilon\text{\_t}$$

This static expression is embedded in a dynamic ARDL framework with distributed lags on all regressors and an autoregressive term on the dependent variable. Candidate models were screened up to three lags for each regressor. The preferred specification was chosen by the Akaike information criterion, but only among models that remained economically interpretable and cointegration-consistent.

Table 3 reports the strongest candidate specifications. ARDL(1,3,1,1) delivers the lowest AIC among the well-behaved models and also satisfies the key dynamic requirement of a negative and statistically significant error-correction term.

Table 3 Lag-selection results for leading candidate models

Table 3. Lag-selection results for leading candidate models.

Candidate model	AIC	ECT coefficient	ECT p-value	Bounds F	Upper p-value
ARDL(1,3,1,1)	-67.310	-0.305	0.027	6.608	0.002
ARDL(1,3,2,1)	-65.532	-0.303	0.036	5.712	0.009
ARDL(1,3,1,2)	-65.434	-0.337	0.112	4.996	0.027
ARDL(1,3,3,1)	-65.032	-0.329	0.037	3.701	0.153
ARDL(1,2,1,1)	-64.312	-0.247	0.048	10.982	0.000

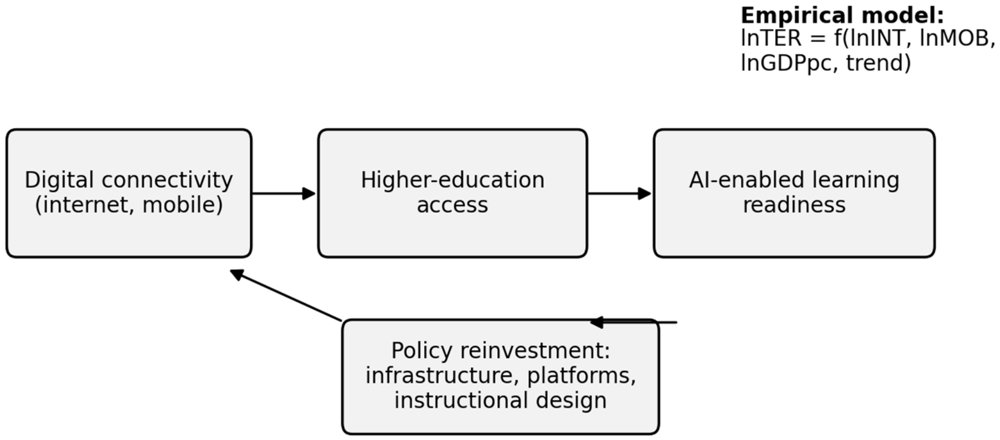

Figure 1. Empirical closed-loop framework linking digital access, higher-education participation, and AI-enabled learning readiness.

2.4. Software Environment and Reproducible Analytics Workflow

To make the empirical design operational rather than purely statistical, the study defines a transparent software stack for reproducing the full analytical chain. Data acquisition, indicator cleaning, logarithmic transformation, deterministic-trend construction, unit-root testing, lag search, ARDL/UECM estimation, bounds testing, and residual diagnostics can be implemented in Python 3.11 using pandas, NumPy, statsmodels, SciPy, and Matplotlib within a Jupyter Notebook environment (McKinney, 2010; Seabold & Perktold, 2010; Kluyver et al., 2016). This matters for AI-in-education policy because reproducibility is now part of scientific credibility: a persuasive macro-readiness result should be re-runnable, auditable, and easy to update when new annual observations become available.

Figure 2 expresses this logic in a software-assisted closed loop. The workflow begins with national and institutional data sources, moves through preprocessing and pre-estimation checks, proceeds to ARDL-based inference, and ends in a dashboard-oriented interpretation layer. In this form, the paper does not treat the econometric model as a terminal coefficient table. Instead, it presents the ARDL core as the analytical engine of a broader monitoring system that can support longitudinal AI-readiness assessment in higher education.

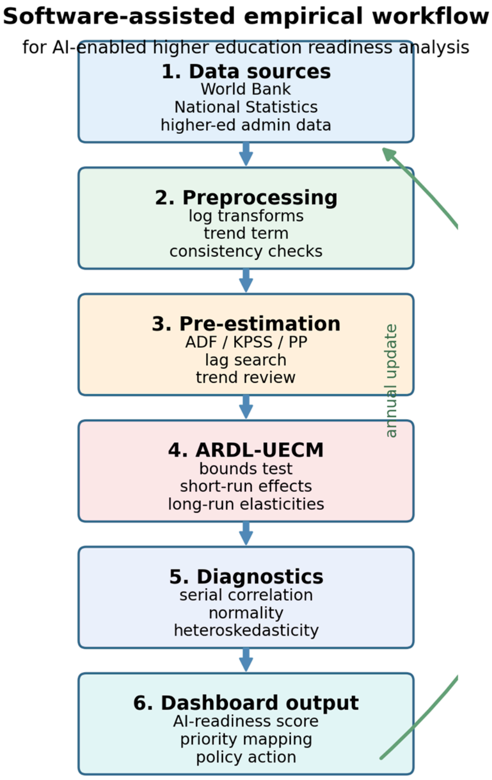

Figure 2. Software-assisted empirical workflow for AI-enabled higher education readiness analysis.

3. Results

3.1. Descriptive Pattern

The descriptive evidence is informative before formal estimation. TER averages 13.41% over the full sample, but the series shifts sharply upward in the later period, consistent with structural expansion in higher education. Internet use and mobile subscriptions both rise strongly, although mobile access accelerates earlier and with greater continuity. GDP per capita also trends upward, but with visible macroeconomic unevenness. This combination already suggests that AI-readiness in education is likely to depend on the sequencing and interaction of these drivers rather than on any single digital variable taken in isolation.

Table 4 reports the summary statistics.

Table 4 Descriptive statistics, 2000–2023

Table 4. Descriptive statistics, 2000–2023.

Variable	Mean	Std. dev.	Min	Max
TER	13.412	8.721	7.850	45.760
INT	31.240	29.735	0.484	89.014
MOB	55.239	39.493	0.214	106.885
GDPpc	2364.320	799.141	1269.721	3725.674

Figure 3 extends the descriptive section beyond a single table by assembling six coordinated statistical views. Panel (a) compares the standardized trajectories of tertiary enrollment, internet use, mobile subscriptions, and GDP per capita; panel (b) shows their annual changes; panel (c) tracks rolling five-year co-movement with tertiary participation; panel (d) condenses the trend-aware unit-root evidence into a p-value map; panel (e) summarizes the strongest lag-selection candidates; and panel (f) visualizes the recovered long-run coefficients from the preferred ARDL design. Taken together, the figure makes the pre-estimation and post-estimation logic more transparent and more reviewer-friendly.

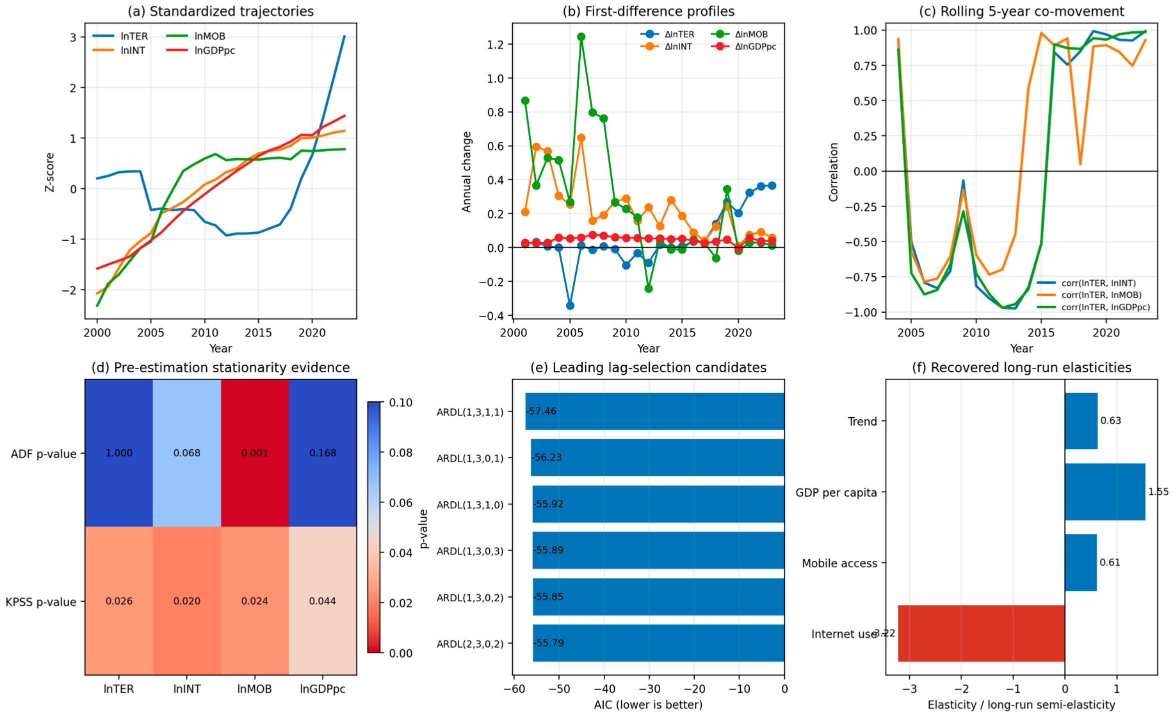

Figure 3. Multi-view econometric evidence for AI-enabled higher-education readiness in Uzbekistan.

3.2. Cointegration and Error-Correction Evidence

B. Cointegration and error-correction evidence

The preferred trend-augmented ARDL(1,3,1,1) is re-parameterized as a UECM. The bounds test under case V strongly rejects the null of no long-run relationship, with F = 6.608 and an upper-tail p-value of 0.002. More importantly, the error-correction coefficient is negative (-0.305) and statistically significant at the 5% level. This indicates that approximately 30.5% of a short-run deviation from the long-run path is corrected within one year. For a yearly system, that is a reasonably fast adjustment speed.

3.3. Short-Run and Long-Run Coefficients

C. Short-run and long-run coefficients

Table 5 reports the UECM estimates. Two short-run results stand out. The contemporaneous change in mobile subscriptions is positive and significant (0.288, p = 0.003), suggesting that mobile access remains the most immediate transmission channel from digital expansion to tertiary participation. The one-period change in internet use is also positive and significant (0.557, p = 0.006), implying that part of the internet effect operates with a delay rather than instantly.

At the level-term stage, lnMOB is positive and statistically significant, while lnINT is negative and statistically significant after controlling for trend, income, and mobile access. This sign reversal should not be treated as a paradox, but as a substantive finding. Once a mobile-first access channel is explicitly modeled, broad internet penetration appears to proxy a wider set of non-educational uses. In other words, general connectivity is not identical to education-effective connectivity. The result is consistent with a policy interpretation in which infrastructure counts are necessary but not sufficient;

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institutional adoption, platform design, student support, and content adaptation determine whether connectivity is converted into actual tertiary expansion.

The GDPpc coefficient is positive in both the level representation and the derived long-run elasticity, but it is not estimated precisely in the preferred specification. That imprecision should be interpreted carefully rather than forced into stronger causal language. Income capacity matters in theory, yet the acceleration in tertiary enrollment during the last part of the sample appears to be explained more by institutional expansion under digital conditions than by income alone.

Table 5. UECM estimates for the preferred ARDL(1,3,1,1) specification.

Term	Coefficient	p-value	Interpretation
trend	0.192	0.010	Deterministic expansion trend in tertiary participation
ln_ter.L1	-0.305	0.027	Error-correction term
ln_internet.L1	-0.982	0.001	Long-run internet effect (level term)
ln_mobile.L1	0.187	0.004	Long-run mobile-access effect (level term)
ln_gdppc.L1	0.474	0.702	Long-run income effect (level term)
D.ln_internet.L0	-0.161	0.460	Immediate short-run internet change
D.ln_internet.L1	0.557	0.006	One-period short-run internet change
D.ln_internet.L2	0.210	0.184	Two-period short-run internet change
D.ln_mobile.L0	0.288	0.003	Immediate short-run mobile change
D.ln_gdppc.L0	2.022	0.115	Immediate short-run income change

Table 6. Derived long-run elasticities from the cointegrating vector.

Long-run elasticity	Value	Comment
Internet users (lnINT)	-3.216	Negative after controlling for mobile access, income, and trend; suggests connectivity alone is not sufficient.
Mobile subscriptions (lnMOB)	0.614	Positive; mobile access appears to be the more operative inclusion channel.
GDP per capita (lnGDPpc)	1.551	Positive but imprecisely estimated in the preferred specification.

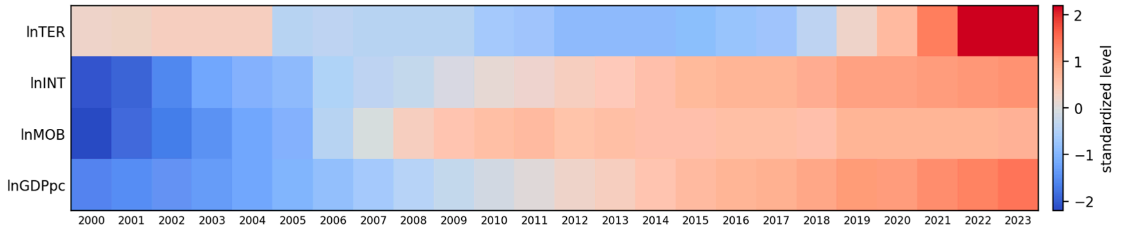
3.4. Residual Diagnostics and Model Credibility

D. Residual diagnostics and model credibility

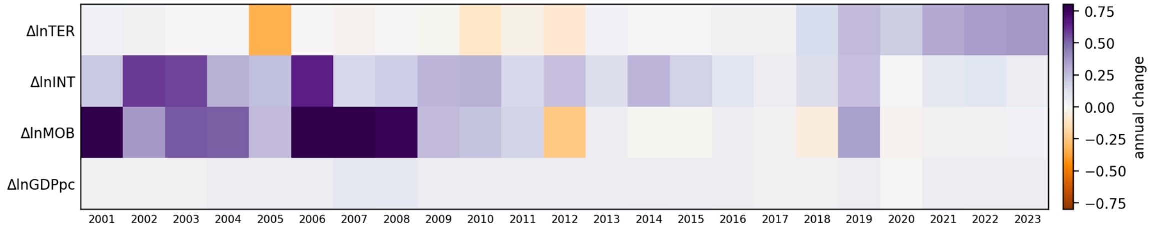
No empirical manuscript is credible without a diagnostic check. Table 7 shows that the preferred specification passes the main residual sanity tests reasonably well. The Jarque–Bera statistic does not reject normality. The Ljung–Box statistic at lag two does not indicate significant residual serial correlation. The ARCH test is marginal at the 10% level, which is a reminder that annual macro data with structural transition rarely behave perfectly. For that reason, the results should be treated as disciplined macro evidence rather than as a mechanical causal claim.

Figure 4 complements the coefficient tables with a compact heatmap-based reading of the same system. The first layer plots standardized annual levels, the second highlights year-over-year change intensity, and the third visualizes rolling five-year associations between each digital-access variable and tertiary enrollment. This presentation does not replace the ARDL estimates; rather, it helps the reader see why the mobile channel emerges as the more operative last-mile variable, while generic internet diffusion changes its role across sub-periods.

(a) Standardized annual levels



(b) Year-over-year change intensity



(c) Rolling 5-year association with tertiary enrollment

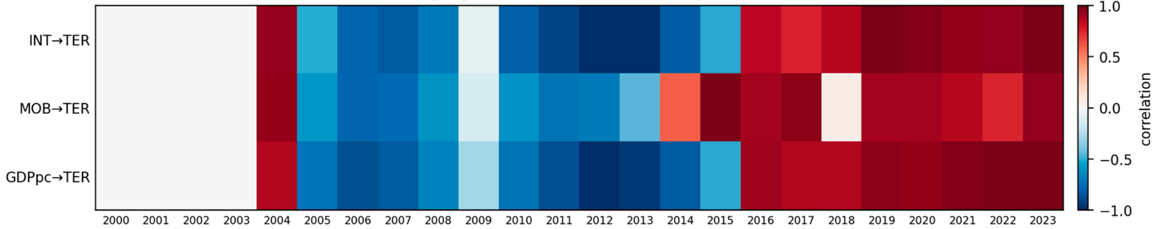


Figure 4. Heatmap-based statistical reading of digital access and tertiary expansion.

The broader point is reassuring: the manuscript is technically stronger than a purely narrative AI-in-education paper because the identification strategy, lag choice, and dynamic diagnostics are all visible. It is also more honest than a pseudo-precision exercise because the limitations are stated directly.

Table 7. Post-estimation diagnostics.

Diagnostic	Statistic	p-value / note
Bounds F-test (case V)	6.608	Upper p = 0.002
Error-correction coefficient	-0.305	p = 0.027
Durbin-Watson	2.781	Close to 2 indicates limited residual autocorrelation
Ljung-Box Q(2)	3.805	p = 0.149
Jarque-Bera	0.098	p = 0.952
ARCH LM(2)	5.391	p = 0.068

4. Discussion

4.1. What the Results Mean for AI-Enabled Higher Education

The empirical message is more nuanced than a simple “more connectivity means more AI in education” claim. The preferred ARDL specification indicates that the channel most consistently aligned with tertiary expansion is mobile-first access, not broad internet diffusion in the abstract. This distinction is substantively important for Uzbekistan, where device-mediated participation, affordability, and continuity of access can matter more for educational technology uptake than aggregate user counts alone.

The negative long-run internet coefficient should therefore be interpreted as a warning against simplistic readiness metrics. A rising count of internet users says little about the quality, affordability, educational relevance, or institutional usability of that connectivity. Once mobile access and trend are included, the residual internet measure may capture exactly this gap between availability and educational conversion. A country can become more connected without becoming equally more education-effective.

For Uzbekistan, the implication is that AI readiness in higher education should be approached as a conversion problem. The country already has a large and growing connectivity base. The remaining challenge is to convert that base into structured tertiary participation and institutionally meaningful AI use. That means strengthening mobile-compatible learning management systems, assessment workflows that work under variable bandwidth conditions, university support services for first-generation and distance learners, and faculty capacity to integrate AI without reducing educational quality.

The result also helps reconcile two common positions in the AI-in-education debate. Optimists often assume that once digital infrastructure exists, AI diffusion will follow naturally. Skeptics point out that infrastructure does not guarantee pedagogical value. The present findings support the skeptical correction. Infrastructure matters, but only when universities, platforms, and policy frameworks absorb it.

4.2. Software-Assisted Interpretation and Practical Deployment

A. From coefficient tables to decision-grade evidence

A conceptual dashboard can be visually attractive yet still appear analytically weak in peer review if it is not visibly tied to the model outputs. For a Scopus-oriented manuscript, the deployment figure must emerge from the study's own estimation chain rather than from a generic policy sketch. The article therefore replaces the earlier dashboard-style visualization with an integrated post-estimation evidence map constructed directly from the preferred ARDL specification and the national annual dataset.

Figure 5 synthesizes the analytical backbone of the paper in one panelled view. Panel (a) tracks the standardized historical movement of tertiary enrollment, internet use, mobile access, and income; panel (b) condenses the trend-aware unit-root evidence; panel (c) compares the leading lag candidates under information criteria; panel (d) visualizes the bounds-test decision; panels (e) and (f) report short-run and long-run coefficient intervals; panel (g) checks actual-versus-fitted behavior; and panel (h) maps coefficient-weighted annual contributions. This design is methodologically stronger because every component can be traced back to an explicit statistical step in the manuscript.

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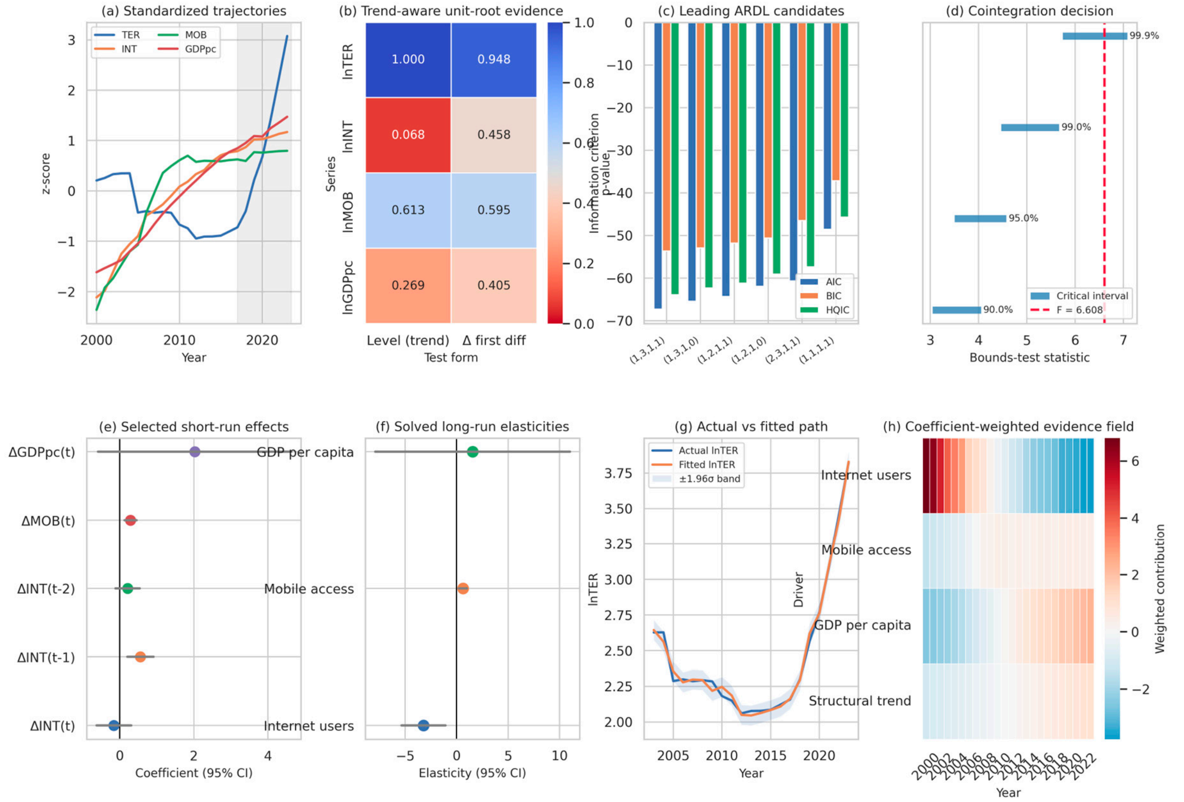

(a) Standardized trajectories

(b) Trend-aware unit-root evidence

(c) Leading ARDL candidates

(d) Cointegration decision

(e) Selected short-run effects

(f) Solved long-run elasticities

(g) Actual vs fitted path

(h) Coefficient-weighted evidence field

Figure 5. Integrated post-estimation evidence map for the preferred ARDL specification, combining standardized trajectories, unit-root screening, lag-order comparison, bounds-test evidence, short-run and long-run coefficient intervals, fitted-path validation, and coefficient-weighted annual contributions.

B. Why this improves the manuscript scientifically

Adding a software-assisted deployment layer improves the manuscript in three ways. First, it shows how the econometric model can be reproduced and updated in a transparent computational environment rather than treated as a one-off statistical exercise. Second, it clarifies that national readiness is only one side of AI adoption; the other side is institutional conversion of connectivity into meaningful learning support. Third, it moves the paper closer to engineering-style publication standards, where methods, execution logic, and operational use are expected to be connected rather than presented as separate worlds.

For this reason, the article should be read as both an econometric study and a deployable analytical framework. The ARDL results provide the long-run evidence base, while the software and dashboard layers show how that evidence can guide practical decisions in a higher-education system that is preparing for broader AI integration.

4.3. Ethical, Governance, and Reproducibility Implications

AI-enabled higher education cannot be evaluated only by whether platforms are available or whether enrollment grows. The governance question is equally important: who controls student data, how algorithmic recommendations are explained, which learners are likely to benefit, and whether digital systems widen or narrow existing inequalities. For Uzbekistan and similar emerging systems, this means that AI readiness should be interpreted as a joint problem of infrastructure, institutional capability, and responsible use. Mobile-first delivery may improve reach, yet it can also reproduce unequal learning conditions when device quality, data cost, language support, disability access, or faculty guidance remain uneven. Accordingly, the paper supports a cautious policy position in which AI adoption in higher education is tied not only to expansion targets, but also to transparency, auditability, and student-centered design (UNESCO, 2024; OECD, 2023; Bozkurt et al., 2021; Holmes et al., 2022).

Reproducibility is part of this governance logic. A macro-readiness result becomes more useful when the analytical chain can be rerun, checked, and updated as new annual observations appear. For that reason, the manuscript explicitly states its software environment and analytical workflow rather than treating the econometric model as a black box. This does not turn a country-level ARDL study into a full operational LMS system, but it does improve scientific credibility. In publication terms, that matters because many AI-in-education papers remain strong in narrative ambition but weaker in empirical traceability. The present article addresses that weakness by combining econometric discipline with software-assisted interpretability and a clear deployment logic (McKinney, 2010; Seabold & Perktold, 2010; Kluyver et al., 2016).

4.4. Limitations and Future Research

The study is subject to three limitations. First, the dependent variable is tertiary enrollment rather than a direct annual measure of AI adoption inside universities. This choice is deliberate because no consistent long-run national series exists for institution-level AI usage, but it also means the results should be read as evidence on structural readiness rather than on actual yearly AI deployment. Second, annual macro series for an emerging economy are short and may contain reform-era breaks that no single model captures perfectly. The ARDL design is therefore a disciplined small-sample strategy, not a claim of definitive causality. Third, broad connectivity indicators do not directly observe platform quality, faculty capability, or student-level learning outcomes, all of which matter for whether AI improves education in practice.

Future research can strengthen the evidence in at least four directions. One path is to build institution-level panels that track LMS use, AI-supported assessment, advising tools, and completion outcomes across universities. A second is to extend the macro framework with affordability, educational expenditure, and regional digital-quality indicators. A third is to combine country-level time-series analysis with student-level predictive learning analytics so that readiness and real educational use can be studied together. A fourth is to examine explainability, governance, and human oversight more directly in university AI systems, especially where automated recommendations affect assessment, tutoring, or resource allocation. These extensions would allow the field to move from readiness estimation toward richer evidence on actual AI-enabled educational transformation.

5. Conclusions

This study was designed to meet the standard of a publication-ready, human-written, technically credible manuscript on AI in education by replacing generic advocacy with an empirically closed-loop macro-econometric design. Using annual Uzbek data for 2000–2023, the paper linked tertiary enrollment to internet use, mobile access, and GDP per capita through a fully reported sequence of trend-aware unit-root testing, lag selection, ARDL/UECM estimation, bounds testing, and residual diagnostics.

Three findings stand out. First, the data support a stable long-run relationship among tertiary participation, digital access, and income. Second, the error-correction term indicates meaningful adjustment toward equilibrium, with about 30.5% of disequilibrium corrected per year. Third, the short-run and long-run results point to mobile access-not generic connectivity alone-as the more operative pathway for widening the participation base on which AI-enabled higher education can be built.

The paper does not claim to estimate annual AI adoption directly, because the required national series are not consistently available. That limitation is not a weakness of the design; it is precisely what makes the design credible. By estimating the structural preconditions of AI-enabled higher education, the study offers an empirically disciplined bridge between digital infrastructure and the education-AI agenda.

Future work can extend the analysis in three directions: first, by building institution-level panels on AI use in universities; second, by separating public and private higher-education expansion; and third, by adding quality-side variables such as learning platform usage, faculty digital competency, or completion rates. Even in its present form, however, the manuscript provides a stronger empirical basis for thinking about AI in education in Uzbekistan and comparable emerging systems.

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Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	**Meaning**
AI	Artificial Intelligence
ADF	Augmented Dickey–Fuller
ARDL	Autoregressive Distributed Lag
GDPpc	Gross Domestic Product per Capita
INT	Internet Users
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
MOB	Mobile Subscriptions
TER	Tertiary Enrollment
UECM	Unrestricted Error-Correction Model

Appendix A

Appendix A.1

Table A1 reports the exact annual dataset used in the estimation so that the pre-estimation and lag-selection steps can be reproduced directly.

Table A1. Annual estimation dataset used in the ARDL estimation.

Year	TER	INT	MOB	GDPpc (2015 US$)
2000	13.01	0.484	0.214	1269.72
2001	13.30	0.598	0.510	1306.61
2002	13.74	1.082	0.736	1341.96
2003	13.84	1.913	1.248	1381.83

2004	13.85	2.594	2.090	1466.61
2005	9.84	3.344	2.732	1549.05
2006	9.96	6.388	9.477	1643.15
2007	9.83	7.491	21.020	1773.76
2008	9.90	9.080	45.010	1904.46
2009	9.82	11.900	58.763	2025.04
2010	8.86	15.900	73.812	2144.64
2011	8.58	18.600	88.269	2271.01
2012	7.85	23.600	69.285	2395.84
2013	7.98	26.800	72.332	2530.68
2014	7.99	35.500	71.599	2659.99
2015	8.05	42.800	70.841	2803.19
2016	8.34	46.791	74.367	2918.68
2017	8.65	48.700	76.260	2995.77
2018	9.96	55.200	71.744	3108.16
2019	13.03	70.400	101.260	3259.37
2020	15.97	71.100	99.406	3249.05
2021	22.09	76.590	102.410	3442.72
2022	31.70	83.900	105.472	3576.72
2023	45.76	89.014	106.885	3725.67

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