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DETERMINANTS OF THE DIGITAL GAP: A COMPARATIVE ANALYSIS OF CENTRAL EUROPE AND SOUTHEAST ASIA, 2002-2024

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ABSTRACT

This study examines the determinants of the digital divide and identifies differences in key factors driving digital development between countries in Central Europe and Southeast Asia over the period 2002–2024. The digital gap is understood as disparities in digital infrastructure, digital public service delivery, and human capital that influence broader economic and social development. The analysis integrates institutional quality (government effectiveness, rule of law, and political stability), economic development (log GDP per capita and income inequality), and skills formation inputs (government spending on education and tertiary enrollment) to explain cross-country and temporal variation in digital performance. Given the limited number of countries, the study employs an econometric strategy suitable for small panel data. Dynamic relationships are estimated using bias-corrected least squares dummy variables (LSDVC), while robustness is assessed through static fixed-effects estimation with Driscoll–Kraay standard errors. To address model uncertainty and multicollinearity, Bayesian Model Averaging (BMA) is applied with family constraints to identify the most robust predictors. The results show that income inequality constitutes the main constraint on inclusive digital development in Central Europe, whereas tertiary education expansion is the strongest driver in Southeast Asia. Across both regions, institutional credibility emerges as a universal foundation for sustainable digital progress. The novelty of this study lies in its cross-regional comparative approach using a harmonized digital development index, the combined use of LSDVC and BMA in a small-panel context, and the identification of both universal and region-specific determinants relevant for digital policy design.

Keywords: *Digital gap, Bayesian Model Averaging, Dynamic panel data, ICT inequality, institutional quality, Southeast Asia, Central Europe, digital transformation*

1. INTRODUCTION

The digital gap creates a gap which extends past the basic need for internet access. The results show how well different countries support their digital infrastructure and how many digital public services they offer and what level of digital skills their population needs to succeed in the digital economy. The existing economic and social inequalities between countries will become more severe because of these differences which block people from joining the global knowledge economy and slow down their progress toward sustainable development goals (Muhammad et al., 2025). The persistence of the digital divide necessitates immediate and coordinated policy responses in emerging and transitional economies, as it shapes their long-term competitiveness, investment attractiveness, and quality of life outcomes.

Over the past two decades, digital transformation has progressed rapidly in both Central Europe and Southeast Asia, despite the regions having started from distinct economic systems and institutional frameworks. The EU digital programs together with cross-border integration and regulatory harmonization have brought advantages to Central European nations. The area maintains economic disparities between its two parts because its developed areas possess superior infrastructure and skilled workforce than its underdeveloped areas. The digital development levels in Southeast Asia show different stages because Singapore leads digital development yet other countries face challenges in digital progress because they lack essential infrastructure and skilled workers and insufficient institutional frameworks (Gill et al., 2007). The different digital access levels between regions create a chance to study how digital inequality develops through common factors which affect all regions while also showing how specific circumstances influence the process.

The process of making digital development data comparable between different regions needs standardised measurement systems which also need to be consistent. The process of digital gap measurement faces two main obstacles because researchers need to develop methods which produce both accurate and equivalent results between different areas. The various indices concentrate on elements which include network readiness and digital economy integration and e-government capacity assessment. Research studies face difficulties when trying to compare their results because they used different measurement methods. In this study, the United Nations E-Government Development Index (EGDI) is used as the primary measure of the digital gap. The EGDI consists of three harmonized composite indices which include the Online Service Index (OSI) and the Telecommunication Infrastructure Index (TII) and the Human Capital Index (HCI). The EGDI system used to evaluate e-government readiness, but it now evaluates complete national digital development through OSI for digital public service quality and TII for ICT access and HCI for education-based human capital development. The EGDI system enables organizations to perform relative performance assessments which allow them to conduct standardized international benchmarking instead of using absolute development metrics (Kromidha, 2012). The framework allows researchers to perform comparative analyses between different regions which possess different structural components. The EGDI system enables digital development measurement of nations through standardized indicators which assess public sector digital capabilities. The current data fails to show complete digital transformation of private businesses and their involvement in platform-based economies and their digital business activities (Chen et al., 2026). The research examines digital development through studies of institutional elements and human resource development rather than complete digital economy framework assessment.

Previous research has identified several categories of factors that influence digital development. The quality of institutions which includes government effectiveness and rule of law and political stability determines how well regulation's function and how investments perform and the success rate of public digital programs (Adam, 2020). The two indicators GDP per capita and Gini coefficient function as economic development proxies which research shows lead to digital development progress. Investment in digital infrastructure and technological adoption is closely linked to GDP per capita, as higher income levels expand the fiscal and private resource base available for innovation. Nonetheless, high levels of income inequality, typically captured by the Gini coefficient, may hinder inclusive digital transformation by restricting access to digital tools and capabilities (Fuchs, 2009; Zhang, 2013). In parallel, sustainable participation in the digital economy relies on robust human capital formation, where public education investment and tertiary enrolment serve as key indicators of long-term digital competitiveness (Heckman, 2000).

Research has established these relationships, but scientists need to conduct more studies which analyze these factors through comparable methods across different economic systems with their own institutional frameworks. Roodman (2009) shows that small panel datasets which have short time periods, and many variables and instruments will generate results that are both inaccurate and less efficient.

The research addresses these problems by implementing a basic empirical model which analyzes an 18-country panel database spanning from 2002 to 2024 to determine the fundamental digital gap factors affecting Central Europe and Southeast Asia. The main estimation method employs bias-corrected least squares dummy variables (LSDVC) from Bun and Carree (2005) to generate reliable dynamic panel results when working with limited sample sizes.

The analysis employs static fixed-effects estimation with Driscoll–Kraay standard errors to address cross-sectional dependence and heteroskedasticity. To account for model uncertainty, the fixed-effects specifications are further subjected to Bayesian Model Averaging (BMA). The BMA framework evaluates seven theoretically grounded variables grouped into three conceptual categories: institutional quality (government effectiveness, rule of law, political stability), economic development (log GDP per capita, Gini inequality), and human capital formation (government expenditure on education and tertiary enrolment rates). To minimise multicollinearity, family restrictions are imposed, ensuring that no model includes more than one variable from the same category. This approach allows for the calculation of posterior inclusion probabilities (PIPs), thereby identifying the most robust and consistently significant predictors across the full model space.

The research applies digital development measurement through model averaging and dynamic estimation to a cross-regional panel dataset which produces multiple findings for digital development and inequality studies. The study first determines which factors strongly affect digital access throughout different institutional settings and economic systems. The research uses small-sample-consistent dynamic panel modeling with model averaging techniques to study digital inequality while solving two major problems which include finite-sample bias and model uncertainty. The research provides policy-relevant findings to governments and regional organizations and development partners who want to create specific programs which will help reduce digital access disparities between different regions.

This study contributes to the literature in the following ways. The research uses small-sample-consistent dynamic panel estimation with Bayesian Model Averaging to analyze a cross-regional dataset through a method that provides strong results for panels which GMM methods cannot handle. The research introduces fresh comparative data which examines how institutions together with inequality and skill levels affect different regions across Central Europe and Southeast Asia. The third finding converts economic model results into recommendations for specific regional policies which demonstrate that Central European digital development becomes more inclusive through income equality reduction and Southeast Asian digital progress accelerates through expanded tertiary education and both regions benefit from better institutional credibility.

The research results help academic studies about digital inequality while creating functional solutions which minimize digital access inequalities. The research provides new evidence about digital divide factors which exist between two different geographic areas while using advanced statistical methods to analyze small data sets with digital indicators that follow international standards.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature on digital divide measurement and the key determinants of digital access disparities. Section 3 outlines the data, variable construction, and methodological framework. Section 4 presents the empirical findings derived from the dynamic panel model, static fixed-effects estimations, and Bayesian Model Averaging (BMA) analysis. Finally, Section 5 discusses the policy implications of the results and offers concluding remarks.

2. LITERATURE REVIEW

2. 1. THE DIGITAL DIVIDE: DEFINITIONS AND DIMENSIONS

The digital divide describes how different populations and geographic areas and nations maintain separate levels of digital technology accessibility and operational skills and technological advantages (Van Dijk, 2020; OECD, 2019; Hunady et al., 2025). The initial research from 1999 to 2000 investigated how people could access digital technology through internet connections (Van Djik, 2020).

Research institutions together with policy organizations understood that digital inequality required more than access to technology to fully understand its complete nature. The current understanding of digital infrastructure development uses multiple factors which include physical network quality and cost accessibility and user digital skills and organizational preparedness and service delivery system connection (ITU, 2020, UNCTAD, 2021; ASEAN, 2022).

The third-generation digital divide represents the current state of digital divide research which scholars continue to develop according to recent academic studies. Research on digitalization today investigates how digitalization creates different results for people in society instead of focusing on their fundamental ability to access the internet (Van Djik, 2020). Digital technology provides equal access to all people and nations but their economic and social benefits from using this technology differ significantly. The third-generation digital divide between countries emerges from their institutional strength and their economic disparities and their workforce abilities.

The digital gap between nations emerges from two sets of factors which include structural elements such as geographic location and economic status and educational background and policy-based elements which include regulatory systems and funding choices and digital competence programs (World Bank, 2024). The economic difference between developed countries and developing countries coexists with domestic regional inequalities which produce social and political and economic disparities (Castells, 2011). The World Bank (2024) identifies the connection between these two areas as the main priority for achieving inclusive growth and social resilience.

The main challenge in digital gap research requires scientists to create assessment criteria which allow them to measure national data points and track changes between different time points. The present set of indices monitors separate indicators which show digital development progress. The network readiness index (NRI) evaluates how well nations use ICT systems to enhance their digital transformation efforts within their economic systems. The digital economy and society index (DESI) evaluates EU digital performance through its assessment of connectivity and digital skills and online service availability. The ASEAN digital integration index (ADII) was designed for southeast Asian economies, using a five-pillar structure which is different from the DESI.

The United Nations e-government development index (EGDI) functions as the research tool to assess digital access inequalities throughout this research. The EGDI consists of three equal-weighted components which combine to form a single composite index. The online service index (OSI) and telecommunication infrastructure index (TII) and human capital index (HCI) make up the three components of the EGDI.

The EGDI system was created to evaluate e-government readiness, but its three pillars directly correspond to the three main aspects of digital development which include OSI for digital public service quality and scope and TII for ICT infrastructure quality and access and HCI for human capital development through education and skills training.

The EGDI functions as a performance rating system which enables users to conduct relative assessments between different countries and regions (United Nations, 2025). The research uses EGDI scores to enable both interpretation and comparison of the data.

2. 2. THEORETICAL FOUNDATIONS LINKING INSTITUTIONS, INEQUALITY, HUMAN CAPITAL, AND THE DIGITAL GAP

The relationship between institutional quality and digital development stems from institutional theory and digital governance theory. Organisations operate more effectively when their environment consists of stable rules and predictable patterns because these conditions reduce uncertainty and lower transaction costs which enables them to sustain long-term investments and system coordination. The digital environment depends on robust rule of law systems and capable governance and stable political institutions to establish trust and achieve regulatory compliance and data protection and deliver digital public services effectively which leads to long-term digital adoption and spread.

Income inequality is central to digital divide theory and capability inequality theory. The digital divide theory shows that people who lack money and educational background and skills will continue to experience digital access disparities which affect their ability to participate and achieve success online. Digital access becomes limited to social and economic possibilities because income inequality prevents people from using their capabilities to achieve better outcomes. The availability of digital infrastructure and services does not prevent high inequality from restricting digital development inclusiveness because it maintains social differences between different geographic areas and social segments.

The two theories human capital theory and digital skills theory show that digital development needs higher education institutions to develop essential skills through their training programs. The human capital theory shows that educational spending produces better productivity results and enhanced innovation abilities. The digital skills theory shows that workers need to learn digital competencies and technical abilities to successfully use digital systems. The framework shows that tertiary education together with education funding serves two purposes which include preparing workers for their jobs and enabling digital service availability throughout the entire population.

The models of ICT diffusion and economic development theory indicate that GDP per capita and government effectiveness help start digital expansion but their ability to explain growth becomes less significant when institutional quality and human capital and inequality levels are considered.

2. 3. INSTITUTIONAL QUALITY AND THE DIGITAL GAP

The quality of institutions stands as the primary factor which will determine how digital technology will evolve in the future. The indicators which include rule of law and government effectiveness, and political stability show positive relationships with ICT diffusion and digital public service delivery and private sector digital solution adoption (Andrés et al., 2010; Yang et al., 2024; Oliinyk, 2024).

Strong institutions establish environments which enhance investor confidence and improve regulatory operations while they combat ICT procurement corruption and allow organizations to create enduring digital strategies. The research by Agbozo and Asamoah (2019) and Slezák (2023) demonstrates that digital government success depends on two factors which include government operational effectiveness and the strength of their legal system.

The world economic forum (2023) indicates that nations with strong political stability draw in additional foreign capital which goes into ICT sector development. Conversely, poor institutional environments lead to inefficient public digital investments.

Research from the previous few years shows how digital investment behavior responds to existing institutional frameworks. The research by Privara & Caplanova (2025) investigates EU and southeast Asian markets to demonstrate that ICT spending and digital commerce implementation lead to productivity increases but these benefits emerge based on how well institution's function. The research results show that governance serves as the fundamental factor which decides how digitalization creates enduring advantages for all stakeholders.

The European union membership process has led to better governance and ICT policy framework development throughout central Europe according to the European commission (2023). The digital adoption speed in southeast Asia depends on the institutional capacity of each nation because ASEAN (2022) reports different levels of capacity between countries. The different characteristics between regions require researchers to evaluate institutional quality as their main factor for studying regional differences.

2. 4. ECONOMIC DEVELOPMENT AND THE DIGITAL GAP

In addition to institutions, national economic conditions also play a fundamental role in shaping digital readiness. Macroeconomic conditions shape a country's capacity to finance digital infrastructure and bridge the digital gap. GDP per capita, income inequality, and industrial composition influence both public investment in ICT and private sector adoption (Chinoracky et al., 2025).

Higher-income economies generally demonstrate higher broadband penetration rates, more advanced online services, and greater digital literacy (Zhang, 2013). GDP per capita, in logarithmic form, is frequently used as a proxy for the overall resource base available for digital transformation.

However, aggregate income measures can mask inequalities in access and use. The Gini coefficient, a standard measure of income inequality, captures the extent to which wealth distribution may influence digital inclusion (Wang, 2024).

Studies have shown that high inequality can limit the uptake of digital tools among lower-income populations, thereby constraining the societal benefits of digital investment (Vicente & López, 2011; Helsper, 2021). In both Central Europe and Southeast Asia, disparities in income distribution can result in uneven digital readiness across regions and demographic groups.

2. 5. SKILLS FORMATION INPUTS AND THE DIGITAL GAP

Human capital functions as a lasting element which enables digital readiness because it establishes the supply of workers who have digital competencies and the requirement for digital service operations. Digital inclusion depends on the population's capacity to use digital tools effectively. While the HCI component of EGDI measures human capital outcomes, this study distinguishes between outputs (HCI) and inputs, here termed skills formation inputs.

The system receives three types of data which include government spending for education and tertiary student enrollment numbers that show how well the workforce receives digital training (UNESCO, 2023; Rajasekaran et. al.,2024). The educational funds enable better educational services to expand their reach for more students through traditional educational facilities. The enrollment numbers in tertiary education indicate which population members choose to pursue advanced learning that ICT-based industries require. The research investigates two essential factors which affect human capital development through its analysis of financial records and student enrollment information.

Research data shows that nations which allocate sufficient funding to education will obtain superior results from their digital technology deployment for economic and social development. The research conducted by Ma et al. (2019) shows that government education funding initiatives help reduce economic obstacles which students face because of their initial financial background.

The ASEAN member states face two main obstacles which prevent them from modernizing their ICT systems because they lack sufficient funds, and they choose to support their established sectors (ASEAN, 2022). The research by Afzal et al. (2023) demonstrates that specific government investments for digital education and ICT infrastructure development will reduce digital inequality in areas with limited financial resources. Public expenditure effectiveness shows different results based on governance systems which requires both transparent financial reporting and strategic planning according to the OECD (2023).

The ASEAN member states have started to link their digital transformation initiatives with their national development strategies (ASEAN, 2025). The ASEAN Digital Masterplan 2025 and the EU Digital Decade policy program serve as regional coordination frameworks which provide strategic plans to boost digital capabilities and international digital connectivity. The implementation of these policies shows significant differences between nations in both regions because their institutions face various barriers and their governments pursue different objectives (ASEAN, 2025; European Commission, 2023).

The number of students in tertiary education together with their academic achievements determines their digital technology usage patterns (Nyamweya et al., 2024). Digital literacy deficits in particular countries stop their modern infrastructure systems from achieving their maximum operational potential. Research shows that education duration matters less than curriculum design which needs to focus on teaching digital skills that have evolved according to the OECD (2023).

A recent study by Naatu et al. (2024) shows that digital competencies function as a connecting factor which links physical infrastructure development to digital service usage in developing nations. UNESCO (2023) supports the implementation of digital competencies throughout general education systems as a lasting policy solution which should focus on lower-middle income countries.

2. 6. GAPS IN THE EXISTING LITERATURE

Research about digital development factors has produced many studies but scientists continue to face multiple research method problems. The analysis of digital transformation through cross-sectional and pooled panel designs fails to show how digital transformation develops over time because these methods do not understand how digital transformation develops through time. The field lacks sufficient comparative regional research between Central Europe and Southeast Asia which prevents researchers from obtaining valuable knowledge for policy development.

The current economic research field has developed new statistical methods which solve these existing challenges. Bias-corrected least squared dummy variables (LSDVC) are used to obtain consistent dynamic panel estimates in small samples. The Bayesian Model Averaging (BMA) method with family constraints produces posterior inclusion probabilities (PIPs) to measure model uncertainty according to Steel (2020) and Kaplan (2021).

The research by Antonakakis and Tondl (2015), Steel (2020), and Sobierag and Metelski (2021) shows BMA effectively identifies stable policy indicators which work across different nations, but this method has not been widely adopted in digital inequality research. Robustness is assessed through static fixed-effects estimation with Driscoll-Kraay robust standard errors (Hoechle, 2007).

The research shows that digital development programs achieve their best results when institutions have high quality and when economic growth occurs, and people develop their skills. Research on comparative and cross-regional studies which uses standardized measurement tools to analyze these elements is not commonly found. The research applies the EGDI to measure digital gaps through multiple dimensions while using appropriate econometric methods for analyzing small panel data to identify digital inequality predictors with high probability and strong predictive power.

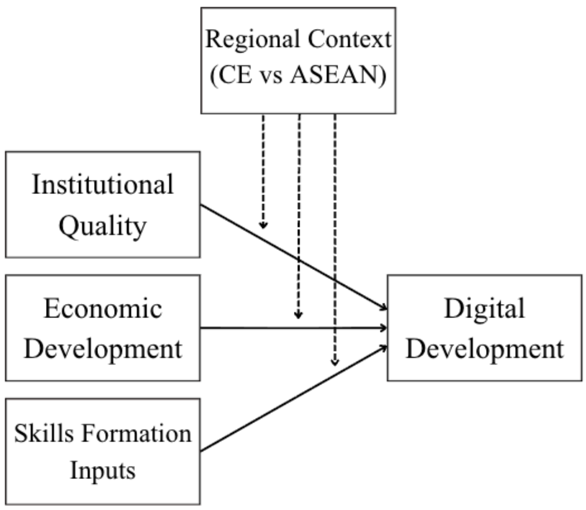
The research gap regarding digital divide determinants becomes apparent through this literature review which unites theoretical knowledge with empirical evidence and methods for studying digital divides across different nations. The research solves this knowledge deficit through its methodical research approach which analyzes digital data to create evidence that guides policy creation.

The research unites duplicate findings from various sections of the literature into one analysis which examines the empirical framework through its directly applicable mechanisms.

2. 7. CONCEPTUAL FRAMEWORK AND THEORETICAL MECHANISMS

The research framework which guides this study appears in Figure 1. The framework unites institutional theory with digital divide theory and human capital theory and economic development theory to explain how structural elements and policy decisions affect digital development results in different nations.

Figure 1. Conceptual framework of digital development determinants and regional heterogeneity



Source: Created by Author

Institutional quality is expected to have a direct influence on digital development by shaping the credibility, predictability, and effectiveness of regulatory and governance environments. Strong rule of law, government effectiveness, and political stability reduce uncertainty, support trust in digital systems, and enable sustained investment in digital infrastructure and public services. Economic development conditions influence digital outcomes by determining the resource base available for infrastructure expansion and service provision, while income inequality constrains the ability of disadvantaged groups to benefit from digital access, thereby limiting inclusive digital progress.

Skills formation inputs represent upstream investments in human capital that affect digital development through workforce readiness and effective technology use. Higher education and education spending enhance digital skills, innovation capacity, and adoption of advanced digital services.

The framework further recognizes that these relationships may operate differently across regional contexts. Differences in institutional maturity, economic structure, and human capital development between Central Europe and Southeast Asia imply that the strength of these effects is not uniform. Accordingly, regional context is modeled as a conditional factor influencing selected relationships rather than as a direct determinant.

This conceptual framework distinguishes direct effects from conditional regional effects and provides a theoretically grounded structure for the subsequent econometric analysis.

3. DATA AND METHODOLOGY

3. 1. DATA SOURCES AND SAMPLE CONSTRUCTION

This study utilizes a balanced panel dataset covering 18 countries from Central Europe and Southeast Asia over the period 2002–2024. The country selection reflects data availability and comparable data for the dependent variable and the independent variables of interest. The 10 countries in Central European sample includes Austria, Croatia, Czech Republic, Germany, Hungary, Lithuania, Poland, Slovakia, Slovenia, and Switzerland. The 8 countries in Southeast Asian sample includes Cambodia, Indonesia, Lao PDR, Malaysia, Philippines, Singapore, Thailand, and Vietnam. These regions offer a valuable comparative context, given their divergent digital development, institutional structures, and policy environments.

The dependent variable, the digital gap, is proxied by the EGDI published by the United Nations Department of Economic and Social Affairs (UN DESA). Data were sourced from the Zenodo Repository, cross-checked and updated from UN DESA. The EGDI is a composite index based on three equally weighted components: the Online Service Index (OSI), the Telecommunication Infrastructure Index (TII), and the Human Capital Index (HCI). Although originally developed to benchmark e-government readiness, the EGDI's multidimensional structure captures broader aspects of digital development. OSI evaluates the scope and quality of online services provided by governments. TII measures ICT Infrastructure and access. And HCI assesses human capital outcomes.

Because the EGDI is published once every two years, annual EGDI values were constructed using log-linear interpolation based on growth rates between observed periods. The method bases its analysis on steady proportional expansion which works best for development metrics that show multiplicative and path-dependent growth patterns throughout time. Compared to simple linear interpolation, the log-linear method better preserves proportional changes in index values. As a robustness check, the main results were also confirmed using linear interpolation, indicating that the findings are not sensitive to the interpolation method. The researchers converted all EGDI values into a 0–100 range for better understanding and to enable comparison between different values.

The process of building a balanced panel demanded special attention to handle all missing data points which occurred between different country-year combinations. The differences between international sources regarding reporting frequency and data availability result in missingness rather than actual data deficiencies. For the dependent variable, interpolation was applied as described above. The research used independent variables which came from countries that maintained continuous data availability throughout the entire research duration. No additional imputation was employed. The method maintains ability to compare data between countries because it prevents imputation techniques from creating false data points which would occur when using aggressive methods in studies with few participating countries.

The study contains three separate categories which serve as independent variables. The first category consists of institutional quality which includes three components: government effectiveness (GEF) and rule of law (ROL) and political stability (POS). The GEF system evaluates how citizens view public service delivery, and it also assesses the development of policies and their execution, and the trust people have in their government. ROL evaluates how well countries follow their laws and protect property rights and enforce contracts and maintain independent courts. And POS captures the likelihood of political instability or politically motivated violence. The stability level increases when the value becomes higher. Data were sourced from the Zenodo Repository (The EU Open Research Repository) and World Bank's Worldwide Governance Indicators (WGI).

The second category is the economic development which includes GDP per capita (constant 2015 US dollars, log-transformed) and the Gini coefficient (income inequality). Data were sourced from the Zenodo Repository, World Bank's World Development Indicators (WDI), and OECD statistics.

The third category is the skills formation inputs which represent upstream investments in human capital formation. It includes government expenditure on education (percentage of GDP) and tertiary enrolment rate. Data were sourced from UNESCO Institute of Statistics and WDI.

To ensure comparability, all independent variables were normalized to a 0 - 100 scale using the methodology outlined in the ASEAN Digital Integration Index framework (ASEAN, 2021). Percentage-based indicators were multiplied by 100 where necessary, while raw numerical indicators were log-transformed and rescaled using observed minima and maxima in the dataset.

3. 2. METHODOLOGY

3. 2. 1. EMPIRICAL STRATEGY

The empirical strategy is designed to address the constraints of a small-N, moderate-T panel dataset (18 countries over 21 years), while ensuring robustness against biases arising from dynamic specification, heteroskedasticity, serial correlation, cross-sectional dependence, and model uncertainty.

3. 2. 2. DYNAMIC PANEL MODEL AND SMALL-SAMPLE BIAS CORRECTION

The primary estimation approach employs the bias-corrected least squares dummy variable (LSDVC) estimator following Bun and Carree (2005). LSDVC is particularly suitable for panels with a limited cross-sectional dimension, as it corrects the finite-sample bias that emerges from the correlation between the lagged dependent variable and the error term. This makes it appropriate for dynamic specifications where persistence in digital outcomes is expected.

3. 2. 3. STATIC FIXED EFFECTS AND ROBUST INFERENCE

As a robustness check, a static fixed-effects (FE) specification that excludes the lagged dependent variable is estimated. Although this model avoids potential weak-instrument bias inherent in some dynamic estimators, it may omit important persistence effects. To address heteroskedasticity, serial correlation, and cross-sectional dependence, Driscoll-Kraay standard errors are computed. These standard errors are heteroskedasticity-consistent and robust to both temporal and spatial dependence in the residuals.

3. 2. 4. ENDOGENEITY CONSIDERATIONS

Potential endogeneity is addressed primarily through model design rather than instrumental-variable techniques. Persistence is controlled through the dynamic specification, unobserved heterogeneity through fixed effects, and robustness through consistency across LSDVC, static FE, and Bayesian Model Averaging (BMA) results. While bidirectional relationships may exist between digital development and variables such as institutional quality or education, the inclusion of lagged dependent variables and country-specific fixed effects mitigates short-term reverse causality. The convergence of results across alternative estimators further strengthens confidence that findings are not driven by endogeneity bias.

3. 2. 5. ADDRESSING MODEL UNCERTAINTY: BAYESIAN MODEL AVERAGING

To account for model uncertainty and potential multicollinearity among regressors, Bayesian Model Averaging (BMA) is applied to the static FE framework. The BMA procedure evaluates all admissible combinations of seven theoretically grounded independent variables grouped into three categories:

- Institutional quality: Government Effectiveness, Rule of Law, Political Stability
- Economic development: Log GDP per capita, Gini coefficient
- Human capital formation: Education expenditure, Tertiary enrolment

To mitigate multicollinearity, particularly among highly correlated institutional indicators, family restrictions are imposed, allowing at most one institutional variable and one human capital variable in each specification. Although this constraint reduces the total model space, it still permits nearly fifty theoretically admissible specifications spanning institutional, economic, and skills-related predictors.

Posterior Inclusion Probabilities (PIPs), model-averaged coefficients, and associated standard errors are reported to identify the most robust determinants across the model space. In practice, this means that the institutional dimension is represented by the indicator that demonstrates the highest and most stable posterior support across competing specifications.

3. 2. 6. CONSIDERATIONS ON SYSTEM GMM

System GMM was initially explored as an additional robustness check for endogeneity and dynamic persistence. However, when applied to the dataset, the estimation produced a singular matrix due to the limited panel size and high instrument-to-observation ratio. This problem is common in small-N panels. Roodman (2009) emphasizes that system GMM is designed for panels with large N and small T. Simulation evidence shows that GMM remains biased when N is less than 100 particularly in the presence of persistent regressors (Moral-Benito et al., 2019). For this reason, the analysis relies on the combination of bias-corrected LSDVC, static fixed-effects with robust errors, and Bayesian Model Averaging. This approach ensures that model uncertainty and dynamic features are addressed within the scope of the available data without the instability of overspecified GMM models.

3. 3. DIAGNOSTIC TESTS AND MODEL VALIDATION

To ensure the reliability of the empirical results, a set of diagnostic and validation procedures is applied across all estimation strategies. For the LSDVC specification, small-sample properties are evaluated by comparing bias-corrected coefficients against standard dynamic FE estimates to confirm the correction procedure. Bootstrap standard errors are computed following Bruno (2005) to account for finite-sample variability.

For the static FE specification, model adequacy is verified through tests for groupwise heteroskedasticity (modified Wald), serial correlation (Wooldridge test) (Drukker, 2003), and cross-sectional dependence. Where such issues are detected, inference relies on Driscoll–Kraay standard errors, which are robust to both temporal and spatial dependence.

Finally, robustness is judged by the coherence of results across methodologies. Convergence in coefficient signs, magnitudes, and statistical significance between LSDVC, static FE, and BMA strengthens confidence in the empirical credibility of the findings and mitigates concerns of model dependence.

Methodological Integration and Validation

The empirical strategy adopted in this study is structured as a hierarchical and mutually validating framework rather than a reliance on a single estimator. The dynamic LSDVC model serves as the primary specification to capture persistence and mitigate small-sample bias in panel estimation. Static fixed-effects models with robust standard errors provide a complementary benchmark that does not rely on dynamic assumptions. Bayesian Model Averaging further evaluates model uncertainty by identifying determinants that remain influential across a wide set of admissible specifications. The convergence of results across these methods strengthens confidence in the empirical findings and indicates that the conclusions are not driven by a particular modeling choice.

3. 4. IMPLEMENTATION

All empirical analyses are conducted using R statistical software (version 4.5.1 “Great Square Root”, released on 2025-06-13), which provide a flexible environment for panel econometric estimation and model averaging. The implementation relies on a set of specialized R packages tailored to the estimation techniques described in Section 3.2 and 3.3. Package plm (Croissant & Millo, 2008) is employed for fixed-effects estimation. Package panelr (Long, 2020) is used for dynamic bias-corrected LSDVC estimation. Package sandwich (Zeileis, 2004; Zeileis et al., 2020) and lmtest (Zeileis & Hothorn, 2002) are used for robust variance estimation. Package clubSandwich (Pustejovsky, 2025) is used to implement Driscoll–Kraay standard errors. Finally, package BMS (Zeugner & Feldkircher, 2015) and BMA (Raftery et al., 2015) are used to enable Bayesian Model Averaging.

To ensure transparency and replicability, the final dataset and R code used in the analysis are archived and made publicly available on Zenodo database. The repository will include the harmonized panel dataset (2002–2024), R scripts with all cleaning, transformation, and estimation procedures, and documentation describing variable construction and replication steps. This open-science approach enables full reproducibility of the reported results and allows researchers and policymakers to extend the analysis for future comparative studies.

4. ANALYSIS OF RESULTS

4. 1. DESCRIPTIVE STATISTICS

Table 1 reports summary statistics for the dependent and independent variables, disaggregated by region. The E-Government Development Index (EGDI), which serves as the dependent variable, is available for 2003–2024, while the explanatory variables are observed for 2002–2023. To ensure comparability across regions, all independent variables were normalized to a 0–100 scale following the ASEAN Digital Integration Index (2021) methodology. This harmonization allows differences in magnitudes to be interpreted consistently. The data of 10 Central European and 8 ASEAN countries provide a cross-regional comparative perspective on digital development gaps.

On average, Central European countries display higher EGDI and less dispersion compared to ASEAN countries, reflecting their more advanced stages of digital infrastructure, online service provision, and human capital development. Among the explanatory factors, income equality and governance indicators (rule of law, political stability) are higher in Central Europe, whereas ASEAN countries exhibit greater variation, particularly in government effectiveness and political stability.

Table 1. Descriptive Statistics

Variable	CEU - Mean	CEU - SD	CEU - Min	CEU - Max	ASEAN - Mean	ASEAN - SD	ASEAN - Min	ASEAN - Max
EGDI	70.49	12.88	42.31	96.15	51.18	23.27	8.97	100.00
GEF	78.94	12.58	57.00	99.47	57.41	27.09	4.92	100.00
ROL	78.55	15.46	44.41	100.00	45.90	27.85	3.23	99.03
POS	77.03	11.26	50.00	99.58	38.90	29.82	0.00	100.00
GDP	71.96	14.51	49.00	100.00	42.53	24.32	0.00	94.23
GINI	31.69	9.37	14.29	54.29	67.73	16.42	40.00	100.00
EDU	58.88	7.56	42.65	72.06	33.81	18.73	0.00	100.00
TEE	67.48	13.43	38.00	95.63	37.86	22.51	0.00	100.00

Notes: Reported statistics are Mean, Standard Deviation, Minimum, and Maximum. The dependent variable (EGDI) is observed for 2003–2024, while the independent variables are observed for 2002–2023. Number of observations for Central Europe is 12 years x 10 countries and for ASEAN is 12 years x 8 countries. Variable definitions: EGDI = E-Government Development Index; GEF = Government Effectiveness; ROL = Rule of Law; POS = Political Stability; GDP = Log GDP per capita; GINI = Gini coefficient of income inequality; EDU = Government expenditure on education (% of GDP); TEE = Gross tertiary education enrollment ratio (%)

Source: Author's analysis based on data from ITU database

A comparison of regional averages in Table 1 highlights clear differences. Central Europe outperforms ASEAN in institutional quality (government effectiveness, rule of law, and political stability) and in economic development, with substantially higher GDP per capita. In contrast, ASEAN exhibits lower average EGDI scores but greater dispersion, reflecting significant heterogeneity across member states. Greater variability in income inequality and tertiary enrolment further underscores divergent development paths. These descriptive patterns suggest that structural and institutional asymmetries contribute to the persistence of digital gaps between the two regions.

Table 2. Correlation Matrix of Variables

Variable	EGDI	GEF	ROL	POS	GDP	GINI	EDU
GEF	0.86						
ROL	0.86	0.96					
POS	0.57	0.68	0.77				
GDP	0.86	0.93	0.96	0.80			
GINI	-0.57	-0.64	-0.71	-0.75	-0.72		
EDU	0.49	0.61	0.64	0.50	0.58	-0.59	
TEE	0.81	0.79	0.83	0.65	0.81	-0.62	0.57

Note: Variable definitions: EGDI = E-Government Development Index; GEF = Government Effectiveness; ROL = Rule of Law; POS = Political Stability; GDP = Log GDP per capita; GINI = Gini coefficient of income inequality; EDU = Government expenditure on education (% of GDP); TEE = Gross tertiary education enrollment ratio (%). Correlations are calculated on a balanced panel of 18 countries (10 Central Europe, 8 ASEAN) over 2003–2024 for EGDI and 2002–2023 for independent variables

Source: Author's analysis based on data from United Nation database

Table 2 presents the correlation matrix for the dependent and explanatory variables. Institutional indicators such as government effectiveness and rule of law are highly correlated (ρ ≈

0.96), raising multicollinearity concerns if included jointly. GDP per capita is also strongly associated with institutional quality, reflecting the close link between development and governance. In contrast, education spending and tertiary enrolment show moderate correlations with EGDI, suggesting they support digital development but operate somewhat independently of income and institutional factors.

These patterns justify careful model specification and motivate the use of Bayesian Model Averaging (BMA) with family constraints to address multicollinearity and model uncertainty. Overall, higher income, stronger institutions, and greater educational investment are associated with better digital outcomes, while inequality appears to constrain progress.

Pre-estimation diagnostics (Table 3) reveal heteroskedasticity, serial correlation, and cross-sectional dependence common in macro-panel data, supporting the use of bias-corrected LSDVC and static fixed-effects models with Driscoll-Kraay standard errors.

Table 3. Panel Diagnostic Tests for Heteroscedasticity, Serial Correlation, and Cross-Sectional Dependence

Test	Purpose	Statistic	p-value	Interpretation
Modified Wald Test for Groupwise Heteroscedasticity	Tests heteroscedasticity in FE model	$\chi^2 = 124.7$	0.000	Reject H_0 → heteroscedasticity present
Wooldridge Test for Serial Correlation in Panel Data	Tests first-order autocorrelation	F = 18.32	0.000	Reject H_0 → serial correlation present
Pesaran Cross-Sectional Dependence (CD) Test	Tests cross-sectional dependence	CD = 4.51	0.000	Reject H_0 → cross-sectional dependence present
Breusch–Pagan LM Test (Cross-Sectional Dependence)	Alternative CD test for small N	LM = 36.84	0.000	Cross-sectional dependence confirmed

Notes: The presence of heteroscedasticity, serial correlation, and cross-sectional dependence motivates the use of (i) clustered standard errors in the dynamic FE (LSDVC) model and (ii) Driscoll–Kraay two-way clustered standard errors in the static FE robustness checks

Source: Author's analysis based on data from United Nation database.

4. 2. LSDVC ESTIMATION

Table 4 presents the dynamic panel estimates using the bias-corrected LSDVC approach. The lagged dependent variable is positive and significant, indicating persistence in digital development. In other words, countries that already perform well in digital development tend to sustain and build on that advantage over time. Whereas those lagging face difficulties catching up. This reflects the cumulative nature of digital progress, where earlier investments in infrastructure, online services, and human capital create momentum that continues.

Table 4. Dynamic FE (LSDV) Estimates for EGDI (Clustered SEs by country)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
L.EGDI	0.7831***	(0.0335)	23.36	0.0000
GEF	0.1244**	(0.0614)	2.03	0.0430
ROL	0.2751**	(0.1226)	2.24	0.0248
POS	0.1819***	(0.0486)	3.74	0.0002
GDP	0.2019	(0.1664)	1.21	0.2250
GINI	-0.1046**	(0.0470)	2.23	0.0267
EDU	0.0572**	(0.0279)	2.05	0.0412
TEE	0.1015**	(0.0457)	2.22	0.0270

Note: Dynamic FE (LSDV) model with country and year fixed effects; standard errors clustered by country. Significance: * p<0.10, ** p<0.05, *** p<0.01.

Source: Author's analysis

The LSDVC results indicate that institutional credibility, income inequality, and skills formation are key drivers of digital development. Institutional variables exhibit the largest effects, while inequality acts as a systematic constraint and skills inputs provide complementary support.

Although the dynamic LSDVC model captures persistence and path dependence in digital development, the inclusion of a lagged dependent variable may absorb part of the contemporaneous variation. To test the sensitivity of the results to this specification, the following subsection re-estimates the determinants using a static fixed-effects model with robust standard errors.

4. 3. ROBUSTNESS CHECK: STATIC FE WITH DRISCOLL-KRAAY ERRORS

To evaluate the sensitivity of the findings to model specification, Table 5 presents static fixed-effects estimates with two-way clustered (Driscoll-Kraay) standard errors. The results confirm that institutional quality remains a key determinant of digital development: Rule of Law and Political Stability are positively and significantly associated with EGDI, whereas Government Effectiveness is not. Income inequality retains a significant negative effect, while GDP per capita is positive but insignificant. Among human capital variables, tertiary enrolment remains a strong positive predictor, whereas education spending loses significance once dynamic effects are excluded.

Table 5. Static FE Robust – Two-Way Clustered SEs by country and Year

Variable	Estimate	Std. Error	t value	Pr(>|t|)
GEF	0.0577	(0.0663)	0.8704	0.3841
ROL	0.2844***	(0.0625)	4.5543	5.26e-06
POS	0.1899***	(0.0418)	4.5397	5.63e-06
GDP	0.6129	(0.3881)	1.5795	0.1142
GINI	-0.0955**	(0.0443)	2.1544	0.0312
EDU	0.0647	(0.0417)	1.5516	0.1210
TEE	0.0811**	(0.0292)	2.7774	0.0058

Note: Static FE model - standard errors clustered by country and year. Significance: * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Source: Author's analysis

The loss of significance for government effectiveness and education spending suggests that their effects operate primarily through cumulative dynamics rather than contemporaneous variation.

Table 6. Model Fit Comparison between Dynamic and Static Specifications

Metric	R-Squared	Adj.R-Squared	AIC	BIC
Static FE	0.966	0.962	2216.12	2393.19
Dynamic FE	0.988	0.986	1734.87	1909.75

Note: The table reports key model fit statistics for the dynamic and static fixed-effects specifications. R^2 and adjusted R^2 measure explanatory power, while AIC and BIC provide information criteria for model selection

Source: Author's analysis

According to Table 6, the dynamic LSDVC model achieves higher explanatory power and substantially lower information criteria, indicating a superior fit. This highlights the importance of accounting for persistence in digital development and correcting for small-sample bias. Even so, the static FE results with clustered standard errors confirm the robustness of institutional quality, income inequality, and tertiary education effects. Taken together, both models point to consistent drivers of the digital gap.

Although the static fixed-effects estimates confirm the importance of several key determinants identified in the dynamic model, differences in statistical significance across specifications suggest that inference may depend on model selection. To address this issue explicitly and evaluate the robustness of the results across alternative model combinations, the next subsection applies Bayesian Model Averaging.

4. 4. MODEL UNCERTAINTY: BAYESIAN MODEL AVERAGING (BMA)

To evaluate the robustness of explanatory variables under model uncertainty, Bayesian Model Averaging was applied. Table 7 reports the Posterior Inclusion Probabilities (PIPs) and model-averaged estimates. Rule of law (ROL) and income inequality (GINI) stand out with full posterior support. This pattern reveals the centrality of governance quality and equitable income distribution in digital progress. Tertiary enrollment (TEE) follows with a high inclusion probability, suggesting a strong association with digital progress. Political stability (POS) shows moderate inclusion probability while government effectiveness (GEF), education spending (EDU), and GDP per capita (GDP) show relatively weak effect once model uncertainty is accounted for.

Table 7. Bayasian Model Averaging Results

Regressor	PIPs	Posterior Mean	Posterior St Dev
ROL	100.0	0.2712	0.0926
GINI	100.0	-0.1083	0.0641
TEE	78.2	0.0685	0.0315
POS	42.4	0.1763	0.0973
GEF	25.5	0.0872	0.0779
EDU	23.6	0.0624	0.0531
GDP	22.7	0.7314	0.5449

Note: PIP = Posterior Model Probability: Posterior estimates were obtained through Markov Chain Monte Carlo (MCMC) sampling with sample size = 1,000

Source: Author's analysis

Table 8 illustrates the influential model configurations. The highest posterior model probability corresponds to a specification including rule of law (ROL), income inequality (GINI), and tertiary education enrolment (TEE). This model accounts for 72 percent of posterior model probability (PMP). Extending the model by adding political stability (POS) raises the cumulative posterior model probability (CPMP) to 90 percent.

Table 8. Top Three Influential Models Identified by Bayesian Model Averaging

Rank	Variable Inclusion	PMP	CPMP	AIC
1	ROL, GINI, TEE	0.7216	0.7216	2782.47
2	ROL, GINI, TEE, POS	0.1830	0.9046	2784.37
3	ROL, GINI, TEE, GEF	0.0416	0.9462	2814.24

Note: ***=sig at 1%, **=sig at 5%, and *=sig at 10%

Source: Author's analysis

The BMA results confirm the robustness of institutional quality, income distribution, and higher education as key determinants of the digital gap. The next section shifts the focus to a comparative perspective, highlighting how these determinants play out across Central Europe and Southeast Asia and what regional patterns can be observed.

To ensure consistent interpretation across estimation strategies, model fit and effect magnitudes were compared across the dynamic FE (LSDVC), static FE with Driscoll–Kraay errors, and Bayesian Model Averaging (BMA) models. Adjusted R^2 and information criteria confirm that the dynamic LSDVC specification provides the strongest overall fit, reflecting the persistent nature of digital development.

To facilitate effect size comparability, all explanatory variables were normalized to a common 0–100 scale prior to estimation. As a result, the estimated coefficients can be interpreted as standardized effects, indicating the percentage-point change in EGDI associated with a one-unit increase in each predictor. Table 9 summarizes goodness-of-fit indicators and standardized effect sizes for the key determinants across models.

Table 9. Goodness-of-Fit and Standardized Effect Size Comparison Across Models

Model	Adj. R^2	Rule of Law (ROL)	Income Inequality (GINI)	Tertiary Enrollment (TEE)	Political Stability (POS)
Dynamic FE	0.986	0.275	−0.105	0.102	0.182
Static FE	0.962	0.284	−0.096	0.081	0.190
BMA	PIP-based	0.271	−0.108	0.069	0.176

Note: All coefficients are standardized effects

Source: Author's own analysis

Overall, the comparison of goodness-of-fit measures and standardized effect sizes indicates a high degree of consistency across estimation approaches. The stability of the key coefficients suggests that the main results are not driven by a particular modeling choice, providing confidence in the empirical identification of the core determinants of digital development.

While the preceding analyses focus on average relationships across the full sample, such effects may vary across regional contexts with different institutional and economic structures. The next subsection therefore examines whether the impact of these determinants differs systematically between Central Europe and Southeast Asia.

4. 5. COMPARATIVE INSIGHTS AND REGIONAL PATTERNS

The empirical analysis in earlier sections identified institutional quality, income distribution, and higher education as robust predictors of digital development. However, their effects are unlikely to be uniform across regions. Central Europe and Southeast Asia differ markedly in institutional legacies, economic structures, and human capital formation, suggesting that the drivers of digital progress may operate with varying intensity in each context. To examine such differences empirically, regional dummy interactions were introduced for rule of law (ROL), income inequality (GINI), and tertiary education enrollment (TEE).

Table 9 shows the fixed-effects estimates with an interaction term between rule of law and the ASEAN regional dummy (ROL*ASEAN). This specification tests whether the effect of inequality on digital development differs between Central Europe and Southeast Asia.

Table 10. Fixed-Effects Estimates with Rule of Law and ASEAN Interaction (ROL*ASEAN)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
ROL	0.2498***	(0.0923)	2.7059	0.0072
GINI	-0.1078***	(0.0413)	-2.6117	0.0094
TEE	0.0788	(0.0550)	1.4331	0.1528
ROL*ASEAN	0.1089	(0.1499)	0.7269	0.4678

Note: Static FE model - standard errors clustered by country and year. Significance: * p<0.10, ** p<0.05, *** p<0.01

Source: Author's own analysis

According to Table 10, rule of law (ROL) is positively and significantly associated with EGDI (0.2498). The result indicates that stronger institutions support higher levels of digital development. However, the interaction term with ASEAN is small and statistically insignificant (0.1089), suggesting that the strength of the institutional effect does not differ between Central Europe and Southeast Asia. In other words, regardless of region, improvements in the quality of legal and regulatory frameworks provide a broadly similar boost to digital development. This finding highlights the universal importance of institutional trust and predictability in advancing digital development.

Table 11 presents the fixed-effects estimates with an interaction between income inequality and the ASEAN regional dummy (GINI*ASEAN). This specification assesses whether the impact of inequality on digital development differs between Central Europe and Southeast Asia.

Table 11. Fixed-Effects Estimates with Income Inequality and ASEAN Interaction (GINI*ASEAN)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
ROL	0.2370***	(0.0908)	2.6070	0.0095
GINI	-0.1094**	(0.0445)	-2.4606	0.0144
TEE	0.0988**	(0.0501)	1.9721	0.0490
GINI*ASEAN	0.2134***	(0.0819)	2.6069	0.0095

Note: Static FE model - standard errors clustered by country and year. Significance: * p<0.10, ** p<0.05, *** p<0.01

Source: Author's own analysis

The coefficient for Gini remains negative and significant (-0.1094). These results indicate that income inequality is a stronger constraint on digital development in Central Europe than in Southeast Asia. One possible explanation is that ASEAN economies may experience greater resilience to inequality effects due to faster gains in infrastructure and education access.

Table 12 reports the fixed-effects estimates with an interaction between tertiary education enrollment and the ASEAN regional dummy (TEE*ASEAN). This specification assesses whether the effect of higher education on digital development differs between Central Europe and Southeast Asia.

Table 12. Fixed-Effects Estimates with Tertiary Education Enrollment and ASEAN Interaction (TEE*ASEAN)

Variable	Estimate	Std. Error	t value	Pr(>|t|)
ROL	0.2864***	(0.0939)	3.0490	0.0025
GINI	-0.0730**	(0.0303)	-2.4055	0.0167
TEE	0.1160**	(0.0545)	2.1293	0.0340
TEE*ASEAN	0.1162**	(0.0527)	2.2056	0.0281

Note: Static FE model - standard errors clustered by country and year. Significance: * p<0.10, ** p<0.05, *** p<0.01

Source: Author's own analysis

The positive and significant coefficient for tertiary enrolment (0.1160) indicates that expanding higher education strengthens digital development, with particularly strong effects in Southeast Asia where human capital remains a binding constraint. These findings underscore the pivotal role of higher education in accelerating digital transformation in emerging economies.

Three key insights emerge. First, institutional quality is a consistent driver of digital development across both regions. Second, income inequality constitutes a stronger structural barrier in Central Europe. Third, expanding tertiary education generates larger digital returns in ASEAN. These comparative results highlight the importance of region-specific policy strategies.

Across estimation approaches, governance quality emerges as the most robust determinant of digital performance, emphasising the role of institutional credibility and regulatory stability. However, policy priorities differ advanced economies should focus on digital inclusion and equitable access, while emerging economies should prioritise human capital expansion alongside institutional strengthening. Digital strategies should therefore be region-differentiated rather than uniform.

From an evidentiary perspective, the conclusions drawn in this section are supported by consistent results across multiple empirical strategies. The convergence of findings from static fixed-effects models, dynamic LSDVC estimation, and Bayesian Model Averaging indicates that the results are not driven by a single modelling choice. In addition, the use of standardized panel data methods strengthens cross-country comparability, while the findings remain aligned with existing literature that emphasizes the primacy of institutions over income levels once governance and inequality are accounted for. Together, these features provide a strong empirical basis for the study's conclusions.

5. DISCUSSIONS AND CONCLUSION

5. 1. SYNTHESIS OF MAIN FINDINGS

The convergence of results across dynamic LSDVC, static fixed-effects, and Bayesian Model Averaging provides strong evidence that three variables: Rule of law, income inequality and tertiary enrolment are the most robust determinants of digital development. Their consistent significance across alternative specifications indicates that they function as structural drivers rather than model-dependent artefacts.

Institutional quality, proxied by the rule of law, exhibits a stable and positive effect across all models, confirming that credible governance is a necessary precondition for digital transformation. Strong institutions reduce uncertainty, enhance regulatory credibility, and enable economic and educational resources to translate into digital progress.

Income inequality shows a persistent negative association with digital outcomes, suggesting that distributional imbalances constrain digital inclusion even when infrastructure and skills are available. Digital strategies must therefore prioritise equitable access alongside aggregate performance.

Tertiary enrolment underscores the central role of higher-level human capital formation in sustaining digital advancement. By contrast, GDP per capita, government effectiveness, and education spending lose robustness once dynamics and model uncertainty are considered, indicating that resource levels matter primarily through institutional quality and inclusiveness rather than as independent drivers.

Overall, the evidence suggests that digital development is path dependent, shaped more by institutional credibility and equitable distribution than by income alone, with higher education serving as a durable engine of long-term transformation.

5. 2. REGIONAL INSIGHTS

The comparative analysis shows that while the core determinants of digital development are relevant in both Central Europe and Southeast Asia, their relative importance differs across regions. This highlights the role of context in shaping how institutional, economic, and human capital factors translate into digital outcomes.

Institutional quality, proxied by the rule of law, exerts a consistent positive effect in both regions, suggesting that credible governance is a universal precondition for digital transformation. By contrast, income inequality has a stronger negative impact in Central Europe, where infrastructure and educational attainment are largely established, making inclusiveness the primary constraint.

Tertiary enrolment displays the opposite pattern: its marginal effect is stronger in Southeast Asia, where expanding higher education directly enhances digital capacity, while in Central Europe the impact is weaker due to saturation effects.

These asymmetries imply differentiated policy priorities: Central Europe should focus on improving inclusiveness, whereas Southeast Asia should prioritise human capital expansion to accelerate convergence.

5. 3. POLICY IMPLICATIONS

The findings suggest differentiated policy priorities for Central Europe and Southeast Asia, alongside shared governance challenges.

In Central Europe, the primary objective is to enhance digital inclusiveness. This requires targeted inequality-mitigation measures such as broadband subsidies, digital vouchers, and training for vulnerable groups. EU cohesion funds should be strategically allocated to reduce regional disparities in infrastructure and skills, while national digital strategies must embed equity to ensure accessible e-government services and broadband rollout for lower-income and marginalised populations.

In Southeast Asia, the central opportunity lies in human capital expansion. Increasing access to tertiary education through scholarships and public–private partnerships, aligning curricula with digital industry demands, and strengthening digital literacy at earlier education levels are critical to sustaining digital gains.

For both regions, governance reform remains fundamental. Transparent institutions, independent regulatory bodies, and anti-corruption safeguards are essential for fostering trust and ensuring effective deployment of digital resources.

Overall, Central Europe should prioritise inequality mitigation and institutional credibility, whereas Southeast Asia should focus on expanding and upgrading higher education alongside governance strengthening to accelerate digital convergence.

5. 4. LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

This study has several limitations. First, although the analysis incorporates institutional, economic, and human capital determinants, it does not account for cultural and behavioural factors such as risk aversion, institutional trust, privacy concerns, or openness to innovation, which can significantly influence digital adoption (Lin et al., 2021; Aleisa, 2024). These factors often interact with institutional variables, yet comparable cross-country data are limited. Future research could address this gap through survey-based or qualitative approaches at the micro level.

Second, the analysis relies solely on the E-Government Development Index (EGDI). While harmonised and multidimensional, EGDI primarily reflects public-sector digitalisation and may not fully capture broader digital economy dynamics. Complementary measures such as the Network Readiness Index (NRI), Digital Economy and Society Index (DESI), or ASEAN Digital Integration Index (ADII) could provide a more comprehensive perspective, subject to harmonisation constraints.

Third, the small-N, moderate-T panel limits methodological options. Although LSDVC, fixed effects with Driscoll-Kraay errors, and Bayesian Model Averaging mitigate several biases, the findings should be interpreted cautiously. Replication using larger samples, extended time horizons, or mixed-method designs would enhance robustness and external validity.

Future research should therefore expand both conceptual and empirical scope to deepen understanding of regional digital disparities and strengthen policy relevance.

5. 5. CONCLUSION

This study examined the determinants of digital development across 18 countries in Central Europe and Southeast Asia over the period 2002–2024. Using a parsimonious econometric framework that combines bias-corrected LSDVC estimation, static fixed effects with robust standard errors, and Bayesian Model Averaging, it identified the most robust predictors of the digital gap. The findings consistently highlight institutional quality (rule of law), income inequality, and tertiary education enrolment as the key structural drivers, while GDP per capita loses explanatory power once institutional and distributional factors are accounted for.

The results also reveal important regional contrasts. Although the rule of law is universally significant, inequality constitutes a stronger constraint in Central Europe, whereas tertiary education expansion generates larger digital returns in Southeast Asia. These patterns underscore the context-dependent nature of digital transformation and the persistence dynamics that risk reinforcing divergence between leaders and laggards.

The study contributes methodologically by applying small-sample-consistent dynamic estimation and model averaging to a comparative regional panel, and substantively by linking institutional credibility, distributional equity, and human capital formation to digital outcomes. Policy implications are region-specific: enhancing inclusion in Central Europe, expanding higher education capacity in Southeast Asia, and strengthening governance credibility in both regions.

Overall, narrowing the digital gap requires more than infrastructure investment. Digital transformation depends fundamentally on credible institutions, equitable economic structures, and sustained human capital development tailored to regional conditions.

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