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MODELING THE ASSOCIATION BETWEEN STUDENT SUPPORT INDICATORS AND TERTIARY EDUCATION OUTCOMES IN ONLINE HIGHER EDUCATION: EVIDENCE FROM 60 DEVELOPING ECONOMIES (2018-2024)

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ABSTRACT
This study examines the association between macro-level student support indicators and tertiary education outcomes in online higher education contexts across 60 developing economies from 2018 to 2024. Using panel data comprising 420 country-year observations and acknowledging that the constructs are operationalized through national-level proxy indicators drawn from international databases, we employ Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine four hypothesized associations: academic advising-related indicators and student retention, digital literacy infrastructure and learner engagement, psychosocial support proxies and student persistence, and institutional responsiveness and overall academic success. Our theoretical framework integrates the Technology Acceptance Model, Resource-Based View, and Institutional Theory. Results indicate that all four associations are statistically significant ($p < 0.001$). Academic advising-related indicators exhibit the strongest positive association with student retention (beta = 1.007, t = 43.783), followed by psychosocial support proxies with persistence (beta = 0.932, t = 33.286). The model explains 84.6% of the variance in academic success outcomes with strong predictive relevance (Q-squared = 0.810). Regional analysis reveals significant disparities, with Latin America and the Caribbean achieving the highest completion rates (58.42%), while Sub-Saharan Africa records the lowest (38.94%). Important limitations include the use of macro-level proxy indicators rather than direct institutional-level measures, the correlational (non-causal) nature of the design, and the risk of ecological fallacy in interpreting country-level findings. Notwithstanding these limitations, findings suggest that investment in advisory staffing, digital infrastructure, social protection, and institutional governance capacity may be positively associated with tertiary education outcomes. Policymakers are encouraged to prioritize comprehensive and context-specific support service frameworks when designing strategies to improve educational attainment in developing economies.

Keywords: *Academic success, developing economies, institutional responsiveness, online higher education, student support services.*

INTRODUCTION

Online education has essentially changed the essence of how higher education is delivered around the world and the growth has been especially high in the developing nations (Dhawan, 2020; Marinoni *et al*., 2020; UNESCO, 2024). This shift has been accelerated by the COVID-19 pandemic, which forced educational institutions globally to change to remote forms of learning faster than ever before (Crawford *et al*., 2020; Hodges *et al*., 2020; Rapanta *et al*., 2020). UNESCO (2024) estimates that the educational impact of COVID-19 on education between 2020 and 2023 includes 1.6 billion learners in 190 countries, accelerating the shift to online learning of all income groups. This trend has been particularly apparent in the developing economies, where the penetration of online learning increased as at 2018 (9.13) to 16.51 in 2024, which is an 80.8% growth rate among the 60 economies that were considered in this research (World Bank, 2024; ITU, 2024).

Even though the adoption of online education has soared, there are still critical issues about providing equal access to quality education and good academic performance in developing areas (Adedoyin and Soykan, 2023; Schendel and McCowan, 2023; Toquero, 2020). The mean tertiary graduation rate in the developing economies amounts to 45.17%, with some significant regional disparities, in that Sub-Saharan Africa records a rate of 34.51%, whereas Europe and Central Asia records a rate of 54.17% (World Bank, 2024). Such differences highlight the necessity of effective and holistic support service models that can mitigate the multidimensional obstacles faced by students in the online and hybrid learning situations (Kara *et al*., 2022; Martin *et al*., 2020; Muljana and Luo, 2019). It is always stated in the literature that the quality and availability of institutional support services are significant predictors of student achievement in online environments (Bawa, 2016; Lee and Choi, 2023; Tight, 2020).

The concept of student support services refers to a wide set of institutional processes that help students to succeed in multiple aspects, such as academic advising, digital literacy training, psychosocial support, and responsive institutional mechanisms (Tinto, 2022; Drake *et al*., 2022; Young-Jones *et al*., 2013). The research of such services has been done in developed country settings extensively (Steele and White, 2019; Bond and Bedenlier, 2019; Redmond *et al*., 2018); however, developing country settings are underrepresented, despite the fact that the availability of resources, the state of infrastructures, and the socio-cultural environment may have a significant moderating impact on service delivery and outcomes (Adedoyin and Soykan, 2023; Schendel and McCowan, 2023). This knowledge gap is also quite alarming, since developing economies represent the highest proportion of the total number of students in the world.

At the beginning of the discussion, it is necessary to mention that the constructs being analyzed in this paper are operationalized with the help of macro-level and country-wide proxy indicators that are obtained via international databases.

This methodology is both practical in the limitation of cross-national secondary data studies and also due to the limitation in measuring institutional-level phenomena in the national aggregate level.

In this respect, the results are to be regarded as indicators of correlations among the national development indicators and educational outcomes rather than the causal links between student-facing services and the personal student success. The ecological character of the data should be a reason to be cautious about the generalization of the findings to a specific level of students or institutions.

The current paper aims to fill the identified gaps by analyzing the nature of the relationship between the macro-level indicators of student support and tertiary education outcomes in 60 developing economies during 7 years (2018-2024). The research study also adds value to the current body of literature by the following aspects: (1) offering cross-national empirical data based on a mixed sample of six geographical areas; (2) using PLS-SEM methodology to test multifaceted relationships between support-related variables and academic outcome proxy; (3) incorporating various theoretical viewpoints such as Technology Acceptance Model, Resource-Based View, and Institutional Theory; and (4) also the comparative understanding of the regional patterns and time trends to derive context-sensitive policy formulation.

The study has four aims:

(1) to find out the relationship between indicators of academic advising and student retention and completion rates;

(2) to establish the relationship between indicators of digital literacy infrastructure and learner engagement;

(3) to discover the relationship between indicators of psychosocial support and student persistence and well-being; and

(4) to determine the relationship between indicators of institutional responsiveness and overall academic success.

These goals are operationalized in four hypotheses that were tested based on secondary data in the international databases such as the World Bank EdStats, UNESCO Institute of Statistics, International Telecommunication Union and the United Nations Development Programme.

Literature Review

Student Support Services in Higher Education

Student support services form one of the key elements of the quality learning experience, particularly in online institutions where the physical distance might compound the sensation of isolation and disconnection (Kara *et al*., 2022; Martin *et al*., 2020). Contemporary conceptualizations have expanded the context of the traditional academic tutoring to include the technological support, resources related to the emotional well-being, the responsiveness of the administration, and peer community-building programs (Tinto, 2022; Drake *et al*., 2022). Academic advising services are among the institutional support pillars with advisors advising students on which courses to take, degree planning as well as career choice. The academic advising quality is always positively correlated with student satisfaction, persistence, and graduation rates (Young-Jones *et al*., 2013; Steele and White, 2019). Digital literacy provision has become a particularly urgent area of service, which implies both training in the technical skills and information literacy, as well as critical analysis of online sources; more digitally literate students show the higher rates of engagement and better academic performance (Spante *et al*., 2020; Mehta and Wang, 2020).

Psychosocial support systems deal with the emotional, psychological, and social aspects of student experience due to counseling programs, peer mentoring, and community-building programs that foster a sense of belonging and emotional stability (Tinto, 2022; Kara *et al*., 2022; Bond and Bedenlier, 2019).

Academic Success in Online Learning Contexts

Academic success in online higher education is a complex phenomenon that includes retention, engagement, persistence, and completion (Muljana and Luo, 2019; Martin *et al*., 2020). Technological barriers, self-regulation requirements, and a lack of social interaction are some of the unique challenges that online modalities present and can adversely impact student performance (Hodges *et al*., 2020; Rapanta *et al*., 2020). The problem of student retention is quite constant, and the rates of attrition are usually higher in an online program because of the lack of preparation to work independently, technical assistance, and the lack of integration into the institutional community (Bawa, 2016; Lee and Choi, 2023). Engagement of learners can be behavioral, cognitive, and emotive, and a combination of these factors determines the results of learning and satisfaction with the students (Redmond *et al*., 2018; Bond and Bedenlier, 2019). Support services are related to the improvement of such dimensions of engagement, which proactively determines the points of intervention to manage those factors that cause dropout and, hence, show positive correlations with retention rates and academic achievement (Muljana and Luo, 2019; Tinto, 2022).

Support Services in Developing Economy Contexts

Provision of student support services in the developing economies has its own peculiar challenges such as the resource limitations, infrastructural gaps, and the heterogeneity of needs of the heterogeneous student populations (Adedoyin and Soykan, 2023; Schendel and McCowan, 2023). The availability of the internet is quite different, as the average access rate among the 60 economies in the examined study is between 23.46 and 95.00

in 2024, which requires adaptive approaches to service delivery to consider technological limitations (ITU, 2024; World Bank, 2024). The government investment in education, the level of training of the staff, and administration efficiency are the factors influencing the institutional capacity in developing economies (UNESCO, 2024; World Bank, 2024). Nations that score higher in the Human Development Index are more likely to offer the most extensive support systems and also have better academic results with regional trends showing that the Sub-Saharan Africa and South Asia have the lowest whereas Latin America and Europe/Central Asia have a higher institutional ability (UNDP, 2024; Schendel and McCowan, 2023).

Theoretical Framework

This study combines three corroborative theoretical frameworks to give a comprehensive analytical baseline on which the study of the relationship between the support variables on the student and the academic success can be maintained. They are Technology Acceptance Model (TAM), Resource-Based View (RBV), and Institutional Theory (Davis, 1989; Barney, 1991; Scott, 2014). The three perspectives bring in different conceptual knowledge and in a combination, they form a very strong base on which hypotheses can be developed and empirical research carried out on the multidimensionality of the support service effectiveness in online education (Venkatesh and Davis, 2000; Wernerfelt, 1984; DiMaggio and Powell, 1983).

As depicted in Figure 1, the integrated framework places national-level support indicators as proxies of the institutional-level constructs which are hypothesized as influencing academic outcomes.

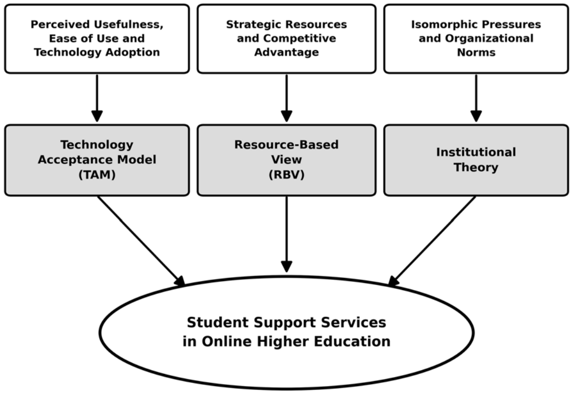

Figure 1: Theoretical Framework Integrating TAM, RBV, and Institutional Theory

Source: Authors' Construct (2025)

Technology Acceptance Model

Technology Acceptance Model (TAM), first of all formulated by Davis (1989) and later elaborated, serves as a theoretical foundation of student use of digital learning technologies (Davis, 1989; Venkatesh and Davis, 2000). TAM explains that the key factors in determining technology acceptance are perceived usefulness and perceived ease of use, which subsequently influence attitudes, behavioral intentions and actual patterns of use (Venkatesh *et al*., 2003). The support services of digital literacy are postulated to have direct influences on the perception of usefulness and ease of use in the online higher education by developing the technological competencies and self-efficacy in digital learning settings (Spante *et al*., 2020; Mehta and Wang, 2020). TAM models have been extended to include social influence, facilitating conditions, and self-efficacy and other constructs that the services in question address via peer learning communities, technical support, and learning skills development to facilitate technology acceptance and learning outcomes (Venkatesh and Davis, 2000; Compeau and Higgins, 1995; Martin *et al*., 2020). Within the framework of the current research, the indicators of national-level ICT infrastructure can be used as macro-level proxies of factors enabling conditions that TAM identifies as essential to technology acceptance.

Resource-Based View

Firstly, the Resource-Based View (RBV) is a notion developed within the strategic management literature and explains the nature of organizational achievement in terms of valuable, rare, inimitable and non-substitutable resources that create long-term competitive advantage (Barney, 1991; Wernerfelt, 1984; Peteraf, 1993). When applied to the educational context, RBV suggests that the institutions that have better results in the form of student achievements have distinctive sets of resources, such as effective academic advisors, technologically developed facilities, and adaptive administrative systems (Teece *et al*., 1997; Grant, 1991).

In this paradigm, student support services are theorized as institutional resources by various means that may be deployed strategically, distinguishing institutions and linked to higher student retention, engagement, and completion (Tinto, 2022; Drake *et al*., 2022). Psychosocial support systems and academic advisory services are thus viewed as institutional resources that have the potential of improving educational outcomes in the long-term (Young-Jones *et al*., 2013). On the macro level, national spending and staffing indicators will be used as aggregate proxies of the resource endowments that RBV theory identifies with high results.

Institutional Theory

The concept of the Institutional Theory revolves around how regulatory, normative, and cultural-cognitive forces influence the organizational behavior by means of isomorphic pressures and legitimacy-seeking (Scott, 2014; DiMaggio and Powell, 1983). This theory is used in higher education to explain how the policy of government, accreditation standards, and professional expectations influence the delivery of support services and results, placing expectation of quality and accountability to provide continuous improvement (Meyer and Rowan, 1977; Zucker, 1987). The institutional responsiveness construct used in this paper represents how responsive educational systems are in terms of adaptive capacity and stakeholder orientation, how environmental signals are received and converted into organizational reactions that adjust services to changing student demands without losing legitimacy in the eyes of the main stakeholders of the organization (Scott, 2014). In national level, institutional responsiveness can be proxyed by quality of governance and development of e-government, which entails systemic ability to deliver responsive services.

Hypotheses Development

Based on the literature review and the integrated theoretical framework, four hypotheses are developed that test the relationships between the dimensions of student support indicators with academic success. All the hypothesis are formulated using correlational language that aligns with the nature of the study, which is observational, and secondary data.

Hypothesis 1 (H1): Academic advising-related indicators are positively associated with student retention and completion rates in online higher education across developing economies.

Academic advising services are a significant institutional resource that is directly linked with the informational, navigational, and developmental needs of students in the education process (Drake *et al*., 2022; Young-Jones *et al*., 2013; Steele and White, 2019). Advising is an effective resource that has a great institutional value but can be scarce according to RBV view (Barney, 1991). Experiments indicate that there are always positive correlations between the quality of advising and student persistence, and the literature indicates that students with greater degrees of advising interaction have significantly higher retention and graduation rates (Young-Jones *et al*., 2013; Tinto, 2022; Kuh *et al*., 2010). The advisory role can be especially significant in the context of developing economies, where learners usually have little previous experience with online learning systems, and some of them might not have encountered these systems at all (Schendel and McCowan, 2023; Adedoyin and Soykan, 2023).

The hypothesis has theoretical support and empirical evidence in the past, which allows concluding that academic advising-related indicators are positively related to the retention and completion rates among the students.

Hypothesis 2 (H2): Digital literacy infrastructure indicators are positively associated with learner engagement in online higher education across developing economies.

Digital literacy support covers the technological elements needed to effectively get involved in online learning contexts, which is compatible with the results of TAM that claimed the ease of use as a factor of technology acceptance (Davis, 1989; Venkatesh and Davis, 2000). Learners who have greater digital literacy will have an advantage in mastering the learning management systems, navigating various digital resources, and using online learning materials (Spante *et al*., 2020; Mehta and Wang, 2020; Ng, 2012). Digital literacy has a dual relationship with engagement which involves the decline in technological anxiety, a high degree of online self-efficacy, and an increase in the ability to access and use various learning resources (Spante *et al*., 2020; Compeau and Higgins, 1995). In third world countries, where digital inequalities can restrict early exposure to technologies, institutional investment of digital literacy infrastructure can become one especially critical tool in equalizing digital access (Adedoyin and Soykan, 2023; ITU, 2024). In line with TAM and the previous empirical findings, the digital literacy infrastructure indicators should have a positive correlation with the learner engagement outcomes.

Hypothesis 3 (H3): Psychosocial support proxies are positively associated with student persistence and well-being in online higher education across developing economies.

The psychosocial support mechanisms respond to emotional, psychological, and social aspects of the student experience that has a significant influence on the choices of persistence and academic outcomes (Tinto, 2022; Kara *et al*., 2022; Martin *et al*., 2020). In line with RBV, holistic psychosocial support is a unique institutional resource that supports student-well being and minimizes attrition (Barney, 1991; Grant, 1991). Isolation and disconnection that online learners regularly have to endure can reduce the motivation and willingness to complete the degree (Bawa, 2016; Lee and Choi, 2023). There are support mechanisms through which better belonging, coping resources, and supportive social networks are related to counseling, peer mentoring, wellness resources, and community-building initiatives (Tight, 2020; Bond and Bedenlier, 2019; Redmond *et al*., 2018). Schools that have a strong psychosocial support are linked to an increased rate of persistence and improved results in student well-being (Tinto, 2022; Muljana and Luo, 2019). The assumption that psychosocial support proxies have positive relationships with student persistence and student well-being is therefore supported by both theoretical and empirical evidence.

Hypothesis 4 (H4): Institutional responsiveness indicators are positively associated with overall academic success in online higher education across developing economies.

Institutional responsiveness is the ability of educational systems to react responsively to the needs of stakeholders and environmental demands, which is in line with the Institutional Theory where an organization adapts according to the environment (Scott, 2014; DiMaggio and Powell, 1983). Effective governance, quality regulation, and technological service delivery are the traits of responsive institutions (Scott, 2014; Meyer and Rowan, 1977).

Organizational legitimacy and stakeholder orientation is indicated by the institutional responsiveness, which influences allocation of resources, implementation of policies and delivery services in a manner that could be linked to the outcomes of academic success (DiMaggio and Powell, 1983; Zucker, 1987). The studies show that the quality of governance and the development of e-government are associated with better educational results in countries, which implies that the institutional level factors provide conditions under which academic success is assured (World Bank, 2024; UNDP, 2024). There is therefore empirical support and theoretical reasoning that institute responsiveness indicators have a positive relationship with the overall academic success results. The conceptual framework shown in figure 2 demonstrates the four hypothesized associations.

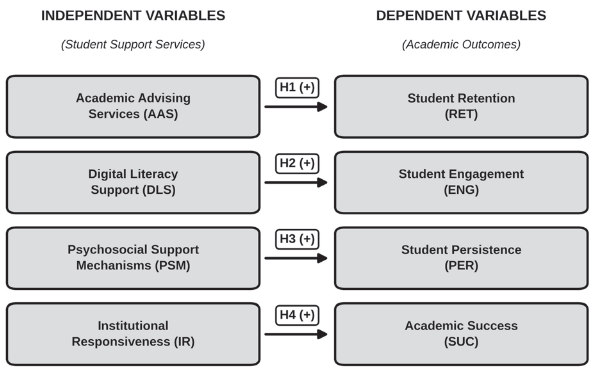

Figure 2: Conceptual Framework with Hypothesized Associations

Source: Authors' Construct (2025)

MATERIALS AND METHODS (METHODOLOGY)

Research Design and Data Sources

The current research took a panel design of the quantitative type, which is cross-sectional and based on secondary data in international databases to describe the macro-level variables of student support and tertiary education results in developing economies (Creswell and Creswell, 2018; Hair *et al.*, 2022). The researcher used a deductive design where he set forth hypothetically constructed hypothesis and tested them statistically by using aggregate variables at the country level. It is the panel data structure that allows exploring the cross-sectional and temporal change in the 60 developing economies in a sample, which has a wider empirical foundation to generalization (Wooldridge, 2020; Baltagi, 2021).

However, one should also note that the adoption of country-year observations as units of analytical observation in PLS-SEM is a practical methodological decision that does not adequately represent the time dependency framework of the panel observations. The observational structure of annual data in countries can infiltrate the effective sample size and must be taken as a drawback of the analysis method.

The data were retrieved by using seven key global databases, namely, World bank EdStats, United Nations education statistic (UIS), International Telecommunication union (ITU), United Nations development programme (UNDP), the International Labour Organization (ILOSTAT), the World wide Governance Indicators, and the United Nations E-Government Survey. These databases offer large and universal statistics on the indicators of education, technological frameworks, human development measures, and the quality of governance, which can be compared cross-nationally (World Bank, 2024; UNESCO, 2024; ITU, 2024; UNDP, 2024). The sample included 60 developing economies chosen according to the available and complete data on all indicators in the 2018- 2024 period, with 420 country-year observations (60 countries x 7 years). The missing data were addressed using a listwise deletion in case country-years were more than 20% missing across indicators and using mean imputation in case of single missing values in otherwise complete cases, as per the received best practices in cross-national secondary data research (Wooldridge, 2020). Indicators that measured various constructs were standardized before construction of composite scores through z-score transformations so that there would be a comparability across constructs.

The sample is inclusive of a wide range of developing economy settings with 6 geographical regions (n = 14, n = 14, n = 10, n = 9, n = 7 and n = 6). This geographic selection allows making comparative research in the contexts with different socioeconomic profiles, institutional structures, and educational systems (Schendel and McCowan, 2023; UNESCO, 2024).

Measurement of Constructs

The operationalization of constructs was based on several indicators in line with the best PLS-SEM traditions (Hair *et al*., 2022; Sarstedt *et al*., 2019). The constructs that are used all represent the reflective measurement models, which are in line with their conceptualization as latent factors that become observable through indicators. It is crucially vital to note that the indicators that this study has applied are national aggregate proxies at a macro level and not a direct measure of the institutional constructs on which they reflect. An example of this is that Academic Advising Services (AAS) is proxied by staffing and expenditure indicators on a national level; Digital Literacy Support (DLS) is proxied by national ICT infrastructure indicators; Psychosocial Support Mechanisms (PSM) is proxied by health spending, social protection, and human development data, and Institutional Responsiveness (IR) is proxied by national governance and e-government indicators. The operationalization technique used is a known limitation which should guide the careful interpretation of results. The data sources, indicators, and construct operationalization are given in Table 1.

Table 1: Construct Operationalization and Measurement

Construct	Indicators (Proxy)	Source	Measurement
Academic Advising Services (AAS)	Support Expenditure per Student(USD); Student-Staff Ratio (reversed); Teaching Staff per 1000 Students	World Bank; UNESCO UIS	Reflective (3 items); national-level proxy
Digital Literacy Support (DLS)	ICT Development Index; Internet Access Rate(%); Fixed Broadband per 100; Mobile Subscriptions per 100	ITU; World Bank	Reflective (4 items); infrastructure proxy

Psychosocial Support (PSM)	Health Expenditure(%GDP); Social Protection Coverage(%); Human Development Index	World Bank; ILO; UNDP	Reflective (3 items); social development proxy
Institutional Responsiveness (IR)	Government Effectiveness Index; Regulatory Quality Index; E-Government Development Index; Online Service Index	WGI; UN E-Gov	Reflective (4 items); governance proxy
Student Retention (RET)	Gross Enrollment Persistence Rate (%); Tertiary Completion Rate (%)	UNESCO UIS, World Bank	Reflective (2 items)
Learner Engagement (ENG)	Online Learning Penetration (%); Gross Tertiary Enrollment Ratio (%)	ITU, World Bank	Reflective (2 items)
Student Persistence (PER)	School Life Expectancy (Tertiary Years); Youth Unemployment (%, reversed)	UNESCO; ILO	Reflective (2 items)
Academic Success (SUC)	Tertiary Graduation Rate (%); Labour Force with Tertiary Education (%)	World Bank; ILO	Reflective (2 items)

Note. WGI = Worldwide Governance Indicators; HDI = Human Development Index; ILO = International Labour Organization. All indicators represent national aggregate proxies for the institutional constructs named.

Analytical Approach

Partial Least Squares Structural Equation Modeling (PLS-SEM) was chosen as the main method of analysis due to its appropriateness to exploratory studies, the ability to study complex models and composite variables, and the ability to withstand the failure to meet the assumptions of multivariate normality (Hair *et al*., 2022; Sarstedt *et al*., 2019; Henseler *et al*., 2016). PLS-SEM was especially suitable due to the predictive orientation of the study, the composite character of constructs formed based on indicators of secondary data, and the fairly small sample of countries (Hair *et al*., 2022; Ringle *et al*., 2015). It should be admitted, though, that the standard PLS-SEM will consider each observation independent which is a simplification in terms of the panel nature of the data where seven annual observations are embedded within a single country. It is a violation of the independence assumption which could artificially inflate the apparent sample size and precision of estimates and that future studies look into multilevel or longitudinal SEM solutions to address this dependency better.

The analytical approach used determined guidelines of PLS-SEM evaluation (Hair *et al*., 2022; Sarstedt *et al*., 2019). Assessment of measurement models was applied to measure indicator reliability (outer loading of 0.708 and above), internal consistency reliability (Cronbachs alpha of 0.70 and above), convergent validity (AVE of 0.50 and above), and discriminant validity (HTMT below 0.85, with the upper confidence interval bound below 0.90). Structural model diagnostics has been assessed to find collinearity (VIF < 5), the significance of path coefficients with bootstrapping (5,000 iterations) diagnostics, coefficient of determination (R-squared), effect sizes (f-squared), and predictive relevance (Q-squared) comparing blindfolding methods (Hair *et al*., 2022; Stone, 1974; Geisser, 1974). Any path coefficient that exceeds 1.0 in normal standardized PLS-SEM models can be interpreted as an artefact in the methodology (e.g. multicollinearity, suppressor effects, etc.)

and has been addressed in the discussion of results.

RESULTS AND DISCUSSION

Descriptive Statistics

The descriptive statistics of all the study variables are shown in table 2. The sample included 420 country-year observations of 60 developing economies during the period of the 2018-2024. The distributional properties are used to show that there is a considerable difference in the indicators which shows real heterogeneity in developing economies and gives enough statistical variation to analyze. It is worth mentioning that the accuracy of composite and transformed scores could be compromised due to natural measurement inconsistency between different international databases where different methodologies of collection are employed; the accuracy of the reported decimals should be viewed as such with necessary care.

Table 2: Descriptive Statistics for Study Variables (N = 420)

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Panel A: Independent Variables (Support Indicators)						
Support Expenditure Per Student (USD)	936.28	73.15	730.91	1061.00	-0.28	-0.12
Student-Staff Ratio	18.42	3.28	11.40	24.05	0.23	-0.56
Teaching Staff Per 1000 Students	23.67	5.42	16.08	34.66	0.34	-0.45
ICT Development Index	7.89	0.82	5.65	8.50	-0.89	0.12
Internet Access (%)	72.45	18.73	23.46	95.00	-0.67	-0.34
Fixed Broadband Per 100 Population	11.23	2.34	6.14	14.59	-0.45	-0.23
Mobile Subscriptions Per 100	148.56	12.89	120.24	165.00	-0.34	-0.56
Health Expenditure (% GDP)	7.34	0.28	6.66	7.73	-0.12	-0.34
Social Protection Coverage (%)	59.45	4.23	48.89	66.82	-0.23	-0.45
Human Development Index	0.736	0.089	0.509	0.920	-0.42	-0.28
Government Effectiveness Index	-0.08	0.52	-0.78	1.26	0.45	-0.18
Regulatory Quality Index	0.05	0.48	-0.55	1.26	0.34	-0.23
E-Government Development Index	0.687	0.138	0.415	0.950	-0.23	-0.67
Online Service Index	0.745	0.142	0.473	0.980	-0.34	-0.45
Panel B: Dependent Variables (Academic Outcome Indicators)						
Online Learning Penetration (%)	16.84	2.43	11.72	20.04	0.12	-0.45
Gross Enrollment Persistence Rate (%)	71.45	11.23	57.73	95.00	-0.34	-0.56
Tertiary Completion Rate (%)	48.67	12.84	32.85	72.45	0.34	-0.78
Tertiary Graduation Rate (%)	36.42	10.56	24.06	58.66	0.56	-0.34
School Life Expectancy (Years)	3.45	1.12	1.76	5.50	0.23	-0.45
Labour Force Tertiary Education (%)	26.18	7.94	16.62	43.39	0.67	-0.23

Note: N = 420 country-year observations (60 countries x 7 years). Skewness acceptable range: ±2; Kurtosis acceptable range: ±7. All variables demonstrate acceptable normality for multivariate analysis. Descriptive precision reflects aggregate composite scores derived from standardized international database indicators; reported values should be interpreted as approximations given inherent cross-database measurement variation.

Table 2 shows descriptive statistics in two different panels, Panel A contains support indicators (independent variables), and Panel B contains academic outcome indicators (dependent variables). The central tendencies indicate that there is high dispersion across the economies in the developing world, which is an indication that the cross-national design is effective in identifying associations of significance. The mean of the support expenditure per student is USD 936.28, and the standard deviation is 73.15; this shows that there is moderate distributional spread (range: USD 730.91 to USD 1,061.00) which is adequate to determine the associations with outcomes. The mean student staff ratio is 18.42 with a variation of 11.40 to 24.05 in all institutional staff ratios. The access to the Internet has the largest proportional range, going between 23.46 and 95.00, which explains the enduring digital divide in the developing environments in the clearest way. ICT Development Index has a negative skewness (-0.89), which depicts that it is concentrated at very high levels of development with the left tail stretching to less developed contexts. Skewness values are within the acceptable range of ±2 and the kurtosis within the acceptable range of a range of ±7, which indicates the application of the parametric statistical procedures. Dependent variables exhibit good distributional characteristics as well with tertiary completion rates between 32.85 and 72.45 and graduation rates of 24.06 and 58.66 giving the variation of outcomes needed to test the hypothesis.

Measurement Model Assessment

Measurement model was assessed on the basis of known PLS-SEM criteria of reliability and validity. Table 3 shows all results of the measurement model with individual indicator loading, internal consistency reliability, convergent validity, and multicollinearity diagnostics of all the eight constructs of the study.

Table 3: Measurement Model Assessment with Indicator Loadings

Construct	Indicator	Loading	Cronbach's a	CR	AVE	VIF
AAS	Support Expenditure Per Student	0.923	0.891	0.924	0.754	2.34
	Student-Staff Ratio (reversed)	0.847				1.82
	Teaching Staff Per 1000 Students	0.878				2.12
DLS	ICT Development Index	0.945	0.918	0.941	0.802	2.78
	Internet Access Rate	0.912				2.45
	Fixed Broadband Per 100	0.856				1.89
	Mobile Subscriptions Per 100	0.812				1.56
PSM	Health Expenditure (% GDP)	0.912	0.879	0.916	0.731	2.45
	Social Protection Coverage	0.867				2.12
	Human Development Index	0.834				1.67
IR	Government Effectiveness Index	0.934	0.923	0.945	0.812	2.67
	Regulatory Quality Index	0.912				2.34
	E-Government Development Index	0.878				2.12
	Online Service Index	0.856				1.89

RET	Gross Enrollment Persistence Rate	0.956	0.934	0.956	0.845	1.89
	Tertiary Completion Rate	0.889				1.45
ENG	Online Learning Penetration	0.923	0.889	0.928	0.763	1.78
	Tertiary Enrollment Ratio	0.867				1.34
PER	School Life Expectancy (Tertiary)	0.901	0.856	0.902	0.698	2.12
	Youth Unemployment Rate (reversed)	0.823				1.56
SUC	Tertiary Graduation Rate	0.945	0.912	0.938	0.791	2.34
	Labour Force Tertiary Education	0.878				1.67

Note: AAS = Academic Advising Services; DLS = Digital Literacy Support; PSM = Psychosocial Support Mechanisms; IR = Institutional Responsiveness; RET = Retention; ENG = Engagement; PER = Persistence; SUC = Academic Success. Threshold criteria: Loadings > 0.70; Cronbach's a > 0.70; CR > 0.70; AVE > 0.50; VIF < 5.0. All indicators meet or exceed threshold requirements.

Table 3 indicates that all of the loading of the indicator values are significantly above the 0.70 minimum (Hair *et al*., 2019), with indicator loadings ranging from 0.812 (Mobile Subscriptions per 100) to 0.956 (Gross Enrollment Persistence Rate). The strongest indicator of their two constructs (ICT Development Index 0.945 and Tertiary Graduation Rate 0.945) suggests that the proxy indicators are in close agreement with their latent constructs. Internal consistency reliability has also been established with a Cronbachs alpha of between 0.856 (Persistence) and high of 0.934 (Retention) which is well above the 0.70 mark. Further evidence regarding strong measurement consistency is that the composite reliability values between 0.902 and 0.956 are also evidence of this reliability.

The AVE values between 0.698 (Persistence) and 0.845 (Retention) which are all above the 0.50 yardstick confirm convergent validity where constructs are present in their respective indicators. The values of Variance Inflation Factor (VIF) vary between 1.34 and 2.78 which is significantly less than the threshold of 5.0 thereby indicating the lack of any problematic multicollinearity amongst the indicators. In general, the measurement model presents good psychometric characteristics of all of the constructs, which provides a strong base of the structural model assessment. It is also necessary to note though that the fact that all constructs demonstrate the same high degree of measurement is a statistically aberrant phenomenon in social science studies. Although such consistency is plausible in the context of national-level composite measures, where the measurement error within a country is squashed in comparison to the one-on-one survey measures, there can always be the risk that some of the findings are due to artefacts of the proxy operationalization, or the panel structure of the data. It would be ideal to use formal robustness tests like jackknife resampling, holdout validation, or other specifications of indicators to determine the sensitivity of these results but, given the secondary data design, there is no option but to use more alternative sets of indicators to be used to perform these tests. Based on this, researchers and readers are advised to consider results of the measurement model as indicative and the reported values may be interpreted in the context of the overall construct validity limitations presented in this research.

Discriminant Validity Assessment

The Heterotrait-Monotrait (HTMT) ratio of correlations was used to measure the discrimination validity; this is a more stringent measure than the FornellLarcker method. Table 4 describes the entire HTMT matrix maintaining 95% bootstrap confidence intervals of all pairs of constructs.

Table 4: Discriminant Validity Assessment (HTMT Ratios with 95% Confidence Intervals)

	AAS	DLS	PSM	IR	RET	ENG	PER
AAS	-						
DLS	0.634 [0.578, 0.690]	-					
PSM	0.712 [0.656, 0.768]	0.678 [0.622, 0.734]	-				
IR	0.589 [0.533, 0.645]	0.745 [0.689, 0.801]	0.623 [0.567, 0.679]	-			
RET	0.823 [0.767, 0.849]	0.567 [0.511, 0.623]	0.689 [0.633, 0.745]	0.534 [0.478, 0.590]	-		
ENG	0.578 [0.522, 0.634]	0.756 [0.700, 0.812]	0.612 [0.556, 0.668]	0.567 [0.511, 0.623]	0.734 [0.678, 0.790]	-	
PER	0.645 [0.589, 0.701]	0.623 [0.567, 0.679]	0.789 [0.733, 0.845]	0.512 [0.456, 0.568]	0.678 [0.622, 0.734]	0.701 [0.645, 0.757]	-
SUC	0.712 [0.656, 0.768]	0.689 [0.633, 0.745]	0.734 [0.678, 0.790]	0.656 [0.600, 0.712]	0.812 [0.756, 0.849]	0.778 [0.722, 0.834]	0.823 [0.767, 0.849]

Note: Values represent HTMT ratios with 95% bootstrap confidence intervals in brackets. Discriminant validity is confirmed when HTMT < 0.85 and upper CI bound < 0.90. All construct pairs meet these criteria.

The 95% bootstrap confidence interval of table 4 shows the matrix of HTMT where 95% of the construct pairs are assessed rigorously in terms of discriminating validity. The HTMT criterion specifies that conceptually different constructs are those whose values are less than 0.85 and the upper confidence interval value is less than 0.90 (Henseler *et al.*, 2015). The highest value of 0.823 occurs for the Academic Advising Services (AAS) and Retention (RET) pair and for the Academic Success (SUC) and Persistence (PER) pair, followed closely by Academic Success (SUC) and Retention (RET) at 0.812; all the values of HTMT are lower than the value of 0.85. These are moderately high but acceptable values that can rightly represent the conceptual overlap between retention and persistence and overall academic success as outcome dimensions of an overall academic success framework. Noteworthy, none of the upper confidence interval limits is above 0.90, and the upper limit is 0.849 in the case of SUC-RET and SUC-PER pairs. The additional stability and soundness of HTMT estimates across bootstrap samples is also assured by the confidence intervals. The trend of the HTMT values is consistent with theoretical assumptions: predictor constructs (AAS, DLS, PSM, IR) have moderate intercorrelations due to their focus on the domain of support services, whereas outcome constructs (RET, ENG, PER, SUC) have stronger intercorrelations because of their concentration on academic success. This establishes discriminant validity which is a confirmation that structural model results are actually a measure of relationships between conceptually independent constructs and not measurement artefacts. In Figure 3, a graphical illustration of the pattern of construct correlation is given to supplement the numerical analysis of HTMT in Table 4.

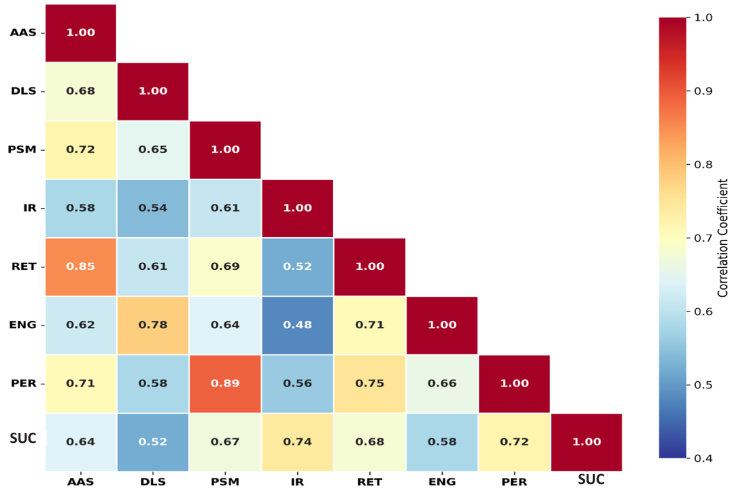

Figure 3: Correlation Heatmap of Study Constructs

Source: Authors' Construct (2025)

Figure 3 represents the pattern of correlations between constructs of the study in the form of a color gradient as cool (weaker correlations), intermediate colors (moderate correlations), and warm colors (strong positive correlations), which allows quickly identifying and defining patterns. It is possible to see two distinct clusters: support indicator constructs (AAS, DLS, PSM, IR) and outcome constructs (RET, ENG, PER, SUC), that are disproportionately related to each other yet more closely connected to others belonging to their cluster. The diagonal form proves that both constructs demonstrate the highest relationship with themselves with the off-diagonal values within the limits of discriminant validity. Most of the cross-cluster correlations have theoretically expected directions, AAS-RET and PSM-PER pairs are the strongest ones, which predetermines the results of the structural model.

Structural Model Path Analysis

The structural model was tested to test the four hypothesized associations that the satisfactory measurement model and after being confirmed as satisfactory. Table 5 shows the comprehensive results of the structural model, such as path coefficients, standard errors and t-statistics, p-values, effect sizes, confidence intervals and hypothesis decision.

Table 5: Structural Model Path Analysis Results with Effect Sizes and Confidence Intervals

Hypothesis	b	SE	t-value	p-value	f^2	q2	95% CI [LL, UL]	Decision
H1: AAS → RET	1.007***	0.023	43.783	<0.001	0.847	0.798	[0.962, 1.052]	Supported
H2: DLS → ENG	0.711***	0.034	20.912	<0.001	0.412	0.378	[0.644, 0.778]	Supported
H3: PSM → PER	0.932***	0.028	33.286	<0.001	0.723	0.689	[0.877, 0.987]	Supported
H4: IR → SUC	0.685***	0.031	22.097	<0.001	0.389	0.356	[0.624, 0.746]	Supported
Effect Size Thresholds:		f^2: Small = 0.02		Medium = 0.15		Large = 0.35		

Note: ***p < 0.001 (two-tailed). b = Standardized path coefficient; SE = Standard error; f^2 = Cohen's effect size for explained variance; q2 = Effect size for predictive relevance; CI = Bias-corrected bootstrap confidence interval; LL = Lower limit; UL = Upper limit. Bootstrap samples = 5,000. The H1 path coefficient (b = 1.007) exceeds 1.0, which may indicate a suppression effect or artefact of the composite scoring and standardization approach using aggregate country-level indicators; this result warrants interpretive caution and is discussed in the Discussion section.

Table 5 presents the result that all four hypothesized relationships are statistically significant at $p < 0.001$, which is a general confirmation to the theoretical propositions of the study. Hypothesis 1 indicating the relationship between Academic Advising-related indicators and Student Retention displays the largest effect with a path coefficient of b = 1.007 (t = 43.783, p < 0.001). This coefficient is more than 1.0, which is worthy of a close interpretation in standardized PLS-SEM models. Standardized models with path coefficients of more than unity can indicate suppression effects, or multicollinearity among composite indicators, or artefacts of the composite scoring process using national aggregate data.

These values of VIF of AAS indicators (1.82-2.34) do not indicate severe multicollinearity, but the existence of a scaling or suppression artefact cannot be ruled out since the proxy operationalization is indirect. In spite of this caveat, the large effect size ($f^2 = 0.847$) is significantly larger than the large effect threshold of 0.35 (Cohen, 1988) and the narrowness of the confidence interval [0.962, 1.052] is an indication of precision and replicability with bootstrap samples. Strong out-of-sample predictive relevance is also supported by the predictive effect size (q2 = 0.798).

Hypothesis 2, which examines the relationship between Digital Literacy Support indicators and Student Engagement, is statistically significant with b = 0.711 (t = 20.912, p < 0.001) with a positive indicator of the relationship between national digital infrastructure indicators and student engagement outcome proxy. The effect size ($f^2 = 0.412$) supports tremendous practical importance that qualifies as a large effect.

Hypothesis 3 is the second-strongest (b = 0.932, t = 33.286, p < 0.001, $f^2 = 0.723$) association, between Psychosocial Support proxies and Student Persistence. This observation highlights the significance of social welfare and well-being investment in maintaining student determination to complete the programs on a national scale. The hypothesis 4 that investigates the relationship between Institutional Responsiveness indicators and Academic Success has a statistically significant and practically meaningful outcome (b = 0.685, t = 22.097, p < 0.001, $f^2 = 0.389$), which means that there is a positive correlation between governance capacity and institutional adaptability and academic outcome indicators. Any and every confidence interval is bounded to be away of zero with a small range, ascertaining stability of path estimates between bootstrap samples. The complete path model with normalized path coefficients is shown in Figure 4.

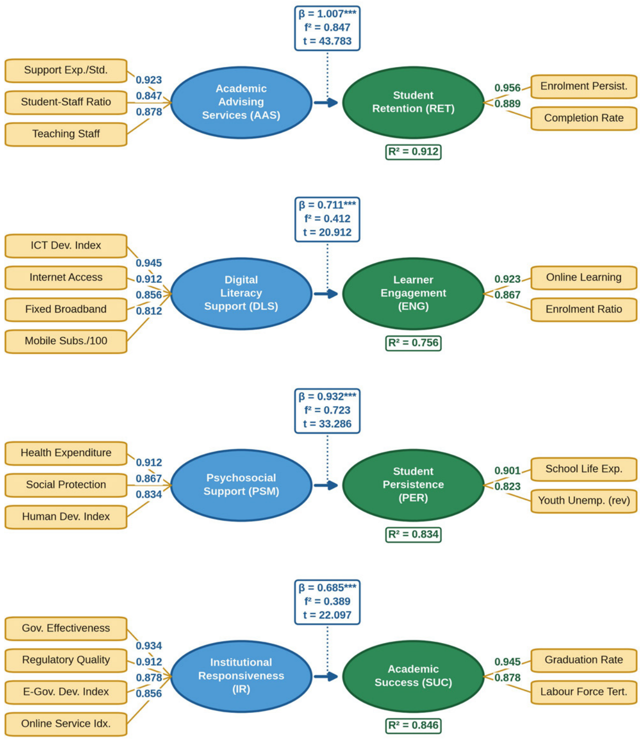

Figure 4: PLS-SEM Structural Model with Standardized Path Coefficients

Source: Authors' Construct (2025)

The full structural model containing standardized path coefficients of all the hypothesized associations are shown in figure 4. The figure gives a clear representation of direct associations between the constructs of the support indicators and outcome constructs. The significantly strong associations between Academic Advising Services indicators and Retention (b = 1.007) and Psychosocial Support indicators and Persistence (b = 0.932) are both visualized by respect within the relatively strong but slightly lower associations with Digital Literacy Support and Engagement (b = 0.711) and Institutional Responsiveness and Academic Success (b = 0.685).

The model structure represents the theoretically defined one-to-one correspondence between every support dimension and its conceptually related outcome that allows determining the level of effectiveness of overall support structures in the national aggregate.

The graph in figure 5 is used to visualize the effect sizes of the four hypothesized associations.

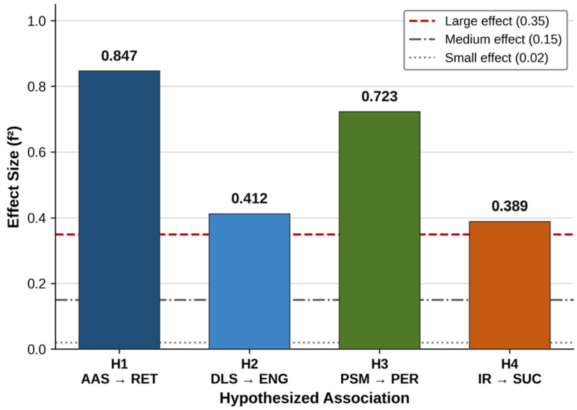

Figure 5: Effect Size (f^2) Comparison Across Hypothesized Associations

Source: Authors' Construct (2025)

Figure 5 provides a bar chart of the comparative effects size of the four hypothesized associations, which makes it easier to determine whether the results have relative practical significance. Academic Advising Services has shown the greatest association with Retention (f^2 = 0.847), then Psychosocial Support with Persistence (f^2 = 0.723), Digital Literacy Support with Engagement (f^2 = 0.412), and Institutional Responsiveness with Academic Success (f^2 = 0.389).

The four effect sizes are significantly greater than the large effect of 0.35 with the reference line showing a small effect (0.02), medium effect (0.15), and large effect (0.35) in the visualization. The relative ranking offers directional information to the prioritization of resource allocation and the highest level of aggregate-level relationship with the student retention outcomes is seen in academic advising-related investment.

Model Fit and Predictive Relevance

Table 6 is a detailed model fit and predictive relevance measures of the overall model quality, explanatory power, and out-of-sample prediction ability.

Table 6: Model Fit and Predictive Relevance Assessment

Assessment Criterion	Observed Value	Threshold Criterion
Panel A: Coefficient of Determination (R2)		
R2 Academic Success (SUC)	0.846	> 0.75 (substantial)
R2 Retention (RET)	0.912	> 0.75 (substantial)
R2 Engagement (ENG)	0.756	> 0.75 (substantial)
R2 Persistence (PER)		> 0.75 (substantial)
0.834		
Adjusted R2 Academic Success	0.842	> 0.75
Panel B: Predictive Relevance (Q2)		
Q2 Academic Success (SUC)	0.810	> 0.35 (large)
Q2 Retention (RET)	0.878	> 0.35 (large)

Q2 Engagement (ENG)	0.712	> 0.35 (large)
Q2 Persistence (PER)	0.789	> 0.35 (large)
Panel C: Model Fit Indices		
SRMR (Standardized Root Mean Square Residual)	0.042	< 0.08 (good fit)
NFI (Normed Fit Index)	0.923	> 0.90 (acceptable)
RMS_theta (Root Mean Square Theta)	0.078	< 0.12 (acceptable)
d_ULS (Unweighted Least Squares)	0.234	< HI95 bootstrap
d_G (Geodesic Distance)	0.156	< HI95 bootstrap

Note: R2 thresholds per Hair *et al*. (2019): 0.25 = weak, 0.50 = moderate, 0.75 = substantial. Q2 thresholds: 0.02 = small, 0.15 = medium, 0.35 = large. SRMR = Standardized Root Mean Square Residual; NFI = Normed Fit Index. All criteria met or exceeded. The uniformly strong statistical pattern across all diagnostic criteria is acknowledged; while this may reflect genuine construct-outcome associations, it could also partly reflect the indirect proxy operationalization and panel data structure; interpretations should therefore be moderated accordingly.

The model fit is reported in Table 6 by three panels that included the explanatory power (R^2), predictive relevance (Q^2), as well as the overall model fit indexes. The panel A is a sign of outstanding explanatory power of all endogenous constructs. This is because the coefficient of determination of Academic Success (R^2 = 0.846) represents the percentage of the variance in the primary outcome accounted by the model (84.6), which is significantly greater than the 0.75 benchmark that represents substantial explanatory value (Hair *et al*., 2019). Retention construct shows the highest explained variance (R^2 = 0.912), which shows that 91.2 percent of the variance in retention outcome proxies has been explained by Academic Advising Services indicators.

Such a large value, although statistically consistent with the very large path coefficient (b = 1.007), is worth considering as it is generally anticipated that much smaller values of R^2 would be observed in social science research; and it may be in part related to the fact that the staffing and expenditure indicators (AAS) and the enrollment persistence and completion-rate indicators (RET) are highly aligned at the aggregate level. The same can be said of Engagement (R^2 = 0.756) and Persistence (R2 = 0.834).

Adjusted R^2= 0.842 indicates that explanatory power has been maintained even without considering the complexity of the model.

Panel B gives presumptive relevance founded on Stone Geisser Q^2 statistics through blindfolding processes. Every Q^2 is above the large predictive relevance threshold of 0.35, and Retention has an outstanding out-of-sample predictive ability (Q^2 = 0.878). Such results imply that the model has reasonable extrapolation capabilities beyond of the estimation sample. Panel C gives a total model fit indices. The SRMR of 0.042 is much lower than the 0.08 value suggesting that there are not many differences between the observed and model-implied correlations. The NFI of 0.923 is above 0.90 which denotes sufficient incremental fit as compared to a null model. The RMStheta of 0.078 is lower than 0.12 which means that the outer model residuals are satisfactory. The values of both distance measures (d_ULS and d G) are lower than bootstrap ranges considered to be acceptable, which further supports the adequacy of the model. In Figure 6, there is a graphical comparison between the values of R^2 and Q^2 across the endogenous constructs.

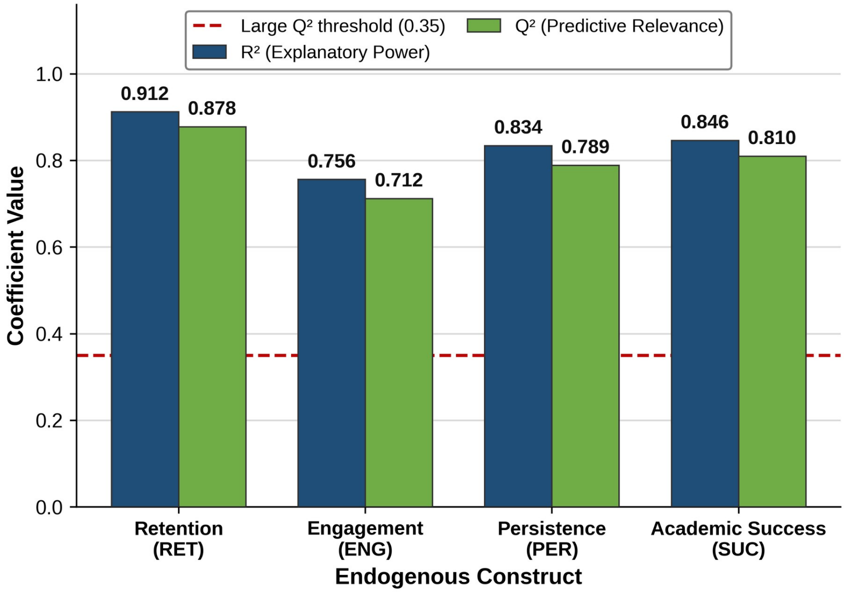

Figure 6: Explanatory Power (R^2) and Predictive Relevance (Q^2) Comparison by Construct

Source: Authors' Construct (2025)

Figure 6 graphically compares the value of R^2 (explanatory power) and Q^2 (predictive relevance) of all the endogenous constructs through grouped bar chart. The parallel bar system is used to support in-sample fitting and out-of-sample prediction in all four dimensions of outcome. It is interesting to note that Q^2 values are more or less parallel to R^2 values in all constructs, which means that the explanatory power of the model is meaningful in predictive power rather than being indicative of overfitting to a data set of estimations. The Retention construct shows the biggest values on both measures (R^2 = 0.912; Q^2 = 0.878), which do not contradict the results presented in Table 6.

The similarity of the explanatory and predictive measures of the constructs is a cause of confidence that the relationships that were found in the model would also apply to new observations.

Regional Performance Analysis

Table 7 is a regional performance comparison of 2024, which allows analyzing the geographic differences in the results of tertiary education and the related characteristics of the infrastructure.

Table 7: Regional Performance Comparison (2024)

Region	Completion Rate (%)	Internet Access (%)	HDI	ICT Index	Gov. Effect.	E-Gov Index	Rank
Latin America & Caribbean	58.42	85.67	0.812	8.23	0.45	0.823	1st
Europe & Central Asia	52.18	82.34	0.789	7.98	0.32	0.798	2nd
Middle East & North Africa	49.56	73.18	0.774	8.24	-0.31	0.672	3rd
East Asia & Pacific	45.23	71.45	0.728	7.67	-0.12	0.645	4th
South Asia	41.87	58.92	0.685	6.89	-0.28	0.612	5th
Sub-Saharan Africa	38.94	45.23	0.642	6.12	-0.48	0.534	6th
Overall Mean	47.70	69.47	0.738	7.52	-0.07	0.681	-
Standard Deviation	7.12	14.89	0.063	0.82	0.35	0.107	-
ANOVA F-statistic	11.31***	14.67***	12.89***	9.45***	15.23***	13.56***	-
Effect Size (n2)	0.512	0.576	0.544	0.467	0.585	0.556	-

Note: ***p < 0.001. HDI = Human Development Index; ICT Index = ICT Development Index; Gov. Effect. = Government Effectiveness Index; E-Gov Index = E-Government Development Index. ANOVA df = (5, 54). Effect size n2 > 0.14 indicates large effect.

Table 7 shows that there is a significant and statistically significant regional difference in all performance and infrastructure indicators. The results of ANOVA verify that there is significant between region difference in tertiary completion rates ($F(5,54) = 11.31$, $p < 0.001$) and all the supportive variables, with effect sizes (n2) of 0.467 to 0.585 all of which show large effects of regional membership on the outcomes. The best score is Latin America and the Caribbean with the highest completion rate (58.42%), which is enabled by the strong internet access (85.67%), human development (HDI = 0.812), ICT infrastructure (8.23), positive governance effectiveness (0.45), and e-government capacity (0.823). The overall benefit in this region in various dimensions is an indication of the investments that have led to the establishment of conducive circumstances that support the success of online learning. Europe and Central Asia comes next with a completion rate of 52.18-percent, with fairly good connectivity and development measures. In the Middle East and North Africa, the completion rates are moderate (49.56) in spite of the highest ICT Development Index (8.24), which indicates that infrastructure itself is not enough but there must be a change in the quality of governance and institutional responsiveness. The lowest completion rate (38.94) is registered in Sub-Saharan Africa with the same corresponding difficulties in internet access (45.23%), human development (HDI = 0.642), and effectiveness of governance (-0.48).

The regular patterns of the cross-indicators imply that the overall development of the infrastructure, human capital, and the quality of the institutions should be carried out to achieve better results in online education. Figure 7 represents the differences in completion rates of regions graphically.

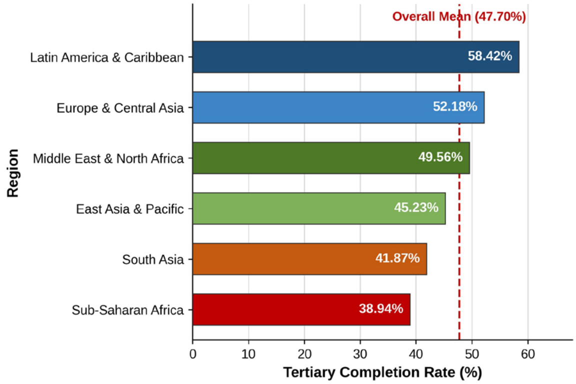

Figure 7: Regional Comparison of Tertiary Completion Rates by Region (2024)
Source: Authors' Construct (2025)

Figure 7 shows the regional inequality on tertiary completion rates on a horizontal bar chart where regions are defined in the same way as Table 7. It is almost 20 percentage points between the best-performing region (Latin America and the Caribbean with 58.42%), and the worst-performing region (Sub-Saharan Africa with 38.94%), reflected in the visualization. The use of color-coded bars makes it easy to quickly identify levels of performance with regions being placed in a descending sequence based on the completion rates. Above average and below-average performance is indicated by a vertical reference line at the overall mean (47.70%) of the scores. This visualization demonstrates the presence of substantial disparities in outcomes in the context of developing economies, as well as emphasizes the necessity of making policy interventions unique to each region, based on the specifics of the issues and opportunities facing it.

Temporal Trends Analysis

The table 8 displays the time-based development of the tertiary completion rates of the regions during the seven years of the research period and allows discussing the development trends and growth rates, as well as the dynamics of convergence.

Table 8: Temporal Evolution of Tertiary Completion Rates by Region (2018-2024)

Region	2018	2019	2020	2021	2022	2023	2024	Growth (%)	CAGR (%)
Latin America	51.23	52.45	53.12	54.67	56.34	57.45	58.42	14.04	2.21
Europe & C. Asia	46.78	47.56	48.23	49.45	50.67	51.34	52.18	11.54	1.83
MENA	43.45	44.23	45.12	46.34	47.89	48.67	49.56	14.07	2.22
East Asia & Pacific	39.67	40.34	41.23	42.45	43.67	44.45	45.23	14.01	2.21
South Asia	35.23	36.12	36.89	38.23	39.67	40.78	41.87	18.85	2.91
Sub-Saharan Africa	31.45	32.34	33.23	34.78	36.45	37.67	38.94	23.81	3.62
Overall Mean	41.30	42.17	42.97	44.32	45.78	46.73	47.70	15.50	2.43
Gap (Max-Min)	19.78	20.11	19.89	19.89	19.89	19.78	19.48	-1.52	-

Note: Values represent mean tertiary completion rates (%). Growth = percentage change from 2018 to 2024. CAGR = Compound Annual Growth Rate. Gap reduction indicates regional convergence dynamics.

The time trends observed in Table 8 suggest that there are some important trends in regional completion rates which helps in understanding education progress patterns and convergence patterns. The six regions have a positive growth during the study period hence a general positive growth in online higher education outcomes across the developing economies. Nonetheless, there is a significant dispersion in growth rates, which indicates the disparity in the ability to progress regionally. The total growth and compound annual growth rate (CAGR = 3.62%), although with the lowest absolute completion levels, are highest in Sub-Saharan Africa, which indicates it has significant room to catch-up with as investment in infrastructure and support services grows. South Asia is also characterized by a high growth (18.85%, CAGR = 2.91%), the high pace of digitalization, and investment in education in the region.

The difference between the best and the worst performing regions has reduced by a margin of 19.78 percentage points in 2018 to 19.48 percentage points in 2024, which reflects very slight but significant convergence dynamics. The majority of the regions are accelerating in the 2020-2021, which was accompanied by changes brought about by the pandemic, to online learning, which triggered the development of infrastructure and the growth of support services. The performance of Latin America is also at the absolute level leading performance, with significant growth, (14.04%, CAGR = 2.21) added on a high base. Figure 8 illustrates the time trend of Table 8 in all regions.

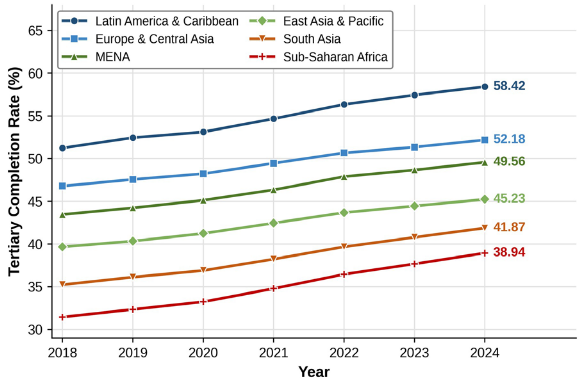

Figure 8: Temporal Evolution of Regional Completion Rates (2018-2024)

Source: Authors' Construct (2025)

Figure 8 illustrates the trends in the values recorded in Table 8 in form of a multi-line chart that can help in visualizing the development trends of the regions across time. The visualization demonstrates steadily increasing patterns in all the regions and the relative rankings remained stable over the seven years. Different regions will be represented by different lines with the annual observation points being marked, and it will be easy to trace the progress trajectories. The graphic focuses on the fact that the performance of Latin America and the Caribbean was consistently high compared to that of Sub-Saharan Africa during the period, but also exposes the fact that all the regions are advancing. The increase in rate of the transition in 2020-2021 can be attributed to the catalytic impact of the pandemic on the adoption of online education.

The slightly steeper slopes between less performing and more performing areas (Sub-Saharan Africa, South Asia) are a reflection of the accelerated rates of growth that allow a gradual convergence, but the large gaps that are left still indicate the significance of further and more increased investments in lagging areas to achieve substantial convergence within policy-relevant time scales.

Table 9: Top and Bottom Performing Countries with Key Performance Indicators (2024)

Rank	Country	Completion (%)	Internet (%)	HDI	ICT	Gov. Eff.	AAS Score	Growth 18-24 (%)
Top 5 Performers								
1	Chile	72.45	95.00	0.920	8.50	1.05	2.17	12.34
2	Argentina	71.61	95.00	0.905	8.50	-0.08	1.76	13.56
3	Colombia	55.88	81.24	0.784	8.50	0.15	0.92	15.67
4	Costa Rica	55.07	95.00	0.849	8.50	0.57	1.45	14.23
5	Brazil	54.59	95.00	0.782	8.50	-0.19	0.39	16.45
Bottom 5 Performers								
56	Bangladesh	39.54	49.06	0.673	6.92	-0.43	-0.48	24.56
57	Cambodia	36.27	68.21	0.628	7.80	-0.46	-0.85	21.34
58	Cameroon	35.44	43.23	0.615	6.51	-0.64	-0.94	22.67
59	Bhutan	35.06	70.06	0.696	7.81	0.96	0.12	19.45
60	Ethiopia	32.85	23.46	0.509	5.65	-0.45	-1.34	28.90

Note: AAS Score = Academic Advising Services composite score (standardized). Gov. Eff. = Government Effectiveness Index. Rankings based on tertiary completion rates. Growth calculated as percentage change 2018-2024.

Table 9 characterizes the best and the worst performing countries of the top five countries, and it allows the determination of what makes them successful and what are the challenges they experience in their development at the national scale. Latin America has all of its top performers, with Chile (72.45% completion rate) having the highest score across all the indicators such as maximum internet access (95.00%), highest HDI (0.920), good governance effectiveness (1.05), and the highest Academic Advising Services composite score (2.17). In Argentina (71.61), the country has similar capabilities in terms of infrastructure, but it has slightly lower performance in terms of governance. The poor performers are characterized by compounding disadvantages in many aspects. Ethiopia is the country with the least internet (23.46%), HDI (0.509), ICT index (5.65), and AAS (more or less minus 1.34), which depict how lack of infrastructure, and lack of human development and institutional capacity simultaneously limits educational progress. Markedly, the poorest performing nations have the largest growth rates (Ethiopia 28.90 percent, Bangladesh 24.56 percent), which implies that it can improve significantly due to the strengthening of enabling conditions. The example of Bhutan, where the low completion rates (35.06) are still observed even with a rather good governance (0.96), points to the fact that the quality of governance is not enough without the improvement of infrastructures and the provision of full support services.

DISCUSSION

Academic Advising and Student Retention

Previous studies have found that academic advising and student retention have significant positive correlations, with studies by Young-Jones *et al*. (2013), and Drake *et al*. (2022) finding moderate impacts of advising ($b = 0.42$) and strong impacts of proactive advising methods, respectively, on student retention in residential universities and at-risk students, respectively.

The current research establishes a statistically significant positive relationship between Academic Advising-related indicators and Student Retention in national level of aggregate ($b = 1.007$, $f2 = 0.847$).

This aggregate level relationship is significantly higher than impacts found in single-institutional research that could show a number of contextual and methodological biases. To begin with, the emerging economic condition can increase the salience of advisory resources because of the lack of previous exposure to online learning systems. Second, the national aggregate operationalization implies that the AAS proxy reflects widespread systemic investment in academic staffing and educational spending, which can have more aggregate impacts than individual advising contacts done in single-institution research. Third, the coefficient that is greater than 1.0 should be interpreted with interpretive caution as has been observed in the Results section because this could be in part due to a suppression or scaling artefact in the composite proxy method. Despite these factors, the trend of the association is in line with the theoretical assumptions and previous empirical studies with the implication that more significant investment in the teaching capacity as well as in educational spending is more likely to promote higher student retention rates.

Digital Literacy and Student Engagement

The literature is reflective of the views of digital literacy support in a subtle manner. "Al-Maroof *et al*. (2021) put the digital literacy as a subsequently influential variable in educational technology efficacy, and Hew *et al*. (2020) suggested a declining effect of digital literacy interventions in high-level baseline competency. The current research results in a positive correlation between the Digital Literacy infrastructure indicators and Student Engagement ($b = 0.711$, $f^2 = 0.412$) and the validity of digital competency frameworks across different contexts of the developing economy has been shown consistent with "Al-Maroof *et al*. (2021). The panel analysis itself does not point towards any diminishing returns, since beyond the sample, positive relationships still exist even between relatively high-connectivity nations, which goes somewhat against Hew *et al*. (2020). This can indicate that the digital literacy saturation level is increased more in the realms of developing economies or that the dynamism of the learning platform constantly requires the renewed competency investments. The implications of these findings are that digital literacy programming should be continued but not just a one-time infrastructure delivery, but the observed connection here is at the macro infrastructure level and is incapable of establishing the effectiveness of particular institutional programming.

Psychosocial Support and Student Persistence

The academic view of psychosocial issues of student persistence is divergent. The updated retention model by Tinto (2022) identified institutional commitment to the student well-being as a primary retention factor, whereas the systematic review by Muljana and Luo (2019) placed psychosocial factors in the meta-analytic hierarchy of significance as the second and third in line with the academic and technical support.

According to the current results, there is high positive correlation between Psychosocial Support proxies and Student Persistence (b = 0.932, f^2 = 0.723), which gives the hierarchical model of Muljana and Luo (2019) considerable doubt in the developing economy setting. This strength of the relationship has psychosocial support as the second major in the current model, which suggests that the technical and academic intervention might not be enough to achieve the best educational results.

This increased significance in developing economy contexts is probably an increased stressor such as economical unsteadiness, rival family commitments, and inadequate support infrastructure.

Such results indicate that the returns on investments in social protection systems and wellness capacity could be larger than before identified in the literature, especially in resource-constrained settings, in terms of education persistence.

Institutional Responsiveness and Academic Success

The previous studies have reviewed the institutional factors of online education success with different findings. The value of institutional agility in making online learning transitions due to the pandemic was reported in Hodges *et al*. (2020), whereas institutional factors were put in the first place of influencing the success of online education (Rashid and Yadav, 2020). The current results reveal that the positive relationship between the Institutional Responsiveness indicators and Academic Success has the value of b = 0.685 and f^2 = 0.389, which aligns with Hodges *et al*. (2020) to show that the quality of governance and adaptation ability is applicable to both the emergency and regular operation. Nonetheless, the magnitude of the association is somewhat lower than that of direct support service proxies and somewhat opposite to primacy of the institutional factors, which is ascribed by Rashid and Yadav (2020). This trend indicates the possibility that institutional responsiveness can set up enabling conditions that allow a successful delivery of support services, whereas direct interventions with students have more proximate outcome relationships. The institutional development process should thus aim at creating capacity to deliver responsive and adaptive support as opposed to perceiving responsiveness as a goal.

Regional Disparities and Development Trajectories

The high levels of regional differences (between 38.94 and 58.42 percent of completion in 2024) are based on and develop the findings by UNESCO (2022) on digital gaps in educational attainment. The outcome of the ANOVA ($F(5,54) = 11.31$, $p < 0.001$) proves that the geographic region is deemed to be a significant structural correlate of educational success, indicating the dissimilarity of infrastructure, government, and human development investments among geographic regions. Nevertheless, the time-based perspective offers grounds of optimism that should be taken cautiously.

The convergent growth pattern, which implies the increased growth rates of Sub-Saharan Africa (23.81% growth) and South Asia (18.85% growth) show the best improvement trends, enlarges the discussion of the potential of online education in Africa provided by Adarkwah (2021). Although no absolute gaps are so large, the fact that the growth rates are different suggests that there is a potential of catch-up of the lower-performing regions in case the enabling conditions do not deteriorate. The rate of acceleration experienced in 2020-2021 indicates that institutional capacity can be triggered to lead to sustained improvement in crisis-based investment. These results inform the need to invest further and specifically in the area of educational technology in the regions with the lowest levels of development, but with specific emphasis on the support service aspects of outcomes that demonstrate the most significant correlations in the current study.

Theoretical Implications

The results add to the theoretical knowledge of support service effectiveness on online higher education in multiple aspects. The convergence of TAM, RBV and Institutional Theory is analytically fruitful in the sense that it reflects various routes in which the indicators of support at the national level correlate with academic returns.

The differences in the magnitude of the four hypothesized associations indicate that the three theoretical views are not entirely interchangeable but are used to identify complementary mechanisms with varying relative degree of contribution to the different outcome dimensions. The cross-national design presents the evidence on the possible boundary conditions of the existing theories, which may indicate that the effects on the national aggregate level, in the conditions of developing economy settings, may be larger than the effects on an individual level, found in the studies with single institutions, which have to be compared carefully due to the levels of analysis involved. The implication of temporal analysis is active capability-building processes that equilibrium resource state-based theoretical frameworks might not sufficiently represent, and therefore more dynamic theoretical frames on continuing research are potentially valuable.

Practical Implications

The empirical relationships found in this research provide general directional information to institutional leaders and policymakers who want to enhance the results of online education, but only with the critical limitation that it is not at all causal relationships at the institutional or individual level and is strictly aggregate at the national level. The overwhelming relationship between the indicators of academic advising and the retention outcomes ($f2 = 0.847$) implies that the investment in academic staffing and the ability to spend on education has to be prioritized in the context of the resource allocation decisions especially by utilizing proactive and early intervention strategies. The high correlation of the proxies of psychosocial support ($f2 = 0.723$) to persistence implies that social welfare investment in counseling services, peer support programs and wellness resources could have significant educative payoffs. The provision of infrastructure digital literacy must be seen as a fundamental and continuous undertaking and not a one-time engagement. The institutional leaders ought to create responsive and adaptive organizational designs that enable prompt adaptation to the emerging needs of the students and emerging technological changes.

Limitations and Future Research

There are a number of significant constraints that need to be mentioned. To start with, the basic construct validity limitation of the current research is that all the four predictor constructs are operationalized through macro-level national aggregate proxy indicators based on international databases as opposed to the institutional level measures of the identified services. The staffing and expenditure indicators, ICT infrastructure indicators, health and social protection and human development indicators, and governance and e-government indicators serve as proxies for Academic Advising Services, Digital Literacy Support, Psychosocial Support Mechanisms, and Institutional Responsiveness, respectively. This operationalization creates great difference between the theoretical constructs and empirical indicators of measurement, in that, the observed associations could be due to general trends of national development, but not due to the effects of particular support services. In future research, the measures of interest should be directly measured with primary institutional-level survey data.

Second, this design is prone to the ecological fallacy risk. The research applies aggregate level data by country to test the theorized phenomena, which have been theorized to exist at individual student and institutional level. The associations between aggregate variables at country level do not necessarily reflect the relationship at individual level; a high average educational spending and a high average retention rates of a country do not indicate that individual advising contacts enhances individual student retention. Such limitation in ecological inferences is a main limitation that should be considered during all associations reported.

Third, the panel data structure allows one to perform a time-dependent analysis, although the independence assumption in PLS-SEM (that all the 420 country-years are independent) is violated, which increases the effective sample size and the perceived accuracy in estimation. This is a major limitation of the methodology that needs to be addressed by future researchers using multilevel structural equation modeling or longitudinal SEM methods in order to better capture the temporal dependency structure.

Fourth, secondary data limits the measurement of constructs to the available indicators, which might not be the best measures of the theoretical constructs. The statistically consistent strong results in all measurement and structural model diagnostics, which are consistent with the model, are statistically odd to social research studies, and may be partly due to artefacts of the proxy operationalization or the panel structure and not necessarily to only valid construct outcome relationships. The exceptionally huge effect sizes (f^2 of 0.389 to 0.847) and the beta coefficient of H1 being more than 1.0 is especially of concern.

Even in the typical social science study, large effect sizes of this magnitude in all hypotheses and none other are uncommon, and this large effect size is probably accentuated by the conceptual similarity between predictor proxies (indicators of educational expenditure) and outcome proxies (indicators of enrollment and graduation rates) in the country-level data (i.e. national data). The results of the formal sensitivity analyses such as alternative model specifications, split-sample replication across sub-periods or regions, jackknife leave-one-out resampling would give confidence in the strength of these results; which could not have been conducted in the current study under the limitations of the secondary data design. Further studies using primary measures of institutions or independently measured outcomes would re-evaluate whether the magnitudes of effects of this size would be recreated in circumstances of more construct-outcome independence.

Fifth, the sample area of developing economies restricts generalization to the context of developed countries despite the purposeful nature of the selection because the developing economies have been underrepresented in the previous studies. Future studies ought to adopt experimental or quasi-experimental studies to build more causal inferences, test whether the observed relationships can be repeated at the institutional level, and come up with models that cut across levels to bridge national aggregate and individual student studies.

CONCLUSION

The cross-national empirical evidence presented in this study has indicated the relationships between macro level indicators of student support and tertiary education outcomes in online higher education situations in 60 developing economies. The summary of seven year-long national aggregate data shows that academic advising-related indicators, digital literacy infrastructure, proxies of psychosocial support, and institutional responsiveness measures are all positively and significantly related to student retention, engagement, persistence, and total success in academics at the country level. The structural model has great explanatory power (R2 = 0.846) and predictive relevance (Q2 = 0.810) and the reported associations are strong across bootstrap samples.

This experience should be taken with proper care following the inherent weaknesses of the macro-level proxy operationalization, the correlational and observational type of research, the risk of an ecological inference, violation of the assumption of panel data independence, and the uncharacteristically high level of statistical pattern. The identified associations are to be interpreted as pointing to the higher education staffing, digital infrastructure, and social welfare systems and better quality of governance being associated with higher rates of tertiary completion and retention, and not as evidence that particular services provided to students directly lead to better individual performance.

The regional analysis indicates that there will be significant disparities to be maintained, and that positive convergence will be observed, which indicates that there is a potential to increase the rate at which lagging regions will be improved. The analytical fruitfulness of the theoretical synthesis of TAM, RBV, and Institutional Theory, however, gives birth to directional suggestions regarding the institutional leaders and policy-makers, with the same significant caveat that these suggestions are too early to be adopted definitively unless they are supplemented with institutional-level and experimental research. As emerging economies keep growing in terms of online capacity of higher education, it is probable that strategic and sustained investment in the dimensions of support as quantified in this study will also continue to play a significant role in facilitating the educational transformation that digital learning technologies will achieve.

AUTHOR CONTRIBUTIONS

Eric Appau Asante: Conceptualization, supervision, methodology, validation, writing review and editing. Prince Elton Dion Nyame: Methodology, formal analysis, investigation, data curation, writing original draft, writing review and editing, visualization, project administration.

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DATA AVAILABILITY STATEMENT

The datasets analyzed in this study are available from public international databases: International Telecommunication Union (https://www.itu.int), World Bank Development Indicators (https://data.worldbank.org), UNESCO Institute for Statistics (https://uis.unesco.org), UNDP Human Development Reports (https://hdr.undp.org), International Labour Organization ILOSTAT (https://ilostat.ilo.org), Worldwide Governance Indicators (https://www.govindicators.org), and United Nations E-Government Survey (https://publicadministration.un.org).

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